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Optimal non-destructive evaluation of concrete by coupling NDT methods

Bouchra Kouddane

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THÈSE EN COTUTELLE PRÉSENTÉE
POUR OBTENIR LE GRADE DE
DOCTEUR DE
L'UNIVERSITÉ DE BORDEAUX
ET DE L'UNIVERSITÉ
MOHAMMED V DE RABAT

ÉCOLE DOCTORALE SCIENCES PHYSIQUES ET DE L'INGÉNIEUR
SPÉCIALITÉ : MÉCANIQUE

ÉCOLE DOCTORALE SCIENCES ET TECHNIQUES DE L'INGÉNIEUR
SPÉCIALITÉ : GÉNIE CIVIL

Par Bouchra KOUDDANE

**ÉVALUATION NON DESTRUCTIVE OPTIMALE DES BÉTONS PAR
COUPLAGE DES MÉTHODES CND / OPTIMAL NONDESTRUCTIVE
EVALUATION OF CONCRETE BY COUPLING NDT METHODS**

Sous la direction de : Zoubir Mehdi Sbartai (UB) et Nouzha Lamdouar (UM5R)

Soutenue le 09/05/2024

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Évaluation non-destructive optimale des bétons par couplage des méthodes CND

Résumé

Appréhender les caractéristiques mécaniques du béton in situ est essentiel pour déterminer la capacité structurelle à la fois des structures existantes et des nouvelles constructions. La méthodologie récente d'évaluation de la résistance du béton dans une structure existante consiste à intégrer des techniques de Contrôle Non Destructif (CND) avec des mesures destructives (carottage) pour établir un modèle de conversion qui corrèle la résistance mécanique avec les mesures non destructives. Par la suite, le modèle de conversion est appliqué pour estimer la résistance mécanique locale à chaque emplacement de test en fonction des valeurs CND correspondantes.

Le test du rebond (RH) et le test de la vitesse des ondes ultrasonores (UPV) sont largement utilisés pour estimer la résistance à la compression du béton. Cependant, l'exactitude des résultats obtenus par ces méthodes peut être influencée par divers facteurs. Pour atténuer ces effets, la combinaison stratégique de ces deux tests non destructifs offre un moyen efficace d'évaluer la résistance du béton dans les structures existantes. Par conséquent, l'objectif de cette thèse est d'analyser la méthodologie d'évaluation des structures en combinant des techniques non destructives et de fournir des recommandations pratiques qui peuvent améliorer la fiabilité de l'évaluation de la résistance in-situ du béton. À cette fin, un simulateur a été développé pour analyser la méthodologie d'évaluation non destructive en utilisant un vaste ensemble de données provenant de diverses sources, notamment des études in situ, ainsi que des données synthétiques générées.

La principale contribution de cette étude est de proposer une nouvelle approche d'identification de modèle basée sur l'optimisation multi-objectifs pour prédire la résistance moyenne du béton et sa variabilité, en se basant sur la combinaison des mesures CND. Des simulations Monte Carlo ont été réalisées pour vérifier les performances en tenant compte de l'incertitude des mesures CND et de la variabilité du béton. Les résultats ont mis en évidence l'efficacité de la méthode multi-objectifs dans la détermination de la résistance moyenne et la variabilité de la résistance, par rapport à d'autres approches. De plus, cette approche innovante permet d'obtenir une précision améliorée dans l'estimation des propriétés du béton avec un nombre réduit de prélèvements par rapport aux méthodes traditionnelles.

En outre, l'efficacité de diverses stratégies d'échantillonnage suggérées a été évaluée dans cette étude afin de sélectionner les emplacements optimaux pour les extractions de carottes. Une représentation précise et approfondie de la structure examinée peut être obtenue en choisissant soigneusement les emplacements de carottage. À travers des comparaisons approfondies, l'étude vise à déterminer le plan d'échantillonnage qui correspond le mieux aux objectifs spécifiques de l'évaluation de la résistance du béton. Il est suggéré d'utiliser l'échantillonnage

par optimisation de la variance, qui semble être une alternative appropriée pour réduire les incertitudes inhérentes au processus d'évaluation non destructive.

Un autre aspect innovant implique l'établissement d'un cadre conceptuel pour faciliter la conception des coûts du cycle de vie des structures en béton qui se détériorent, en mettant l'accent sur la fiabilité. Ce travail montre l'efficacité de la minimisation du coût total attendu du cycle de vie d'une structure, afin de trouver la stratégie optimale d'inspection et de réparation des structures qui se détériorent au fil du temps. Les résultats ont été obtenus en utilisant deux stratégies différentes : l'une utilisant des intervalles de temps d'inspection uniformes, où l'optimisation est limitée au nombre d'inspections, et l'autre utilisant des intervalles de temps d'inspection non uniformes, où le nombre d'inspections et les intervalles de temps sont tous deux optimisés. En ce qui concerne la stratégie d'optimisation, le plan d'inspection/réparation à intervalles non uniformes est plus rentable et nécessite moins d'inspections/réparations au cours de la durée de vie de la structure.

Mots-clés : résistance in-situ, résistance moyenne, variabilité du béton, vitesse des ondes ultrasoniques, rebond, CND, combinaison, simulation, optimisation, incertitude, stratégie d'échantillonnage, stratégie d'inspection/réparation.

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Optimal Non-Destructive Evaluation of Concrete by Coupling NDT Methods

Abstract

Understanding the in situ mechanical properties of concrete is essential for determining the structural capacity of both existing structures and new constructions. The recent methodology for assessing concrete strength in an existing structure involves integrating nondestructive testing (NDT) techniques with destructive measurements (coring) to establish a conversion model that correlates mechanical strength with nondestructive measurements. Subsequently, the conversion model is applied to estimate the local mechanical strength at each testing location based on the corresponding NDT values.

The Rebound Hammer (RH) test and the Ultrasonic Pulse Velocity (UPV) test are widely used for estimating the compressive strength of concrete. However, the accuracy of the results obtained from these methods can be influenced by various factors. To mitigate these effects, the strategic combination of these two nondestructive tests provides an effective way to evaluate concrete strength in existing structures. Therefore, the aim of this thesis is to analyze the assessment methodology of structures by combining nondestructive techniques and to offer practical recommendations that can enhance the reliability of in-situ concrete strength. For this purpose, a simulator was developed to analyze the methodology of nondestructive assessment using an extensive dataset derived from various sources, including in-situ studies, as well as generated synthetic data.

The primary contribution of this study is to propose a new model identification approach based on multi-objective optimization to predict the mean strength of concrete and its variability, based on the combination of NDT measurements. Monte Carlo simulations were carried out to check the performance by considering the uncertainty of NDT measurements and the variability of concrete. The results highlighted the effectiveness of the multi-objective method in determining both the average strength and the variability of strength compared to other approaches. Furthermore, this innovative approach enables enhanced accuracy in estimating concrete properties with a reduced number of cores compared to traditional methods.

In addition, a thorough and accurate representation of the structure under examination can be achieved by carefully choosing the core locations. The efficacy of various suggested sample strategies has been evaluated in this study in order to select the optimal locations for the core extractions. Through these thorough comparisons, the study aims to discover the sampling plan that best aligns with the specific objectives of evaluating concrete strength. It is suggested to use variance sampling, which appears to be a suitable alternative for reducing inherent uncertainties in the nondestructive assessment process.

Another innovative aspect involves establishing a conceptual framework to facilitate the life-cycle cost design of deteriorating concrete structures, with a focus on reliability. This work demonstrates the efficiency of minimizing the expected total life cycle cost of a structure, in

order to find the optimal strategy for inspecting and repairing structures that deteriorate over time. The results were obtained using two different strategies: one using uniform inspection time intervals, where optimization is limited to the number of inspections, and the other using non-uniform inspection time intervals, where both the number of inspections and time intervals are optimized. Regarding the optimization strategy, the inspection/repair plan with nonuniform intervals is more cost-effective and requires fewer inspections/repairs over the structure's lifetime.

Keywords: in-situ strength, mean strength, concrete variability, ultrasonic pulse velocity, rebound hammer, NDT, combination, simulation, optimization, uncertainty, sampling strategy, inspection/repair strategy.

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Bouchra Kouddane

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LIST OF ABBREVIATIONS / NOTATIONS

NDT	Nondestructive testing
DT	Destructive testing
RC	Reinforced concrete
f_c	Core compressive strength corresponding to one test location
$f_{c\ est}$	Estimated compressive strength corresponding to one test location
a, b_1, b_2, \dots, b_n	Parameters of the conversion model
NC	Number of cores used to identify the model
S_R	Moisture content (%)
f_{ist}	True in-situ compressive strength corresponding to one test location in the case of synthetic data
f_{uncal}	Estimated compressive strength calculated from an uncalibrated prior model selected from literature or standards
$\bar{f}_{c\ est}$	Estimated concrete mean strength
$s(f_{c\ est})$	Estimated concrete strength variability
$s(\bar{f}_{c\ est})$	The standard deviation of the estimated mean strength, which means the variability of the estimated mean strength
$s(s(f_{c\ est}))$	The standard deviation of the estimated strength variability, which means the variability of the estimated concrete strength variability
RME	The relative error on the mean
RSE	The relative error on the standard deviation

LIST OF ABBREVIATIONS / NOTATIONS

RMSE	Root mean square error
NRMSE	Normalized root mean square error
NT	Total number of test locations for NDT measurements
r^2	Coefficient of determination
UPV	Ultrasonic pulse velocity test
RH	Rebound hammer test
V	Ultrasonic Pulse Velocity test result corresponding to one test location
R	Rebound Hammer test result corresponding to one test location
x	Test result, V or R, corresponding to one test location
n_i	The sample size chosen from each stratum, which is proportional to the size of the stratum within the overall population NT and the number of cores NC
CDF	Cumulative distribution function
$RMSE_{fit}$	Fitting root mean square error
$RMSE_{pred}$	Prediction root mean square error
$E(t)$	Young's modulus of the concrete at a specific time
η	Damage intensity
k	The damage growth rate (MPa/year)
PoD	The probability of damage detection, which signifies the likelihood that the NDT method can accurately identify the existing damage

LIST OF ABBREVIATIONS / NOTATIONS

$\eta_{0.5}$	The damage intensity at which the NDT method exhibits a 50% probability of successfully detecting the damage
C_{INSP}	The overall expected inspection cost
T_{insp}	The time at which each inspection occurs
N_{insp}	Number of inspections
C_{REP}	The overall expected repair cost
P_f	The probability of failure
C_{FAIL}	The overall expected failure cost
C_{init}	Initial construction cost
P(R)	The probability of repairing
P(NR)	The probability of not repairing
T	The life-cycle of the structure
t_i	The time interval between two inspections
r	The annual discount rate

LIST OF PUBLICATIONS

Articles in International Peer-Reviewed Journals

Kouddane, B., Sbartai, Z.M., Alwash, M., Ali-Benyahia, K., Elachachi, S.M., Lamdouar, N., Kenai, S., 2022. Assessment of Concrete Strength Using the Combination of NDT - Review and Performance Analysis. Applied Sciences 12, 12190. <https://doi.org/10.3390/app122312190>

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Kouddane, B., Sbartai, M., Elachachi, S.-M., Lamdouar, N., Cherradi, T., 2022. Optimisation multi-objectif pour évaluer la résistance à la compression du béton par combinaison de techniques non destructives. Lille, les 40èmes Rencontres Universitaires de Génie Civil de l'AUGC. <https://doi.org/10.26168/ajce.40.1.16>

Kouddane, B., Sbartai, M., Elachachi, S.-M., Lamdouar, N., 2023. Life-cycle framework based on non-destructive evaluation for optimal inspection/repair plan. Paris, Congrès Français du Génie Civil : Ville du futur et changement climatique (CFGC). (Prix René HOUPERT) <https://doi.org/10.26168/ajce.41.1.59>

Kouddane, B., Sbartai, M., Elachachi, S.-M., Lamdouar, N., 2023. Analyse du coût de cycle de vie d'une structure en détérioration pour un plan d'inspection/réparation optimal. La Rochelle, 12ème Journées de Fiabilité des Matériaux et des Structures (JFMS).

Kouddane, B., Sbartai, M., Elachachi, S.-M., Lamdouar, N., 2023. Stratégies d'échantillonnage pour l'évaluation non destructive de la résistance du béton. Nantes, 8ème Congrès International Francophone DiagnoBéton. <https://doi.org/10.26168/ajce.41.4.22>

RÉSUMÉ SUBSTANTIEL

Introduction

L'évaluation précise de toute structure repose sur la disponibilité d'informations essentielles concernant la géométrie des éléments structuraux, les critères de chargement appliqués, ainsi que les propriétés mécaniques des matériaux impliqués. Dans ce contexte, la détermination de la résistance à la compression du béton in situ émerge comme un élément clé dans l'analyse des structures existantes en béton armé. Deux approches principales sont couramment utilisées à cet effet : les essais sur carottes et le contrôle non destructif « CND ». Les essais sur carottes fournissent des résultats fiables, mais ils sont souvent perçus comme intrusifs et onéreux. D'un autre côté, les techniques non destructives offrent une alternative plus simple et économique. Bien que les techniques non destructives offrent des avantages considérables en termes de coût et de préservation de l'intégrité de la structure, il est essentiel de prendre en compte les limitations et les incertitudes associées à ces méthodes lors de l'interprétation des résultats. Opter pour une combinaison de ces deux approches, en intégrant les avantages des essais sur carottes en termes de fiabilité et de précision avec la simplicité et la rentabilité des méthodes non destructives, s'avère être la méthode la plus efficace.

Le test du rebond et le test des ondes ultrasonores représentent deux méthodes non destructives fréquemment utilisées dans la pratique pour évaluer la résistance du béton. Le test du rebond « RH » mesure la dureté de la surface du béton en évaluant l'impact du marteau sur cette surface. D'autre part, le test des ondes ultrasonores « UPV » évalue la vitesse à laquelle les ondes ultrasonores se propagent à travers le béton. Souvent, ces deux techniques sont utilisées conjointement afin d'obtenir une évaluation plus complète et précise de la résistance du béton dans une structure donnée. Cependant, l'un des défis majeurs dans l'utilisation de ces méthodes réside dans l'élaboration d'un modèle de conversion précis. Ce modèle de conversion est essentiel car il établit une relation entre les mesures du CND obtenues et les propriétés mécaniques du béton, en particulier sa résistance à la compression. L'objectif fondamental de cette étude est d'assurer une estimation aussi précise et fiable que possible, ce qui requiert un contrôle rigoureux de la qualité du modèle de conversion.

Méthodes et Outils

Dans une première phase, notre objectif est de définir les principaux éléments de la stratégie d'évaluation, distinguant ainsi deux étapes essentielles : le programme d'investigation et l'estimation de la résistance du béton. Le programme d'investigation est élaboré en fonction des ressources disponibles, que ce soit en termes de budget ou de délais. Il englobe plusieurs aspects essentiels comme le choix de la technique CND à utiliser, que ce soit la mesure de rebond, la mesure de vitesse des ultrasons ou une combinaison des deux, la détermination du nombre de mesures pour chaque type d'essai, ainsi que le nombre de répétitions, sans oublier la méthodologie de sélection des emplacements de tests. L'estimation de la résistance constitue une étape cruciale exigeant une analyse approfondie des données d'essais et un traitement minutieux afin d'obtenir un modèle de conversion pertinent. Elle comporte le choix de la forme du modèle de conversion, pouvant être linéaire, polynomiale, exponentielle, et le choix de l'approche pour identifier ses paramètres. En fin de compte, le modèle choisi est appliqué pour estimer la résistance mécanique locale dans les endroits où seuls les résultats des essais non destructifs sont disponibles. Ces valeurs estimées peuvent alors être exploitées pour calculer à la fois la résistance moyenne et sa variabilité.

Dans cette étude, l'analyse détaillée des ressources se basera principalement sur l'exploration des données issues des résultats des méthodes CND ainsi que des mesures de résistance à la compression des carottes. Deux catégories de séries de données sont utilisées tout au long de cette recherche : celles provenant de structures réelles et celles générées de manière synthétique. Le jeu de données expérimentales est collecté dans le cadre de partenariats de recherche avec d'autres chercheurs (Ali Benyahia et al., 2017). Les informations du jeu de données proviennent d'une procédure d'investigation approfondie menée sur un bâtiment existant. Les données synthétiques sont générées à l'aide de simulations de Monte Carlo, une technique établie pour générer des échantillons aléatoires basés sur des distributions de probabilité connues. Ces simulations sont minutieusement élaborées pour reproduire des situations réalistes et rendre compte des interactions complexes qui influent sur la résistance du béton.

L'intérêt de la combinaison « SonReb »

La combinaison de plusieurs méthodes d'essais non destructifs suscite un intérêt particulier en tant qu'approche prometteuse pour améliorer la prédiction de la résistance du béton. Le terme « Sonreb », qui associe les termes « Sonic » et « Rebound », décrit les caractéristiques clés de la méthode de contrôle qui combine la mesure de la vitesse de propagation des ondes

ultrasonores avec la mesure de l'indice de rebond. En employant simultanément ces deux tests, la méthode SonReb est en mesure de compenser les variations potentielles causées par différents facteurs qui pourraient influencer les résultats. Cette approche améliore la précision et la fiabilité de l'évaluation de la résistance du béton. Pour prédire avec précision la résistance à la compression du béton à partir des mesures obtenues par la méthode SonReb, plusieurs méthodes sont couramment utilisées. Celles-ci englobent des approches telles que la modélisation informatique, l'intelligence artificielle et les modèles de régression multiple. L'objectif principal de ces méthodes est de développer un modèle de conversion robuste et précis qui puisse estimer de manière fiable la résistance du béton. Une telle précision dans la prédiction de la résistance du béton contribue directement à une meilleure évaluation de la sécurité et de la performance des structures en béton, ainsi qu'à des décisions plus éclairées en matière de maintenance et de réhabilitation.

Développement d'une nouvelle approche d'identification de modèle : approche multi-objectifs

Il est essentiel de souligner que les approches classiques pour estimer la résistance du béton se concentrent généralement sur la détermination de la valeur moyenne de la résistance, sans prendre explicitement en compte la variabilité de la résistance. Ainsi, une nouvelle approche, nommée approche « bi-objectifs » a été proposée par (Alwash et al., 2016). Contrairement aux méthodes conventionnelles, cette approche a pour principaux objectifs d'estimer avec précision la valeur moyenne et la variabilité de la résistance du béton. Cependant, elle présente l'inconvénient de ne pas pouvoir être utilisée dans le cas de la combinaison de plusieurs techniques non destructives. C'est pourquoi nous proposons de résoudre ce problème en introduisant une nouvelle méthode basée sur l'optimisation multi-objectifs. Cette méthode permet de prédire à la fois la moyenne et la variabilité de la résistance lorsqu'au moins deux méthodes d'essais non destructifs sont utilisées.

Pour évaluer l'efficacité de cette approche, des simulations Monte Carlo sont conduites, prenant en considération l'incertitude des mesures CND ainsi que la variabilité propre au béton. Trois paramètres d'évaluation essentiels sont pris en compte : la résistance moyenne, la variabilité de la résistance et l'erreur quadratique moyenne estimée. Dans cette optique, une vaste gamme de données, à la fois expérimentales et simulées, provenant d'essais destructifs et non destructifs, est minutieusement examinée. L'analyse des données synthétiques est ensuite comparée aux

résultats obtenus à partir de l'ensemble des données expérimentales. Cette comparaison rigoureuse vise à évaluer l'efficacité de l'approche multi-objectifs proposée.

L'approche multi-objectifs utilisée dans cette méthodologie d'évaluation se concentre sur l'optimisation de trois fonctions objectives pour évaluer la résistance moyenne et son écart type à l'aide du CND. Ces fonctions comprennent l'erreur quadratique moyenne « RMSE », l'erreur relative sur la moyenne « RME » et l'erreur relative sur l'écart type « RSE ». L'erreur quadratique moyenne donne une indication sur la précision des prédictions d'un modèle par rapport aux données observées. L'erreur relative sur la moyenne évalue dans quelle mesure le modèle reflète la tendance centrale des données. L'erreur relative sur l'écart type évalue la capacité du modèle à rendre compte de la variabilité ou de la dispersion des données. Un code MATLAB a été élaboré pour effectuer le processus d'optimisation en utilisant un algorithme génétique afin de trouver les paramètres du modèle de conversion qui minimisent simultanément les trois fonctions objectives. Cette étude met en évidence le principe fondamental de la méthodologie d'optimisation et présente les premiers résultats attestant de l'efficacité de l'approche multi-objectifs dans la prédiction de la résistance à la compression. En parallèle, cette approche permet d'optimiser le nombre de carottes nécessaires, ce qui se traduit par une amélioration de l'efficacité, de la rentabilité et une réduction de l'impact sur les structures en béton. Cette combinaison stratégique d'essais non destructifs offre ainsi un moyen complet et efficace d'évaluer la résistance du béton dans les structures existantes.

Améliorer l'évaluation non destructive de la résistance en optimisant la sélection des emplacements de carottage

Compte tenu de la problématique de fiabilité dans l'estimation de la résistance in situ des structures en béton, cette étude se concentre sur un élément clé du processus d'investigation, à savoir la sélection des emplacements pour l'extraction des carottes de béton. Plusieurs plans d'échantillonnage sont examinés, notamment l'échantillonnage conditionnel (RILEM), l'échantillonnage par similarité, l'échantillonnage stratifié proportionnel et l'échantillonnage par optimisation de la variance. Une analyse statistique rigoureuse est menée sur ces différents plans d'échantillonnage afin d'évaluer leur efficacité par rapport à la méthode traditionnelle de carottage aléatoire. L'objectif de cette analyse est de mesurer de manière quantitative les effets résultant de divers facteurs. Ces facteurs comprennent l'utilisation des deux approches bi-objectifs et multi-objectifs pour identifier les paramètres des modèles, l'augmentation progressive du nombre de carottes prélevées, la mise en œuvre de différentes stratégies

d'échantillonnage et l'utilisation de techniques de CND individuelles ou combinées. L'objectif de cette étude est d'identifier le plan d'échantillonnage le mieux adapté aux objectifs spécifiques de l'évaluation de la résistance du béton. Les résultats mettent en évidence une amélioration significative de la précision dans l'évaluation de la résistance du béton, lorsqu'on combine les méthodes CND (approche multi-objectifs) et lorsqu'on utilise l'échantillonnage par optimisation de la variance. Ce plan d'échantillonnage présente des atouts majeurs en réduisant les incertitudes inhérentes au processus d'évaluation. Cet avantage est d'autant plus prononcé lorsque le nombre de carottes est limité, une situation courante en pratique. En outre, opter pour l'échantillonnage de variance au lieu du carottage aléatoire peut diminuer le nombre de carottes requis pour un niveau de confiance donné. De plus, cette approche présente l'avantage de ne pas entraîner de coûts supplémentaires, tout en offrant la possibilité d'améliorer la précision des résultats de l'évaluation.

Optimisation des stratégies d'inspection et de maintenance pour les structures en béton

L'évaluation de la durée de service des ouvrages en béton constitue un pilier essentiel de l'ingénierie civile. Elle repose sur une compréhension approfondie des mécanismes de dégradation structurelle, qui sont influencés par de nombreux facteurs, tels que l'environnement, les charges appliquées, la qualité des matériaux et la conception structurelle. Parmi les méthodes couramment utilisées pour l'évaluation des structures en béton, le contrôle par ultrasons est un outil de contrôle non destructif largement employé. Dans cette étude, une approche novatrice est présentée pour optimiser la stratégie d'inspection et de réparation au fil de la durée de vie de la structure en béton. L'objectif principal de cette méthodologie est de minimiser le coût total du cycle de vie de la structure, tout en garantissant que les contraintes et exigences spécifiques soient respectées. Pour ce faire, les variables de décision prises en considération sont les moments auxquels les inspections et les réparations doivent être effectuées, ainsi que le nombre optimal d'inspections et de réparations à réaliser tout au long de la durée de vie de la structure. En optimisant ces variables de décision, il est possible d'élaborer une stratégie d'inspection et de réparation efficiente, économique et répondant aux normes de sécurité requises.

Dans l'optique de considérer l'influence du nombre d'inspections sur la stratégie d'inspection/réparation, il est essentiel de mener une analyse approfondie en explorant une plage de valeurs appropriée. Cette plage est définie entre 1 et 10 inspections au cours de la durée de

vie de la structure. Il est primordial de définir le nombre optimal d'inspections permettant de minimiser le coût global, tout en assurant des performances adéquates de la structure. Pour résoudre cette problématique d'optimisation, un programme informatique spécifique a été développé en utilisant le langage Python. Ce programme effectue le calcul du problème de minimisation en prenant en considération la plage de valeurs définie pour le nombre d'inspections. Il évalue les coûts attendus associés à chaque configuration et identifie celle qui optimise le coût global.

Il convient de noter qu'une stratégie d'inspection optimale prend en compte de nombreux aspects, notamment la qualité de l'inspection par CND, le taux de dommages attendu, le coût potentiel d'une défaillance, le taux d'actualisation net. Le programme prend également en considération la possibilité d'inspections uniformes ou non uniformes afin d'optimiser la stratégie d'inspection/réparation au cours de la durée de vie de la structure. L'utilisation d'intervalles d'inspection non uniformes représente une avancée majeure dans l'optimisation des stratégies d'inspection et de maintenance des structures en béton. Cette approche tient compte de la nature évolutive de la détérioration des structures au fil du temps. Contrairement aux intervalles d'inspection fixes, les intervalles non uniformes s'adaptent dynamiquement en fonction des besoins spécifiques de la structure et des conditions changeantes. En adaptant la fréquence des inspections en fonction de l'état réel de la structure et des indicateurs de dégradation, on peut cibler les moments où les inspections sont les plus cruciales. Cette flexibilité dans la planification des inspections offre l'opportunité d'optimiser la répartition des ressources et de répondre de manière plus efficace aux impératifs de sécurité et de fiabilité des structures, ce qui contribue à prolonger leur durée de vie de manière économique et durable.

Chapter One: Introduction

1 Problem statement

Several constructions, including bridges, tunnels, dams, and buildings, are built using concrete as the main construction material. Concrete is recognized for its good strength and durability, making it an ideal choice for constructing structures that must endure a variety of structural and environmental problems over time. Additionally, concrete is a cost-effective option due to the availability and affordability of its raw materials, including cement, aggregates, and water. Moreover, concrete's flexibility in shaping allows architects to transform their creative visions into reality. However, the aging of reinforced concrete structures necessitates a greater focus on evaluating material properties due to the lack of information about the mechanical characteristics of the original construction materials. Consequently, conducting an experimental campaign becomes imperative to assess the condition and performance of an existing reinforced concrete building.

Throughout their operational lifespan, structures experience a gradual decline in performance due to diverse environmental stressors (Liu and Frangopol, 2006). To ensure the safety and prolong the operational lifespan of these deteriorating structures, extensive researches have been dedicated to establishing cost-effective maintenance approaches (Estes and Frangopol, 2001; Frangopol et al., 1997; Garbatov and Guedes Soares, 2001; Kong and Frangopol, 2003). This involves precise modeling of applied loads, precise prediction of structural behavior, accurate estimation of management and maintenance costs over time, and the formulation of well-calibrated solutions (Liu and Frangopol, 2006). Improving the accuracy in assessing and predicting structural performance, achieved through the appropriate use of nondestructive testing techniques, leads to well-timed and optimal maintenance interventions. The methodologies explored in this study are universal and can be applied to a broad spectrum of structures affected by various forms of degradation.

Among the various mechanical and physical properties of concrete, compressive strength holds immense significance in the design of structural elements and in the calculation of their load-bearing capacity. During the construction of new structures, quality control is essential to ensure that the concrete meets specified standards and adheres to all relevant regulations. Additionally, when there are uncertainties regarding the concrete quality in a new construction project, it

becomes essential to assess the in-situ compressive strength as a means of addressing these concerns. Furthermore, when a structure's intended use changes, the concrete strength must be reassessed in order to precisely determine the structure's capacity in accordance with the updated specifications. Moreover, assessing concrete strength is crucial when evaluating damage resulting from fire, fatigue, overload, or environmental degradation. Finally, as our efforts to enhance building resilience against earthquakes continue to grow, it becomes imperative to conduct precise on-site evaluations of concrete strength in existing structures.

There are several testing methods available to estimate the in-situ strength of concrete. The core test is a direct method commonly used for this purpose, but it has significant drawbacks. Drilling can be technically challenging in some cases and even impossible in others, potentially compromising the stability of the structure. The second concern is, of course, economic, as the number of cores significantly increases the testing cost. Consequently, exploring nondestructive methods for assessing the condition of existing structures offers a good alternative from both an economic and technical perspective. Nondestructive methods are widely used to assess in-situ concrete strength (Alwash, 2017; Breysse, 2012; Breysse et al., 2019). These methods offer several advantages such as simplicity, speed, and cost-effectiveness compared to the core test. They also provide broader coverage of the structure and offers access to additional information. This includes insights into the spatial variability of concrete properties and the identification of homogeneous areas within the structure. However, they do not directly measure in-situ strength. Instead, they measure other properties, and compressive strength is derived from a correlation (conversion model) between the measured properties and strength.

A significant limitation that prevents the effective use of nondestructive testing results and core strength measurements lies in the fact that existing standards (ACI Committee 228, 2003; EN 13791, 2007) primarily focus on the procedures for conducting individual measurements. Unfortunately, they often fail when it comes to providing comprehensive guidance on how to execute an investigation program (Breysse, 2012; Breysse and Martínez-Fernández, 2014). For instance, the existing standards do not provide sufficient detail on essential aspects such as the cores sampling plan, which includes determining the specific positions for core extraction. Additionally, they do not specify the quantity of NDT measurements necessary to achieve a desired level of confidence or accuracy in the assessment. Moreover, these guidelines do not provide valuable insights into model identification approaches and the effectiveness of combining multiple NDT methods for a more robust evaluation. This gap in comprehensive

guidance can present challenges for engineers aiming to design and execute effective and reliable concrete assessment programs.

These observations show that a more thorough investigation program is required in order to consider these concerns and achieve the desired level of precision in strength evaluation. Therefore, as a solution to the identified limitations, the existing methodology revolves around creating a unique conversion model adapted to the combination of NDT methods. This model is developed using the multi-objective approach, by integrating data from both destructive and nondestructive tests. The strength of the concrete is then evaluated using the developed model at specific test locations where nondestructive measurement values are available for the concrete under consideration. The assessment strategy provides flexibility, requiring important determinations regarding the quantity of core test and the combination of suitable nondestructive methods along with their optimal testing locations. Additionally, essential decisions involve selecting the most effective inspection and repair strategy for deteriorating concrete structures with a focus on reliability. The management planning for deteriorating structures can be framed as an optimization problem, involving the consideration of several performance indicators such as system reliability, availability, condition and safety indices, as well as cost.

2 Scope of thesis

In the context of existing constructions, several situations such as renovation, modification, changes in usage or events like fires or earthquakes often necessitate a thorough evaluation of the concrete's strength within the structure. This assessment is indispensable for achieving a precise and comprehensive understanding of the structural capacity of the building (ACI 228, 2003). Evaluating and improving in-situ strength is an important step towards ensuring structural safety and resilience against potential defects. An evaluation of the damage growth model can serve as a valuable tool in assessing the decline in strength of a concrete structure when subjected to an aggressive environment. Indeed, a comprehensive understanding of deterioration mechanisms is fundamental. Furthermore, through life-cycle analysis, we can systematically evaluate the impacts of deterioration process, maintenance and repair actions on the performance and service life of structures (Liu and Frangopol, 2006; Moan, 2005).

In practical applications, key assessment benchmarks include the mean compressive strength, Young's Modulus, and the characteristic compressive strength. While the mean compressive strength represents a fundamental parameter, Young's Modulus is also important for structural

evaluations. Young's Modulus can be estimated indirectly from the compressive strength using empirical relationships (Aladejare et al., 2021; Vu et al., 2021). Furthermore, another important element of this assessment strategy is the determination of the characteristic strength. This parameter relies on both the mean compressive strength and the variability of compressive strength (Alwash, 2017; Breyse et al., 2019). Furthermore, in situations where the concrete strength exhibits high variability or when the different parts of the structure have varying composition or quality, it is advised by standards such as (ACI Committee 228, 2003; EN 13791, 2007) to divide the investigated structure into multiple test regions. In the current study, it is assumed that each dataset used for analysis belongs to a single test region. This research places a primary focus on estimating local strength values, mean strength, and variability in concrete strength. By carefully estimating these parameters, it is possible to accurately determine both the characteristic strength and Young's Modulus. This can help equipping engineers with essential data to make well-informed decisions concerning design, safety, and the overall performance of structures.

Estimating the concrete strength within the structure can be done by directly extracting cores from it, which is considered the most accurate method in terms of estimation precision. Nevertheless, this approach can be expensive and is not always permitted due to the potential structural degradation it may cause. NDT provides a partial solution by offering a rapid, cost-effective, and repeatable alternative (Ali-Benyahia et al., 2019; Alwash, 2017; Bień et al., 2015; Facaoaru, 1969). Nondestructive methods, such as Rebound Hammer, Ground Penetrating Radar, Acoustic Emission testing, Thermography and Ultrasonic Pulse Velocity, are extensively employed in the field of civil engineering and construction to evaluate the in-situ strength of concrete (Jones, 1962; McCann and Forde, 2001; Verma et al., 2013). Nevertheless, in the context of this research, the attention is directed towards two specific methods: Rebound Hammer and Ultrasonic Pulse Velocity. The selection of these two methods is based on various factors, primarily their extensive use in evaluating existing reinforced concrete structures. Their popularity within the construction industry and engineering community stems from their practicality, efficiency, and reliability. The Rebound Hammer provides a quick and straightforward way to estimate concrete strength by measuring the rebound resulting from an impact, making it suitable for on-site evaluations. On the other hand, the Ultrasonic Pulse Velocity method employs high-frequency sound waves to assess concrete properties, offering a non-invasive way to inspect concrete quality and integrity. The SonReb technique suggests combining the two methods to offset their low reliability if considered separately. For years,

this concept has been introduced with the aim of enhancing the evaluation process compared to relying on a single NDT method (Ali-Benyahia et al., 2019, 2017; Breysse et al., 2008; Sbartai et al., 2018). In order to combine the Ultrasonic Pulse Velocity and Rebound Hammer, many empirical, multi-parametric models were proposed in the literature as linear, power, exponential, or polynomial (Bensaber et al., 2023; Craeye et al., 2017; Cristofaro et al., 2020; Qasrawi, 2000). However, it is important to note that these models do not precisely represent the specific concrete being examined. This highlights the need to establish new models for each different situation, based on a robust model identification approach.

To assess the quality of nondestructive concrete strength estimation, this study relies on an extensive inspection campaign involving rebound and ultrasonic testing, as well as coring, conducted on structural elements of an existing construction, including columns and beams. Approximately 100 sets of data triplets (100 core strength measurements and 100 nondestructive testing measurements) are collected for this study. Due to the limited number of experimental data, synthetic simulations are also performed. To generate this synthetic dataset, we will employ the Monte Carlo simulation technique. This method allows generating a diverse set of random samples characterized by known probability distributions, giving us a valuable and controlled dataset for our analyses and evaluations. We will also conduct an extensive statistical analysis of the data and model performance to quantify the impact of various factors. These factors include the number of cores used for calibration, the model identification approach, the effective use of a combination of two techniques and the implementation of the different sampling strategies.

In the last chapter, a comprehensive framework is developed to address various aspects including probabilistic optimization, reliability, uncertainties related to damage propagation and inspection methods, deterioration model, expected life-cycle costs and nondestructive testing. The aim of this framework is to find the optimum inspection and maintenance planning for a deteriorating structure. The methodology employed in this study is specifically used for analyzing bridges structures that experience damage. However, it is important to note that these approaches can be applied to any type of structure that undergoes various forms of deterioration. It is also important to note that maintenance actions depend on the outcome of inspection. If any damage is detected, it is important to apply maintenance as soon as possible. However, in practice, the lack of financial resources might make it more difficult to apply maintenance right away after damage is detected. It should be noted that in this study, the decision to initiate repair after damage detection is probability-based.

3 Objective and general research methodology

The main objective of this thesis is to conduct a comprehensive analysis of nondestructive assessment, aiming not only to estimate the concrete strength within the structure but also to evaluate and characterize the quality of this estimation. A comprehensive literature review on the evaluation of concrete strength through the combination of nondestructive testing techniques in conjunction with cores is provided. The significance of Rebound Hammer and Ultrasonic Pulse Velocity in concrete strength assessment is extensively discussed, covering the principles, devices, methodologies, and factors affecting test outcomes. Moreover, the reliability of results obtained from these NDT methods is considered, and relevant standards are referenced to ensure testing practices.

When assessing in-situ concrete, the ability to predict its strength becomes imperative due to the inherent variability that exists in the composition of concrete mixes. This necessitates the development of empirical models that establish a relationship between on-site nondestructive measurements and the concrete characteristics within the structure. The primary objective of this thesis revolves around analyzing and comparing the quality of estimation using various model identification approaches. The focus of this evaluation is to assess both the mean strength and variability of concrete strength by integrating NDT methods; using both synthetic data and experimental data. Our work will also cover original contributions in designing an optimal testing program. This program involves a well-balanced combination of NDT techniques and the multi-objective optimization approach to capture both the mean strength and concrete strength variability.

Furthermore, as part of this study's scope, an exhaustive evaluation of the effectiveness of several proposed sampling methods is conducted. The aim is to provide guidance on selecting the most appropriate location for core extraction. By rigorously examining the different sampling approaches, the study aims to enhance the precision and effectiveness of the core extraction process, ultimately contributing to more reliable and accurate results in the evaluation of concrete strength. In addition, the analysis conducted within this study aims to quantify the collective impacts stemming from various factors. These factors include the number of cores collected, the model identification approach being used, the implementation of the different sampling strategies, and the use of either individual or combined nondestructive testing techniques.

Moreover, the thesis introduces a conceptual framework designed to simplify the computation of life-cycle costs for deteriorating concrete structures, with a primary focus on enhancing their reliability. In this framework, the case study revolves around a reinforced concrete bridge susceptible to damage. The focus of this study lies in the gradual decrease of stiffness, quantified by Young's modulus, over time. The use of nondestructive procedures is therefore required due to the nature of the damage. This study shows the efficiency of minimizing the expected total life-cycle cost in order to find the optimal inspection/repair strategy of structures that deteriorate over time. The cost analysis covers all elements that contribute to the overall life-cycle cost of the system. To achieve this, the study employs an event tree model, which provides a systematic way to arrange and evaluate the repair possibilities. In addition, the analysis takes into account several critical factors, including the quality of inspection methods, the impacts of damage rate on structural reliability, the impact of cost associated with failure and the influence of the time value of money. The methodology developed in this study has the capability to integrate economic considerations such as cost-effectiveness, and safety concerns such as ensuring structural integrity and preventing failures. The current thesis will adhere to the research methodology outlined in Figure 1.1.

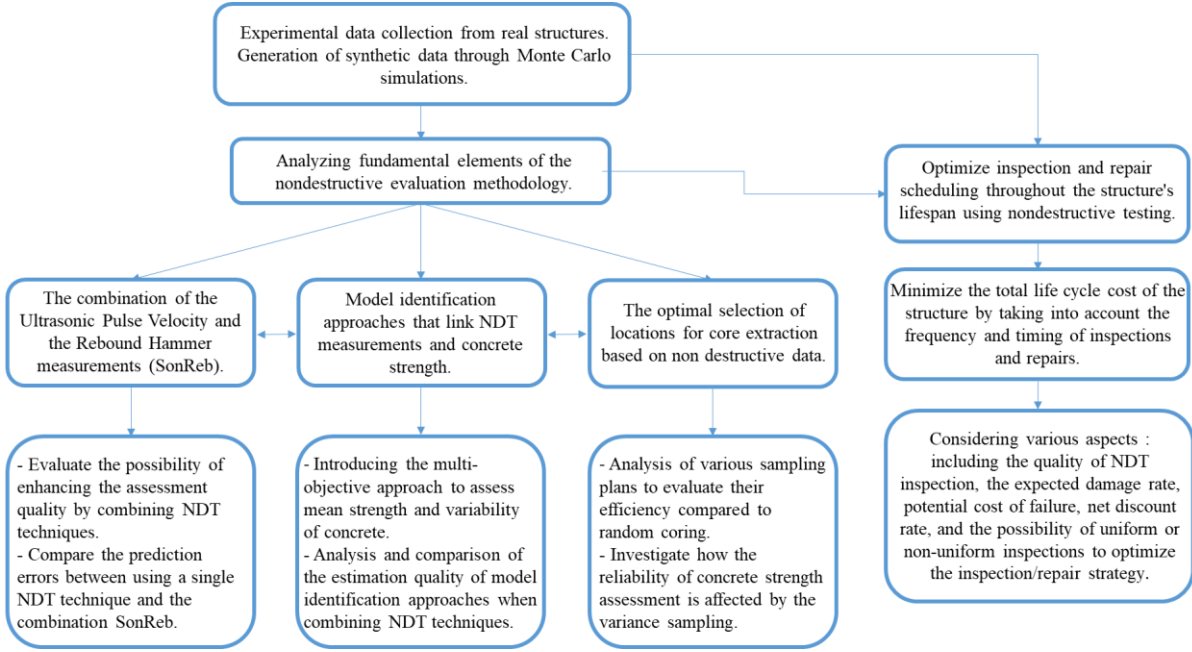


Figure 1.1 General research methodology

Chapter Two: Assessment of Concrete Strength

Using the Combination of NDT - Review and Performance Analysis

1 Introduction

In some cases, instead of being demolished and reconstructed, existing structures undergo modifications to extend their lifespan or to adapt them to a new assigned function. In such cases, structural assessment is required to determine the capacity of structures and to examine their ability in accommodating new potential loadings. The assessment of any structure requires information about the geometry of structural members, the loading criteria, and the mechanical properties of the materials being used. The determination of compressive strength can be viewed as the key element in the assessment of existing reinforced concrete structures regarding their structural performance.

When estimating in situ concrete strength, one could consider two main approaches: core tests and nondestructive testing. Core tests, considered as destructive tests, are more reliable but also more intrusive and expensive. On the other hand, nondestructive testing methods are simpler and less expensive, but they may yield uncertain predictions of concrete strength. To achieve the most accurate and cost-efficient results, a combination of both core tests and NDT techniques is often preferred. This approach allows for reliable estimates of concrete strength while minimizing the need for extensive and costly core testing. By using NDT in conjunction with core tests, engineers can improve the evaluation of the concrete's overall integrity and performance while also guaranteeing reliable results and permitting extensive testing.

For this purpose, Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV) tests are widely used in practice and are often combined to obtain a better assessment of concrete strength. Rebound Hammer test measures the surface hardness of concrete, which is related to its compressive strength. On the other hand, Ultrasonic Pulse Velocity test assesses the propagation of ultrasonic waves through the concrete, providing insights into its density and homogeneity. These NDT methods offer valuable information about the condition and quality of concrete without causing damage to the structure. However, one of the major challenges of

nondestructive assessment is identifying an accurate conversion model that relates NDT measurements (observable variables) to concrete properties (material variables). The conversion model is essential for interpreting the NDT results and estimating concrete strength. This model should account for various factors, including concrete mix design, curing conditions, age, and other environmental factors that may affect the test results. Researchers and engineers are constantly working to improve conversion models through extensive experimental studies and statistical analyses. The primary objective is to increase the precision of nondestructive assessment methods, thereby enhancing their practical utility in evaluating concrete strength.

This chapter begins by providing a concise overview of the commonly used nondestructive testing methods such as Rebound Hammer and Ultrasonic Pulse Velocity, as well as destructive testing methods like core sampling. It further explores the impact of key factors that influence in situ strength estimation. In addition, this chapter provides an overview of the current methodologies used in practical applications for assessing the in-situ strength using the combination of NDT techniques. It explores the significance of addressing variability in concrete strength assessments and the use of different model identification approaches. The last section explores the “trade-off effect” in model calibration and the use of statistical indicators to measure the precision of concrete strength estimation. It concludes by highlighting the importance of addressing errors and improving the precision of test results to enhance the accuracy of prediction models.

2 Assessing strength through core testing

The “destructive” methods refer to techniques that require the removal of a localized portion of material from an existing structure. In the case of reinforced concrete (RC) buildings, the mechanical characterization of the material is typically performed through coring. Coring involves extracting cylindrical samples from the structure, which are then used for compression tests in a laboratory to determine the compressive strength value. Core testing is extensively employed in real practice due to its direct and precise nature for estimating concrete strength in reinforced concrete structures. Multiple standards provide specifications for applying this method to test concrete in structures (American Concrete Institute (ACI), 2010; EN 12504-1, 2000).

The assessment methodology for evaluating concrete strength through core testing can be summarized in the following main steps:

1. **Planning an investigation program:** The first step involves careful planning to determine the number and specific locations for core sampling. This depends on the structural elements under consideration and the desired level of accuracy in the assessment.
2. **Core drilling:** Once the locations are identified, specialized drilling equipment is used to extract cores from the concrete elements. It is essential to select core samples that accurately reflect the properties of the concrete in the area being assessed.
3. **Testing cores:** The extracted cores are then subjected to compressive strength testing in accordance with relevant standards (ASTM C39/C39M-14, 2014; EN 12504-1, 2000). The testing process involves applying a load on the core until failure occurs, and the maximum load is recorded to determine the compressive strength.
4. **Interpreting the core strengths:** The obtained core strength results are carefully analyzed and compared to the specified design strength. Factors related to size effect including core diameter, length, location, and the condition of the concrete surface are taken into account during interpretation. Statistical analysis may also be performed to assess the variability of the results, providing additional insights into the “quality” of the concrete.

2.1 Designing an investigation program

Planning an investigation program involves determining the optimal number and locations of cores to be extracted from a concrete structure. The number and strategic location of cores are critical to obtaining representative and reliable data while minimizing potential damage to the structure. The standard (EN 12504-1, 2000) does not provide any specific guidance regarding the number of cores, focusing instead on the process of core extraction, examination, and compression testing. On the other hand, the standard (EN 13791:2007, 2007, p. 1) requires a minimum of 15 cores (with a minimum nominal diameter of 100 mm) for strength assessment. However, when using 50 mm cores, the recommended number of cores specified by the standard should be multiplied by three for each test region. This ensures sufficient coverage and reliability in the assessment process. In addition, the European Standard (EN 13791:2007, 2007) provides two model identification approaches, namely “Alternative 1” which employs a regression analysis approach and “Alternative 2” which follows a calibration approach, for evaluating individual compressive strength values, mean strength, concrete variability, and ultimately the characteristic strength. According to this standard, the minimum number of cores required is 18 for “Alternative 1” and 9 for “Alternative 2”. Similarly, the (ACI 228, 2003) standard also stipulates a minimum of 12 cores to establish a reliable strength estimation.

The number of cores required by the aforementioned standards is often considered impractical and excessively high, as noted by (Alwash et al., 2016; Breysse and Martínez-Fernández, 2014). Consequently, practitioners tend to overlook these limitations and instead opt for in-situ concrete assessment methods that rely on predictive equations recommended by device manufacturers or strength equations calibrated with a smaller number of cores (Ali-Benyahia et al., 2017; Alwash et al., 2015; Breysse and Martínez-Fernández, 2014).

In general, the coring location is selected independently to NDT test results (predefined or random coring). This process of core selection carries inherent risks and can result in misleading evaluations, especially when a limited number of cores is extracted from locations where the strength is higher or lower than the average strength of the entire building. Nevertheless, several researchers have pointed out that a targeted selection of coring locations, guided by prior information obtained from NDT results, can effectively cover the entire range of material strength variability within a structure (Breysse et al., 2020; Sbartai et al., 2021). By strategically extracting cores from different parts of the structure, a more representative and comprehensive understanding of the overall strength can be obtained. This approach is particularly beneficial in structures with significant variations in concrete properties due to different construction phases, material qualities, or environmental conditions. By capturing this variability through targeted core sampling, engineers are able to fully comprehend the overall strength profile (Alwash et al., 2015; Sbartai et al., 2021).

2.2 Core drilling

As outlined in various manuals and standards such as (ACI CODE-318-19(22), 2022; ASTM C42/C42M-13, 2013; Bungey and Millard, 1996; EN 12504-1, 2000), the recommended approach for assessing concrete strength in existing structures is to use core extraction through drilling techniques. This method is especially useful in areas of high stress or in locations where there are genuine concerns about the concrete's quality. Core drilling involves the careful extraction of cylindrical samples (cores) from the concrete elements of the structure. These cores are then subjected to compressive strength testing to determine the in-situ concrete strength. Typically, core drilling is conducted in critical regions, such as load-bearing columns, beams, and slabs, as well as locations suspected to have lower concrete quality due to factors like poor workmanship, age, or environmental exposure.

When conducting core sampling for concrete testing, a core specimen is extracted from the structural member using a core drilling equipment. This equipment typically consists of a

cutting tool with diamond bits attached to the core barrel. To ensure the integrity of the core specimen, it is crucial to minimize any movement during the drilling process. Therefore, the drilling rig should be firmly anchored to the concrete member, providing stability and reducing the risk of damaging the core. In addition, it is essential to position the drilling rig perpendicular to the surface from which the core is being extracted. This ensures that the core is cut in a precise and undistorted manner. Cutting a distorted core could lead to inaccurate test results and compromise the reliability of the assessment. During the core drilling process, the drill bit is often lubricated with water. This serves multiple purposes: it reduces friction and heat generated during drilling, preventing the drill bit from overheating, and it helps to flush out concrete debris from the drilled hole, allowing for smoother and more efficient drilling (McPhee et al., 2015).

Prior to core drilling, it is essential to determine the dimensions of the core, including its diameter and length, which in turn determines the ideal length-to-diameter ratio (L/D). Several authors have suggested that the diameter dimension has no significant impact on the compressive strength of the specimen (Lewis, 1976; Meininger, 1968). The standard core diameter for concrete strength testing is typically 100 mm. However, some studies, such as the ones conducted by (Campbell and Tobin, 1967; Sassoni and Mazzotti, 2013; Vu et al., 2021), have shown that using smaller core diameters can result in lower measured strength values. To ensure more accurate and representative strength assessments, engineers often use standardized core diameters (e.g., 100 mm) in critical areas where accuracy and reliability are crucial for structural evaluation and decision-making.

2.3 Testing the extracted cores

In the laboratory, after core specimens are extracted, it is essential to conduct a visual examination to assess their condition and gather valuable information that can help in the interpretation of the compressive strength testing results. The visual inspection of core specimens can provide various important details, including:

1. **Aggregate size and shape:** By observing the exposed surface of the core, engineers can learn more about the aggregate size and shape present in the concrete mix. This information is important for understanding the concrete's composition and potential mechanical properties.
2. **Presence of voids:** Voids within the core can affect its structural integrity and mechanical behavior. Detecting the presence and size of voids helps in evaluating the overall quality and density of the concrete.

3. Depth of carbonation: Visual inspection can evaluate the depth of carbonation and provide insights into the concrete's exposure to environmental conditions.
4. Presence of cracks: Surface cracks on the core can indicate potential weaknesses in the concrete. The depth and width of the cracks are essential in understanding the extent of structural damage or deterioration.
5. Presence of reinforcement: If the structure contains embedded reinforcement, the visual inspection can reveal its position and condition, providing important information for structural assessment.
6. Drilling damage or defects: Core extraction may cause drilling-related damage or defects, such as chipping or irregularities. Identifying these issues is crucial for ensuring the core's reliability during compressive strength testing.

Prior to conducting compression testing on a core specimen, it is necessary to prepare each core by sawing its ends. This process ensures that the specimen achieves a suitable length, flat ends, and is perpendicular to the longitudinal axis of the core (Ali Benyahia, 2017). Another key factor to consider is the curing process, which has a significant impact on the strength value. A common practice is to immerse the samples in water for a minimum of 40 hours prior to conducting the compressive test. This soaking period ensures that all specimens have a consistent moisture level.

The compression test of concrete core specimens is a fundamental procedure for determining their compressive strength, which is an important parameter for assessing the structural integrity and performance of concrete in existing structures. The test is conducted following standardized procedures outlined in relevant standards, such as EN 12390-3 and ASTM C39. During the compression test, a cylindrical core specimen is placed vertically between the platens of a hydraulic testing machine. The load is gradually applied to the specimen until it fails or fractures. The compressive strength of the core is calculated by dividing the maximum load sustained during the test by the cross-sectional area of the core. The cross-sectional area is determined based on the average diameter of the core (ASTM C39/C39M-14, 2014; EN 12390-3, 2003).

2.4 Interpreting the strengths of the tested concrete cores

Test results often exhibit some degree of variability, primarily attributed to random fluctuations in concrete characteristics and in situ stress conditions. Additionally, systematic variations in in situ properties can be observed along individual structural members or throughout the entire

structure. Several studies have addressed the difference between in situ strength and core strength (American Concrete Institute (ACI), 2010; Breysse, 2012; EN 12504-1, 2000). Factors such as the size and geometry of core specimens, coring direction, the presence of reinforcing bars and the impact of drilling damage can all influence the test results obtained from core specimens, ultimately contributing to the observed differences.

With regard to this issue, some relationships to convert the compressive strength of a core specimen f_{core} into the equivalent in situ value f_c have been proposed in the literature. For this purpose, (Masi, 2006) has provided a relationship to convert the strength of a core specimen, denoted as f_{core} , into an equivalent in-situ value, represented as f_c .

$$f_c = (C_{H/D} \cdot C_{dia} \cdot C_a \cdot C_d) \cdot f_{core} \quad (2.1)$$

Where:

- $C_{H/D}$ = correction for height/diameter ratio h/D, equal to $C_{H/D} = 2 / (1.5 + D/h)$;
- C_{dia} = correction for diameter of core D, equal to 1.06, 1.00 or 0.98 for a diameter D respectively equal to 50, 100 or 150 mm, as suggested in (ACI 228, 2003);
- C_a = correction for the presence of reinforcing bars, equal to 1 for no bars, and varying between 1.03 for small diameter bars (\emptyset 10) and 1.13 for large diameter bars (\emptyset 20);
- C_d = correction for damage due to drilling. ACI, 2003 suggests a constant value of 1.06 for the conversion factor C_d to obtain the equivalent in-situ strength from core specimen strength. However, in the technical literature, alternative values such as $C_d = 1.10$ are proposed. Additionally, considering that drilling damage tends to be more significant in lower quality concrete, it is recommended to use $C_d = 1.20$ for $f_{core} < 20$ MPa and $C_d = 1.10$ for $f_{core} > 20$ MPa.

It is important to note that the strength obtained from Equation 2.1 does not align with the standard strength specified in building codes for designing new structures. This is due to the variations in aging, casting conditions, and the age difference between core specimens and standard specimens.

2.5 Key factors influencing the results through core testing

Several factors can influence the results obtained from core testing, and understanding these factors is crucial for accurate and reliable assessments. The following are key factors that can affect test results:

1. Concrete mix proportions: Variations in the proportions of cement, aggregates, water, and admixtures in the concrete mix can significantly influence its strength and properties.
2. Curing conditions: The curing process, which involves maintaining the concrete at a controlled temperature and humidity, directly affects its final strength. Inadequate curing can lead to reduced strength.
3. Age of concrete: Concrete gains strength over time due to the ongoing hydration process. The strength of concrete will increase with age, and test results may vary depending on the concrete's maturity.
4. Core orientation: During core drilling, the orientation of the extracted cores can influence the measured strength values. Cores taken perpendicular to the surface may have different strengths than those taken parallel to it.
5. Core surface condition: The surface condition of the extracted cores can affect test results. Rough or uneven surfaces may affect the contact and load distribution during testing, leading to variations in strength measurements.
6. Testing conditions: The testing conditions, including the setup of the testing machine, loading rate, and alignment, can affect the measured compressive strength.
7. Moisture content: The moisture content of the concrete at the time of testing can influence the results. Higher moisture levels may affect the compressive strength values.
8. Presence of defects: Cracks, voids, and other defects in the concrete can weaken its overall strength. The presence of such defects should be considered when interpreting test results.
9. Sample size: The size of the tested sample, such as cores or cylinders, can affect the measured strength. Smaller samples may not be fully representative of the concrete's true strength.

3 Nondestructive assessment of concrete structures: the contribution of Rebound Hammer and Ultrasonic Pulse Velocity

3.1 The need for nondestructive testing (NDT) in structural assessment

Coring, as a destructive testing method, offers higher accuracy compared to nondestructive testing techniques. However, the coring method is expensive, invasive, time-consuming, and difficult to perform. In order to reduce the number of cores NC, destructive testing by coring can be associated with nondestructive testing. This approach allows for the evaluation of

concrete strength while providing a deeper understanding of strength variability within the structure. Numerous advantages have been documented regarding the use of NDT techniques, including their fast execution, ability to map defects in concrete elements and track changes in concrete properties over time. Furthermore, they offer a significant reduction in structural damage compared to core drilling and overall cost savings (Breysse, 2012; Jones, 1962; Malhotra and Carino, 2003).

The first attempts made to assess concrete strength using nondestructive techniques were likely carried out in Germany around 1934 (Jones, 1962). Soon after, several indentation type methods were developed, namely the Testing Pistol by Williams, the Spring Hammer by Frank, and the Pendulum Hammer by Einbeck (Malhotra and Carino, 2003), with the first results being presented in 1936 by Williams. However, the widespread adoption of these techniques was mainly observed after 1948, with the contributions of Ernst Schmidt, who developed the “Rebound Hammer” method, which was inspired by the Shore method used to determine the metals surface hardness.

Since the aforementioned techniques primarily focused on assessing the condition of the concrete surface, there was a need to develop new testing techniques to evaluate the concrete below the surface. This led to the development of test methods that involved determining the depth of penetration of probes, such as steel rods or pins, into the concrete. Meanwhile, since the 1930s, several resonant frequency methods were being used in the laboratory to assess the concrete elasticity modulus, and later on, the Pulse Velocity method was also adopted to assess the degradation and cracking of concrete. From the 1960s onwards, this method started to be used in-situ to estimate the concrete strength, and still on the same decade, combined methods have emerged.

(Cianfrone and Facaoaru, 1979; Leshchinsky, 1991) combined Ultrasonic Pulse Velocity and Rebound Hammer to improve the reliability and precision of the concrete strength estimation. (Breysse, 2012) provides a description of the SonReb method, which combines the measurements of Ultrasonic Pulse Velocity (UPV) and Rebound Hammer (RH), as discussed by RILEM Technical Committee TC 207-INR. According to (Breysse, 2012), the combination SonReb is derived from Sonic and Rebound. The fundamental idea behind the SonReb method is that by employing both Rebound and UPV measurements, which are affected by the same factors in distinct ways, the combined use of SonReb can minimize the impact of these factors and improve the precision of the estimated concrete strength. For instance, humidity tends to produce a higher UPV value and a lower RH measurement. Similarly, the age of the concrete

affects the results by increasing the RH value and reducing the UPV measurements. By considering both tests simultaneously, the combined method can account for the varying effects of these factors and provide a more reliable estimation of concrete strength.

The combination of other techniques, like penetration resistance (Machado et al., 2009a), pull-out tests (Ferreira et al., 2021) or drilling (Marinković et al., 2010) was also extensively studied. Furthermore, The combination of infrared thermography, electrical resistivity and capacitance to assess the water content/damage state of material along a profile is described in detail in (D. Breysse, 2012) and (Sirieix et al., 2007).

A summary of the distinctive features of different concrete strength testing methods is provided in Table 2.1. It offers a comparison among the testing methods under consideration in terms of their cost, speed of execution, destructiveness and reliability of strength correlation.

Table 2. 1 The key benefits of nondestructive tests

Test method	Cost	Speed of test	Damage	Reliability
Coring	High	Slow	Moderate	Good
Ultrasonic Pulse Velocity	Low	Fast	None	Poor
Rebound Hammer	Very Low	Fast	None	Poor
Pull-out	Moderate	Fast	Minor	Moderate/Good
Penetration Resistance	Moderate	Fast	Minor	Moderate

3.2 Strength assessment using Rebound Hammer

3.2.1 The technique's principle

The Schmidt Hammer, also known as the Rebound Hammer, is a portable NDT instrument used to assess the surface hardness or strength of concrete. The Rebound Hammer test is widely used in practice due to its simplicity, portability, and ability to provide a quick estimate of concrete

strength without causing any damage to the structure. During the test, the rebound hammer is pressed against the concrete surface, and a spring-loaded mass inside the hammer is released to strike the surface. The rebound distance of the mass from the surface is then measured using a scale on the hammer. The rebound distance is an indicator of the hardness of the concrete, which is related to its compressive strength.

The simplicity, speed, and nondestructive nature of the rebound hammer test have contributed to its widespread use in the field of concrete evaluation. However, it is essential to note that while this test offers a quick estimation of concrete strength, it does not provide precise compressive strength values. For accurate and detailed strength assessments, further laboratory-based core testing or other destructive methods may be necessary. Nonetheless, the rebound hammer remains a valuable tool for initial assessment and quality control in concrete inspection and construction projects.

3.2.2 Devices and methodology

The device is based on the rebound principle, which is an indicator of the hardness of concrete. The ideal surfaces for testing using the rebound hammer method are the vertical faces of concrete structures, allowing for horizontal impact during the testing process. The plunger has to be pressed perpendicularly against the surface of the test specimen and the pressure has to be increased until the hammer impacts. In order to mitigate the influence of surface condition on test results, it is advisable to smoothen a rough surface using a grinding stone (Breysse and Martínez-Fernández, 2014). It is advisable to define a testing area on the concrete under examination, measuring approximately 300 mm x 300 mm. Create a grid with squares ranging from 25 mm to 50 mm in size, where the intersections of these lines are regarded as impact points for the percussion rod. The minimum distance between two impact tests should be 25 mm, and no test should be carried out within 25 mm of the edge of the tested surface (ASTM C805, 2013; EN 12504-2, 2003).

To determine the rebound index, in compliance with standard EN 12504-2 and ASTM C805, the following procedure is employed for testing using the rebound hammer (Figure 2.1). This systematic process explains how to use the rebound hammer to obtain rebound index values and interpret their significance:

1. Equipment preparation: Verify that the rebound hammer is appropriately calibrated and that its impact plunger is in optimal condition.
2. Surface preparation: Clean the test surface thoroughly, removing loose debris, dirt, or any coatings that could affect rebound readings. Ensure the surface is smooth.

3. Test point selection: Determine the specific locations on the concrete surface where the rebound hammer will be applied. These points should be representative and cover the desired testing area.
4. Positioning and orientation: Hold the rebound hammer firmly, keeping it perpendicular to the test surface. Align the impact plunger with the selected test point.
5. Impact application: Apply firm pressure to the rebound hammer against the concrete surface, causing the impact mechanism to strike the plunger onto the concrete.
6. Rebound measurement: Observe the rebound distance indicated on the scale of the rebound hammer. Record the corresponding rebound index value associated with the rebound distance.
7. Test repetition: Perform multiple tests at various locations to obtain a sufficient number of rebound index values for accurate representation. Maintain consistent testing conditions throughout.
8. Result interpretation: Compare the obtained rebound index values with the specified threshold values or ranges outlined in the relevant standards EN 12504-2 or ASTM C805. Evaluate the structural condition by taking into account the rebound index values and considering factors such as the strength and uniformity of the concrete.

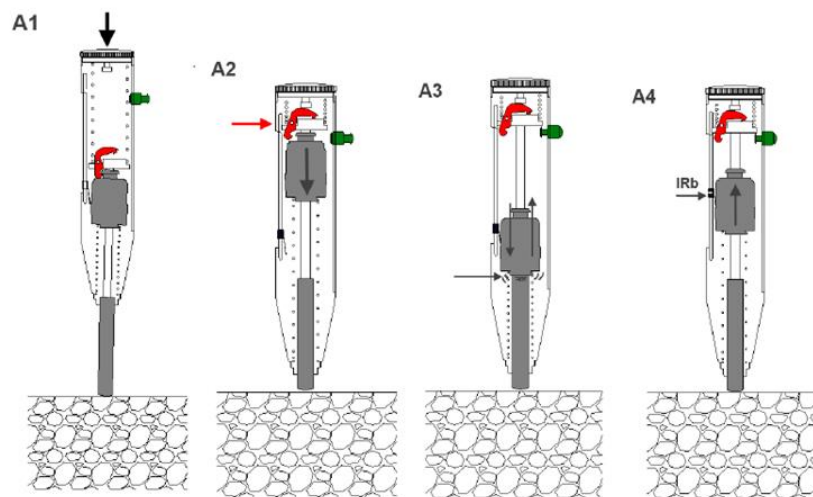


Figure 2. 1 *The operational process of the Rebound Hammer test (Alwash, 2017)*

3.2.3 Factors influencing the test results

Recent studies of (Kheder, 1999a; Kim et al., 2009; Szilágyi et al., 2011) have investigated the influence of various factors on Rebound Hammer. These works have demonstrated that the outcomes are significantly influenced either by the specific concrete mix (including factors like

aggregate size, water/cement ratio, and admixtures) or by the surrounding conditions (such as moisture levels, concrete maturity, curing methods, and surface carbonation).

A common factor that influences the reading is the carbonation of the concrete. The depth of carbonation in concrete can vary depending on the cement hydration products and exposure to CO₂. As carbonation occurs, the surface hardness of the concrete increases, which directly affects the rebound value measured by the Hammer test. On carbonated surfaces, the rebound index can be up to 50% higher compared to non-carbonated surfaces (Kim et al., 2009; Yang et al., 2018).

Similar to the effect of carbonation, high temperatures also have a significant impact on the surface hardness and compressive strength of concrete. Studies conducted by (Panedpojaman and Tonnyayopas, 2018) have shown that high temperatures negatively affect compressive strength. When concrete is exposed to fire, up to around 420 °C, the rebound index remains relatively unchanged. However, the compressive strength of the concrete decreases significantly. This reduction in compressive strength is attributed to the formation of calcium carbonate crystals in the pore structure, causing the hardness to decrease at a slower rate. Consequently, the Rebound Hammer test becomes unsuitable for accurately determining the compressive strength of concrete under such high-temperature conditions.

In addition, the moisture content of concrete has a direct influence on its compressive strength. Recent studies (Malhotra and Carino, 2003; Mehta and Monteiro, 2014; Monteiro and Gonçalves, 2009; Szilágyi et al., 2014) have demonstrated that as the concrete moisture content increases, the Rebound Index decreases by approximately 20-25%. This reduction in Rebound Index is attributed to the growth of inner pore pressure within the concrete, which can lead to a decrease in compressive strength. Interestingly, when the concrete is initially dried in an oven, its strength increases. This highlights the dynamic nature of concrete strength with changes in moisture content and the importance of considering the moisture condition when assessing its properties.

(El Mir and Nehme, 2017) conducted extensive testing on several hundred concrete specimens, studying the coefficient of variance in Rebound values. Their research revealed that certain factors such as greater carbonation depth, higher water/cement (w/c) ratio, or higher porosity of the concrete contribute to an increase in the coefficient of variance, leading to reduced repeatability in rebound values. On the other hand, concrete mixes containing additions like metakaolin or silica fume, as well as high-strength and high-performance self-compacting

concrete, exhibited a lower coefficient of variance in rebound values. These findings highlight the influence of various concrete mix characteristics on the reliability and consistency of the test results.

Furthermore, the condition of the concrete surface plays a significant role in the accuracy of rebound readings. Irregularities, roughness, or unevenness on the surface can lead to variations in the rebound values, affecting the reliability of the test results. To minimize these influences and obtain consistent readings, it is recommended to prepare the surface before conducting the test.

(Breysse, 2012) compiled a table summarizing the key factors that influence rebound measurements, as highlighted by various authors. Refer to Table 2.2.

Table 2. 2 Influencing factors on average rebound measurements (Breysse, 2012)

Concrete mix	Aggregate	Maximum size ^b
		Type (hardness/density) ^a
	Cement paste	Percentage ^c
		Type of cement ^c
Humidity ^b		
Factors influencing surface and near-surface condition		Age/carbonation ^a
		Surface regularity and rugosity ^b
		Type of formwork and curing ^b
Others		Rigidity of the component (thickness) ^b
		Temperature ^c
		Voids ^a

^a High influence

^b Average influence

^c Moderate influence

3.2.4 Reliability of test results obtained from Rebound Hammer

Several codes (ASTM C805/C805M-13a, 2013; BS 1881-202, 1986; EN 206, 2013; JJG 817-1993, 1993) adopted a comparable approach, imposing strict limitations on the utilization of the Schmidt Hammer. For instance, (ASTM C42/C42M-13, 2013) confines the use of Rebound methods to three specific purposes:

1. Evaluating the in-place uniformity of concrete: By performing measurements at various locations on a concrete surface, engineers can assess the uniformity of strength and hardness throughout different sections of a structure. This information helps identify potential areas that may require additional reinforcement to ensure the overall integrity and durability of the concrete.
2. Identifying areas in a structure where concrete quality is poor: When certain parts of a structure exhibit lower rebound values, it may indicate the presence of poor-quality concrete or concrete that has deteriorated over time. Understanding this information is crucial for assessing structural integrity and determining any potential repair requirements.
3. Estimating in-place strength: By correlating rebound values obtained from the Schmidt Hammer with actual compressive strength data gathered through destructive testing, a relationship can be established. This correlation allows engineers to estimate the in-situ strength of concrete.

Every Schmidt Hammer apparatus comes equipped with correlation curves that have been developed by the manufacturer (Szilágyi et al., 2011). Figure 2.2 illustrates a calibration curve that represents the estimated compressive strength in relation to the rebound number. This calibration is specific to Hammer Type N and cylinder specimens (Proceq SA, 2016). However, it is not advisable to rely solely on these curves because the in-situ materials and testing conditions may differ significantly from those present during the instrument's initial calibration. As a result, using these correlation curves may lead to inaccurate estimations of concrete strength. To ensure reliable results, specific calibration curves must be created using the real materials and conditions encountered during on-site testing.

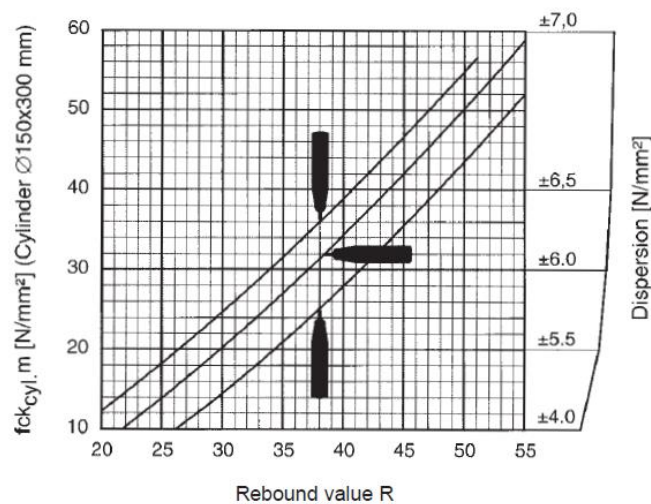


Figure 2. 2 Conversion curve for the average compressive strength of cylinder samples (Proceq SA, 2016)

Over the past 50 years, an extensive range of both laboratory and on-site experimental programs have been conducted with the aim of establishing relationships that can correlate Rebound Hammer with concrete compressive strength. A vast number of models have been proposed, offering “conversion curves” based on laboratory experiments involving various concrete mixes or from field data (Breysse and Martínez-Fernández, 2014; Liu et al., 2009)).

(Pereira and Romão, 2018) extensively examined various aspects related to selecting appropriate conversion models between destructive and nondestructive test results, employing specific regression approaches. They recommended using power models to establish the relationship between the rebound index and compressive strength, especially in existing structures where the strength variation coefficient is higher than 10%. On the other hand, (Rashid and Waqas, 2017) suggested an alternative approach, proposing the use of a second-order polynomial model instead of a power model. (Alwash et al., 2017; Kocáb et al., 2019; Panedpojaman and Tonayopas, 2018) employed a random selection method for test locations and then used regression or bi-objective model identification approaches to determine the relationship between strength and the rebound index.

Numerous other research studies have been conducted to assess the reliability of the Hammer test for estimating concrete compressive strength. Recent scientific investigations (Kocáb et al., 2019; Monteiro and Gonçalves, 2009; Szilágyi et al., 2014) indicate that the hammer test can indeed yield valuable information about concrete quality, given that the device is properly calibrated for the specific type of concrete being examined. The American Concrete Institute

(ACI) recommends that before conducting nondestructive tests in the field, rebound correlation curves should be developed from laboratory tests, performed on standard concrete specimens with materials identical to those used in the concrete structure being evaluated. However, there is significant disagreement among researchers regarding the accuracy of estimating concrete strength using readings from Schmidt Hammer (Brozovsky, 2014; Hobbs and Tchoketch Kebir, 2007). The lack of consensus on a common model and the limited effectiveness of the existing models documented in the literature have led to disappointment. Many engineers are hesitant about the practical utility of NDT in this context, as the diverse models available often fail to provide accurate and reliable estimations of concrete compressive strength.

3.2.5 Standards and guidelines available for the Rebound Hammer

The Rebound method is addressed by multiple standard specifications, which offer guidelines for assessing the properties and characteristics of concrete, such as surface hardness and compressive strength. These standards are essential for quality control, structural assessment, and ensuring the durability and safety of concrete structures.

- ASTM C 805, Standard test method for rebound number of hardened concrete, in: Annual book of ASTM standard, ASTM C805-85, Detroit, 1994.
- BS 1881 - Part 202 - Recommendations for surface hardness tests by the rebound hammer, BSI, UK 1986.
- EN 12504-2, Testing concrete in structures - Part 2. Nondestructive testing - determination of rebound number, 2001.
- EN 13791, Assessment of in-situ compressive strength in structures and precast concrete, CEN, Brussels, 28p, 2007.

These standards vary in terms of their origin and coverage. ASTM C 805 is specific to rebound testing, while the British standard (BS 1881 - Part 202) and the two European standards (EN 12504-2 and EN 13791) adopt a more comprehensive approach, addressing nondestructive testing and concrete assessment in a broader context. The choice of which standard to follow may depend on regional regulations, industry practices, and project requirements.

3.3 Strength assessment using Ultrasonic Pulse Velocity

3.3.1 The technique's principle

The Pulse Velocity test is a nondestructive testing technique employed to measure the velocity of ultrasonic waves as they propagate through a material. The equipment consists of an

electrical pulse generator, a pair of transducers, an amplifier, and an electronic time measurement device allowing the measurement of the elapsed time between the emission of a pulse generated by the transmitter transducer and its reception by the receiver transducer. It is possible to connect the instrument to an oscilloscope to observe the pulse being received (Naik et al., 2003).

The electro-acoustical transducer, which is placed in contact with one surface of the concrete member being tested, generates wave pulses. These pulses propagate through the concrete, and a receiving transducer captures the waves. The time taken for the signal to travel from the emission point to the reception point is measured, and since the distance between the probes is known, the wave velocity can be determined:

$$V = \frac{L}{T} \quad (2.2)$$

Where:

V: impulse velocity (m/s);

L: length of the path (m);

T: time taken for the impulse to traverse the length (s).

When a solid mass experiences an impulse, the resulting waves can be categorized into three types: surface waves, transverse waves (S-waves), and longitudinal waves (P-waves). Surface waves exhibit elliptical particle displacement and are the slowest among the three. On the other hand, transverse waves have particle displacement perpendicular to the direction of travel, making them faster than surface waves. Longitudinal waves, which involve particle displacement in the direction of travel, are the fastest and considered the most significant as they offer more valuable information (Turgut and Kucuk, 2006a).

UPV technique have a remarkable capability in detecting internal defects within a material, offering a significant advantage over other nondestructive tests like the Schmidt Hammer, which are restricted to surface inspections. In addition, based on the principles of elastic wave propagation, the pulse velocity V is proportional to the square root of Young's modulus of elasticity E. Assuming that E is, in turn, proportional to the square root of the compressive strength as suggested in (EN 1992-1-1:2004/AC:2010, 2003).

In an elastic and homogeneous solid material, the speed of compression waves (P-waves) is determined by:

$$V = \sqrt{\frac{K \times E}{\rho}} \quad (2.3)$$

Where:

V: velocity of compression waves;

$$k = \frac{1 - \mu}{(1 + \mu)(1 - 2\mu)}$$

E: dynamic modulus of elasticity;

ρ : density;

μ : dynamic Poisson's ratio.

3.3.2 Devices and methodology

Among nondestructive testing methods, the PUNDIT (Portable Ultrasonic Nondestructive Digital Indicating Tester) is a highly popular and widely used device for nondestructive testing. Engineers and researchers in the field commonly employ the PUNDIT due to its portability, ease of use, and ability to deliver reliable results. Alternative UPV devices include:

- CUTE 103A (Concrete Ultrasonic Testing Equipment) manufactured by Canopus in India.
- The 58-E4800 UPV tester produced by Control Group in Italy, which also has an upgraded version known as the PULSONIC 58-E4900 Ultrasonic Pulse Analyzer. This advanced version is equipped with an oscilloscope that enables the measurement of the Dynamic Modulus of Elasticity of concrete samples (Ndagi et al., 2019).

The path of the ultrasonic pulse is determined by the positioning of the wave emitter and the signal receiver. These components can be placed in different configurations, such as direct, semi-direct, or indirect positions (Figure 2.3).

- The “direct transmission” is an arrangement type where both the transmitting and receiving transducers are coupled on the surface of the concrete directly opposite each other. (Malhotra and Carino, 2014) suggested that when determining the quality of concrete, opting for the direct method would be the best option since it provides a well-defined path that could be measured easily. (Hannachi and Guetteche, 2012) concluded that the direct arrangement is the most commonly employed method for NDT because it allows for maximum transmission and reception of pulse energy, making it the most satisfactory approach.

- The “semi-direct transmission” is employed in cases where it is not feasible to reach both sides of a concrete member or when there is a high concentration of reinforcement bars. When employing a semi-direct arrangement, it is recommended to adhere to specific technical guidelines to ensure the attainment of reliable results. As noted by (Bungey, 1980), these guidelines include maintaining a small angle between the transducers and keeping the path length short. Neglecting these guidelines could lead to signal diffraction due to the attenuation of the transmitted pulse.
- The last method is known as the “indirect transmission” where the transducers are positioned on the same platform (Jedidi and Machta, 2014). This means that both the ultrasonic wave emitter and the signal receiver are positioned on the same side of the concrete member. The ultrasonic pulse is transmitted into the concrete, and the received signal is analyzed to assess the concrete properties. Indirect transmission is typically used when direct or semi-direct transmission is not possible due to constraints such as limited access to opposite faces of the concrete member or the presence of reinforcement bars.

While the “direct transmission” offers the highest level of accuracy in evaluating material properties, it can be challenging to gain access to both sides of the material. If the concrete is reinforced, the best solution is to locate first the rebar with an electromagnetic device and thus to test between them. The semi direct technique is easy to use but the distance between the two transducers is not as precisely defined as in the previous method. Out of the three testing methods, the indirect method is known to give the most unreliable result. This method is primarily employed when only one side of the element is accessible and there is a need to determine the crack depth or identify multiple layers within the same element (Hannachi and Guetteche, 2014). Each transducer arrangement has its advantages and limitations, and the choice of the appropriate method depends on the specific testing requirements and the condition of the concrete structure being assessed.

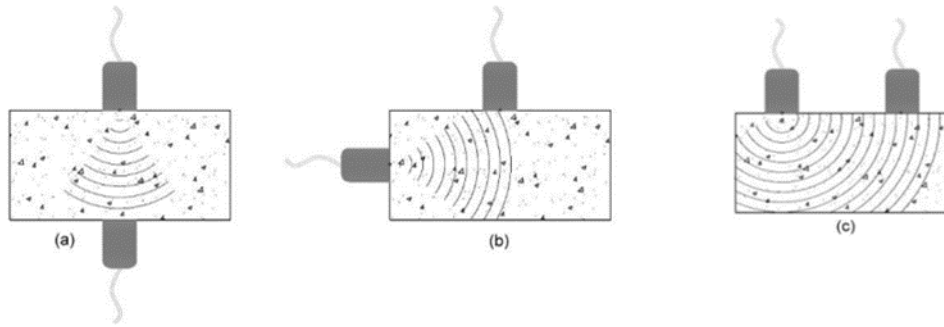


Figure 2. 3 Arrangement of transducers for measuring ultrasonic pulse velocity; (a) direct, (b) semi-direct, (c) indirect (Alwash, 2017)

3.3.3 Factors influencing propagation velocity

The Pulse Velocity is not influenced by the geometry or shape of the concrete material being tested. However, the main influencing parameters on the output of the UPV are the type, content and hardness of the aggregates, the presence of cracks/voids in the structure and the moisture content of the concrete (Jones, 1953). In other words, the parameters which undermine the hypothesis of homogeneity and integrate more heterogeneity into the material. The water/cement ratio and relative humidity also affect the readings in Pulse Velocity.

In a research by (Hannachi and Guetteche, 2014), it was found that samples containing aggregates with rounded edges gave up lower propagation speeds than samples containing crushed aggregate. Aggregates with rounded edges have smoother surfaces and may allow the ultrasonic waves to disperse or scatter more as they pass through the concrete. On the other hand, crushed aggregates with irregular surfaces can result in a more direct and focused transmission of the ultrasonic pulse, leading to higher propagation speeds.

The British Institute of NDT has observed that concrete samples cured under saturated conditions have higher pulse velocity than samples cured in open air. However, the degree of saturation as a parameter has also been found to affect the pulse speed by almost 4% (Bungey, 1980). The difference in pulse velocity is attributed to the presence of water in the pores of the concrete. When concrete is saturated, the water in the pores acts as a coupling medium for the ultrasonic waves, allowing them to travel more efficiently through the material. On the other hand, in samples cured in open air, the lack of water in the pores may hinder the transmission of the ultrasonic waves, resulting in slightly lower pulse velocities.

In a study conducted by (Panzera et al., 2008), the effect of a low water/cement ratio on the Ultrasonic Pulse Velocity was investigated. The study aimed to investigate how a low

water/cement ratio affects the propagation of ultrasonic waves through the concrete. The researchers found that regions in the concrete with low compaction or voids exhibited lower pulse velocities compared to well-compacted areas. This observation suggests that the presence of low compaction or voids could be an indication of a poor water/cement ratio in the concrete. A low water/cement ratio typically results in a more densely packed and well-compacted concrete, leading to higher pulse velocities in ultrasonic testing. On the other hand, a high water/cement ratio can cause increased porosity and voids within the concrete, resulting in lower pulse velocities during UPV testing.

In studies conducted by (Jones, 1953; Karaiskos et al., 2015; Ndagi et al., 2019), it was demonstrated that the effect of the distance between transducers is more noticeable due to errors caused by the heterogeneous nature of concrete. However, when the test is performed in situ, where the length of the member is larger, this effect is less pronounced. The study focused on understanding how the distance between the transducers influences the accuracy of the measurements. In the laboratory setting, where concrete specimens are smaller and more homogeneous, the effect of the distance between transducers was found to be more noticeable. This is because errors caused by the inherent heterogeneity of the concrete were more pronounced in a confined laboratory environment. On the other hand, in testing situations involving larger concrete members, the effect of the distance between transducers was found to be less pronounced. In addition, presence of steel in concrete should as much as possible be avoided when selecting the position of the transducers especially in weaker concrete where the effect is more pronounced. If this is unavoidable, correction factors are available for use in the correction of the effect of reinforcement.

According to (Hwang et al., 2018; Sturup et al., 1984), the Pulse Velocity measurements are not significantly affected by temperature unless it exceeds 200°C. When the temperature exceeds 200°C and reaches temperatures around 400°C, correlations between pulse velocities and temperature start to show a range of +2% to +5% in air-cured concrete and +1.7% to +4% in water-saturated concrete. This indicates that at higher temperatures, there is a noticeable influence on the pulse velocity measurements, which can lead to variations in the estimated compressive strength. To address this issue, (Al-Khafaji, 2017; Jones and Façoaru, 1969; Nanayakkara et al., 2022) recommend making corrections to the UPV measurements when the temperature of the concrete samples exceeds 200°C. (Breysse, 2012) presented a summary of the most influential factors in Table 2.3.

Table 2. 3 Influencing factors on average UPV measurements (Breysse, 2012)

		Percentage ^a
Concrete mix	Aggregate	Maximum size ^b
		Type (density) ^a
	Cement paste	Percentage ^c
Type of cement ^c		
Humidity ^b	Others	Fly ash content ^b
		Water/cement ratio ^a
Others		Age ^b
		Rebar ^b
		Voids, cracks ^a

^a High influence

^b Average influence

^c Moderate influence

3.3.4 Reliability of test results obtained from Ultrasonic Pulse Velocity

The British Standard (BS EN 13791, 2007) allows the combined use of the UPV test and the core test to assess the in situ strength of existing concrete structures. This is likely due to the simple execution of the UPV test and its cost-effectiveness, which allows for a larger amount of valuable data to be gathered. On the other hand, (Popovics and Rose, 1994) have questioned and criticized the reliability of UPV tests for predicting concrete strength, making it more commonly used for assessing the homogeneity of concrete. Furthermore, (Komloš et al., 1996) discovered that assessing certain properties of concrete using UPV can be highly uncertain and impractical. This is primarily due to the significant influence of numerous factors on UPV measurements and the lack of consistency in procedures and recommendations among different national standards.

Based on laboratory studies, numerous researchers have identified models that establish correlations between concrete strength and pulse velocity. In a comprehensive review by (Breysse, 2012), over 70 models of various types (linear, power, exponential and polynomial) were identified. Some of these conversion models are depicted in Figure 2.4. However, these curves exhibit wide dispersion, indicating that there is no universally applicable concrete strength-pulse velocity model. This observation underscores the significant impact of the influencing factors mentioned earlier and emphasizes that models should be applied exclusively to cases from which they are derived (Alwash, 2017).

To enhance the usefulness of UPV, it is essential to complement it with other nondestructive and destructive testing methods. Combining UPV with core testing, Rebound Hammer or other techniques can provide a more comprehensive assessment of concrete strength and structural integrity.

On the other hand, when it comes to assessing cracks, UPV has been found to be relatively reliable. However, (Tomsett, 1980) discovered that this reliability does not hold true for cracks filled with water. The presence of water alters the path of the pulse, introducing potential inaccuracies in the UPV readings for such situations. Therefore, special attention and consideration are necessary when evaluating cracks in the presence of water to ensure the accuracy and validity of the UPV results.

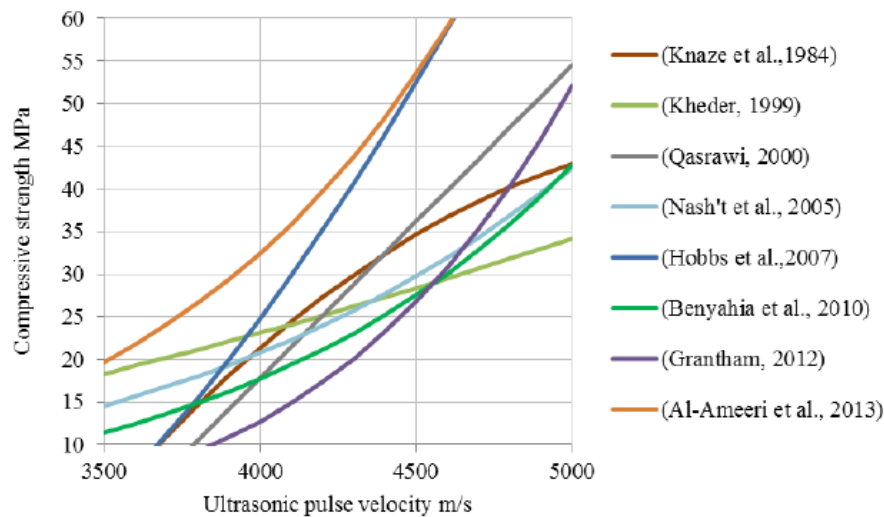


Figure 2. 4 Conversion curves established by various researchers to estimate the compressive strength of cubes using ultrasonic pulse velocity (Alwash, 2017)

3.3.5 Standards and guidelines available for the testing of Ultrasonic Pulse Velocity

The Ultrasonic Pulse Velocity technique is covered by several standard specifications. These standards ensure consistent and reliable testing procedures, making the Ultrasonic Pulse Velocity a widely used nondestructive technique for assessing the strength and quality of concrete structures.

- ASTM C-597-0, standard test method for pulse velocity through concrete.
- EN 12504, testing concrete structure in part 4; determination of ultrasonic pulse velocity.
- ASTM D6760-02, standard test method for deep foundation integrity of concrete by ultrasonic crosshole testing.

- ASTM C-1383 test method for measuring the P-wave speed and the thickness of concrete using the impact echo method annual book of ASTM standards vol.04.02.
- IAEA guidebook on non- destructive testing of concrete structures, Vienna 2002.
- ACI 228.1R-03 ACI committee report; in place methods to estimate concrete strength.

These standards differ in their origin, scope, and specificity. ASTM C-597-0 and EN 12504 primarily focus on UPV technique, while ASTM D6760-02 is more specialized in deep foundation integrity testing. ASTM C-1383 focuses on measuring the P-wave speed and concrete thickness using the impact echo method, which is similar to UPV technique. The IAEA guidebook provides broader insights into NDT techniques for concrete, including UPV. ACI 228.1R-03 focuses on in-place methods for estimating concrete strength, which may include UPV as one of the techniques. The selection of a specific standard to follow depends on several factors such as regional regulations, industry practices, and specific testing requirements.

3.4 Combination of NDT techniques: principles and limitations

The combined usage of multiple nondestructive testing methods has been explored as a potential approach to enhance the prediction of concrete strength. The combination of UPV and RH in the SonReb approach can provide a more comprehensive and robust evaluation of concrete strength. The SonReb method takes advantage of the complementary nature of UPV and RH tests. By using both tests simultaneously, the method can compensate for potential variations caused by different factors. For instance, the impact of moisture content, which influences UPV results, is counterbalanced by its opposite effect on RH results. This balancing effect contributes to a more dependable and comprehensive estimation of concrete strength when both methods are combined in the SonReb approach. The combination of Ultrasonic Pulse Velocity and Rebound Hammer was developed largely due to the efforts of RILEM Technical Committees 7 NDT and 43 CND. Various studies have explored the use of combined methods for predicting in situ compressive strength. (Qasrawi, 2000) introduced charts based on a combination of RH and UPV tests to estimate the in situ compressive strength of concrete structures. (Huang et al., 2011) proposed a probabilistic multivariable linear regression model that used SonReb measurements and other concrete properties to predict in situ compressive strength. (D. Breyse, 2012) conducted an analysis of test results obtained from laboratory studies and real buildings, demonstrating that the UPV and RH tests, when combined using the SonReb approach, yielded a Root Mean Square Error of approximately 4 MPa in strength assessment.

However, early investigations on this combined usage yielded mixed results. For instance, (Breysse, 2012) concluded that the effectiveness of combining the evaluation of two or more NDT techniques has been controversial. Moreover, (Santos et al., 2020) applied statistical techniques to evaluate the reliability of UPV and RH to evaluate the compressive strength of the concrete in bridges. The results of the statistical analysis provided insights into the effectiveness of UPV and RH for estimating concrete strength. (ACI 228, 2003) reported that a combination of NDT methods only provides marginal improvements over a single method. Nevertheless, recently, there is a growing literature on the benefits of employing multiple NDT techniques to increase reliability and accuracy of predictions. (Sri Ravindraiah et al., 1988) reported promising results on compressive strength estimation of recycled-aggregate concrete using combined UPV and RH. (Kheder, 1999a) investigated concrete strength prediction using UPV and RH in conjunction with concrete mix proportions and density. Furthermore, in a study conducted by (Breysse and Martínez-Fernández, 2014), the authors demonstrated the effectiveness of the combination of RH and UPV techniques in reducing the impact of uncontrolled humidity factors through a Monte Carlo simulation. The authors emphasized the importance of using a sufficient number of concrete cores, typically 6-7 cores, for calibrating the model. In addition, (Sri Ravindraiah et al., 1988) conducted a study on the estimation of compressive strength in recycled-aggregate concrete using the combination of UPV and RH, which yielded promising results. (Kheder, 1999a) also investigated concrete strength prediction by integrating UPV and RH with concrete mix proportions and density. Overall, many case studies exist in which different techniques have been combined, but real added value can only be obtained if the combination is correctly analyzed.

The technical literature contains numerous empirical formulas for estimating the compressive strength of concrete using the SonReb method. Several regression models have recently been developed to predict compressive strength using a combination of UPV and RH (Arioğlu et al., 2001; Hobbs and Tchoketch Kebir, 2007; Pucinotti, 2014). In addition, (Ali Benyahia et al., 2017a) considered various models that integrate destructive tests with individual or combined nondestructive tests (such as RH and UPV) to achieve more accurate estimations of concrete strength. Their findings demonstrated that the combined methods for concrete strength estimation were highly regarded when compared to previous models found in the literature. The SonReb technique is based on the general relationship between the compressive strength of concrete, Rebound Hammer and Ultrasonic Pulse Velocity, as outlined in the tentative recommendations for “in situ concrete strength estimation by combined nondestructive

methods” by RILEM Committee TC 43 CND in 1983. Figure 2.5 shows this relationship in the form of a “monogram”. By knowing the Rebound Hammer and Pulse Velocity, the compressive strength can be estimated. When it comes to estimating the strength of a material, incorporating two nondestructive testing measurements into regression models enhances the accuracy of strength estimation. Following the same rationale, the inclusion of a third (or even a fourth) NDT measurement would further improve the quality of the estimation.

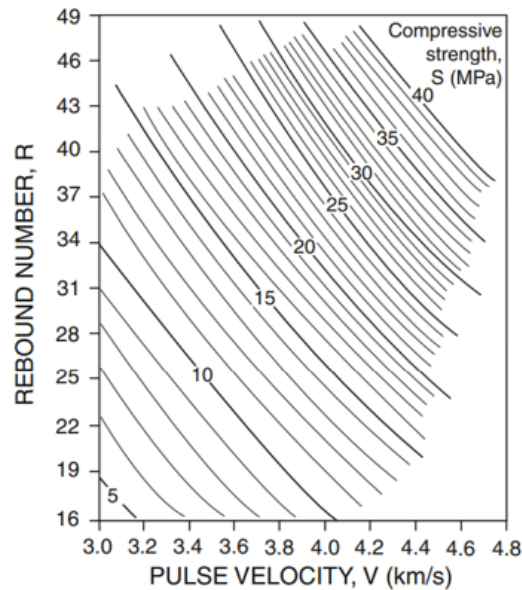


Figure 2. 5 Diagram for calculating concrete strength based on Rebound and UPV measurements (RILEM TC43)

4 Existing model identification approaches

The most commonly employed approaches for predicting compressive concrete strength based on SonReb measurements include computational modelling, artificial intelligence, and parametric multi-variable regression models. Computational modelling relies on complex physical phenomena modelling and can often encounter challenges due to the complexity of the models or the time-consuming nature of numerical computations (Huang et al., 2011). In contrast, parametric multi-variable regression models offer a more straightforward and practical approach for various applications, including the reliability assessment of concrete structures using field data. Artificial intelligence, particularly the Artificial Neural Network (ANN) approach, serves as a nonparametric statistical tool that does not require knowledge of theoretical relationships between input and output variables.

Studies have shown that parametric multi-variable regression models yield accurate correlation formulas for predicting compressive strength (Nobile, 2015). However, new techniques, such as Artificial Neural Network ANN, have been employed to capture the relationship between NDT parameters and concrete mechanical characteristics. The results obtained from the work of (Bonagura and Nobile, 2021) indicated the excellent estimation potential of a multilayer feed-forward neural network trained with a back propagation error algorithm in the evaluation of concrete compressive strength. The Artificial Neural Network ANN approach has also been applied to predict concrete compressive strength using input variables like age, Portland cement, water, sand, etc (Bonagura and Nobile, 2021). Moreover, the ANN approach has been previously suggested to assess the relationship between concrete compressive strength and UPV in the work of (Bilgehan and Turgut, 2010; Trtnik et al., 2009).

Identifying a relevant conversion model involves identifying its statistical parameter values based on the idea of minimizing the gap between estimated and measured strength values at the same location. When a conversion model is identified on a dataset (fitting stage), it is recommended to check the effective capacity of the model and its ability to predict the strength at a new dataset (prediction stage) that has not been used at the fitting stage. It is important to be aware that a fitting model may exhibit high precision but low predictive capacity. The strength assessment quality based on fitting accuracy is therefore irrelevant and often misleading, in particular with low numbers of cores NC. However, when the number of cores ranges from 9 to 20, the prediction and fitting errors tend to stabilize (Ali Benyahia et al., 2017a; Alwash et al., 2016).

Several model identifications approaches can be used to identify the conversion model. Calibration approaches and the regression approach are the most commonly used in practice to generate a conversion model for assessing concrete strength (Luprano et al., 2015). In the other hand, (Alwash et al., 2016) proposed a new model identification approach, called “bi-objective approach”. This approach proved to be efficient in estimating the mean concrete strength and concrete variability with a number of cores lower than what is specified in the standards. A Bayesian inference approach was also proposed by (Giannini et al., 2014) to assess concrete strength by combining the results of core and NDT tests. Moreover, a data fusion technique that combines measurements obtained from various NDT techniques has been suggested by (Ploix et al., 2011) for the evaluation of concrete structures. (Huang et al., 2011) introduced a probabilistic multi-variable regression model that uses SonReb measurements to predict the concrete strength. The proposed approach resulted in a conversion model that was integrated

with the Bayesian updating rule, enabling continuous model updating as additional data become available.

Several performance metrics can be used to evaluate the predictive capability of the developed conversion models:

- The difference in mean and standard deviation between estimated values and true values, which refers to relative errors of mean strength and strength variability. These relative errors provide a measure of the extent to which the estimated mean strength or strength variability deviates from the true mean strength or true strength variability, expressed as a percentage. The relative error is determined by taking the difference between the estimated value and the true value, and dividing it by the true value.
- The error in the estimated local strength, which refers to the prediction error RMSE between the true strength and the estimated strength. It represents the discrepancy or deviation between the actual strength values and the value predicted using a particular model.
- The variability (scatter) in the estimated values, which refers to the spread or dispersion of the estimated values. It provides information about the degree of uncertainty or inconsistency in the estimates. In order to quantify the variability, statistical measures like the standard deviation or variance are commonly used. Understanding the variability in the estimated values is important as it helps assess the precision and reliability of the prediction model.
- The probability (risk) that the estimated values lie outside an accepted margin of error. This probability is calculated based on the distribution of the estimated values and the chosen margin of error. For example, if a 95% confidence interval is used, there is a 5% probability (risk) that the estimated values will fall outside the accepted margin of error. This implies that there is a 95% confidence that the true values are within the specified margin of error.

As discussed earlier, concrete strength assessment, using the combined method requires a conversion model to establish the relationship between the NDT and core test measurements. This section discusses the existing model identification approaches to produce this conversion model.

4.1 Mono-objective approach using multiple regression (SonReb method)

In multiple regression analysis, the goal is to model the relationship between a dependent (explained) variable and two or more independent (explanatory) variables simultaneously. Each independent variable represents a different NDT technique in this context. The regression approach used for a single NDT technique as an independent variable can be expanded to include multiple NDT techniques as independent variables. Thus, assuming a linear model between the strength and NDT measurement, the resulting regression model is:

$$f_c = a + b_1x_1 + b_2x_2 + \dots + b_nx_n + \varepsilon \quad (2.4)$$

This extended regression model considers the contributions of multiple NDT techniques (with their respective coefficients $(a, b_1, b_2, \dots, b_n)$) to predict the concrete strength (f_c) based on the observed NDT measurements (x_1, x_2, \dots, x_n) for each data point in the dataset. The parameters $(a, b_1, b_2, \dots, b_n)$ are obtained through least squares minimization (Ross, 2009). The least squares method is commonly used to estimate the model parameters in regression analysis. It minimizes the sum of the squares of the differences between the observed values (compressive strength) and the predicted values (obtained from the NDT measurements). This optimization process yields the best-fit values for the model parameters, allowing us to make accurate predictions. The choice of the model type depends on the nature of the relationship between the concrete strength and the NDT measurements. If a linear model does not adequately capture the nuances, one has the option to explore alternative models like exponential or power models. These models can be expressed in a similar form with appropriate adjustments.

Equation 2.4 can also be written in matrix form or more compactly:

$$Y = X \times A \quad (2.5)$$

- Y is the response vector, representing the dependent variable (the compressive strength) for each data point in the dataset. It is a column vector with dimensions $(n \times 1)$, where n is the number of observations in the dataset.
- X is the design matrix, which includes the independent variables (NDT measurements) for each data point. It is a matrix with dimensions $(n \times m)$, where n is the number of observations, and m is the number of independent variables (number of NDT techniques).

- A is the model parameters matrix, representing the coefficients of the regression model. It is a column vector with dimensions $(m \times 1)$, where m is the number of independent variables.

To get the parameters of the model we are looking for, we have to invert the equation or the matrix system. This inversion can be done by the method of least squares for example, but also by the calculation of the inverse matrix. However, it is important to note that directly calculating the inverse matrix can be computationally expensive, and it may not always be the most efficient approach, particularly when dealing with large datasets.

Mathematically, the least squares solution for A can be obtained using the following equation:

$$A = (X^T * X)^{-1} * X^T * Y \quad (2.6)$$

- X^T is the transpose of matrix X .
- $(X^T * X)^{-1}$ is the inverse of the matrix resulting from the multiplication of the transpose of X with X .
- $X^T * Y$ is the matrix multiplication of the transpose of X with Y .

To combine Pulse Velocity and Rebound Hammer with concrete core test results, (Breysse, 2012) have also explored various model forms to establish relationships between these nondestructive testing measurements and the actual compressive strength obtained from the core samples. Some of the commonly considered model forms include bilinear, double power and exponential. In a state-of-the-art paper by (Breysse, 2012), a compilation of approximately 69 different models from the existing literature was presented. Table 2.4 presents several of these models derived by different researchers. The variety of model forms and coefficients highlights the diversity of approaches in the field of concrete strength estimation using NDT. By comparing and analyzing the performance of these different models, researchers and practitioners can select the most accurate and reliable model for their specific application, ensuring more precise assessments of concrete strength.

Table 2. 4 Models developed by different researchers to estimate concrete strength

Linear model	Exponential model	Power model
$f_c = 8.63V + 1.416R - 51.581$ (Soshiroda et al., 2006)	$f_c = 7.695 \times 10^{-11} V^{2.6} R^{1.4}$ (Facaoaru, 1969)	$f_c = e^{0.446V + 0.048R}$ (Machado et al., 2009b)
$f_c = 17.13V + 0.866R - 62.684$ (Kenai and Bahar, 2003)	$f_c = 1.15 \times 10^{-10} V^{2.6} R^{1.3}$ (Breysse, 2012)	$f_c = 0.67e^{0.72V + 0.04R}$ (Sri Ravindraiah et al., 1988)
$f_c = 5.0614V + 1.532R - 39.57$ (Ramyar and Kol, 1996)	$f_c = 0.00153 \times 0.611 V^3 R^3$ (Kheder, 1999b)	$f_c = 1.974e^{0.000542V + 0.01605R}$ (Cristofaro et al., 2017)
$f_c = 44.8V + 0.77R - 194$ (Turgut and Kucuk, 2006b)	$f_c = 0.00004 \times V^{0.80840} R^{1.88148}$ (Menditto et al., n.d.)	
$f_c = 0.01385V + 0.26511R - 34.51583$ (Faella et al., 2011)	$f_c = 10^{-4.251} V^{1.281} R^{0.686}$ (Cristofaro et al., 2017)	
$f_c = 0.01174V + 0.37R - 28.44$ (Cianfrone and Facaoaru, 1979)	$f_c = 9.27 \times 10^{-11} V^{2.6} R^{1.4}$ (RILEM, 2014)	

f_c is the core compressive strength
R is Rebound Hammer test result
V is Ultrasonic Pulse Velocity test result

4.2 Calibration approach

In order to estimate concrete strength using both UPV and RH tests, several empirical, multi-parametric models have been proposed in the literature (Ali-Benyahia et al., 2017; Chandak and Kumavat, 2020; Cristofaro et al., 2020). However, the presence of multiple models suggests that each model might offer accurate strength predictions only within the specific cases for which it was developed. It is important to note that there is no universal model that can be applied to all types of concrete. Due to the inherent variability in concrete mixes used in existing structures, it is essential to adopt a calibration procedure for on-site concrete strength assessment. The calibration process aims to modify an existing model to suit the specific concrete being evaluated. By adjusting the model based on the unique characteristics of the concrete mix in question, the calibrated model can provide more accurate strength predictions for the specific structure or element under consideration. This calibration process is crucial for

ensuring reliable and accurate strength assessments in real-world applications, where concrete mixes can vary significantly between different structures and construction projects. Two options for calibration are commonly used in practice (EN 13791, 2007) : the shifting factor method, and the multiplying factor method.

4.2.1 Shifting Factor Method (Δ -Method)

The Δ -method involves adjusting the prior model by a constant Δ , resulting in the calibrated model. This calibration constant Δ is calculated based on the measurements of indicators and observables obtained at specific points within the concrete being evaluated. The calibration by the shifting method is easy to carry out and inexpensive. However, the parameter Δ cannot modify the conversion model to include the effects of all influencing parameters. Moreover, it does not modify the model sensitivity coefficients (i.e., if the model is linear, then the calibration has no effect on the slope “sensitivity coefficient”) which may lead in some cases to significant errors.

The concept here is to shift the prior model by a coefficient Δ :

$$f_{c\ est}(x) = f_{c\ uncal}(x) + \Delta \quad (2.7)$$

Where f_{uncal} is the estimated compressive strength calculated from the selected uncalibrated prior model. To implement the Δ -method, the following steps are taken:

- Calculate the mean value of core strengths from the available data \bar{f}_{core}
- Use the uncalibrated prior model to estimate strengths at core locations and compute the mean of these estimated values $\bar{f}_{c\ uncal}$
- Calculate the shifting factor $\Delta = \bar{f}_{core} - \bar{f}_{c\ uncal}$
- Update the uncalibrated model by applying the shifting factor Δ , as shown in Equation 2.7

4.2.2 Multiplying Factor Method (k -Method)

On the other hand, the k -method involves modifying the conversion model by multiplying it with a calibration constant k , resulting in the calibrated model. As in the previous method, the calibration constant k is calculated from the available data on the concrete under consideration. Unlike the calibration method involving shifting, the current approach adjusts all coefficients within the conversion model.

The principle comes to update an uncalibrated prior model by a coefficient k to produce a calibrated model:

$$f_{c\ est}(x) = k * f_{c\ uncal}(x) \quad (2.8)$$

Where f_{uncal} is the estimated compressive strength calculated from the selected uncalibrated prior model. The calculation of the coefficient k involves the following steps:

- Calculate the mean value of core strengths from the available data \bar{f}_{core}
- Use the uncalibrated prior model to estimate strengths at core locations and compute the mean of these estimated values $\bar{f}_{c\ uncal}$.
- Calculate the multiplying factor k , which represents the ratio between the mean value of the measured core strengths and the mean of the estimated strengths from the uncalibrated model $k = \bar{f}_{core}/\bar{f}_{c\ uncal}$
- Update the uncalibrated model by applying the calibration factor k , as shown in Equation 2.8

In both calibration methods, the objective is to refine the uncalibrated prior model to provide a more accurate and reliable representation of the concrete strength for the specific structure under consideration. The choice between the Δ -method and the k -method depends on the particular characteristics of the uncalibrated model and the data available for calibration. Combining calibration methods could potentially provide a more comprehensive and accurate calibration process. However, it is important to note that the feasibility of combining calibration methods depends on the specific context and requirements of the calibration process. Factors such as the complexity of the model, the nature of the calibration data, and the assumptions underlying each calibration method should be carefully considered.

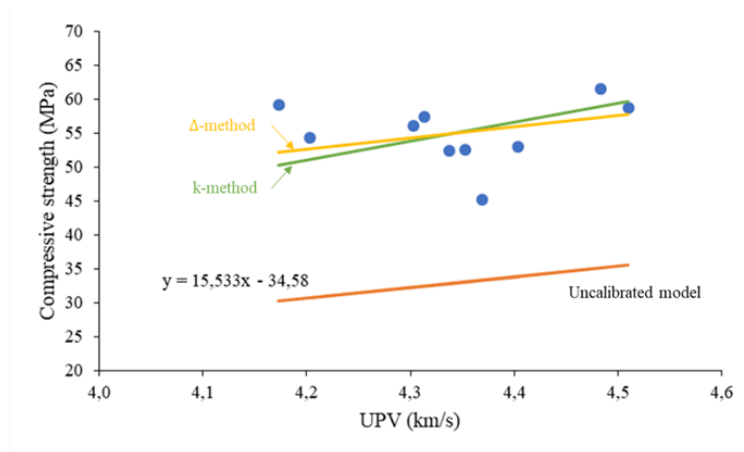


Figure 2. 6 Scatter diagram illustrating the relationship between the compressive strength and UPV with models derived from the calibration approaches

5 Assessing concrete strength variability using NDT

In real-world applications, it is common to assess both the mean compressive strength and the characteristic compressive strength of concrete. The determination of the characteristic strength depends on the mean strength and the standard deviation of the compressive strengths, which represent the variability of the concrete. Therefore, concrete variability is a crucial parameter that requires careful consideration. Characterizing the compressive strength in existing buildings usually involves determining two specific parameters: a location parameter, often the mean value of concrete strength, and a variability parameter, usually either the standard deviation or the coefficient of variation of the data.

The existing approaches for estimating concrete strength often focus on determining the mean value of the strength without explicitly capturing the variability that exists within the concrete. While some standards may recommend certain approaches to estimate strength variability, they may not fully address the complexities of capturing this variability accurately. In light of this, (Alwash et al., 2016) proposed a new approach called the “bi-objective approach”. Unlike traditional methods, the main objective of this approach is to estimate the average value of concrete strength, and to accurately capture the inherent variability that exists within the concrete. By incorporating both the mean and variability aspects, the bi-objective approach seeks to provide a more comprehensive and accurate characterization of concrete strength.

The fundamental concept behind this approach is to gather a data set comprising pairs of NDT measurements (UPV for example) and corresponding core strengths ($f_{c \text{ core}}$) obtained at the

same test locations. This data set is then used to establish a conversion model between concrete strength and ultrasonic test results. Common mathematical models for this relationship typically involve two parameters (a and b), such as linear models, exponential, or power-law models. In the bi-objective approach, the two main objectives are to ensure that the mean strength and standard deviation of real concrete values align with the estimated ones (Alwash et al., 2016):

- Mean strength condition: $\bar{f}_{c\ est} = \bar{f}_{c\ core}$
- Variability condition: $s(f_{c\ est}) = s(f_{c\ core})$

By applying these conditions to a linear model, for example $f_{c\ est} = a + b * V$, we can calculate the unknown parameters as follows:

$$a = s(f_{c\ core})/s(V) \quad (2.9)$$

$$b = \bar{f}_{c\ core} - a * \bar{V} \quad (2.10)$$

Here, \bar{V} and $s(V)$ represent the mean and standard deviation values of the Ultrasonic test results obtained at the core locations, respectively. The bi-objective approach is demonstrated here with the Ultrasonic Pulse velocity as the NDT technique. However, the same principles can be applied to other NDT techniques, as there are no constraints in the parameter development related to the type of NDT method being used.

The limitation of this approach is that it cannot be used in the case of combining multiple nondestructive techniques. The bi-objective method is specifically designed to estimate the variability of concrete strengths using a single nondestructive technique. When multiple NDT techniques are combined, it becomes challenging to directly apply this bi-objective approach. In such cases, other statistical approaches need to be considered to account for the variability of concrete strength.

6 Statistical properties of nondestructive estimation

6.1 Measurements and estimations

The average value of local measurements provides an estimate of the central tendency of the data collected. However, it is essential to note that the average value may not necessarily represent the true value being measured. The presence of variability in the data can cause the average value to deviate from the actual true value. The deviation or spread of the individual measurements around their average is referred to as “precision”. Precision holds significant

importance in the context of measurements and experimental data. It refers to the degree of consistency or reproducibility of repeated measurements under the same conditions. In other words, precision tells us how close individual measurements are to each other, or how tightly they are clustered around the average value. A high precision means that the measurements are clustered closely around their average, while a low precision indicates a more notable degree of variability. In a graph, high precision would result in data points forming a tight cluster with low scatter. However, low precision would lead to data points being more spread out from the average value.

On the other hand, “accuracy” refers to how close the average value of the test measurements is to the true value. In other words, accuracy tells us how well the measurements reflect the true value of the quantity being measured. When measurements are highly accurate, it means that, on average, the recorded values are very close to the true or accepted value of the quantity being measured. Conversely, when measurements are of low accuracy, it means that, on average, the recorded values deviate significantly from the true value. There is a systematic bias in the measurements, leading to a consistent overestimation or underestimation of the true value.

In summary, precision and accuracy are two distinct aspects of the measurement or test process. Precision deals with the consistency and spread of individual measurements around their average, while accuracy focuses on how close the average value is to the true value. Both precision and accuracy are essential in ensuring reliable and meaningful results in scientific and engineering applications.

6.2 The accuracy of nondestructive concrete strength estimation

Due to the presence of errors in the estimation process, there will always be differences between the measured results, estimated results, and the true ones. These discrepancies are known as “errors”. An error represents the difference between the estimated or measured value and the true value. Reducing these errors is a key goal in the process of improving the accuracy of estimations and predictions. The inaccuracies in estimating concrete strength within the structure can be attributed to:

- **Measurement error:** This type of error results from inaccuracies in the measurement process. It includes errors in determining the strength of concrete specimens used for calibration and errors in the nondestructive testing measurements taken on the structure. These errors can occur due to imprecise instruments, variations in test conditions, or human error during the testing process.

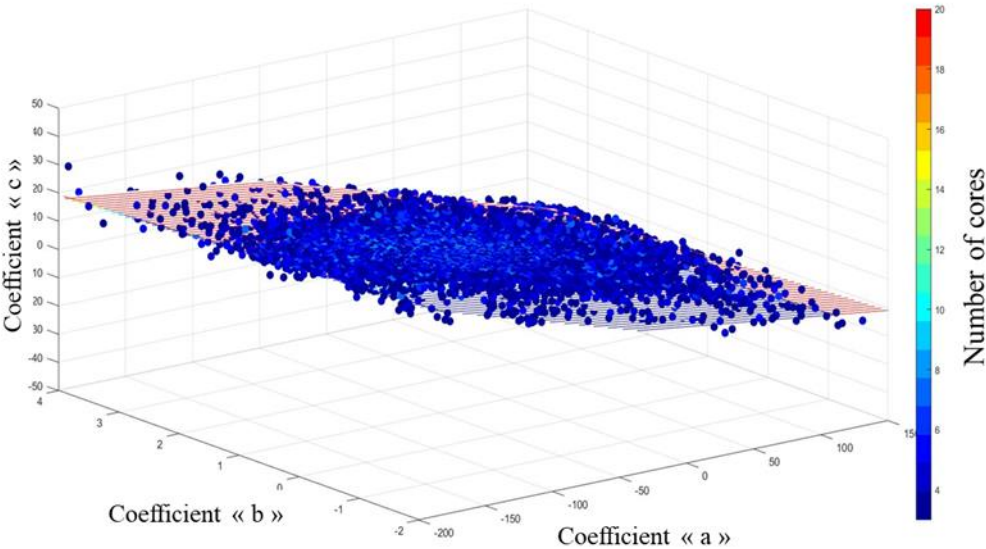
- Inherent variability of the material: It is crucial to understand and account for the material variability at different scales. Concrete is a heterogeneous material with variations in its properties. Some regions may have higher cement content or different aggregate distributions, leading to variations in strength, porosity, and other properties. This inherent microstructural variability contributes to the overall diversity of concrete's behavior.
- Error in the conversion model: Nondestructive estimation often involves the use of statistical models to relate NDT measurements to concrete strength. If the chosen conversion model is not appropriate for the specific type of concrete or the conditions of the structure, it can lead to prediction errors.

In the field of statistics, it is important to understand the different types of uncertainties that can affect measurements and data analysis. Measurement error and intrinsic variability, which can be categorized as random uncertainties, are due to unpredictable and inherent factors in the measurements and properties of the material. On the other hand, the conversion model error can be considered as an epistemic uncertainty. It is related to the imperfect model used to convert NDT measurements into estimated strength. Addressing and understanding these sources of uncertainty is essential to improve the accuracy and reliability of NDT-based concrete property estimation.

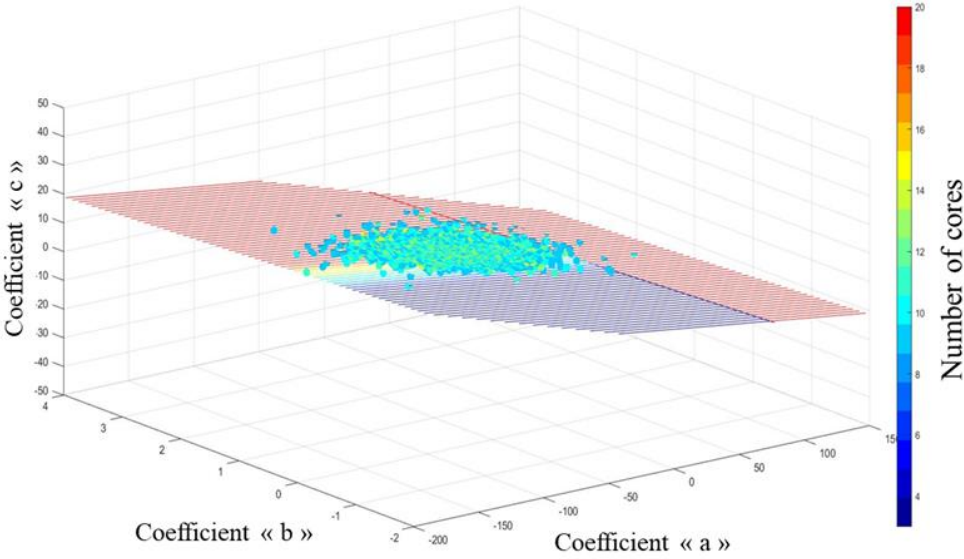
6.3 Relationship between the statistical parameters of the model “trade-off effect”

In this study, the term “model” is used to represent the relationship between NDT measurements and the concrete strength. Each calibration process leads to the establishment of a unique model with its specific set of statistical parameters. These parameters are closely interrelated, and collectively, they form a set known as the “trade-off”. This effect has only been studied for a single NDT method in the work of (Ali Benyahia, 2017; Breysse, 2012). In this section, we examine the trade-off impact when combining NDT methods using a dataset from (Ali-Benyahia et al., 2017) consisting of triplets of V , R , and f_c . To assess the quality of model calibration and investigate the impact of calibration on the model parameters, the number of cores NC undergoing calibration is varied from a minimum of 3 cores to a maximum of 20 cores. This procedure is repeated 10000 times for each number of cores in order to study the stability of the repetitive process. In each repetition, a model with its own statistical parameters is estimated, resulting in a set of parameters that varies from one repetition to another.

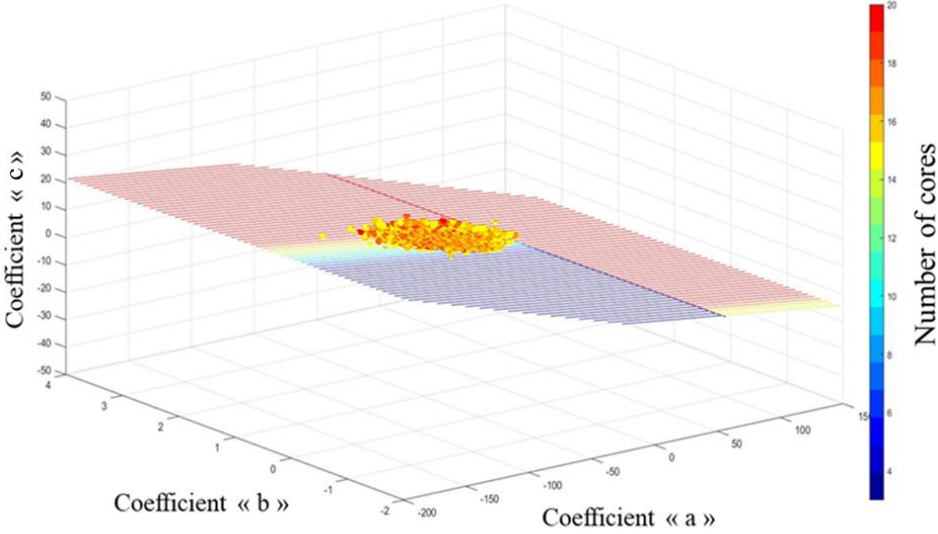
Figure 2.7 illustrates the “trade-off” effect between the statistical parameters ‘a’, ‘b’ and ‘c’ of the multi-variable model. For a given NC, all the parameters (a_i , b_i , and c_i) from repetitions ($i = 1$ to 10000) are situated within the same plane, expressed as ($c_i = f(a_i, b_i)$). This means that the relationship between the statistical parameters a, b, and c follows a linear pattern. Furthermore, regardless of the variation in NC, the sets of parameters (a_i , b_i , and c_i) always remain on the same plane. However, as the number of cores NC increases, the dispersion of these parameters decreases, indicating that the model becomes more stable and consistent. Figure 2.7 confirms that as the NC increases, the values of the parameters a, b, and c for each NC converge closer to the parameters of the entire population model. This suggests that a larger sample size (higher NC) leads to a better estimation of the model parameters, increasing the accuracy of the calibration process. Moreover, the variation in NC significantly influences the degree of dispersion (standard deviation) of the parameters a, b, and c. In other words, increasing NC reduces the variability in the parameter estimates, making the model more reliable and robust. While increasing the number cores can improve the reliability and robustness of the model, it is important to maintain a balance. Adding more observations beyond a certain point may not significantly reduce the variability in the parameter estimates, and it can increase computational costs and time.



(a) Number of cores varies from 3 to 8



(b) Number of cores varies from 9 to 14



(c) Number of cores varies from 15 to 20

Figure 2. 7 Effect of the trade-off as a function of the number of cores

6.4 Statistical indicators for the precision of concrete strength estimation

The precision of estimating concrete strength can be measured using statistical indicators, which come in two forms: absolute precision and relative precision (Shcherbakov et al., 2013).

The Root Mean Square Error (RMSE) represents absolute precision, while the Normalized Root Mean Square Error (NRMSE) measures relative precision.

The Root Mean Square Error (RMSE) is a statistical metric used to assess the accuracy of a predictive model in estimating values compared to the actual measured values. In the context of concrete strength estimation, the RMSE measures the discrepancy between the strength values predicted by a model (referred to as “estimated strength” or “ $f_{c\ est}$ ”) and the concrete strength values that are actually measured on-site (referred to as “measured strength” or “ f_c ”). Mathematically, the equation for RMSE involves summing up the squared differences for all data points, dividing by the number of data points N_c , and then taking the square root of the result (Equation 2.11). A lower RMSE value indicates that the model's estimates are closer to the actual measured values, suggesting a more accurate predictive performance of the model. Conversely, a higher RMSE value implies that the model's estimates have larger deviations from the measured values, indicating lower predictive accuracy.

In the other hand, the Normalized Root Mean Square Error (NRMSE) has been proposed as a metric to address the issue of scale dependency in error measurements (Booij et al., 1999; Shcherbakov et al., 2013). The RMSE is sensitive to the scale of data, meaning that it can be influenced by the magnitude of the observed values. This can make it challenging to compare the accuracy of models across different datasets or variables with varying scales. To overcome this limitation, the NRMSE normalizes the RMSE by dividing it by a reference value that represents the range or spread of the observed values (Equation 2.12). This normalization process allows for a standardized comparison of the prediction errors regardless of the scale of the data.

$$RMSE = \sqrt{\sum_{i=1}^{N_c} (f_{c\ est\ i} - f_{ci})^2 / N_c} \quad (2.11)$$

$$NRMSE = \frac{1}{\bar{y}} \sqrt{\sum_{i=1}^{N_c} (f_{c\ est\ i} - f_{ci})^2 / N_c} \quad (2.12)$$

Where $f_{c\ est\ i}$ is the the estimated compressive strength, f_{ci} is the true compressive strength and \bar{y} is the normalization factor, which is equal to either the maximum measured value or the difference between the maximum and minimum values.

In practical applications, when evaluating the quality of concrete strength estimation, a commonly used statistical indicator is the coefficient of determination denoted as r^2 . This indicator is particularly helpful for assessing the adequacy of a simple or multiple regression model. The coefficient of determination, r^2 , ranges from 0 to 1 and quantifies how well the regression model aligns with the observed (measured) data. A value of 0 for r^2 means that the regression equation does not explain any of the distribution of the measured data. Essentially, the mathematical model used is not providing any useful information about the data distribution, and it cannot predict any observed data values. On the other hand, an r^2 coefficient of 1 indicates that the regression equation perfectly explains 100% of the data distribution. In other words, there is a perfect correlation between the regression model and the observed data. Graphically, the behavior of the coefficient r^2 can be depicted as follows: when the r^2 value is close to 0, the data points are widely scattered around the regression curve. Conversely, as the r^2 coefficient approaches 1, the data points align very closely with the regression curve.

In the process of assessing the precision of identification and prediction models, it becomes imperative to compute the error incurred at each stage of the analysis (identification and prediction). In our particular case, the robustness and reliability of these models are put to the test, and the evaluation is carried out using the statistical parameter RMSE. On one hand, model identification error $RMSE_{fit}$ refers to how well the model captures the relationship between NDT results and concrete strengths on a specific number of test surfaces NC . In simpler terms, it assesses how accurately the model represents the correlation between NDT measurements and concrete strengths on the tested surfaces. If the precision of the test results is low, meaning there is a lack of accuracy and consistency in the measurements obtained, it can negatively affect the accuracy of the conversion model. In turn, this can limit the quality of strength estimation. To address this issue, one might consider increasing the number of test results. However, this is not the most practical approach due to associated costs and statistical considerations. Instead, it is often more effective to focus on improving the precision of the test results themselves by enhancing the repeatability and reproducibility of the measurements. Prediction error $RMSE_{pred}$, on the other hand, evaluates the accuracy and precision of the conversion model when used to estimate the concrete strength on other test surfaces. In this case, only NDT test results are available for the surfaces being assessed, and the model's ability to predict the concrete strength accurately is of critical importance.

7 Conclusion

This chapter provides a comprehensive literature review on the assessment of concrete strength through the combination of nondestructive testing techniques in conjunction with cores. The investigation program's design, involving core drilling and testing, was thoroughly explored as a fundamental process to determine concrete strength accurately. Key factors influencing the results through core testing were highlighted to ensure the reliability and precision of the assessment.

The significance of Rebound Hammer and Ultrasonic Pulse Velocity in concrete strength assessment was extensively discussed, covering the principles, devices, methodologies, and factors affecting test outcomes. Moreover, the reliability of results obtained from these NDT methods was considered, and relevant industry standards and guidelines were referenced to ensure consistent testing practices.

Moreover, the chapter discussed the potential advantages associated with the combination of NDT methods. The SonReb approach, which combines UPV and RH tests, is highlighted for its ability to provide a more comprehensive evaluation of concrete strength. The complementary nature of UPV and RH tests allows the SonReb method to compensate for variations caused by several factors such as moisture content. In addition, incorporating additional NDT measurements could further enhance the accuracy of strength estimation.

The chapter also delved into existing model identification approaches, such as the multiple regression and the calibration approach involving shifting factor (Δ -Method) and multiplying factor (k -Method). These approaches provided valuable tools for combining NDT results with cores to improve the accuracy of concrete strength estimation. Furthermore, the introduction of the bi-objective approach for assessing concrete strength variability using a single NDT technique emphasized its importance in obtaining a comprehensive understanding of concrete variability.

Additionally, the accuracy of concrete strength estimation, the precision of the conversion model, and statistical indicators for assessing the precision of concrete strength estimation were addressed, ensuring a robust and informed assessment process. The chapter also explored the notion of the “trade-off”, analyzing how statistical parameters interact in the calibration process of conversion models. By varying the number of cores NC in the calibration process, the study reveals a clear “trade-off” effect between the statistical parameters, emphasizing the importance of sample size in enhancing model stability and accuracy.

Chapter Three: Multi-Objective Optimization to Evaluate the Concrete Compressive Strength and Its Variability by Combining Nondestructive Techniques

1 Introduction

Nondestructive testing is increasingly used to evaluate the state of existing reinforced concrete structures. Extensive research efforts have been dedicated to the advancement of techniques and data analysis to enhance the assessment of construction materials (Aragón et al., 2019; Ivanchev, 2022; Kog, 2018; Martínez-Molina et al., 2014). Rebound hammer (RH) and Ultrasonic Pulse Velocity (UPV) techniques are often used to evaluate concrete characteristics and estimate compressive strength in the laboratory and in situ (Ivanchev, 2022; Kog, 2018). There are many factors that affect the Rebound Hammer and the Pulse Velocity, such as the moisture content of the concrete, the surface smoothness, water/cement ratio, the nature of the coarse aggregate, the age of the concrete, the size and shape of the concrete, and the rigidity of the concrete specimen (Huang et al., 2011; Schickert and Krause, 2010).

For years, correlating concrete strength simultaneously with RH and UPV, which is the origin of the SonReb method, has been tested in many research works (Alwash, 2017; Aragón et al., 2019; Bellander, 1979; Cianfrone and Facaoaru, 1979; Huang et al., 2011; Ivanchev, 2022; Kog, 2018; Martínez-Molina et al., 2014; Meynink and Samarin, 1979; RILEM, 2014; RILEM TC 43-CND, 1993; Schickert and Krause, 2010). The idea behind combining the Rebound Hammer technique with the Ultrasonic Pulse Velocity technique is based on the logical hypothesis that employing two NDT methods, each affected by different factors, could potentially decrease uncertainties in concrete strength assessment according to (Cianfrone and Facaoaru, 1979).

However, the SonReb approach is considered promising, but only if the additional cost is offset by improved diagnostic quality. It is important to acknowledge that combining nondestructive testing techniques also brings along the inherent limitations of each individual method. In fact,

the quality of any evaluation can be influenced by several factors, including the inherent characteristics of the concrete under examination, the inherent variability in concrete properties, uncontrolled factors, potential measurement errors and model uncertainties. These factors can collectively affect the precision and reliability of the assessment process, highlighting the need for careful consideration and calibration in the application of the SonReb method.

The assessment methodology of combining NDT techniques is similar to using a single NDT technique. It includes performing the NDT measurements, which involve using both the Ultrasonic Pulse Velocity and Rebound Hammer techniques. These measurements provide valuable data on the properties and conditions of the concrete at the test locations. Following the NDT measurements, samples are extracted from the tested areas. The next step is the development of a robust model using the dataset (UPV, RH and compressive strength values). The model is identified and validated using techniques such as cross-validation or dividing the dataset into training and testing sets. This ensures that the model accurately captures inherent relationships within the data and demonstrates strong generalization abilities when confronted with new data. Once the model is validated, it can be used to estimate the concrete's strength at any given test location by inputting the corresponding NDT measurements into the model. In addition, to combine RH and UPV, different forms of model were considered by several researchers. It is important to note that these models were derived from experimental measurements on different concretes; this explains the variety of the models' parameters.

Despite the importance of evaluating strength variability, it has received very little attention. It should be noted that the term “variability” primarily corresponds to the standard deviation, which is the most relevant parameter for describing dispersion. (Alwash et al., 2016) has developed a new bi-objective method able to assess variability with better accuracy than conventional methods (regression analysis or calibration methods). This model identification approach was explained in detail in Chapter 2. The main limitation of this method lies in its inability to combine two NDT techniques for assessing both strength and its variability. For this reason, we propose to address this issue by introducing a new method based on multi-objective optimization for predicting both mean and variability of compressive strength when at least two NDT methods are used.

This chapter introduces the dataset collecting synthetic and experimental test results. A complete description of this dataset is provided in Section 2, outlining its different sources and characteristics. In Section 3, two model identification approaches are analyzed to compare their

effectiveness in evaluating both the mean strength and variability of concrete strength. Through this comparative analysis, we aim to identify the most robust and precise model identification approach for our study. Finally, the proposed models are validated on both synthetic and experimental database, highlighting their ability to accurately predict concrete mean strength and variability.

2 Synthetic data and experimental program

2.1 Synthetic data

Due to the limited number of experimental data, synthetic simulations were performed, allowing the control of some parameters such as the effect of humidity and measurement uncertainty. These simulations were carefully designed to represent real-world scenarios and reflect the complex interactions that influence concrete strength. The synthetic data is generated using Monte Carlo simulation, which is a well-established technique for generating random samples based on known probability distributions. In the context of concrete strength assessment, the use of synthetic data can be particularly valuable in accurately representing the variability and multi-scale patterns observed in real case studies, while also accounting for measurement uncertainty. Synthetic data have already been employed in a multitude of applications and have demonstrated their considerable potential in enhancing data analysis (Alwash et al., 2015; Breysse, 2012; Luprano et al., 2015).

The simulation incorporates probability distribution functions to generate random values for input variables. The correlation between input (strength and moisture content with their mean and standard deviation values) and output (UPV and RH) variables is based on empirical models developed in previous studies, ensuring that the generated synthetic data reflects realistic relationships between variables (Alwash, 2017; Breysse, 2012). The advantage of such approach is to build a synthetic database in order to simulate different configurations and therefore to evaluate the quality of the methodology. The simulation's primary steps are:

- 1) Definition of the simulation input variables and their corresponding ranges of values (in-situ strength and moisture content);
- 2) Generation of random values for the input variables using the appropriate probability distribution function;

- 3) The output variables (RH and UPV) are determined according to established correlations between the inputs and outputs and performing the necessary computations;
- 4) Reiteration of the simulations in order to account for the sampling effect. Since the simulation involves generating random values for the input variables based on probability distribution functions, repeating the simulations multiple times helps to account for this randomness and provides a more robust estimate of the model's performance.

We consider as input variables of the simulation, the in-situ strength as well as the moisture content, with the following mean and standard deviation values respectively:

- $\bar{f}_{ist} = 25 \text{ MPa}$, $s(f_{ist}) = 2 \text{ MPa}$,
- $\bar{S}_R = 75\%$, $s(S_R) = 2.25\%$.

These specific mean and standard deviation values for in-situ strength and moisture content were selected to ensure that the synthetic dataset covers a range of realistic scenarios. By using representative values that align with typical concrete properties and environmental conditions, the objective is to create a dataset that reflects real situations. The impact of strength variability can be explored by varying the $s(f_{ist})$ value within the range of 1 to 10 MPa. Similarly, the influence of variability in concrete saturation rate can be investigated by varying the $s(S_R)$ value within the range of 1% to 10%.

The simulated “true” in-situ concrete strength f_{ist} is generated by assuming a normal distribution $\mathcal{N}(\bar{f}_{ist}, s(f_{ist}))$. In addition, a truncated normal distribution, $\mathcal{N}(\bar{S}_R, s(S_R))$ with $0 \leq S_R \leq 100\%$, is used to generate the values for the degree of saturation S_R . A truncated normal distribution is similar to a normal distribution but it is bounded within a specific range, which can avoid extreme non-physical values. This allows for the generation of degree of saturation values that fall within a defined range of practical values observed in concrete structures.

In order to correlate the inputs with the true in-situ ultrasonic pulse velocity V_t and true in-situ rebound number R_t , synthetic models were developed in (Breysse, 2012):

$$V_t = V_{ref} (f_{ist}/f_{cref})^{1/bf} (S_R/S_{Rref})^{1/bs} \quad (3.1)$$

$$R_t = R_{ref} (f_{ist}/f_{cref})^{1/cf} (S_R/S_{Rref})^{1/cs} \quad (3.2)$$

The reference values are: $R_{ref} = 40$, $V_{ref} = 4000 \text{ m/s}$, $S_{Rref} = 85\%$ and $f_{cref} = 40 \text{ MPa}$.

The strength sensitivity exponents' bf and cf in Equation 3.1 and 3.2 have been respectively taken equal to 4.9 and 2.1. Similarly, the humidity sensitivity exponents' bs and cs have been respectively taken equal to 7.14 and -3.33 (Breysse and Martínez-Fernández, 2014).

Furthermore, to simulate the outputs, random errors are introduced into the originally generated true in-situ values (represented as V_t , R_t and f_{ist}) in order to obtain the simulation outputs. These errors (ε_V , ε_R , ε_f) are incorporated to replicate real-world variability and uncertainties associated with the measurements and assessments.

$$V = V_t + \varepsilon_V \quad (3.3)$$

$$R = R_t + \varepsilon_R \quad (3.4)$$

$$f_c = f_{ist} + \varepsilon_f \quad (3.5)$$

The magnitude of these errors are obtained by assuming a normal distributions with zero mean $\mathcal{N}(0, sd_V)$, $\mathcal{N}(0, sd_R)$ and $\mathcal{N}(0, sd_f)$, the standard deviations represent the within-test variability of the measurements. The possible range of within-test variability has been widely documented in the literature (Breysse, 2012; Szilágyi et al., 2014). Based on the values (sd_V , sd_R , sd_f) provided in Table 3.1 from (Breysse et al., 2017), the measurements can be classified into three quality levels: high (HQ), average (AQ), and low (LQ). Table 3.1 provides the standard deviations for different quality levels, indicating the variability of measurements. It is observed that as the measurement quality improves the magnitude of the measurement error decreases.

Table 3. 1 The within-test standard deviation according to measurements quality levels

	High Quality (HQ)	Average Quality (AQ)	Low Quality (LQ)
sd_V	50 m/s	100 m/s	200 m/s
sd_R	1 unit	2 units	4 units
sd_f	1 MPa	1.5 MPa	2 MPa

In order to create a synthetic dataset, the data simulation process outlined in Figure 3.1 is repeated a number of times equal to the total number of test locations (dataset size = 100) in the synthetic structure. Each repetition of the process generates the outputs (V , R and f_c) corresponding to a single test location.

The cumulative distribution function of core strength is illustrated in Figure 3.2, it provides an understanding of the overall strength distribution corresponding to the synthetic dataset. The mean strength is 24.9 MPa and the variability is 2.52 MPa. Similarly, the cumulative distribution of NDT measurements is illustrated in Figure 3.2; it shows the distribution of measurements obtained through Rebound Hammer and Ultrasonic Pulse Velocity corresponding to the synthetic dataset. The Rebound Hammer data exhibits an average value of 32.93 units and a variability of 2.09 units. The Ultrasonic Pulse Velocity exhibits an average value of 3.53 km/s and a variability of 0.09 km/s.

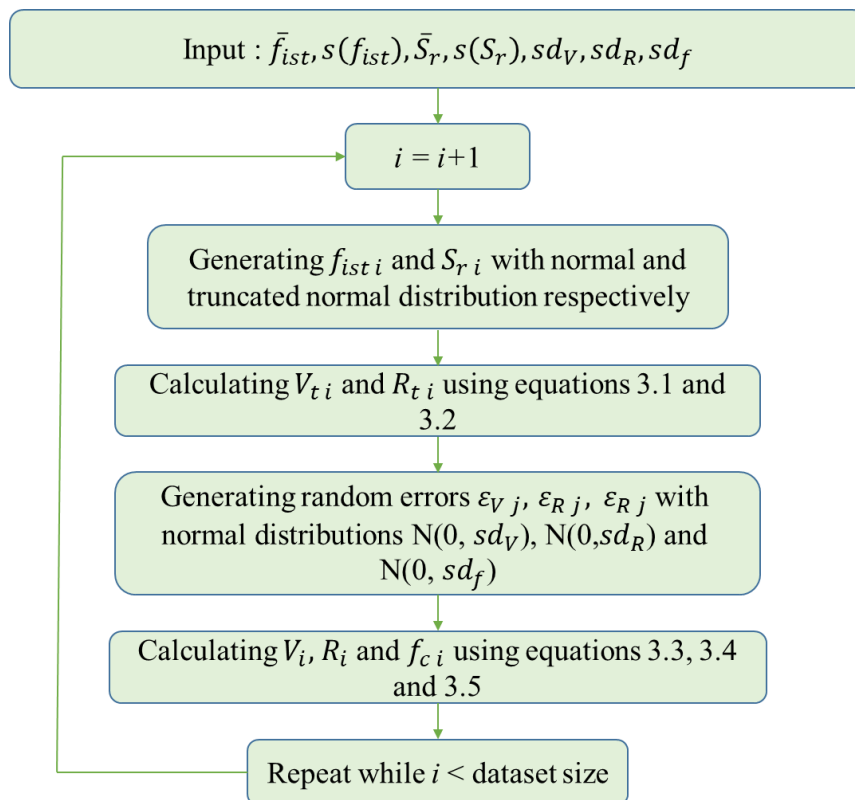
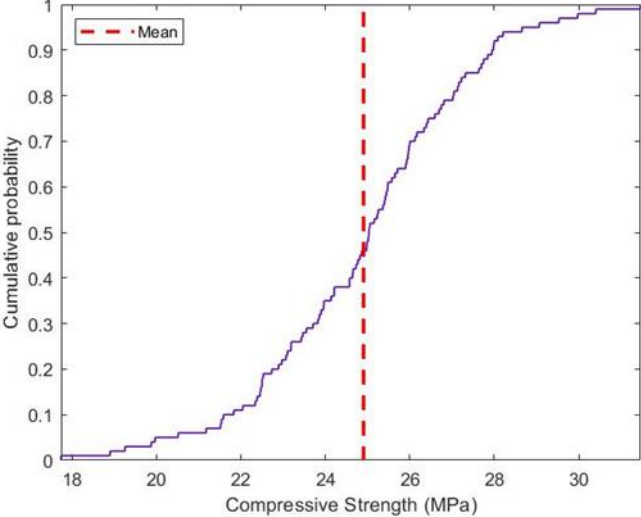
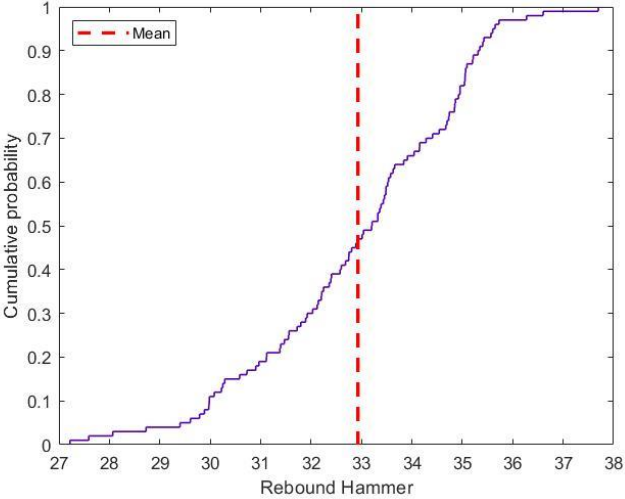


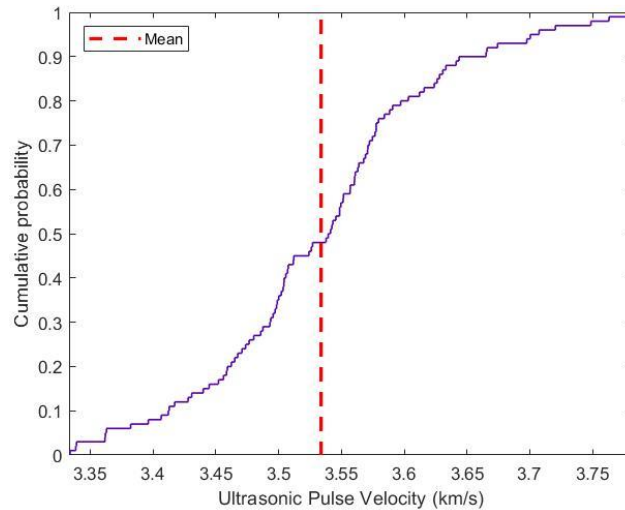
Figure 3. 1 Generating dataset using synthetic simulation



(a) Cumulative distribution of simulated compressive strengths



(b) Cumulative distribution of simulated RH values



(c) Cumulative distribution of simulated UPV values

Figure 3. 2 Cumulative distribution of (a) core strength and (b), (c) NDT measurements corresponding to the synthetic dataset

2.2 Experimental data

The experimental dataset is a large auscultation and coring campaign on structural elements of a building existing since 2004 (Ali-Benyahia et al., 2017). The building is composed of two juxtaposed blocks separated by aseismic joint with two and three floors, respectively. The main structure consists of a reinforced concrete frame system, which includes columns and beams (Ali-Benyahia et al., 2017). During the testing phase, test locations on the element were carefully chosen, avoiding areas with visible cracks or critical sections, as well as regions with reinforcement. The structural elements (columns and beams) were subjected to nondestructive evaluations using Rebound Hammer and Ultrasonic Pulse Velocity. In parallel, compressive tests of the sampled cores were also performed. 155 structural elements (columns and beams), distributed over the two blocks, were subjected to NDT tests, with a number of two to three test locations selected on each element. In total, 205 core samples were assessed by NDT and compressive test according to the standards EN 12504-1 and EN 12390-3. The NDT tests were performed on test locations of 15 x 10 cm², the diameter of the core samples obtained from the structural elements is nominally of 75 mm.

First, the cores were subjected to one UPV test using the direct transmission method, twelve RH test readings in a horizontal position, and one coring test. The rebound test result corresponding to each core is the median value of the set of measurements expressed as a whole

number (EN 12504-2, 2003). The RH tests were performed using a type N device (C181 model), while the UPV tests were conducted using a type E46 device equipped with 50 mm diameter transducers and operating at a frequency of 54 kHz. The cores have been compressed under an applied load to failure with a loading rate of 0.5MPa/s. In order to homogenize the dimensional parameters, the obtained strength values were converted to the equivalent in-situ cube strength values (EN 13791:2007, 2007).

The data collected from the existing building are 205 triplets (core strengths, RH test results and UPV test results) but only 100 triplets are used in this study. It should be noted that the in-situ concrete strength values in the structure are considered unknown. Consequently, the core strengths obtained are primarily used for comparison purposes, to evaluate the accuracy and quality of the estimated strengths. The variability in nondestructive testing results was quantified using the coefficient of variation (CV) at multiple scales. Structural elements were grouped into subsets based on blocks or element types (columns or beams). This approach aimed to identify regions with statistical homogeneity. The variability (CV) of both RH and UPV test results calculated between the average values for each subset of structural elements was about 5 %. This value allows considering all data as a unique homogeneous population. Finally, in accordance with the improved version of the standard EN 13791- 2019, we rigorously examined the distribution of all test result data to confirm adherence to a normal distribution.

Figure 3.3 offers valuable insights into the compressive strength and NDT measurement characteristics of the experimental dataset. The experimental data has a mean strength of 25.98 MPa with a variability of 10.18 MPa. The Rebound Hammer data has an average value of 36.38 units and a standard deviation of 6.43 units. On the other hand, the Ultrasonic Pulse Velocity data exhibits an average value of 3.9 km/s with a standard deviation of 0.5 km/s. The coefficient of determination r^2 for the correlation between experimental compressive strength and Rebound Hammer data is equal to 0.79. This higher r^2 value indicates a relatively stronger correlation between the Rebound Hammer measurements and the experimental compressive strength. On the other hand, the r^2 value for the correlation between experimental compressive strength and UPV data is 0.73. This r^2 value for UPV suggests that, while there is still a correlation between UPV measurements and compressive strength, this correlation is not as strong as with the Rebound Hammer. The UPV data shows a bit more variability, indicating a greater degree of scattering in its relationship with compressive strength. It is worth noting that measurement quality plays a crucial role in the accuracy and reliability of data. If the measurement quality is

compromised, it can lead to increased variability or scattering in the data, making it more challenging to establish a strong and consistent relationship with other variables, such as compressive strength.

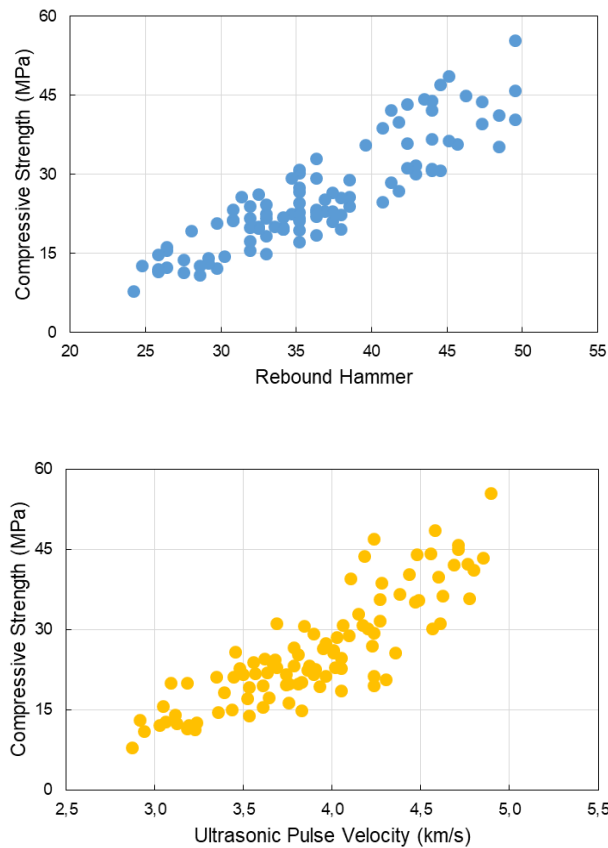


Figure 3. 3 Clouds of NDT measurements and compressive strength for experimental dataset

3 Strength assessment using combination of nondestructive techniques

In this section, we introduce a new model identification approach called multi-objective approach. Alongside, we present the parametric multi-variable regression method, which follows a mono-objective approach and offers relatively straightforward implementation. The primary goal of this study is to assess the predictive performance of the multi-objective and mono-objective approaches. This evaluation is carried out by comparing the predicted compressive strength, derived from NDT measurements, with the actual compressive strength obtained through the destructive testing of cores. This comparative analysis will highlight the potential advantages of employing the multi-objective optimization method over the traditional multiple regression approach in the context of concrete compressive strength prediction.

3.1 Mono-objective approach using multiple regression

Regression analysis is a statistical technique widely used in predictive modeling. In the context of assessing concrete compressive strength, regression is employed to establish a relationship between an independent variable, typically derived from an NDT technique, and the dependent variable, which is the concrete compressive strength f_c . The regression approach used for a single NDT technique as an independent variable can be expanded to include multiple NDT techniques as independent variables. Thus, the resulting regression model that can be employed to approximate the strength is:

$$f_{c\ est} = a + b_1x_1 + b_2x_2 + \dots + b_nx_n + \varepsilon \quad (3.6)$$

- $f_{c\ est}$ is the estimated concrete compressive strength using the regression model;
- x_i represents the measurements obtained from the NDT techniques, n represents the total number of measurements;
- a, b_1, b_2, \dots, b_n are the regression coefficients;
- ε is the error term, representing the difference between the observed strength and the predicted strength.

The parameters (a, b_1, b_2, \dots, b_n) are obtained through least squares minimization (Ross, 2009). This statistical method aims to find the optimal values for these parameters, which result in the best fit of the regression model to the available data. In this context, the least squares minimization technique involves minimizing the sum of the squared differences between the concrete compressive strengths and the predicted strengths based on the NDT. Mathematically, this is represented as:

$$\text{Minimise } \sqrt{\sum_{i=1}^{NC} (f_{c\ est\ i} - f_{ci})^2 / NC} \quad (3.7)$$

Where:

- NC is the total number of data points;
- $f_{c\ est\ i}$ is the predicted compressive strength for the i -th data point using the regression model;
- f_{ci} is the true compressive strength for the i -th data point.

The optimal values of the parameters a, b_1, b_2, \dots, b_n are determined by minimizing the sum of squared differences, resulting in the best-fit regression model that closely approximates the relationship between the NDT measurements x_1, x_2, \dots, x_n and concrete compressive strength f_c .

Another way to represent the relationship between NDT measurements and concrete compressive strength is to use a matrix form or more compactly:

$$Y = X \times A + \varepsilon \quad (3.8)$$

Where:

- A is a column vector with dimensions $n \times 1$, representing the model parameters;
- X is a design matrix with dimensions $n \times m$, where m is the number of compressive strength values and n is the number NDT measurements;
- Y is the response vector representing the compressive strength values with dimensions $m \times 1$;
- ε is the error term with dimensions $m \times 1$, representing the difference between the observed compressive strength values and the predicted values.

To get the parameters of the model we are looking for, we have to invert the equation or the matrix system. This inversion can be done by the method of least squares for example, but also by the calculation of the inverse matrix.

3.2 Multi-objective approach

Optimization is an important concept in decision-making processes, particularly in disciplines such as engineering and economics. In real situations, decision-making is rarely simple or one-dimensional. There are often multiple criteria, objectives, or parameters that need to be considered. This is precisely where the significance of multi-objective optimization comes into play. It allows decision-makers to find the best trade-offs among different objectives, which could be sometimes conflicting and self-excluding.

Multi-objective optimization, also known as multi-criteria decision making, is concerned with mathematical optimization problems involving more than one objective function to be optimized simultaneously. The multiple objective optimization problems have been receiving growing interest from researchers with various background (Coello et al., 2007; Gen and Cheng,

1999; Zaman et al., 2019). Researchers started directing their efforts toward developing algorithms and techniques aimed at addressing multi-objective optimization problems. One notable contribution to the field during this time was the work of (Deb, 2003), which provided an overview of evolutionary algorithms and their application to multi-objective optimization. Moreover, the publication of (Goldberg, 2013) significantly contributed to the widespread adoption of genetic algorithms, a commonly employed technique in multi-objective optimization. Therefore, the formalization of an optimization program includes the same steps whatever the techniques required later for the analysis:

- 1) The definition of the problem and the identification of the variables, in our case it is to identify the parameters of the conversion model;
- 2) The formulation of the objective functions;
- 3) The formulation of the constraints, when they exist.

The multi-objective approach used in the assessment methodology involves an optimization procedure that focuses on minimizing three objective functions to assess the mean strength and its variability with NDT. These functions are the root mean square error (RMSE), the relative error on the mean (RME), and the relative error on the standard deviation (RSE).

$$RMSE = \sqrt{\sum_{i=1}^{N_c} (f_{c\ est\ i} - f_{ci})^2 / N_c} \quad (3.9)$$

$$RME = |\bar{f}_{c\ est} - \bar{f}_c| / \bar{f}_c \quad (3.10)$$

$$RSE = |s(f_{c\ est}) - s(f_c)| / s(f_c) \quad (3.11)$$

Using three errors as objective functions in the multi-objective optimization problem allows for a more comprehensive evaluation of the performance of the model and provides a better trade-off analysis between different aspects of the model's accuracy. The root mean square error provides an indication of how well the model's predictions align with the observed data. The relative error on the mean evaluates how well the model captures the central tendency of the data. The relative error on the standard deviation assesses how well the model captures the variability or dispersion of the data.

Multi-objective algorithms are designed to discover policies that achieve satisfactory trade-offs among the various objectives of a task. A good compromise can be defined in terms of Pareto front dominance (Pareto, 1909), which allows comparison of solutions in a multi-objective problem as shown in Figure 3.4. In this study, a high-performance multi-objective algorithm known as the NSGA-II is used to find the Pareto optimal solutions (Yang, 2014). Genetic algorithm uses the concept of survival of the fittest to produce more desirable individuals in subsequent evolutionary of the population. At each generation, the objective function value of each individual in the population is calculated. The new generation of candidate solutions is then used in the next iteration of the algorithm. Generally, the algorithm ends when a maximum number of generations has been produced or a satisfactory fitness level has been reached for the population.

The NSGA-II algorithm is built upon the principle of Pareto dominance. In multi-objective optimization, this dominance relationship allows for the comparison and ranking of solutions based on their objective values. NSGA-II places a strong emphasis on maintaining diversity within the population. This is achieved through a combination of selection, crossover, and mutation operations. By employing a technique called “non-dominated sorting”, solutions are divided into different “fronts” based on their Pareto dominance relationships. NSGA-II uses a binary selection mechanism for picking individuals for the mating process. In each selection round, two individuals are randomly selected, and their dominance relationship is evaluated. The individual with higher dominance is selected as a parent for reproduction. Moreover, this algorithm employs a simulated binary crossover operator, which enables both exploration and exploitation of the search space. The simulated binary crossover operator mixes the genetic information of parents while maintaining diversity among solutions. NSGA-II incorporates a mutation operator to introduce random changes within the offspring population. It also integrates an elitism mechanism to preserve the best solutions discovered so far across generations. This preserves high-quality solutions and prevents premature convergence of the algorithm. These key concepts and operations constitute the foundation of the NSGA-II algorithm. By adhering to these principles, NSGA-II aims to efficiently search for Pareto optimal solutions by maintaining diversity and effectively balancing the exploration and exploitation of the search space.

A MATLAB code was set to perform the optimization process using genetic algorithm with multi-objective optimization to find the best parameters that simultaneously minimize multiple objective functions. The objective is to estimate the parameters for an empirical linear model

that correlates concrete strength with nondestructive testing measurements (RH and UPV). To do that, a MATLAB function “gamultiobj” was used to implement the multi-objective genetic algorithm solver. The “gamultiobj” function in MATLAB is part of the Global Optimization Toolbox. For detailed information, it is recommended to refer to the official MathWorks documentation. The function takes several input arguments related to the genetic algorithm parameters and the problem being solved. The inputs to “gamultiobj” are the objective function, the number of variables, lower and upper bounds for the decision variables, linear and nonlinear constraints. The outputs are the optimal solution and the function values at the optimal solution. Here is a systematic explanation of the code:

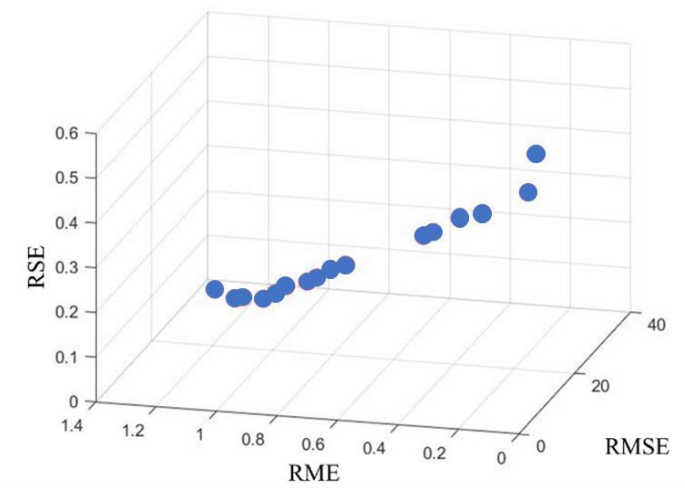
1. The code sets up the initial conditions, such as the number of iterations ($i=10,000$), the minimum and maximum number of samples (3 and 20), and other parameters related to the genetic algorithm (e.g., Population Size Data, Maximum Generations Data);
2. The code then enters a loop, which iterates over different numbers of samples from the dataset. For each iteration, the genetic algorithm is used to find the optimal parameters;
3. Within each iteration, the “gamultiobj” function searches for the model parameters that result in low values of the objective functions;
4. After obtaining the optimized parameters, the code uses them to calculate the estimated concrete strength ($f_{c\ est}$) based on the NDT measurements (R and UV);
5. The code calculates the identification error $RMSE_{fit}$ and the prediction error $RMSE_{pred}$, which are used to evaluate the accuracy of the model.

The parameters of the genetic algorithm are set as follows:

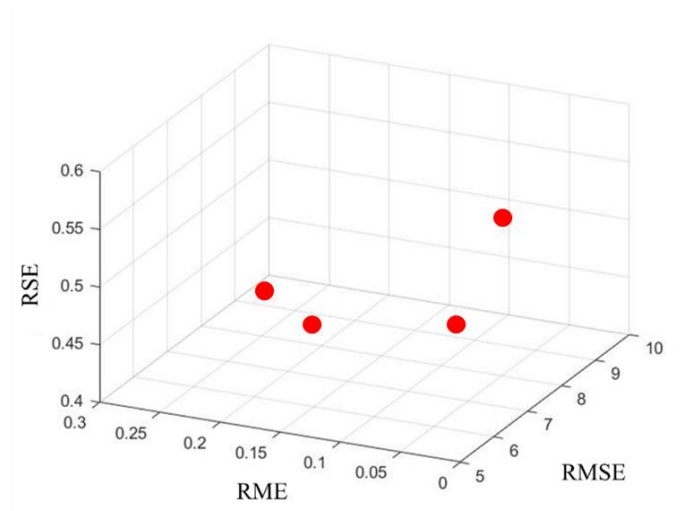
- Maximum generation is 600;
- Population size is 50;
- Function tolerance data is 0.0004;
- Constraint tolerance data is 0.001.

As the number of generations increase, the individuals in the population get closer together and approach the minimum point. The termination tolerance for the objective function was set to 10^{-6} . Parameters were estimated with lower bounds equal to zero, the termination tolerance for the parameter estimates was also taken equal to 10^{-6} .

The Pareto set in Figure 3.4a represents the set of optimal solutions in the multi-objective optimization problem, considering no constraints. Each point represents a trade-off between the root mean square error (RMSE), the relative error on the mean (RME), and the relative error on the standard deviation (RSE), and there is no point that dominates the others in terms of the three objectives. In the other hand, assuming we have additional constraints: that RMSE should not exceed 10 MPa and both RME and RSE should not exceed 1 MPa. In this case, the Pareto set comprises only four points (Figure 3.4b).



(a) Before imposing constraints on the decision variables



(b) After imposing constraints on the decision variables

Figure 3. 4 Pareto front a) before and b) after imposing constraints on the decision variables

4 Analysing the model identification approaches: comparing the prediction capacity of the existing models

4.1 Definition of the assessment strategy

In this section, the predictive ability of the two approaches is investigated, namely mono-objective and multi-objective optimization for the case of combined NDT techniques (SonReb). Mono-objective optimization (multiple regression) focuses on optimizing a single objective, while multi-objective optimization deals with optimizing multiple objectives simultaneously. By exploring both types of optimizations, we aim to evaluate their effectiveness and applicability when NDT techniques are combined. For this purpose, two main sources of data are used in this study: synthetic and experimental datasets.

A simulator was created to carry out the analysis in the current study. The main algorithm of this simulator is depicted in the flowchart in Figure 3.5. The first step in the simulation process is choosing the dataset (NDT measurements and compressive strengths) that will be used throughout the subsequent stages. The present study relies on two main sources of data: experimental data and synthetic data. Identifying the test locations is necessary for organizing any on-site research program in order to perform NDT measurements. The selection of these locations can be either “random” or “conditional”. In the simulator, we have considered the first option, which involves a random selection of locations for the NDT measurements. To assess the quality of model calibration and identify its parameters, the number of cores NC is varied between the minimum number of 3 cores and a maximum equal to 20 cores. The samples selected for each NC are chosen among the 100 cores (population). The next step is to develop a conversion model between NDT data and concrete strengths. Practitioners use various model types and there is no consensus on a specific type (Alwash, 2017). In our study, we chose to use linear models due to their suitability for the particular context of our research. Concerning the model identification approaches, we employed both the mono-objective and multi-objective methods. This step is replicated within the simulator, offering several options regarding both the model type and the approach used for model identification. During each simulation, the simulator is capable of simultaneously identifying multiple models using distinct identification approaches. After identifying each model, the local strengths are evaluated, and subsequently, the mean estimated strength $\bar{f}_{c\ est}$, the variability of estimated strength $s(f_{c\ est})$ and relative errors are calculated. The prediction error is calculated from the differences between the estimated local strengths and the corresponding true in-situ strengths. In the context of the

simulation process, there are inherent uncertainties and random elements involved. For instance, when conducting measurements or selecting test locations, there can be variability due to measurement errors or the stochastic (random) nature of certain factors in the process. To address this issue and obtain meaningful and reliable statistical information, the simulator is designed to repeat the simulation a certain number of times (NI=10,000). Therefore, after NI repetitions, the results for each dataset, each identification approach and each NC value were:

- The average value and standard deviation of the estimated concrete strengths, $\bar{f}_{c\ est}$ and $s(f_{c\ est})$ respectively;
- Standard deviation values for the NI mean strength and concrete variability, $s(\bar{f}_{c\ est})$ and $s(s(f_{c\ est}))$;
- Relative errors and root mean square errors.

The outputs obtained from the simulation process are subject to various post-processing techniques throughout the chapters of this thesis.

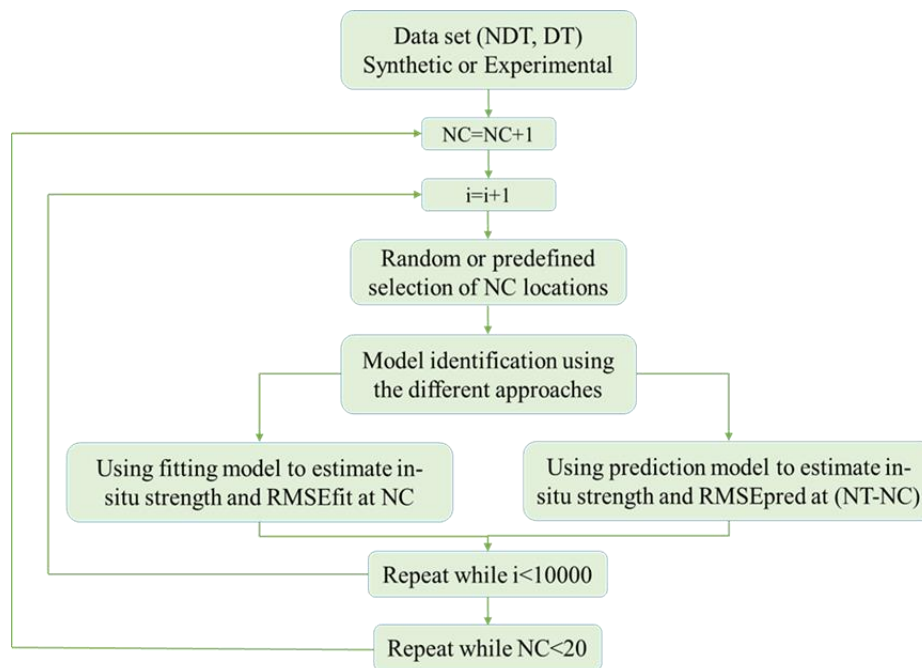


Figure 3. 5 The assessment strategy using Monte Carlo simulation

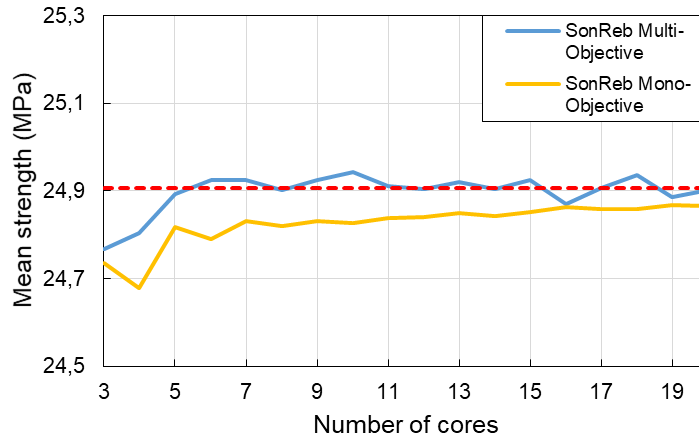
4.2 Predicting the mean strength using the Mono-objective and Multi-objective approaches

In this section, our focus is to analyze and compare the estimation capabilities of the current model identification approaches concerning the assessment of concrete mean strength. We

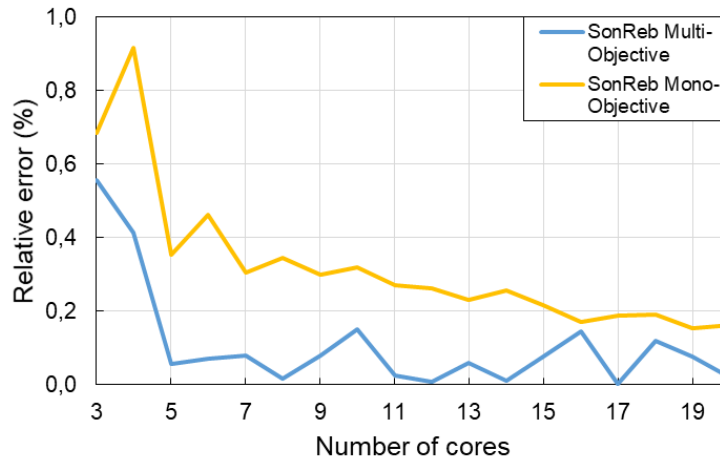
employed both experimental and synthetic data for this purpose, using a linear model for both model identification approaches. Next, $\bar{f}_{c\ est}$ values corresponding to the two identification approaches are plotted on Figure 3.6a (synthetic data) and Figure 3.7a (experimental data) as a function of NC values. Furthermore, for the purpose of comparison, reference lines (in red) have been included on these figures. These reference lines illustrate the mean strength values corresponding to each dataset. Additionally, figures 3.6b and 3.7b present the relative errors in mean strengths corresponding to each dataset, providing a clear representation of the variations and accuracy in the estimated mean strengths. This comparative analysis contributes to a comprehensive understanding of the model identification approaches and their applicability in assessing mean strength.

Regarding the assessment of concrete mean strength, important insights can be drawn from Figure 3.6 and 3.7. According to Figure 3.6a and 3.7a, the mean strength of concrete can be accurately estimated through the effective use of both multi-objective approach and the existing mono-objective method (Multiple Linear Regression approach). Furthermore, increasing the value of NC noticeably enhances the prediction capability, underlining its significant impact on the accuracy of mean concrete strength prediction. The multi-objective approach demonstrates a strong convergence of the strength curve (representing estimated mean strengths) towards the reference line (representing true strengths).

From Figures 3.6b and 3.7b, it is evident that for a small number of cores, the relative errors in estimating concrete strength are significantly high. This suggests that the predictions deviate considerably from the actual true values. However, as the number of cores NC increases, the relative errors decrease. In other words, enhancing the number of cores included in the analysis leads to an improvement in the accuracy of strength prediction. In addition, the multi-objective approach outperforms the mono-objective approach in terms of relative errors. The relative errors associated with the multi-objective approach are smaller, indicating a closer alignment of the predicted mean strengths with the true strengths when $NC \geq 5$.

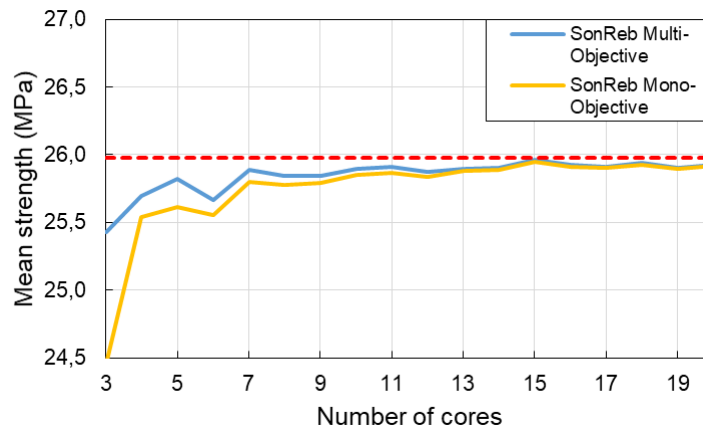


(a) Mean strength

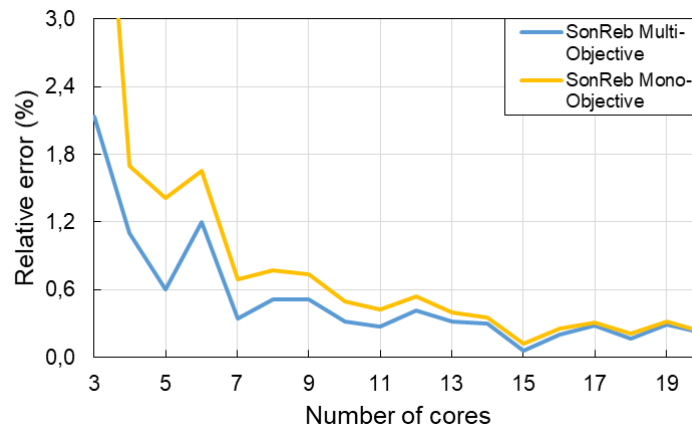


(b) Relative errors

Figure 3. 6 Predicting a) the mean strength and b) relative errors of mean strength, using the Mono-Objective and Multi-Objective approaches (synthetic data)



(a) Mean strength



(b) Relative errors

Figure 3. 7 Predicting a) mean strength and b) relative errors of mean strength, using the Mono-Objective and Multi-Objective approaches (experimental data)

Figure 3.8 presents standard deviation values obtained from a certain number of iterations $NI=10,000$ for the estimated mean strength using both the multi-objective and mono-objective approaches. The sources of uncertainty discussed in Chapter 2, including in-situ strength variability, sampling uncertainty, measurement uncertainty, and model uncertainty, contribute to the scatter observed in the estimated quantity. Therefore, to study the quality of assessment, it is essential to analyze the scatter in the estimated mean strength. The standard deviation values $s(\bar{f}_{c\ est})$ for the multi-objective approach are consistently lower than those for the mono-objective approach across all number of cores NC . This suggests that the multi-objective approach tends to yield more consistent and stable estimations in terms of mean strength. As the number of cores NC increases, both approaches generally display a decrease in standard deviation. Overall, the multi-objective approach shows a clear advantage in terms of estimating mean strength with lower variability and higher precision, especially when dealing with a small number of cores.

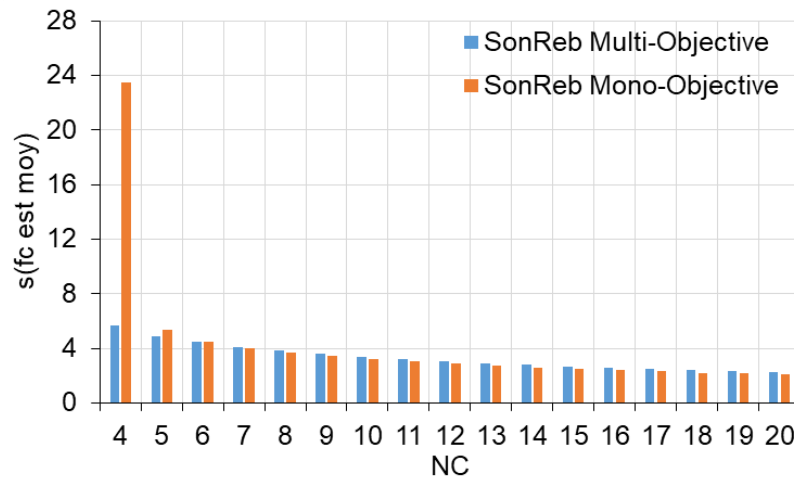


Figure 3. 8 Standard deviation values from NI values of mean strength estimated by the multi-objective and mono-objective approaches for the experimental dataset (all results are in MPa)

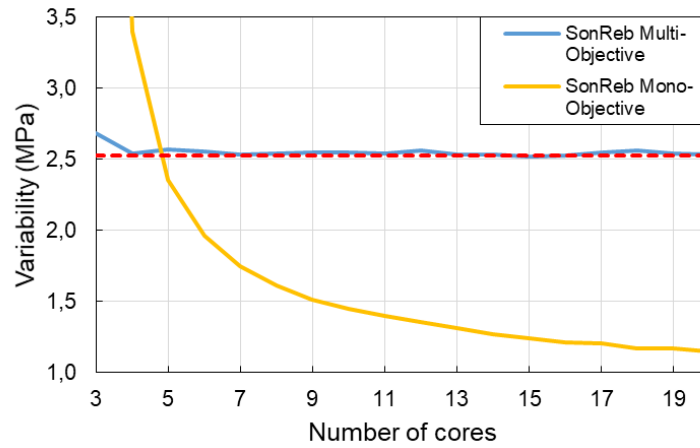
4.3 Predicting strength variability using the Mono-objective and Multi-objective approaches

To assess the validity of the multi-objective approach compared to the mono-objective approach, Figures 3.9 and 3.10 illustrate the results regarding concrete strength variability, when using synthetic and in situ dataset respectively. This variability signifies the estimation of how concrete strength varies due to the inherent variability in the concrete itself. These figures offer a comparison among the model identification approaches under consideration, in terms of the variability of estimated strength $s(f_{c\ est})$ and relative errors.

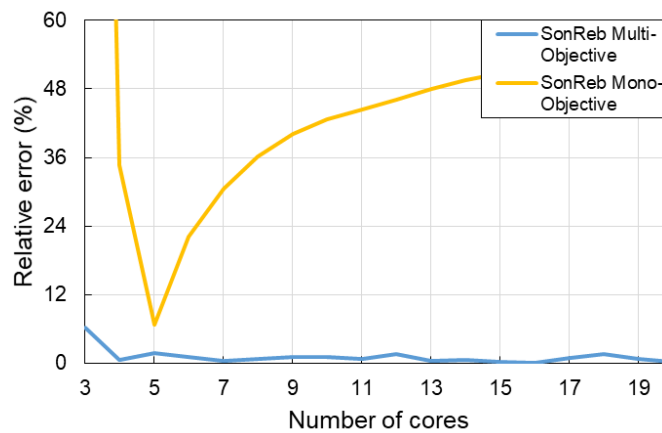
Based on Figure 3.9a and 3.10a, it is evident that the multi-objective approach is the only method capable of accurately estimating the true value of concrete strength variability. In the other hand, the mono-objective method fails to account for the true concrete variability and increasing the number of cores NC does not noticeably improve the predictive ability. The multi-objective approach offers a more comprehensive and accurate estimation of strength variability, addressing the limitations of the mono-objective approach, especially when the number of cores is limited.

The number of cores considered in the analysis significantly influences the accuracy of predicting concrete strength. Figures 3.9b and 3.10b clearly indicate that when the number of cores NC is small, the relative errors in strength variability are notably high especially for the mono-objective approach. Conversely, as the number of cores NC increases, the relative errors reduce. In addition, the relative errors observed in the multi-objective approach are notably

smaller when compared to those in the mono-objective approach. The smaller relative errors signify a better alignment of the predicted strength variability with the true concrete variability, suggesting a higher level of accuracy in prediction.

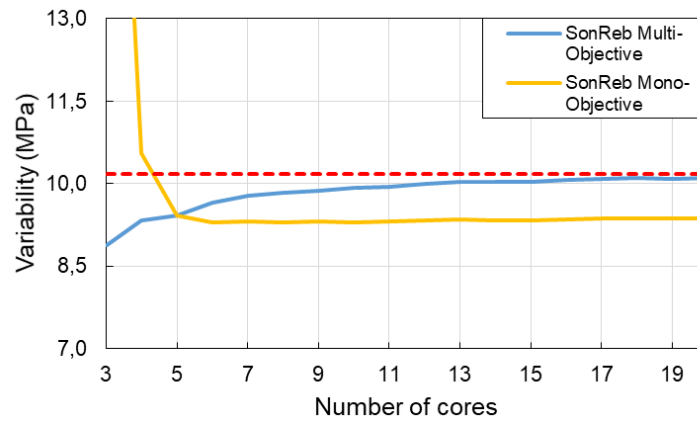


(a) Strength variability

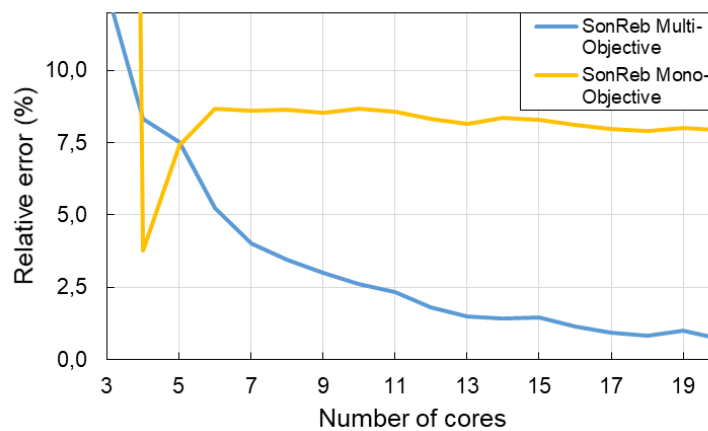


(b) Relative errors of strength variability

Figure 3. 9 Predicting a) strength variability and b) relative errors of concrete variability, using the Mono-Objective and Multi-Objective approaches (synthetic data)



a) Strength variability



b) Relative error

Figure 3. 10 Predicting a) strength variability and b) relative errors of concrete variability, using the Mono-Objective and Multi-Objective approaches (experimental data)

Figure 3.11 presents the standard deviation values calculated from a specified number of iterations NI=10,000 for estimating concrete variability in the experimental dataset. These values reflect the degree of variation in the estimated concrete variability using both the multi-objective and mono-objective approaches. The data presented in Figure 3.11 demonstrate that the multi-objective approach results in lower standard deviation values, indicating greater stability and accuracy in the estimation of concrete variability compared to the mono-objective approach. Furthermore, it is worth noting that as the number of cores increases, there is a consistent decrease in variability in both approaches. This indicates that a greater number of cores leads to more precise and consistent estimations of concrete variability. Overall,

combining NDT techniques using the multi-objective approach leads to more reliable and accurate results in estimating strength variability with just few cores.

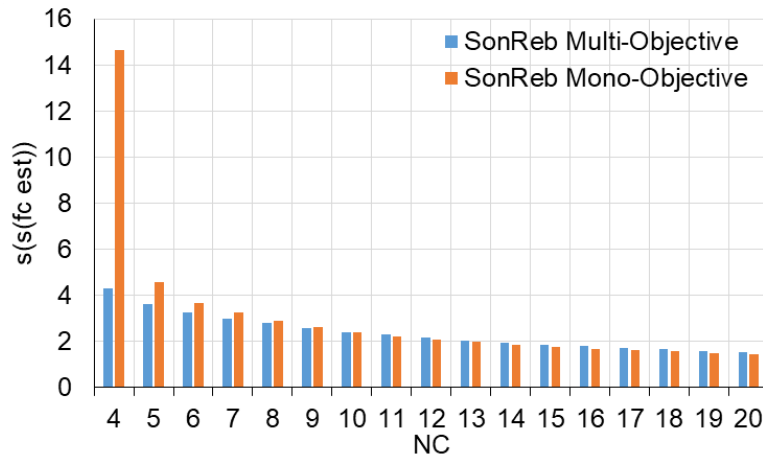


Figure 3. 11 Standard deviation values from NI values of concrete variability estimated by the multi-objective and mono-objective approaches for the experimental dataset (all results are in MPa)

In summary, the analyses conducted in Section 4 sustain the validity of the multi-objective approach in accurately estimating both the mean strength and concrete strength variability, whether using synthetic or experimental data. This innovative approach enables obtaining reliable results with a smaller number of samples compared to traditional methods. Additionally, it is important to underline that this advanced method is cost-effective and does not affect the investigative program.

5 Assessing the precision of concrete strength and variability estimation

As shown in Section 4, the estimated mean strength and concrete strength variability exhibit scattering, with corresponding standard deviations $s(\bar{f}_{c\ est})$ and $s(s(f_{c\ est}))$. These scatters can be attributed to various sources of uncertainty like sampling uncertainty, measurement uncertainty, and model uncertainty. Thus, a comprehensive analysis of the scatter in the estimated quantities becomes essential to evaluate the quality of the assessment.

To achieve this objective, we followed the procedure outlined in Figure 3.3. The dataset employed for this task is synthetic data of 100 triplets (R, V, f_c) , ensuring a controlled and reproducible experimental environment. Within this dataset, NC test locations for cores were

randomly chosen from the NT test locations. The nondestructive measurements obtained from these NC test locations were used to identify two linear models using the mono-objective and the multi-objective approach. For each case, the model was applied to assess the local strengths at the NT test locations, allowing the calculation of the mean strength and concrete strength variability corresponding to each model. For further analysis of results, the cumulative distribution functions (CDF) were displayed. For the case of synthetic data and for each NC value, a series of 10,000 values of $\bar{f}_{c\ est}$ and a series of 10,000 values of $s(f_{c\ est})$ were plotted in terms of cumulative distribution function CDF in Figures 3.12 and 3.13. However, the figures display the curves that correspond to only two NC values (NC = 3 and 10), for brevity considerations. On both Figures 3.12 and 3.13, the red vertical line represents the real value of concrete mean strength and variability ($\bar{f}_{c\ Ref} = 24.91$ MPa and $s(f_{c\ Ref}) = 2.52$ MPa). The assessment quality is higher when the CDF curve is closer to the red line.

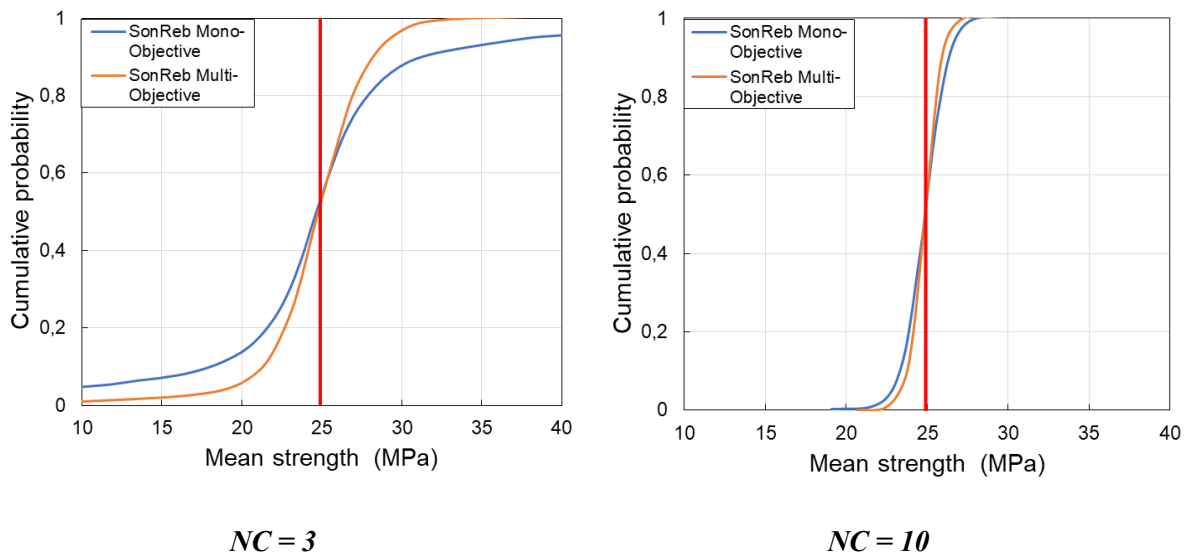


Figure 3. 12 CDF curves of mean strength using Mono-Objective approach and Multi-Objective approach (synthetic data)

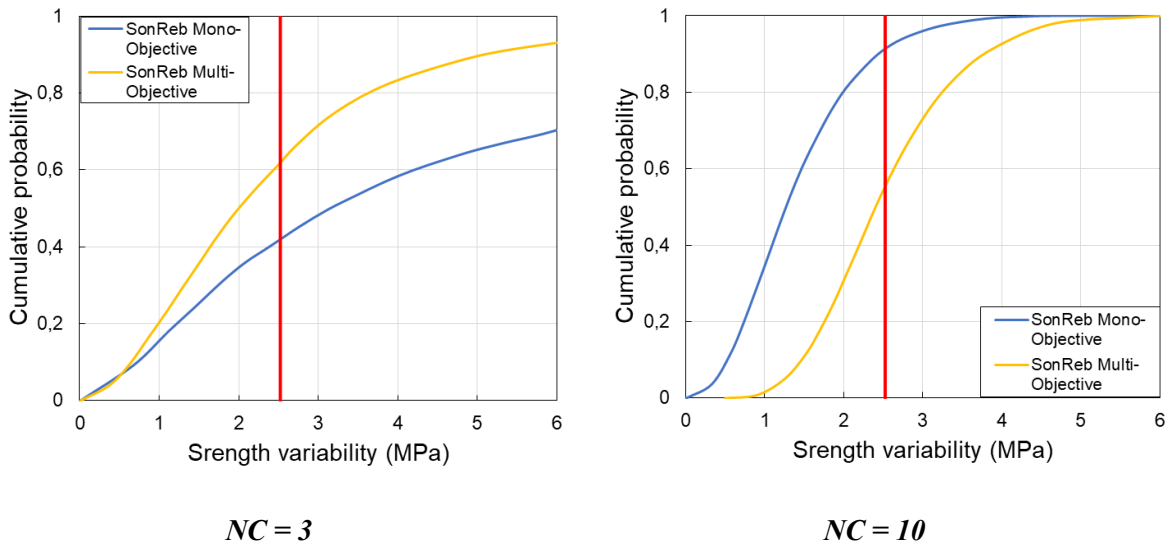


Figure 3. 13 CDF curves of concrete variability using a) Mono-Objective approach and b) Multi-Objective approach (synthetic data)

The quality of assessment is considered better when the CDF curve is closer to the red line, indicating less scatter. Nevertheless, because there are sources of uncertainty, some scatter is unavoidable. This scatter is a result of various factors that cannot be completely controlled. When comparing CDF curves with $NC=3$ and $NC=10$, the analysis reveals that the scatter decreases as the number of cores increases, indicating an improvement in the quality of assessment. As we include more samples, the unpredictable variations decrease, making our results more accurate and closer to the actual mean strength. However, the reduction in scatter becomes almost negligible for higher NC values, suggesting that the cost of increasing NC may not be justified by the marginal improvement in assessment quality. In addition, the reduction in the scatter appears remarkable in the case of using multi-objective approach. With this method, the trend toward convergence to the true in-situ mean strength is more pronounced compared with the mono-objective approach, even when using just 3 cores.

The comparison between the mono-objective and the multi-objective approaches in terms of reliability for assessing the strength variability reveals distinct outcomes in Figure 3.13. In the case of using the mono-objective approach, increasing NC actually minimizes scatter but does not ensure convergence to the real in-situ value. The CDF curves exhibit a left bias, indicating a general underestimation of strength variability, even with large NC . On the other hand, the CDF curves associated with the multi-objective method, shown in Figure 3.13, present a significant reduction in scatter on both sides and a trend to converge, more slowly than for mean strength (Figure 3.12), towards the in-situ value as NC increases. This finding confirms that the

multi-objective approach, as previously shown, provides a reliable solution to improve the concrete variability assessment.

The multi-objective approach offers several potential advantages for assessing the strength characteristics, as demonstrated by the research findings:

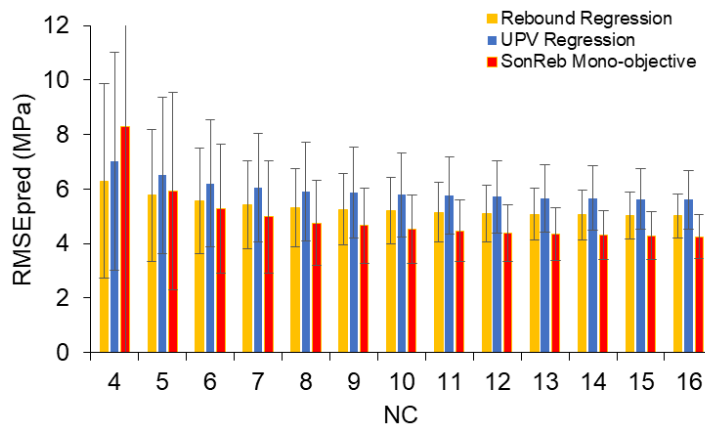
1. Improved accuracy: It has been demonstrated that the multi-objective approach assesses variability more accurately than traditional methods like multiple regression method or calibration approach.
2. Significant reduction in scatter: The study has demonstrated that the multi-objective approach results in a significant reduction in scatter, indicating an improved ability to capture concrete mean strength and its variability.
3. Tendency to converge: The multi-objective approach exhibits a tendency to converge towards the true in-situ values as the number of cores NC increases. This suggests that the multi-objective approach effectively captures the mean strength and strength variability.

6 Investigating the impact of combining NDT techniques on the assessment strategy

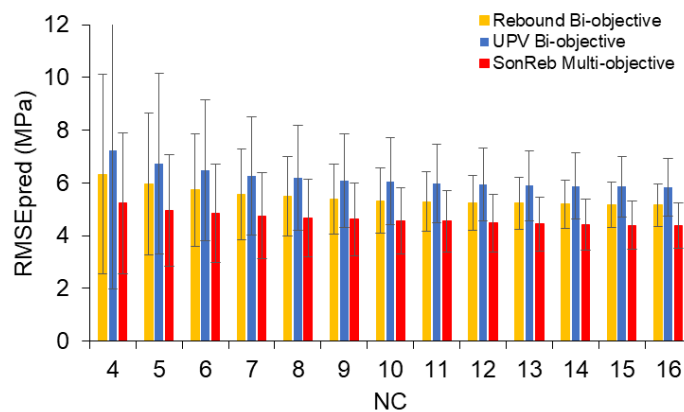
The aim of combining NDT techniques is to improve the precision and reliability of assessments related to concrete properties. The efficiency of the combination studied herein is limited to the case of combining the Rebound Hammer and Pulse Velocity. To evaluate whether the quality of the assessment can be improved by combining NDT techniques, it is necessary to compare the model's prediction capacities (prediction errors) for the proposed combination with those obtained when each NDT technique is applied independently.

In what follows, we consider the experimental database as the foundation of our investigations. The experimental dataset is analyzed using the procedure illustrated in Figure 3.5. The test results (R , V , f_c) of NC test locations were used to identify six linear models (for single UPV, single RH, and the combination SonReb) using the regression and bi-objective approaches for single NDT. Additionally, mono-objective and multi-objective approaches were employed for the SonReb combination. These model identification approaches serve as the framework for our research and allow us to explore various aspects of our investigation with a comprehensive perspective. The identified models consist of linear equations (namely $f_c = a_1 + b_1 * V$, $f_c = a_2 +$

$b_2 \cdot R_c = a + b \cdot V + c \cdot R$) depending on whether the strength is estimated from one or two NDT measurements. For each case, the model was used to assess the local strengths at the NT test locations and consequently to calculate the prediction errors. Figure 3.14 shows the average values of prediction errors $RMSE_{pred}$ for each case, obtained by repeating the simulation NI times ($NI = 10,000$). Figure 3.14 provides a detailed representation of how the prediction errors change with the number of samples NC, gathered from the analysis of the experimental database. The errors are classified based on various techniques, including the Rebound Hammer (RH), Ultrasonic Pulse Velocity (UPV), and the SonReb technique. Figure 3.14 provides valuable insights into the benefits of employing the combination of NDT techniques, specifically the SonReb method, to enhance the accuracy and reliability of concrete property assessment.



(a) RH (regression), UPV (regression), SonReb (mono-objective)



(b) RH (bi-objective), UPV (bi-objective), SonReb (multi-objective)

Figure 3. 14 Prediction errors as a function of the number of samples NC resulting from the experimental database analysis

From Figure 3.14, a clear distinction is evident in the prediction errors between the Pulse Velocity and Rebound Hammer techniques. The errors associated with the Pulse Velocity technique are notably higher compared to those of the Rebound Hammer technique. Since the effects of the sources of uncertainty other than the measurement uncertainty are the same (the same concrete, sample size, NC, etc.) on both techniques. Therefore, the difference between $RMSE_{pred}$ of Pulse Velocity technique and Rebound Hammer technique is mainly due to measurements uncertainty (the quality of measurements).

It is important to consider the impact of different NDT techniques and their combinations on the accuracy of assessment. The quality of the NDT techniques being used and its influence on the efficiency of the combination should be carefully analyzed. In Figure 3.14a, the combination of NDT techniques demonstrates effectiveness beyond a minimum number of cores when employing the multiple regression approach (mono-objective). This suggests that stable results are achieved with approximately six cores, indicating the point at which the combination proves to be effective for concrete strength assessment. Conversely, for a small number of cores ($NC < 6$), using a single technique would yield better results. The detrimental effects of combining a low-quality NDT technique with a high-quality NDT technique, as mentioned in the literature, should be taken into consideration when making estimation decisions. In our case study, with small NC values, combining a low-quality technique (UPV) with a high-quality one (RH) led to higher $RMSE_{pred}$. As mentioned in Chapter 2, the efficiency of combining NDT techniques for concrete strength assessment remains controversial. This controversy is attributed to the relative quality of the individual techniques and is also influenced by the number of cores used in the assessment.

However, the data presented in Figure 3.14b indicates that the combination of NDT techniques is potentially effective in obtaining low prediction errors when the multi-objective approach is considered, even with a small number of cores. By adopting the multi-objective approach, which takes into account various objectives simultaneously, the assessment process becomes more robust and effective. Through a comparison of the prediction errors for combined techniques SonReb, Figure 3.14 offers valuable results into the efficacy and advantages offered by the multi-objective approach in optimizing the assessment process. When dealing with a limited number of cores ($NC < 6$), using the multi-objective approach yields better results compared with the mono-objective approach. Overall, the results highlight the effectiveness of the multi-objective approach, particularly in situations involving a limited number of cores, as it enhances the accuracy and reliability of concrete property assessment. This approach has the

potential to minimize errors and optimize the assessment process when using combined NDT techniques for concrete strength evaluation.

7 Conclusions

The aims of this chapter were mainly concerned with the analysis and comparison of the estimation quality of the different model identification approaches for the evaluation of the mean strength and the variability of concrete strength in the case of combining NDT methods, on synthetic data and a real case study. Based on the aforementioned results, it was shown that multi-objective optimization is highly relevant for evaluating both the mean strength and variability of concrete. The findings of these analyses also highlighted the significant impact of the number of test locations on the accuracy of concrete strength evaluation. Indeed, the multi-objective approach allows at least a reduction of two cores compared with the other model identification approaches, which represents a significant advantage.

The most effective approach for designing a testing program appears to involve a well-balanced combination of NDT techniques and the multi-objective optimization approach. This integrated methodology offers a reliable means of assessing the in-situ variability of concrete strength. By considering multiple objectives simultaneously, it captures the trade-offs between mean strength and variability, leading to a comprehensive and accurate evaluation. Moreover, by strategically choosing an adequate number of test locations throughout the structure or building, the evaluation becomes more representative of the overall concrete strength characteristics. This enables a more robust analysis and a better understanding of the concrete's performance, enhancing the reliability of the assessment.

Overall, the developed methodology offers many advantages such as improved accuracy, significant reduction in scatter, tendency to converge towards the true values, and efficient estimation of strength variability. By adopting the multi-objective method, professionals in the field can improve their understanding of concrete performance, make informed decisions, and ensure the integrity and safety of structures. The significant advantage lies in the fact that this methodology requires only one tool, a custom-developed calculation code, which engineers can easily generate and implement, making it easily accessible and applicable in various settings.

Table 3. 2 A summary detailing the influence of the factors investigated in this study on the assessment quality, evaluated through real and synthetic datasets

Factors	Single NDT technique		Combination SonReb	
	Regression	Bi-objective	Mono-objective	Multi-objective
Estimating mean strength	Good	Good	Moderate	Good
Estimating strength variability	Bad	Good	Bad	Good
Reducing scatters in the estimations	Good	Good	Moderate	Good
Reducing the number of cores	Bad	Bad	Bad	Good

Chapter Four: Improving the Nondestructive Assessment of In-Situ Concrete Strength: Impact of Core Location Selection Process

1 Introduction

The current procedures for nondestructive concrete strength evaluation involve selecting core locations independently of the nondestructive testing locations. This means that the locations where concrete cores are extracted for laboratory testing are already predetermined, regardless of where the NDT tests were conducted. Some studies (Ali-Benyahia et al., 2019; Breyse et al., 2019) have pointed out that this approach may lead to potential biases in the assessment of concrete strength. When the number of cores extracted is limited, there is a risk that a majority of cores may be taken from areas with strength significantly higher or lower than the overall average strength of the concrete. This can lead to misleading conclusions and affect the accuracy of the evaluation.

Several researches have shown that the location of core sampling can have a significant impact on the accuracy of in-situ concrete strength measurements (Ali-Benyahia et al., 2019; Breyse et al., 2020, 2019; Luprano et al., 2015; Sbartai et al., 2021). The conventional approach of randomly selecting core locations may not always yield representative results. The concept of conditional coring aims to address this issue by using information obtained from nondestructive testing data. By doing so, the coring locations are strategically chosen in areas that provide a comprehensive coverage of the concrete's strength range within the structure. This approach can lead to better representation of the actual strength distribution throughout the structure and minimize the risk of bias in the results.

The references (Breyse and Balayssac, 2018; Pfister et al., 2014) likely support and provide evidence for the effectiveness of this method in improving the assessment of concrete properties. A study by (Breyse et al., 2020) found that adopting the conditional coring strategy, where the locations of core extraction are determined based on the NDT test results, can potentially reduce the number of required cores up to three when compared to random coring. This approach optimizes the core sampling process and may lead to a more efficient and cost-

effective evaluation. Moreover, another comparative analysis of various investigation procedures for evaluating concrete by (Alwash et al., 2015) revealed that the conditional coring strategy was the most reliable in estimating the mean concrete strength.

However, there are alternative sampling strategies for the selection of core locations based on specific conditions. This study aims to extend the concept of conditional coring by presenting multiple sampling plans. The primary goal is not only to estimate the true concrete strength but also to assess the quality of the estimation by developing a 95% confidence interval. In order to identify the optimal sampling rule, it is essential to thoroughly assess and compare the different available sampling plans. The methodology of assessing the sampling approaches is examined using the population of size NT (100 triplets) from the experimental data of (Ali Benyahia et al., 2017b). The objective is to simulate the process of an investigator that would conduct nondestructive testing at certain locations, select areas for coring, measure the strength of the cores, and establish a conversion model between NDT and destructive testing based on the data obtained. With this model, the investigator can estimate the strength at all other locations where cores were not taken. These estimated strengths are then compared with the reference strength obtained from the complete dataset. Ultimately, the quality of the assessment is evaluated using an error estimation criterion.

This chapter is organized as follows. In the next section, the authors provide a summary of the sampling methods that have been previously used in other literature. They review existing approaches and techniques that have been employed to address the research problem. Additionally, they introduce alternative sampling rules for selecting core locations. The third section applies the sampling rules discussed in the previous section. The authors use real dataset to evaluate the performance and effectiveness of the proposed methods. The chapter concludes by summarizing the main findings and contributions of the proposed methods.

2 Sampling plans of core locations

2.1 Conditional sampling (RILEM)

The concept of conditional coring revolves around strategically selecting core locations based on the information obtained from on-site nondestructive measurements. The primary objective of this approach is to ensure an optimal coverage of the desired strength range within the structure (Breysse et al., 2020). To achieve maximum coverage of the strength range, the on-site NDT measurements are arranged in ascending order, from the lowest to the highest values.

In addition, to achieve comprehensive coverage of the concrete strength range, a classification process is applied to the NDT values. The classification of NDT measurements is performed differently depending on whether single methods (RH or UPV) or the combined method (SonReb) is used. For the case of using a single method, the NDT measurements are classified individually from 1 to 100, given that our case study use experimental data comprising 100 measurements. However, when the combined method is employed, the classification is based on the average of the two ranks obtained using RH and UPV. This means that the NDT measurements are ranked according to their average rank position from both techniques as presented in Equation 4.1.

$$Rank(RH, UPV) = [Rank(RH) + Rank(UPV)]/2 \quad (4.1)$$

This arrangement allows for the identification of specific groups of NDT measurements, known as NC groups. The value of NC represents the number of cores that will be subjected to calibration. After dividing the dataset into NC groups, a core is then selected randomly from each group. Alternatively, the selection of a core can be done using another method, such as the median value (Ali-Benyahia et al., 2019). The value of NC can vary within a range determined by current practice, typically ranging from 3 to 20 in our case. By implementing this approach, the aim is to guarantee that the core sampling process covers the entire range of concrete strength values from lowest to highest.

Figure 4.1 represents the flowchart that illustrates the steps within the conditional coring process. The first step involves collecting nondestructive testing measurements from the structure of interest. The NDT measurements are classified based on the selected method (single NDT or combination of NDT). The classified NDT measurements are then used to identify specific groups of NDT measurements known as NC groups. For each NC group, a core is randomly selected.

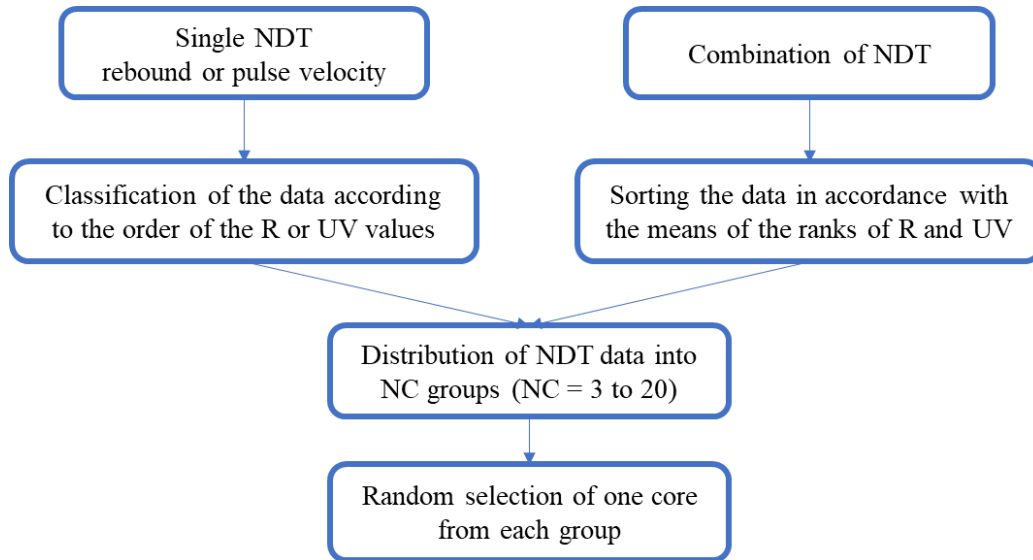


Figure 4. 1 Flowchart illustrating the steps of conditional coring

2.2 Proportional stratified sampling

In order to reduce the variance of the estimations obtained by random sampling. Another common method involves estimating concrete strength from a known population through the process of stratification. In stratified sampling, we assume that the population is spatially stratified and that the subpopulation within each stratum is independent and identically distributed. This means that the variability observed within each stratum is representative of the entire population (Cochran, 1977; Wang et al., 2012). In this approach, the dataset is divided into homogeneous subgroups based on common characteristics of the elements such as classification of NDT readings: high, medium or low. From each subgroup, core samples are randomly selected. Each subgroup's size is inversely correlated with its proportional size within the population (Saleh et al., 2022). By splitting a heterogeneous population into homogeneous subpopulations “strata”, stratification can improve the estimated precision for the expectations over the total population (Wang et al., 2012). A graphical description of the proportional stratified method is illustrated in Figure 4.2.

The key steps of the stratification approach are as follows:

1. Dividing the dataset: The dataset of NDT measurements is divided into distinct strata based on the characteristics of interest. For example, the NDT measurements can be grouped into strata based on the magnitude of the readings.
2. Sample selection: From each stratum, core samples are randomly selected. The sample size chosen from each stratum n_i is proportional to the size of the stratum within the

overall population NT_i and the number of cores NC (see Equation 4.2). However, this sample rule suggested in several references does not take into account the minimum and maximum values of each stratum interval. In this case, the geometric stratification approach is used to find the optimal division points.

$$n_i = (NT_i/NT) * NC \quad (4.2)$$

3. Geometric stratification: To optimize the division points between strata, a geometric stratification approach is used. This involves determining the boundaries of each stratum based on a common ratio 'r', which is calculated using the maximum and minimum values of NDT measurements (see Equation 4.3). Each stratum's boundaries are established as a geometric progression.

$$r = \left(\frac{\max NDT}{\min NDT} \right)^{1/L} \quad (4.3)$$

4. Optimal division points: In our study, the geometric series terms provide the division points for each stratum. These points ensure that the strata cover the entire range of NDT measurement values while also being proportional in size. Each stratum's boundaries are assessed as geometric series terms, with the first term being the minimum NDT measurement value and the succeeding terms representing the minimum NDT measurement $\times r^s$, where $s = 0, 1, 2, \dots, L$. For instance, if there are three desired strata ($L = 3$), and the minimum and maximum rebound values in the dataset are 24.2 and 49.5, respectively, the common ratio 'r' is calculated as $r = (49.5/24.2)^{1/3} = 1.27$. This leads to the creation of three strata: (24.2 – 30.72), (30.8 – 38.99), and (39.6 – 49.5). When selecting core sites from each of these ranges, the size of each stratum is considered to ensure a representative and balanced sampling process.

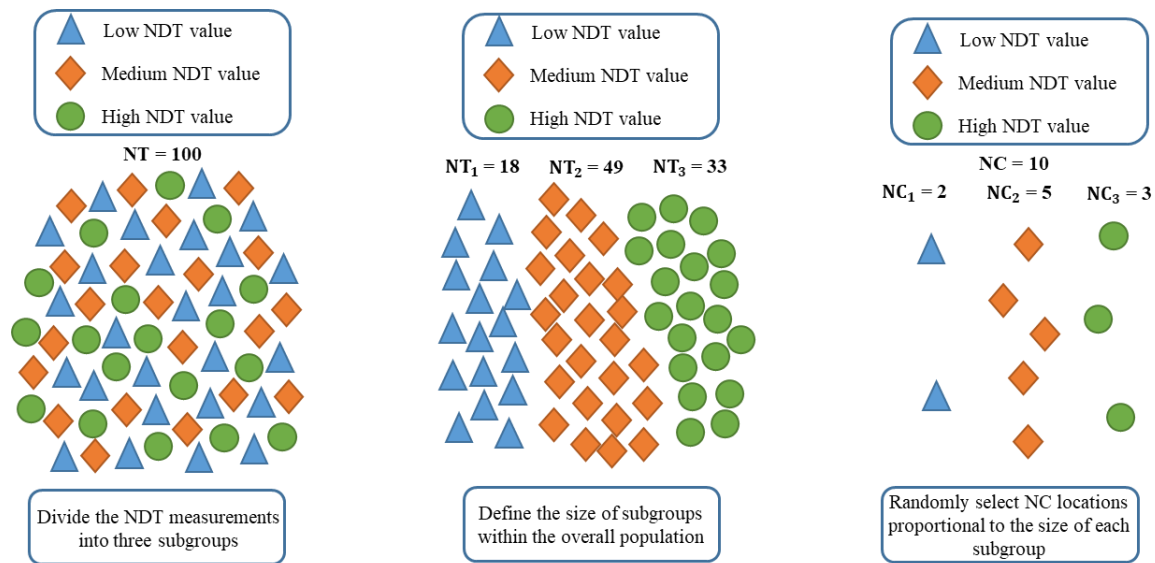


Figure 4. 2 Graphical representation demonstrating the procedure of selecting core locations through proportional stratified random sampling

In summary, stratification is used to enhance the precision of estimations obtained through random sampling by dividing a heterogeneous dataset into more homogeneous subpopulations. The geometric stratification approach optimizes the division points between strata based on a common ratio, leading to accurate and balanced core sample selection. This method ultimately improves the reliability of estimation using Monte Carlo simulations.

2.3 Similarity sampling

The sampling technique described in this context selects core locations in such a way that guarantees the statistical similarity of the distribution of NDT measurements at these core locations with the distribution of the complete NDT measurement dataset (Saleh et al., 2022). Previous studies have explored and compared various metrics of similarity in different machine learning contexts (Boriah et al., 2008; Irani et al., 2016; Weller-Fahy et al., 2015). In this context, three distinct similarity metrics are introduced, namely the Kolmogorov-Smirnov (KS) distance, earth mover's distance (EMD), and Cramér-von Mises (CvM) distance. Indeed, it is essential to note that regardless of the similarity metric being employed, each of these metrics serves the same purpose, which is to facilitate comparisons between two distributions. For our specific study, we chose to use the Kolmogorov-Smirnov (KS) metric to measure distances and evaluate the overlap between the distributions.

The KS metric serves as a measure of distance between two populations, quantifying the differences between their probability distributions. A more intuitive way to compare the two distributions is by analyzing their cumulative distribution functions CDFs. Consequently, the similarity between these distributions can be assessed by quantifying the differences between their respective CDFs. To quantify this difference, a statistic “D” is calculated, representing the largest absolute difference between the cumulative frequency distributions of the two datasets. In practical terms, if a population is believed to follow a specific cumulative distribution function “CDF1”, the cumulative distribution of a randomly selected sample of NC observations “CDF2” is expected to closely match the specified population distribution (see Figure 4.3). The KS distance is then employed to assess the level of similarity between these distributions. However, in order to ensure a more accurate estimation of the variability of concrete properties, it is crucial for the NDT measurements to be spread across the entire structure. This distribution over the entire structure guarantees a comprehensive representation of the concrete's characteristics and properties, leading to more reliable and informative results. Figure 4.3 presents a graphical representation outlining this sampling method.

Implementing similarity sampling involves several steps:

1. Compute the empirical cumulative distribution function “CDF1” of the complete dataset.
2. Randomly select NDT test values at core locations (with a total of NC samples) from the available dataset.
3. Calculate the cumulative distribution function “CDF2” for each set of sampled NDT test values at core locations.
4. Plot the “CDF1” of the complete dataset and the “CDF2” of the sampled NDT test values on the same graph. This visualization helps to assess the similarity between the distributions.
5. Use a similarity metric (such as the Kolmogorov-Smirnov distance) to measure the similarity between each sampled “CDF2” and the “CDF1” of the complete dataset.
6. Compare the similarity values for each sampled “CDF2”. Choose the one that exhibits the highest degree of similarity to the “CDF1” of the complete dataset. The sampled NDT test values associated with the selected “CDF2” represent the core locations that are most similar in distribution to the complete dataset.
7. To enhance robustness, repeat the above steps multiple times (NI=10,000) with different random samples of NDT test values.

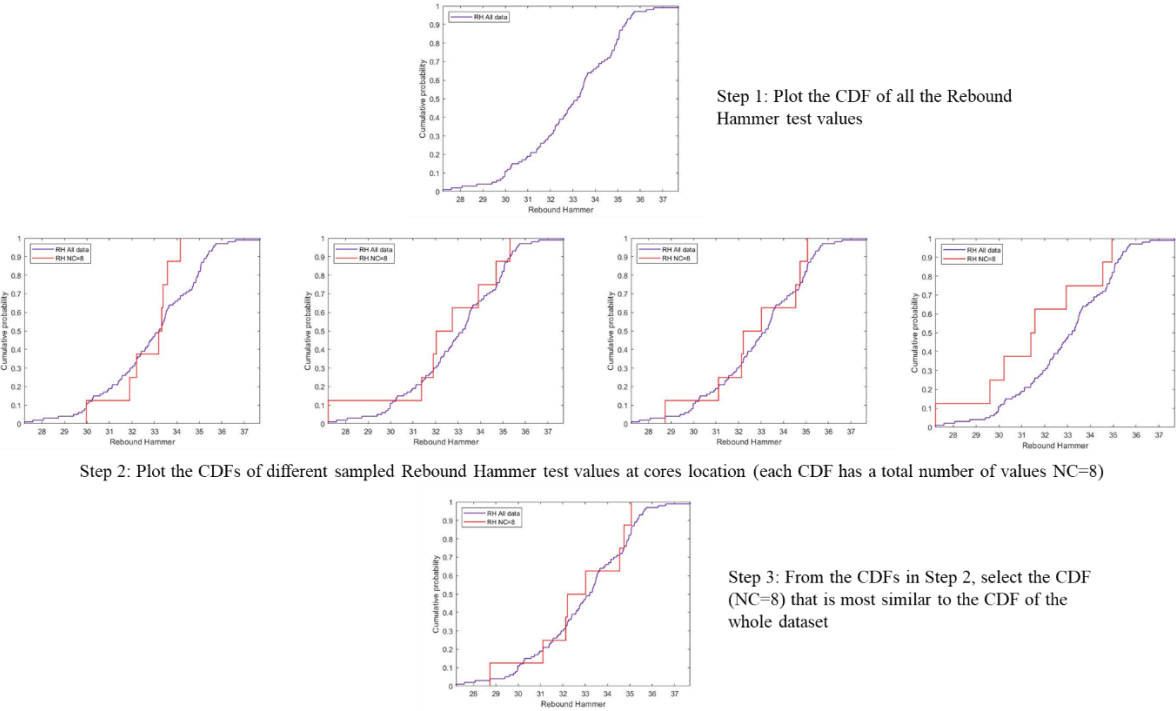


Figure 4.3 Graphical illustration of the selection process for core locations using the similarity between distributions approach

2.4 Variance sampling

Variance sampling methodology aims to select groups of data that cover, as much as possible, the whole range of the NDT measurement distribution. This novel approach involves an exhaustive analysis of all possible combinations of NC testing points. The main goal is to minimize a specific objective function, which quantifies the difference between the variance of NDT measurements obtained from selected core locations and the variance of the total NDT measurement dataset.

To determine the impact of variance sampling on the outcomes of the evaluation method, a special computing code was created. This code, at first, extracts from the database all possible combinations of NC measures that cover the maximum range. At second, the code performs the calculation of the variance of the NDT measurements corresponding to the cored locations and the variance of the total NDT measurements. Starting from these values, the subset of NC data can be considered similar to the set of NT measurements if the difference between the variances is minimum.

To assess the impact of variance sampling on the evaluation process, a dedicated computational code was developed. This code operates in two primary steps:

1. Combinations extraction: Initially, the code retrieves all possible combinations of NC measurements from the database. Each combination is designed to cover the widest possible range of NDT measurement values.
2. Variance calculation and comparison: Afterward, the code computes the variance of NDT measurements linked to the selected core locations and compares it with the variance of the complete NDT measurement dataset. These calculated variances serve as metrics for evaluating the representativeness of the selected NC subset in comparison to the complete set of measurements. The objective is to identify a subset of NC data that exhibits minimal difference in variances.

By iterating through this process, this approach contributes to the robustness and accuracy of the evaluation method by ensuring comprehensive coverage of the measurement variability. The following flowchart (Figure 4.4) explains the steps involved in developing and executing the computational code to assess the impact of variance sampling on the evaluation process.

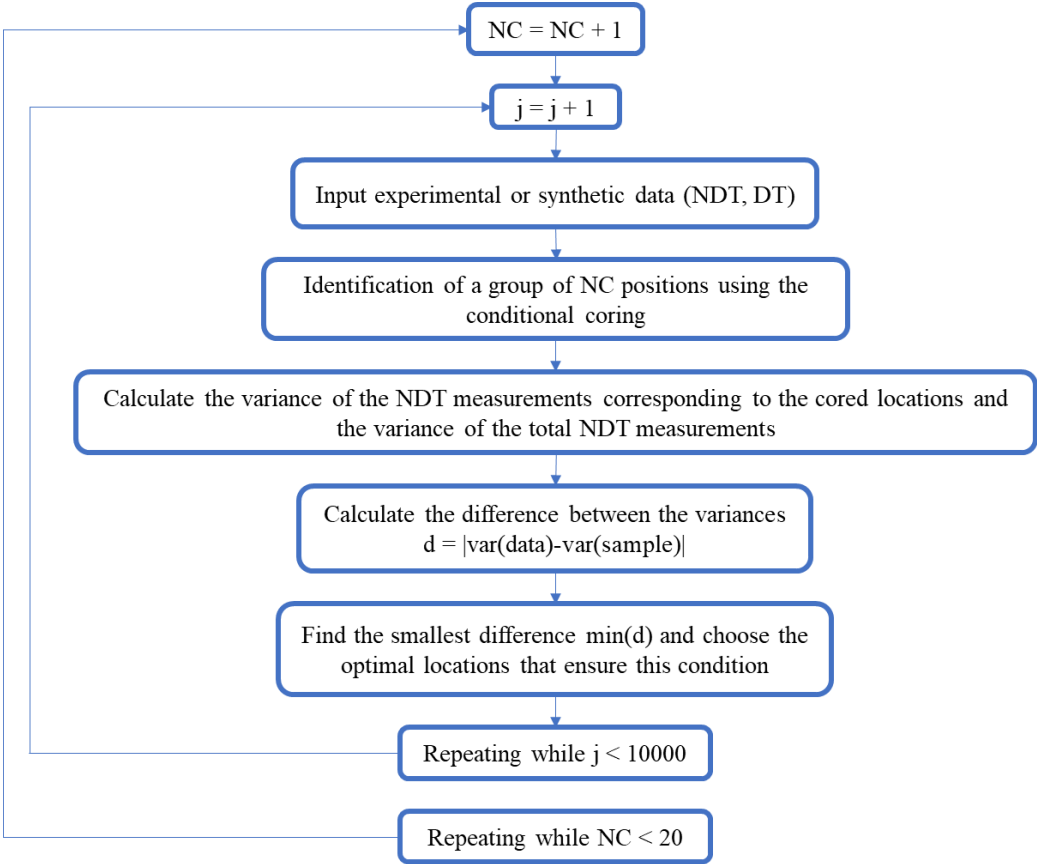


Figure 4. 4 Flowchart describing the selection of core locations using variance sampling strategy

3 Improving concrete strength assessment through NDT based sampling

3.1 Implementation of the suggested sampling approaches

The methodology of assessing the sampling approaches is examined using a population of size $N_T=100$ triplets. The experimental dataset is gathered through research partnerships with other researchers (Ali Benyahia et al., 2017). The dataset information come from a thorough investigative procedure that was run on an existing structure. The in-situ testing involved performing NDT measurements (Rebound Hammer and Pulse Velocity) at 100 test points spread over beams and columns. The collected experimental data indicates a mean strength of 25.98MPa with a variability of 10.18MPa. The Rebound Hammer data has an average value of 36.38 units and a standard deviation of 6.43 units. On the other hand, the UPV data exhibits an average value of 3.9 km/s with a standard deviation of 0.5 km/s.

To apply the different sampling plans, the NDT readings should be organized into ranges. This step would make the application of the sampling rules easier to be performed. The second step includes the application of sampling plans as outlined in the preceding section, to identify core locations based on the NDT measurements. At each core location, the extracted data are NDT measurement and concrete core strength. In this study, two nondestructive techniques (RH and UPV) were employed both individually and in combination to identify the conversion models.

(Alwash et al., 2015) has developed a new bi-objective method able to assess variability with better accuracy than conventional methods (regression analysis or calibration methods), when using a single nondestructive technique. The main limitation of this method is that it does not allow combining two NDT techniques to assess strength and its variability. For this reason, when combining NDT techniques, the multi-objective optimization presented in Chapter 3 is used to predict both mean strength and variability. Therefore, a correlation between core strength and the NDT readings can be built using the data from the sampled NC pairs and following different model identification approaches (bi-objective and multi-objective).

The process of assessing in situ concrete strength using nondestructive testing measurements heavily relies on the quality of the identified conversion model. If the quality of the conversion model is not satisfactory, it indicates a high uncertainty in the results. The calibration process for the conversion model is repeated $N_I=10,000$ times for a given number of cores N_C . In every iteration, a distinct conversion model is derived, with its unique parameters. This variability in

the model parameters is known as the “trade-off” and it is recognized as an important factor (Ali Benyahia et al., 2017b; Kouddane et al., 2022). The quality of the conversion model plays a significant role in the accuracy of in situ concrete strength assessment using NDT measurements.

Figure 4.5 shows the flowchart of the main algorithm in this study. After introducing the data set of $NT = 100$. Considering each sample plan, the simulator selects NC test locations for cores. Then, the simulator identifies a linear conversion model using one of the model identification approaches: the bi-objective approach for a single NDT technique or the multi-objective approach for the combination of NDT techniques. The identified model is applied for the NT test locations in order to assess the estimated strength $f_{c\ est}$ at each test location. The outputs of the simulation are the estimated mean strength, and the estimated concrete strength variability. The simulator repeats the entire procedure $NI = 10,000$ for values of NC that range from 3 to 20 in order to account for the impact of the number of cores. As a result, the simulator produces a set of NI values of the estimated mean strength $\bar{f}_{c\ est}$, and a set of NI values of the estimated strength variability $s(f_{c\ est})$ for each NC value. Subsequently, the outcomes of each series are analyzed. The simulator essentially explores how different factors, particularly the number of test locations, the use of a single or combined NDT techniques and the sampling method employed, influence the estimated concrete strength and its variability.

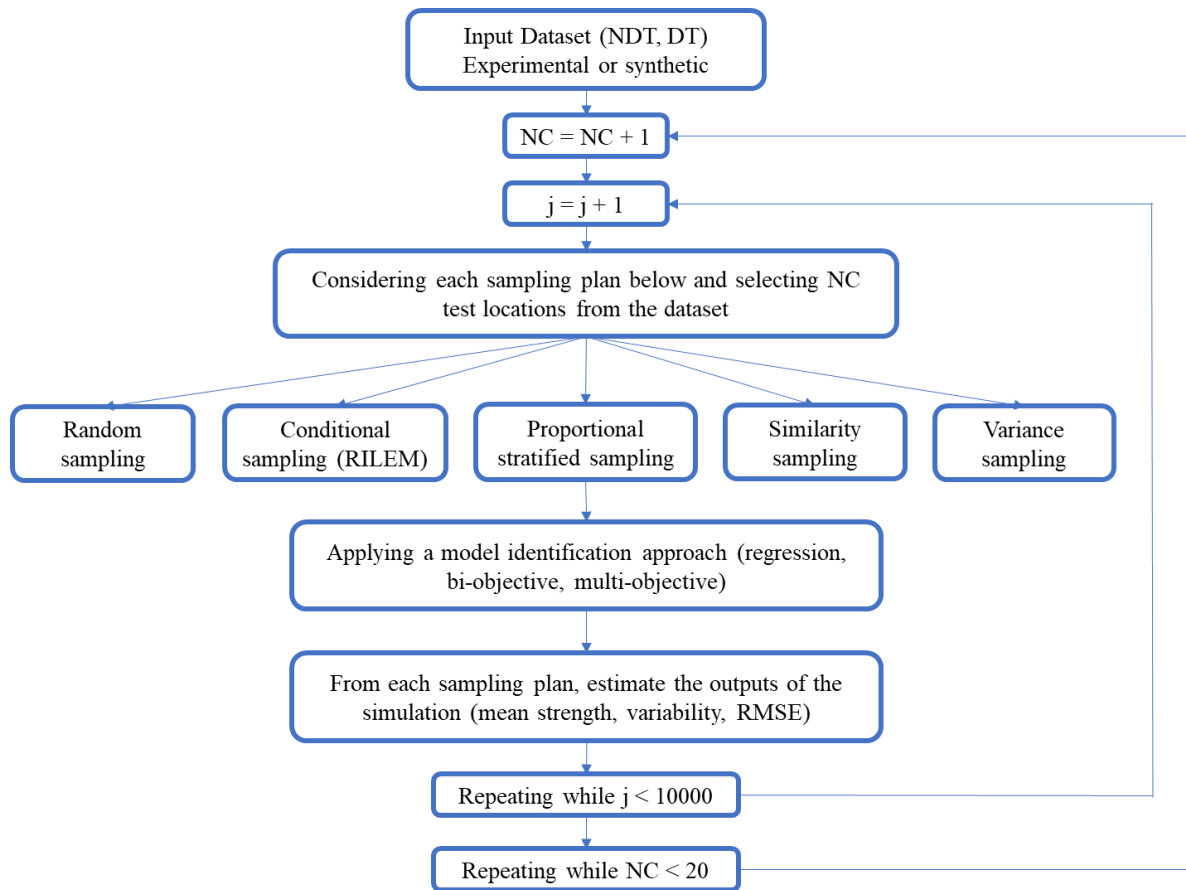


Figure 4. 5 Diagram outlining the evaluation procedure for each sampling plan

The procedure for evaluating concrete strength through random coring process has been thoroughly explained in prior publications (Ali Benyahia et al., 2017a; Alwash et al., 2015; Breyse and Balayssac, 2018). In this context, the application of random coring involves extracting core samples without specific guidance from in-situ NDT data. The alternative approaches involve new sampling methods (conditional sampling, proportional stratified sampling, similarity sampling and variance sampling), where core-sampling locations are chosen based on valuable insights obtained from previous nondestructive testing results. The adoption of these new sampling techniques is justified by the belief that they will generate more reliable conversion models. Consequently, these conversion models are expected to offer improved accuracy in predicting concrete strength.

Following NI iterations (NI=10,000), the conclusive outcomes yielded through the bi-objective (single NDT) and multi-objective (combination of NDT) approaches for each sampling plan are graphically presented in Figures 4.6 to 4.10:

- The average value and variability of the estimated concrete strengths, $\bar{f}_{c\ est}$ and $s(f_{c\ est})$ respectively;
- Standard deviation values for the NI mean strength and variability, $s(\bar{f}_{c\ est})$ and $s(s(f_{c\ est}))$;
- Root mean square errors.

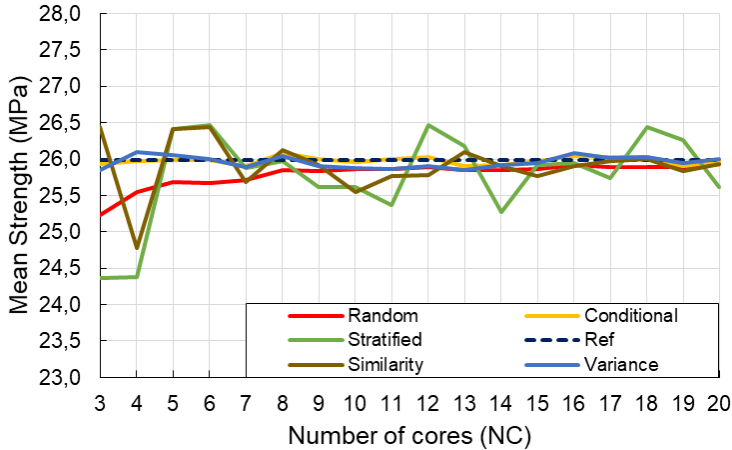
3.2 Assessing mean strength of the different sampling strategies

Regarding the quality of the assessment of concrete mean strength, Figures 4.6 shows the values of the estimated mean strength $\bar{f}_{c\ est}$, corresponding to the use of single or combined NDT techniques, as a function of the NC values. Additionally, reference lines denoting the mean value associated with the experimental dataset are illustrated in Figure 4.6. In addition, the standard deviation values of the estimated mean strengths are provided for context in Figure 4.7.

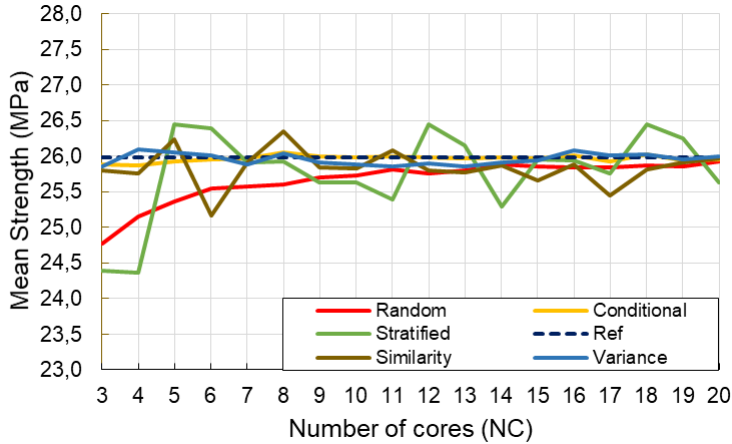
In order to highlight the benefits of the different sampling plans, a comparison is drawn between the curves derived using random coring and those generated by employing the other sampling strategies. Figures 4.6 and 4.7 illustrate the influence of the different sampling strategies in estimating the mean strength. This impact is notably pronounced when addressing smaller NC values, but gradually diminishes as the NC values increase. The curves associated with the application of the bi-objective approach are shown in figure 4.6a and 4.6b (single RH and single UPV). Figure 4.6c present the curves associated with the application of the multi-objective approach when the two NDT techniques are combined (SonReb). Five curves are plotted on each figure; the curves respectively correspond to random sampling, conditional sampling (RILEM), stratified sampling, similarity sampling and variance sampling.

The first important feature that can be seen on the three figures is the major effect of the sampling strategies. It is clear that in all situations (using single or two NDT techniques); sampling strategies (especially variance and conditional sampling) significantly improve performances when compared with random coring for the mean strength assessment. Moreover, it is clear that “variance sampling” aims to reduce uncertainty in the conversion model by ensuring a more comprehensive coverage of the mean strength. Indeed, the statistical variability of model parameters is a natural result of the sampling process, and employing “variance sampling” helps reduce this variability.

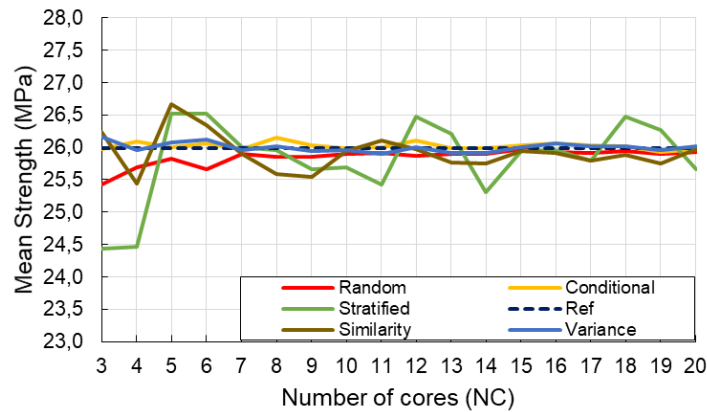
In addition, an important finding is made when the Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV) techniques are combined. The outcomes derived from random coring and other sampling methods, particularly variance and conditional coring, show remarkable similarity in predicting the average strength when using combined NDT. This analysis is intricate because the advantage of combining nondestructive testing methods and the potential benefit of employing sampling strategies are interconnected to some extent. This interaction makes the evaluation and understanding of the combined effects more intricate and requires careful consideration to comprehend the full scope of their impact. In this particular scenario of employing multi-objective approach, random coring demonstrates a notable capability to achieve a reliable estimation of mean strength. In the other hand, using variance sampling with multi-objective approach contributes to further reducing the scattering of model parameters and enhancing the accuracy of strength assessment.



(a) Rebound Hammer (bi-objective approach)



(b) Ultrasonic Pulse Velocity (bi-objective approach)



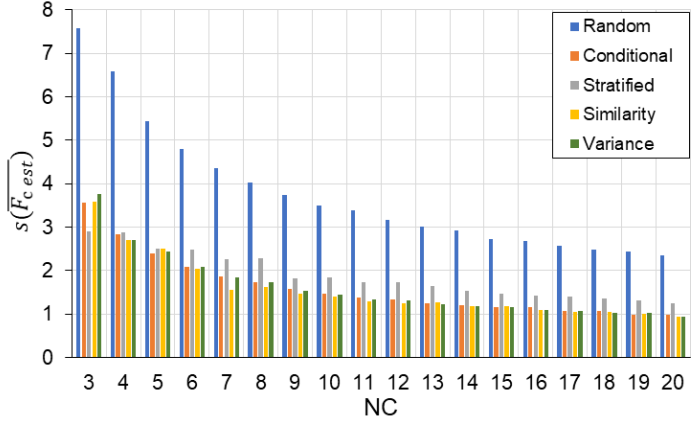
(c) Combination of the two techniques (multi-objective approach)

Figure 4. 6 Mean strength estimation of different sampling plans, considering a) Rebound Hammer, b) Pulse Velocity, c) the combination of both techniques SonReb

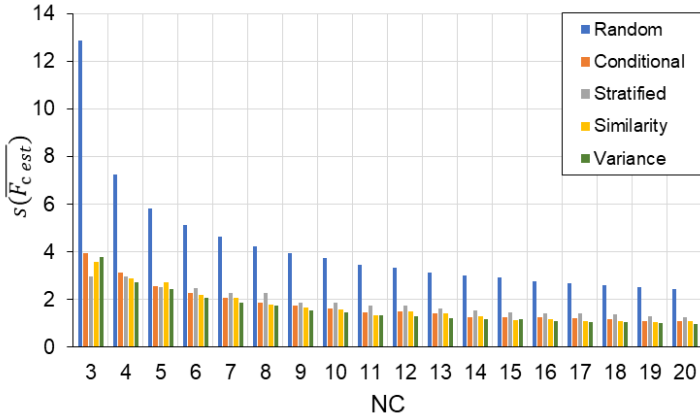
Reaching informed decisions about the appropriate sampling approach demands a thorough methodology. It is important not only to analyze the values of the estimated mean strength presented in Figure 4.6, but also to integrate the insights from the standard deviation of these estimations in Figure 4.7. The observed scatter in the estimated quantity, characterized by standard deviations, is attributed to several sources of uncertainty, including in-situ strength variability, sampling uncertainty, measurements uncertainty, and model uncertainty. As a result, it is crucial to examine the scatter in the estimated mean strength to evaluate the quality of the assessment. This consideration guarantees a thorough evaluation of the most efficient sampling strategy for assessing the mean strength, accounting for both the number of cores used and the selected nondestructive technique.

The examination of the “uncertainties” or “dispersion” in estimating mean strength, as illustrated in Figure 4.7, shows the significance of employing the different sampling plans over random coring. Specifically, when dealing with relatively small numbers of cores NC, the values of standard deviation in the mean strength denoted by $s(\bar{f}_{c\ est})$ demonstrate a significant increase when employing random coring. This increase highlights a notable degree of uncertainty associated with the estimated strength values, thus emphasizing the limitations of using random coring with a small number of cores. However, as the sample size NC increases, a consistent trend is observed: the $s(\bar{f}_{c\ est})$ values start to diminish. In addition, this reduction occurs with a relatively uniform decreasing rate across all the sampling approaches (conditional, stratified, similarity and variance sampling). Variance sampling showed a robust

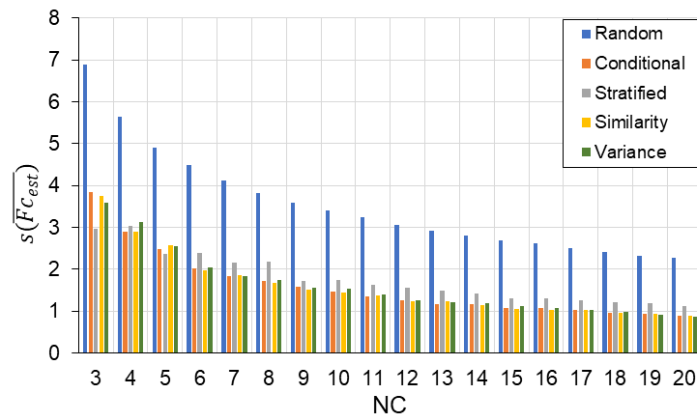
estimation of mean strength (lower $s(\bar{f}_{c\ est})$) compared to other sampling plans), when using a single NDT and combined NDT. Another significant observation relates to the importance of using the combination of NDT techniques. In general, using a combination of NDT techniques enhances the precision and reliability of assessing the mean strength, reducing errors in the estimation and providing a more accurate representation of the actual strength.



(a) Rebound Hammer (bi-objective approach)



(b) Ultrasonic Pulse Velocity (bi-objective approach)



(c) Combination of the two techniques (multi-objective approach)

Figure 4. 7 Standard deviation values (MPa) from NI values of mean strength estimated by a) Rebound Hammer, b) Ultrasonic Pulse Velocity and c) the combination of both techniques SonReb

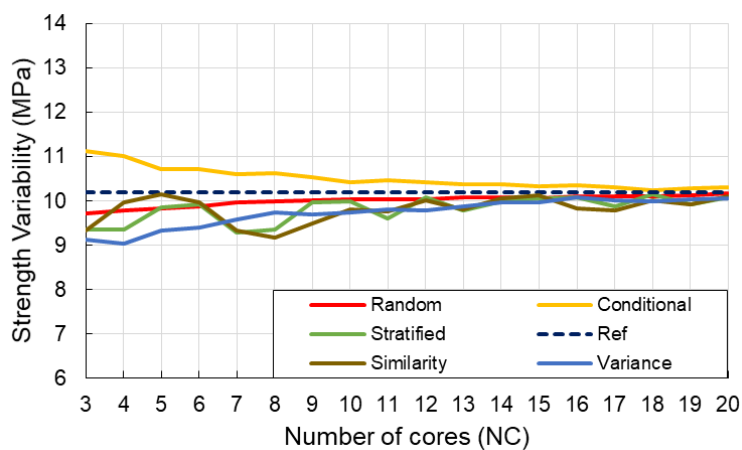
3.3 Assessment of strength variability of the different sampling strategies

In the current strategy, assessing the variability in concrete strength carries equivalent importance to evaluating its mean strength. This is because relying exclusively on the mean strength does not provide a comprehensive understanding of the concrete under study. Furthermore, enhancing the assessment of strength variability leads to an improvement in the evaluation of characteristic strength. The importance of employing the bi-objective approach (for a single NDT technique) and the multi-objective approach (when combining NDT techniques) becomes apparent when examining their ability to accurately capture the true variability in concrete strength (Kouddane et al., 2023; Sbartaï et al., 2021). This ability remains strong even when the number of core samples NC is lower than the minimum stipulated by standards. Regarding the accuracy of assessing concrete strength variability, Figures 4.8 and 4.9 illustrate the outputs of the simulation for various sampling strategies, considering the experimental dataset.

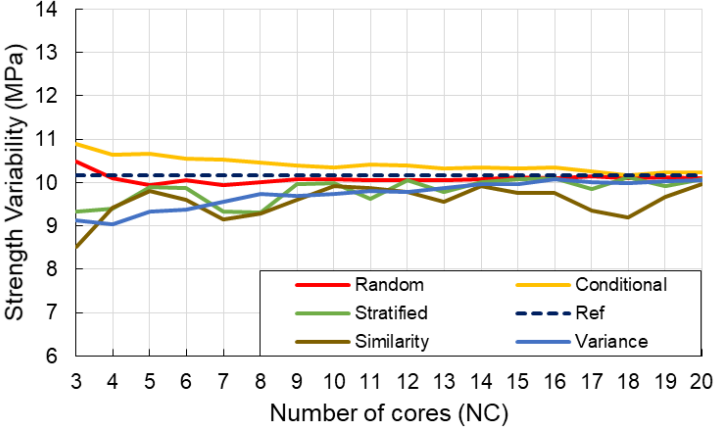
Figures 4.8a and 4.8b display strength variability curves that were generated from applying the bi-objective approach, when using a single NDT technique. Figure 4.8.c shows strength variability curves associated with the multi-objective approach, when using the combination of NDT techniques. According to the study of the actual dataset, both random coring and the other sampling methods correctly estimated the strength variability, with approximately similar performance that improves as NC increases. The random coring consistently exhibits the

potential to capture the concrete strength variability, which aligns with the actual reference values. This is attributed to the use of the bi-objective approach, which provides a good alternative for accurately estimating concrete strength variability. This capability holds significant value, particularly in situations where a limited number of core samples is used. The alternative sampling strategies, on the other hand, do not contribute any additional value to the assessment of strength variability in this case.

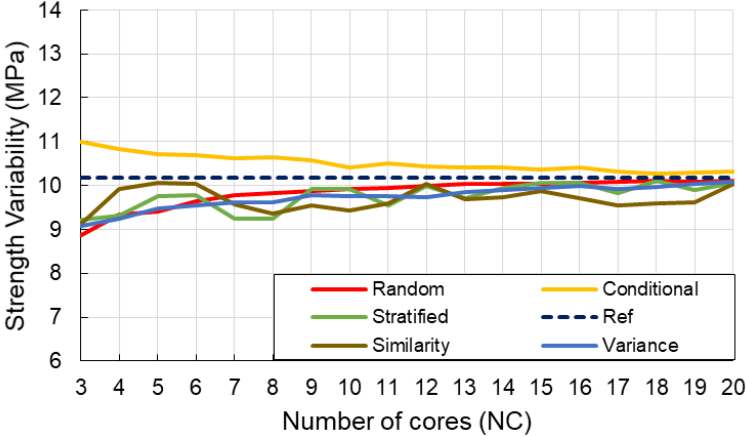
In other words, the outcomes obtained from the analysis of strength variability, employing both the bi-objective and multi-objective approaches, show satisfactory results when using random sampling. Interestingly, the implementation of the other sampling plans does not contribute any supplementary value to strength variability evaluation. The collective interaction of various factors such as the number of cores, the variability of concrete, and the accuracy of NDT methods could potentially reduce the additional value introduced by alternative sampling plans. What makes this study complex is the interaction between the potential benefits of the sampling strategies and the advantages that come from implementing these new model identification methods (bi-objective and multi-objective). This interaction highlights the importance of thoroughly comprehending both factors in order to make well-informed choices when determining the optimal approach for assessing strength variability in concrete structures.



(a) Rebound Hammer (bi-objective approach)



(b) Ultrasonic Pulse Velocity (bi-objective approach)

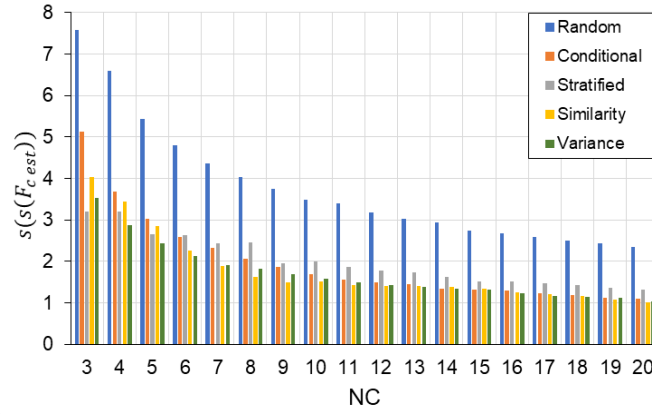


(c) Combination of the two techniques (multi-objective approach)

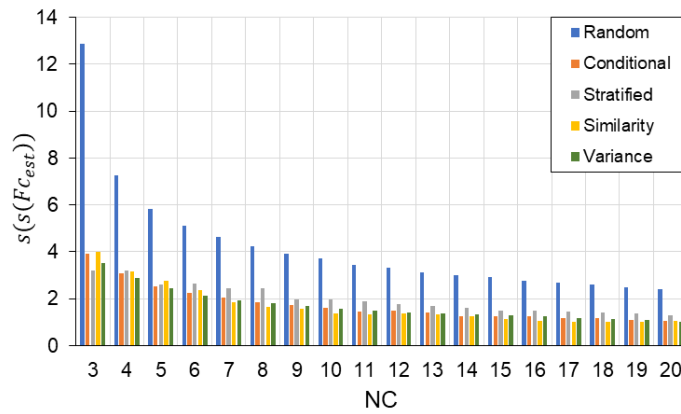
Figure 4. 8 The strength variability estimated by a) Rebound Hammer, b) Ultrasonic Pulse Velocity and c) the combination of both techniques SonReb

The bi-objective and multi-objective approaches offer a unique opportunity to effectively assess the variability of concrete strength. Nonetheless, it is imperative to conduct a meticulous assessment of the dispersion in strength variability $s(s(f_{c\ est}))$. This statistical parameter plays an important role in order to measure the reliability and precision of the estimated strength variability obtained from the assessment process. The standard deviation of concrete variability shows a notable increase when random coring is employed compared with the other sampling plans, particularly in situations where the number of cores is relatively small. This phenomenon can be attributed to the inherent variability that arises from a smaller sample size selected randomly, which amplifies the dispersion of results. In the other hand, using the presented sampling strategies can reduce the standard deviation in the assessment of strength variability. Among the presented sampling plans in Figure 4.9, random sampling exhibits the least

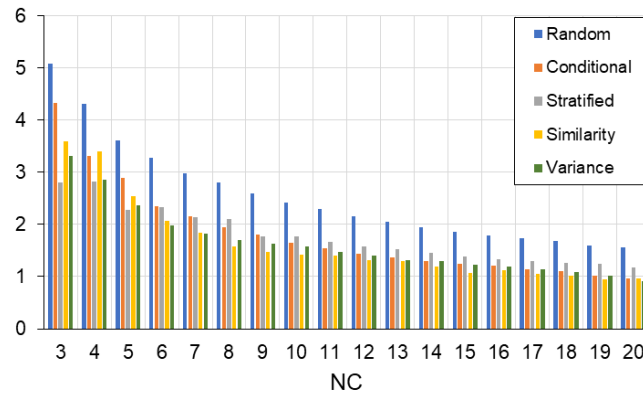
favorable performance concerning the estimation of strength variability with a high dispersion. Conversely, as observed earlier, variance sampling demonstrates the most optimal performance, underscoring its potential significance.



(a) Rebound Hammer (bi-objective approach)



(b) Ultrasonic Pulse Velocity (bi-objective approach)



(c) Combination of the two techniques (multi-objective approach)

Figure 4. 9 Standard deviation values (MPa) from NI values of strength variability estimated by a) Rebound Hammer, b) Ultrasonic Pulse Velocity and c) the combination of both techniques SonReb

3.4 Comparing the prediction capacity in term of prediction errors of the different sampling strategies

Sometimes, the aim of the assessment extends beyond estimating the average concrete strength; instead, the focus might be on understanding local strength variations. In fact, these estimated local strengths f_{cest} could diverge from the actual strength values f_c , leading to the identification of Root Mean Square Errors (RMSE) in the estimations. The Root Mean Square Error for estimating strength at nondestructive testing locations is formally defined in the work of (Liu et al., 2009):

$$RMSE = \sqrt{\sum_{i=1}^{NC} (f_{c i} - f_{cest i})^2 / NC} \quad (4.4)$$

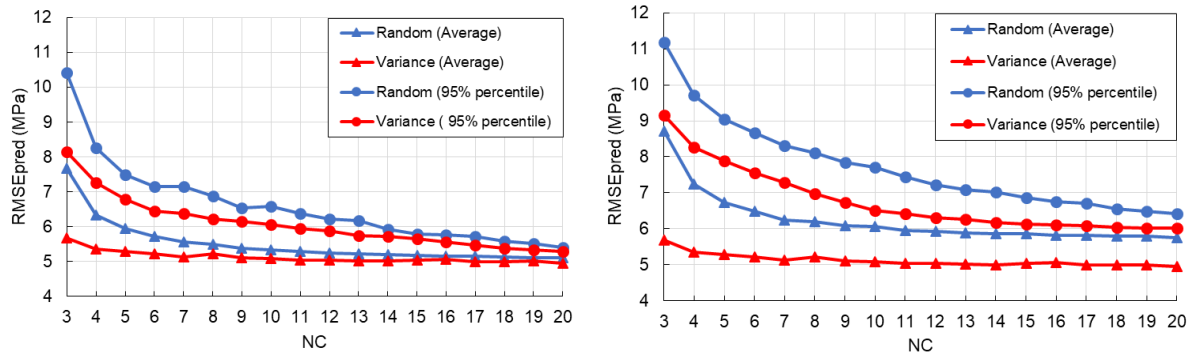
Where $f_{c i}$ and $f_{cest i}$ are the true strength and the estimated local strength respectively.

When a conversion model is developed based on a set of experimental data, there is often confusion regarding its quality. This confusion arises from the difference between the model's ability to fit the calibration data (how well it describes the data used for model development) and its ability to predict concrete strength at new locations where only NDT test results are available. During the fitting stage, which involves calibrating the model using the calibration data set (NC), the model's precision may appear to be excellent. However, this level of precision does not necessarily guarantee accurate predictions at new locations with NDT test results, especially when the number of cores is low (Alwash et al., 2015). Conversely, prediction errors, which occur when using the model to estimate strength at new locations (NT-NC), can be larger than fitting errors observed during the calibration process.

To ensure a more reliable assessment of the conversion model performance, it is essential to consider prediction errors when interpreting its precision and accuracy. This section is devoted to study the prediction capacity of the assessment strategy by comparing the predictive error $RMSE_{pred}$ of “random coring” and “variance sampling”. Among all the investigated sampling methods in concrete strength assessment, “Variance sampling” was chosen for its effectiveness in reducing the uncertainty in estimating concrete strength. This method has demonstrated the

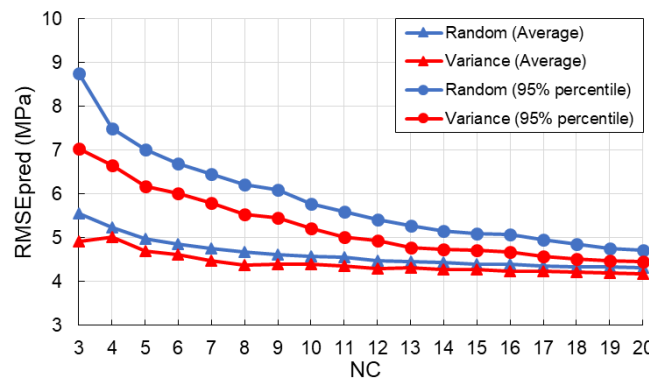
ability to minimize the variability in model parameters, resulting in more reliable and accurate estimations of concrete strength. For the three situations (Rebound Hammer, Pulse Velocity and their combination), the methodology illustrated in Figure 4.5 is applied to the real dataset. The bi-objective and multi-objective methods are used simultaneously to identify the conversion models. After NI iterations (NI=10,000), $RMSE_{pred}$ curves that correspond to each sampling strategy are presented in Figure 4.10. The average $RMSE_{pred}$ value and the 95% percentile of $RMSE_{pred}$ (which represents the RMSE value that is exceeded by only 5% of observations) are graphed. This 95% percentile value is particularly significant as it offers insights into the robustness of the investigation. The results are graphed for individual techniques, such as Rebound Hammer (shown in Figure 4.10a) and Ultrasonic Pulse Velocity (shown in Figure 4.10b), as well as for the SonReb technique (visualized in Figure 4.10c). Within the graphs, the red and blue curves correspond, respectively, to two coring options: “variance sampling” and “random coring”.

The variance sampling yields lower values for both the mean prediction error $RMSE_{pred}$ and the 95th percentile compared to random coring. However, as the sample size NC increases and approaches a range of seven or eight, an interesting transition becomes evident. The performance gap between variance sampling and random coring starts to diminish. This phenomenon implies that the advantage of variance sampling in terms of reducing prediction errors becomes less pronounced as the number of cores increases. In addition, when employing a single nondestructive testing method, both the average prediction error $RMSE_{pred}$ and the 95% percentile exhibit higher values compared with the combination of NDT techniques. This suggests that variance sampling in conjunction with the combination of NDT techniques enhance the precision of strength estimation, particularly in situations where the availability of core samples is restricted.



(a) Rebound Hammer (bi-objective approach)

(b) Ultrasonic Pulse Velocity (bi-objective approach)



(c) Combination of the two techniques (multi-objective approach)

Figure 4. 10 The effect of coring strategy on the predictive $RMSE_{pred}$ for single and combined techniques when analyzing real dataset

4 Conclusion

This chapter introduced a methodological approach aimed at improving the accuracy and precision in evaluating strength within concrete structures. The investigation focused particularly on two key aspects: the sampling process and the combination of two NDT techniques, Rebound hammer (RH) and Ultrasonic Pulse Velocity (UPV). Both aspects were addressed with a primary emphasis on understanding their roles in refining the assessment quality of concrete strength. The analysis conducted in this study aimed to quantify the combined impacts resulting from diverse factors. These factors include the number of cores collected, the implementation of the different sampling strategies, and the use of either individual or combined nondestructive testing techniques.

In order to choose the appropriate locations for core extraction, the effectiveness of various proposed sampling methods has been assessed in this study. The findings derived from this

extensive analysis on experimental data present compelling evidence to support the conclusions. In contrast to random coring, sampling plans based on NDT measurements generally result in a more accurate estimation of both the mean strength and its variability, ultimately reducing the prediction errors. The difference in accuracy between the two processes (random and NDT based coring) decreases overall when NC increases.

Therefore, it is essential to incorporate a well-defined sample strategy when assessing concrete properties. It is recommended to employ variance sampling as it represents a promising alternative for reducing inherent uncertainties in the assessment process. Variance sampling's effectiveness lies in its ability to minimize errors in estimating both the mean strength and strength variability. The rationale behind this can be attributed to the fact that this sampling method aims to closely approximate the variance of NDT test results. Consequently, a strong relationship is established between core strengths and NDT measurements, leading to consistently good performance.

The analysis of prediction errors highlighted the effectiveness of variance sampling in minimizing inaccuracies, especially in situations with limited core samples (from three to seven cores). Furthermore, the use of variance sampling in conjunction with SonReb technique provides a promising approach to improve the precision and reliability of strength estimation in concrete structures, reducing prediction errors to 4MPa. This is particularly valuable in situations where obtaining core samples may be difficult or impractical. Moreover, the suggested approach, which is based on specific conditions, does not incur any extra costs. The only requirement for its implementation is to conduct a preliminary nondestructive testing investigation before finalizing the selection of core sample locations.

Chapter Five: Life-Cycle Framework Based on Nondestructive Testing for The Best Inspection/Repair Strategy

1 Introduction

Throughout the 20th century, concrete became the predominant building material for various constructions, including bridges, tunnels, dams, and buildings. Concrete structures are designed to have a finite useful service life. If damages are not detected and addressed promptly, the service life of concrete can be reduced drastically. Bridges hold a vital role in the transportation network and are essential during emergencies. Bridge deterioration can be attributed to various factors, these include errors and negligence during the design phase, poor construction quality, inadequate maintenance practices, degradation mechanisms caused by aggressive environmental conditions, increased service loads, and exposure to hazards (Kušter Marić et al., 2020; Zerayohannes et al., 2017). These deteriorations often result in the formation of porosity, micro cracks, and larger cracks within the concrete. Conducting inspections on existing bridges is important to identify any potential structural defects. By adopting such preventative measures, one can assure the overall infrastructure system's resilience and reduce any potential socio-economic losses associated with bridge damage or failure. Infrastructure management organizations are actively conducting extensive surveys of existing bridge structures. These surveys aim to assess the safety of the bridges on a large scale, enabling accurate and precise interventions in the most critical areas.

It has become possible to make quantitative predictions about the service life of structures thanks to our growing understanding of the mechanics and kinetics, underlying the several processes that lead to degradation. An evaluation of the damage growth model can be used, for instance, to assess the reduction in strength of a concrete structure exposed to an aggressive environment. This approach, as demonstrated by studies of (Baji et al., 2017; Mori and Ellingwood, 1994), involves a systematic framework for understanding and quantifying the progression of deterioration over time. Moreover, the application of damage growth models extends beyond retrospective analysis. They can be employed proactively to make informed decisions regarding maintenance, repair, and rehabilitation strategies. By simulating the

degradation trajectory of a concrete structure under specific conditions, engineers can predict when critical thresholds of deterioration could be reached. This allows timely intervention and increases the structure's service life.

Understanding the structural degradation mechanisms is essential to quantify the life-cycle performance of structural systems under uncertainty (Kim et al., 2013). Throughout the life cycle of structures, degradation can occur in various forms, either physico-mechanical (such as overloading, freeze and thaw cycles, fire, shrinkage strains, temperature changes, etc.) or physico-chemical (such as corrosion, alkali-aggregate reaction, sulfate attack, etc.). Regardless of the degree of degradation, it results in two different forms of damage: distributed damage, which can manifest as an increase in porosity or a network of micro cracks, as well as local damage, such as delamination or macro cracks (Elachachi et al., 2011).

Visual inspection offers a rapid assessment of the nature of cracks, providing a general understanding of the situation. Based on visual inspection, maintenance actions can be determined. However, in some cases, additional testing may be necessary to enhance confidence in the findings and ensure the reliability of the chosen maintenance measures. To detect concrete degradation in its initial stage, many studies proposed the implementation of nondestructive evaluation techniques as (Ultrasonic, Ground Penetrating Radar, Impact Echo, Infrared Thermography, etc.) (Farhangdoust and Mehrabi, 2019; Robles et al., 2022; Shah and Ribakov, 2009). Acoustic methods with visual inspection are the oldest forms of nondestructive testing. Sound is a means of detecting the presence of voids, cracks or delamination.

To highlight the benefits and shortcomings of alternative NDT techniques, several comparative studies were done (Yehia et al., 2007), (Pushpakumara et al., 2017), (Gucunski et al., 2012). The efficiency and reliability of the existing inspection methods can exhibit significant variations, highlighting the need for careful consideration during the formulation of an inspection program (see Table 5.1). For instance, (Kashif Ur Rehman et al., 2016) provided an interesting overview of current NDT techniques employed for identifying defects in reinforced concrete bridges. Among the nondestructive testing methods, ultrasound testing is commonly employed for concrete structure evaluation. In their work, (Breysse et al., 2008) outlined the multiple objectives of NDT methods, which include detecting the condition of reinforced concrete structures, ranking structures based on their current condition, and comparing different properties using threshold values. The authors highlighted the importance of combining the results obtained from various NDT methods to achieve more comprehensive and accurate

assessments of the structural quality. Additionally, various nondestructive tests were employed to detect cracks and evaluate the overall structural integrity. (Song and Saraswathy, 2007) primarily focused on corrosion detection in various structures, including bridges, buildings, and other types of structures. They underlined the importance of structural health monitoring, electrochemical techniques, durability maintenance, and repair of these structures. One specific area of interest was the measurement of corrosion rates of reinforcing steel in concrete. The authors highlighted the availability of several electrochemical and nondestructive techniques for monitoring corrosion in steel-concrete structures. Moreover, (Kumavat, 2016) conducted a case study involving the assessment of concrete quality in an 8-year-old building using various NDT methods. The nondestructive techniques employed included Ultrasonic Pulse Velocity, Half-Cell Potential, Carbonation Depth, Rebar Locator and Cover Meter. The findings of (Gassman and Tawhed, 2004) showcased the outcomes of a nondestructive testing program conducted to evaluate the damage in a concrete bridge. The impact echo method was employed as a means of assessment. (Yehia et al., 2007) investigated various NDT techniques used for assessing the condition of concrete bridge decks. Their study included experiments with infrared thermography, impact echo, and ground penetrating radar (GPR) to detect common defects in concrete bridge decks. (Maierhofer et al., 2010) focused on the planning and implementation of NDT methods for structural health monitoring. They reviewed several techniques, including wireless monitoring, electromagnetic and acoustic waves, magnetic flux leakage, electrical resistivity, and corrosion rate measurement. In addition, (Sharma and Mukherjee, 2011) employed ultrasonic guided waves to monitor the progression of rebar corrosion in chloride and oxide environments.

The optimization strategy is applicable for any type of damage whose evolution can be modelled over time. This could include structural damage, wear and tear, corrosion, degradation of materials, or any other form of deterioration that occurs gradually. The strategy involves developing mathematical models or algorithms that can represent the progression of such damage over time. Every design strategy or assessment of service life involves a number of essential elements: a deterioration model, acceptance criteria defining satisfactory performance, relevant characteristic material properties, and factors or margins of safety that take into account uncertainties in the overall system (Bismut and Straub, 2019; Somerville, 1992). Several investigations have been conducted to establish the optimal inspection/maintenance strategy for metallic structures subjected to fatigue, assuming that a component is replaced if the intensity of detected damage exceeds a critical value (Thoft-Christensen and Sørensen, 1987).

By introducing NDT inspection methods, this chapter proposes a methodology to optimize the lifetime inspection/repair strategy by minimizing the total life-cycle cost while satisfying different constraints (Figure 5.1). The decision variables in the optimization are the times at which inspections/repairs are carried out and the number of inspections during the service life of the structure. To account for the impact of the number of inspections, the optimization problem can be solved over a range of values (from 1 to 10) to determine the value at which the overall cost is the lowest. A python program was developed to compute the minimization problem and the associated expected costs. The formulations presented in the coming sections are embedded in this program. The optimal inspection plan involves several aspects such as quality of inspection by NDT, damage rate, failure cost, net discount rate, uniform or nonuniform inspections, etc.

Table 5. 1 Comparison of nondestructive testing techniques for concrete inspection and material analysis

NDT Technique	Parameter measured	Principle	Advantages	Limitation
Infrared Thermography	Concrete quality, cracks, defects and voids.	Surface temperature variation.	Simple, easy interpretation, rapid setup, portable and no radiations.	No information about depths or thickness of defects.
Rapid Chloride Test	Chloride Concentration.	Potential difference of unknown solutions is compared with potential difference of solutions with known chloride concentration.	Portable, simple and quick.	Variation in results by the presence of certain materials.
Ultrasonic Guided Waves	Corrosion rate, percentage of corrosion.	Based of propagation of Ultrasonic waves.	Identify locations and magnitude of corrosion.	Not always, reliable, moister variance and presence of reinforcements can affect results.
Phenolphthalein Indicator	Carbonation depth.	Carbonation reduces the pH of the concrete.	Quick, descriptive and easy to use.	Inappropriate for dark aggregates, results affected by saturation.
Acoustic Tomography	Pavement inspection and subsurface condition	Wave are received in opposite side, wave velocity depended on material properties	Useful results, moderate.	Require skills, high cost.

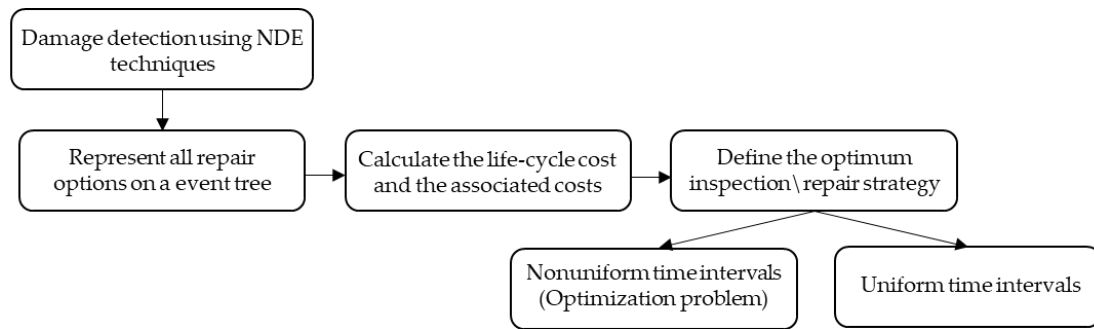


Figure 5. 1 Optimization framework for an inspection/repair plan

2 Probabilistic modelling of structural damage

Several models have been developed to predict the service life of concrete subjected to degradation processes (Alexander and Beushausen, 2019; Clifton, 1991). These models include a wide range of degradation mechanisms, which collectively contribute to a comprehensive knowledge of how concrete's structural integrity can be compromised over time. One of the degradation mechanisms considered in these models is chloride intrusion. Chloride ions, often present in the environment due to factors like de-icing salts or marine exposure, can penetrate concrete and initiate corrosion of the embedded reinforcement. Sulfate attack is another degradation mechanism, which can lead to the formation of expansive products within the concrete, resulting in internal pressures that compromise its structural integrity. Carbonation is yet another essential mechanism considered. As carbon dioxide penetrates concrete, it reacts with calcium hydroxide to form calcium carbonate, resulting in a reduction of the concrete's pH. This reduction in pH can lead to the corrosion of embedded steel reinforcement. The models also incorporate the effects of freeze-thaw cycles, a common phenomenon in cold climates. Water within concrete can freeze and expand, causing internal stresses that lead to cracking and surface deterioration. By including these different forms of deterioration in their analyses, the models offer a complete view of how the structural strength of concrete can be affected over time.

The definition or assessment of damage employed in the study is relevant until a specific stage in the structural degradation process, right before cracks or fissures emerge. Once this threshold is reached and cracks start to develop, the nature of the damage changes and the theoretical framework used for its analysis may become inadequate. Consequently, concepts associated with fracture mechanics or alternative theories become more applicable. In the context of our specific study, the concept of damage intensity, denoted as “ η ”, plays an important role in

assessing the condition of concrete bridge over time. This metric quantifies the degree of existing damage due to Young's modulus decreasing over time, it is defined as the ratio:

$$\eta(t) = \frac{E0 - E(t)}{E0} \quad (5.1)$$

Where $E0$ = represents the initial Young's modulus of the concrete, which is a measure of its inherent stiffness and resistance to deformation under stress. It is an essential indicator of the concrete's original structural integrity. $E(t)$, on the other hand, represents the Young's modulus of the concrete at a specific time, denoted by t , which represents the number of years since the structure was put into service. The damage intensity η can have a value between zero and one, meaning no damage and no residual strength, respectively. This metric provides a quantitative assessment of the rate at which a concrete structure deteriorates over time. This information is essential for making informed decisions about maintenance, repair, and overall structural integrity management.

Young's modulus, a fundamental property of materials, provides essential insights into their elastic behavior by describing their ability to maintain their original shape when subjected to compression, tension, or bending in a specific direction. However, its applicability extends beyond this primary characteristic. In specific situations, the Young's Modulus can be used to investigate and indirectly assess various aspects of the material, including porosity, crack formation, hardness, and even compressive strength. The accurate determination of the Young's Modulus is made feasible through the ultrasonic method, as elaborated by (Lin, 2018). This technique uses ultrasonic waves to measure how fast sound travels through a material, providing insights into its mechanical properties, including Young's modulus. As time progresses, the Young's modulus, denoted as $E(t)$, experiences a gradual and sustained decrease over time, attributed to the inherent effects of the degradation process. Understanding this temporal evolution of the Young's Modulus is essential for anticipating alterations in the mechanical properties of materials, carrying significant implications for the design, maintenance, and sustainability of structures. The choice was done to describe this reduction in Young's modulus by a linear function of time:

$$E(t) = E0 - k * Ti \quad (5.2)$$

Where k is defined as the concrete damage growth rate.

Therefore, after repair, Young's modulus $E(t)$ is calculated as:

$$E(t) = E_r - k * T_i \quad (5.3)$$

In this context, E_r is Young's modulus of the repaired concrete. This value which is generally different from the value taken initially, depending on the type of repair carried out, can be estimated through nondestructive techniques, facilitating the assessment of the structural effectiveness of the repair intervention.

3 Lifetime costs

3.1 Inspection Cost

In the context of bridge inspections, traditional methods often rely on visual assessments. However, in this study, the focus revolves around the diminution of Young's modulus (local scale) or stiffness (global scale) over time. As a result, the nature of the damage needs the adoption of nondestructive techniques. The ability of the chosen NDT method to properly identify and measure the degree of damage is important to the procedure's effectiveness. An inspection method with good quality not only enhances the reliability of the overall assessment but also ensures a more precise determination of the extent of damage.

In the context of our investigation, where we're examining the intensity of damage represented by η , an integral aspect of our study involves formulating a detectability function. This function provides valuable insights into the ability of nondestructive methods to identify on one hand and quantify on another hand damage within concrete structures. When considering the intensity of damage η , the detectability function which must necessarily be a monotonically increasing function is modelled in this study, due to its interesting properties, as a cumulative normal distribution function for each NDT method. By employing a cumulative normal distribution function, we aim to capture the probabilistic nature of damage detection and provide a comprehensive understanding of the effectiveness of these NDT techniques in practical applications.

When assessing a structure with a damage intensity denoted as η at a given time T_i , it is important to consider the probability of correctly identifying the extent of this damage. This probability is defined as the Probability of Damage Detection (PoD), which signifies the likelihood that the NDT method can accurately identify and quantify the existing damage

(Frangopol et al., 1997). The mathematical expression used to approximate the PoD in our study is as follows:

$$PoD = \begin{cases} 0, & \eta \leq \eta_{min} \\ \Phi\left(\frac{\eta - \eta_{0.5}}{0.1 \eta_{0.5}}\right), & \eta_{min} < \eta \leq \eta_{max} \\ 1, & \eta > \eta_{max} \end{cases} \quad (5.4)$$

Here, Φ is the standard normal cumulative distribution function and $\eta_{0.5}$ represents the damage intensity at which the NDT method exhibits a 50% probability of successfully detecting the damage. This value is essential for understanding how sensitive the method is to different degrees of damage. The value of the standard deviation σ is set to $\sigma = 0.1 \eta_{0.5}$, assuming a coefficient of variation of 0.1. Moreover, η_{min} and η_{max} are parameters that help define thresholds within which the sensitivity of NDT method is most effective according to (Frangopol et al., 1997):

$$\eta_{min} = \eta_{0.5} - 3\sigma = 0.7 \eta_{0.5} \quad (5.5)$$

$$\eta_{max} = \eta_{0.5} + 3\sigma = 1.3 \eta_{0.5} \quad (5.6)$$

By subtracting three times the standard deviation from the 50% damage intensity in Equation 5.5, the objective is to establish a reference point within the data. This reference point is chosen because, in a typical distribution, about 99.7% of the data points are expected to fall within three standard deviations below the mean. In addition, by adding 3 times the standard deviation to the 50% damage intensity, Equation 5.6 sets an upper threshold that includes where most of the data is expected to be. Consequently, both formulas set lower and upper thresholds that accounts for the variability of data (σ) due to measurement imprecision. This approach ensures that the method is sensitive to a reasonable range of damage intensity levels while considering measurement uncertainties.

By incorporating the normal distribution within this specified range (η_{min}, η_{max}), our methodology explicitly addresses the inherent uncertainties in NDT methods. This probabilistic framework provides a comprehensive context that takes into account the potential variations in detection accuracy and sensitivity caused by multiple factors, including equipment performance, environmental variables, and material characteristics. Rather than assuming perfect detection of damage, our approach acknowledges the intricate and often unpredictable

nature of inspection outcomes. As a result, it contributes to informed decision-making when it comes to planning maintenance and conducting structural assessments.

In general, the effectiveness of the NDT methods affects the cost of the inspection. The “ideal inspection” refers to a theoretical situation where the inspection method performs perfectly and can detect all damage without any errors. In the work of (Mori and Ellingwood, 1994) the cost associated with the ideal inspection is denoted as α_{ins} . However, real-world inspection methods are not perfect, and they may have limitations in detecting damage. The cost associated with a real inspection method, C_{insp} can be estimated based on the quality of detectability (Mori and Ellingwood, 1994). In order to define the quality of the inspection method, the median detectability of the inspection method $\eta_{0.5}$ is considered. It is used in the relation bellow to show the imperfect nature of the NDT method.

$$C_{insp} = \alpha_{ins}(1 - \eta_{min})^{20} = \alpha_{ins}(1 - 0.7\eta_{0.5})^{20} \quad (5.7)$$

In the context of this study, α_{ins} is assumed as a fraction, 7% of the initial cost C_{init} (Frangopol et al., 1997). Inspection methods vary in their ability to accurately detect damage or defects. Higher-quality methods are more reliable and can detect smaller levels of damage. The equation considers the minimum detectable damage intensity η_{min} , which represents the smallest damage level the inspection method can reliably identify. Furthermore, the way the equation is set up considers that higher quality inspections are typically more expensive.

Thus, the overall expected inspection cost for a plan involving N_{insp} lifetime inspections is:

$$C_{INSP} = \sum_{i=1}^{N_{insp}} \frac{C_{insp}}{(1 + r)^{T_{insp,i}}} \quad (5.8)$$

Equation 5.8 calculates the total expected inspection cost by summing up the costs of all individual inspections C_{insp} (defined in Equation 5.7), considering the time at which each inspection occurs $T_{insp,i}$, and the specified discount rate “ r ”. The inclusion of the discount rate introduces the concept of the time value of money into the equation. Money has a time-related value, and its worth diminishes over time due to factors such as inflation and the potential earning capacity of invested funds. By discounting future costs, the aim is to align these costs with their equivalent present value.

Equation 5.8 is commonly used in cost analysis because it allows for the consideration of both the costs associated with inspections and the time value of money, providing a way to make informed decisions about inspection strategies based on their expected costs. Furthermore, this equation provides a structured method for comparing various inspection plans. By calculating the total expected inspection cost for each strategy, one can assess which strategy is more cost-effective in the end. This can help decision-makers select the most economically efficient approach based on the expected costs associated with inspections.

3.2 Repair Cost

After an inspection is carried out, the next step is to determine whether any necessary repairs are required if damage is identified. The choice of whether to repair or not will be impacted by the level of inspection quality. High-quality inspection methods are often better at detecting problems at an early stage. This is because even tiny defects can be accurately located and repaired. A significant outcome of employing high-quality inspection methods and performing effective repairs is the potential for enhancing the overall reliability of the structure. When damages are fixed quickly and correctly, the structure can be restored to its original level of reliability (Mori and Ellingwood, 1994).

It is important to take into account the possibility that some items requiring repair might escape detection during the inspection process. This can happen when the damage intensity falls below a specified threshold η_{min} . In this case, the likelihood of detecting the damage becomes zero. As a result, no actions will be taken to fix the damage and the structure will stay unrepaired. Nevertheless, because of the inherent uncertainties associated with detecting damage, there is a chance that some instances of damage may go unnoticed during the inspection process. This is especially accurate when the damage intensity is close to the threshold of detection. Consequently, it is possible that certain damage will persist undetected even after both the inspection and the repair actions have taken place. If a repair is performed after an inspection with a median detectability of $\eta_{0,5}$ at time T_i , the damage intensity is expected to decrease. The initial damage intensity of η_i will be reduced to η_{rep} (see Equation 5.9). In other words, the repair action will effectively reduce the level of damage present in the structure. When the damage intensity exceeds the value of η_{max} , which is the upper limit threshold defined earlier in Equation 5.6, the damage in the repaired structure is reduced to its median value $\eta_{0,5}$ (see Equation 5.9).

$$\eta_{rep} = \begin{cases} \eta_i, & \eta_i \leq \eta_{min} \\ \frac{\eta_{min} + \eta_i}{2}, & \eta_{min} < \eta \leq \eta_{max} \\ \eta_{0,5}, & \eta_i > \eta_{max} \end{cases} \quad (5.9)$$

Repaired structures, may not reach the same level of reliability as new structures. Equation 5.9 models the reduction in damage intensity following a repair. However, even after repair, there may be some amount of residual damage or permanent reduction in material properties. Thus, the equation accounts for this reality by specifying that even after repair, the damage intensity η_{rep} will not decrease below a certain level defined by η_{min} , which represents the minimum threshold of considered damage. The repair action aims to mitigate the damages and restore the functionality of the structure, but it generally cannot completely eliminate all damages or restore all properties of the original material.

The interaction between different factors related to the repair process can influence the overall reliability of the structure. In most inspection and repair scenarios, it is assumed that repair cost remains constant throughout the lifespan of the structure. However, this assumption is generally not accurate. In this study, the repair cost is regarded as a function of the replacement cost and the impact of the repair activity. In reality, various factors can influence the cost of repairs over time. Firstly, the materials used in construction and repair techniques can evolve, leading to variations in costs associated with materials and equipment required to conduct repairs. Moreover, the initial condition of the structure at the time of repair can play a significant role. Neglecting preventive maintenance, for instance, might need more expensive and complex repairs due to progressive deterioration. By considering the repair cost as a function of replacement cost and the effect of repair activity, this approach considers the dynamic relationship between these variables. For instance, if replacement cost increases due to inflation or other economic factors, the repair cost might increase proportionally. Additionally, factors including the effectiveness of the repair, its durability, and its impact on the overall performance of the structure could be linked to the effect of the repair activity.

As a result, the repair cost can be expressed in terms of the repair effect e_{rep} as follows:

$$C_{rep} = m * C_{init} * e_{rep}^y \quad (5.10)$$

In this case, we assumed that the replacement cost can be calculated by multiplying the coefficient m with the initial cost C_{init} . The coefficient m is used to scale this initial cost, reflecting the overall magnitude of the replacement cost. Moreover, γ is a model parameter assumed 0.5, it is an exponent that determines how the repair effect influences the repair cost. It introduces a level of sensitivity in the relationship between the repair effect e_{rep} and the repair cost C_{rep} . The value of γ can influence whether the repair cost increases significantly or only moderately as the repair effect intensifies. The assumption of γ being 0.5 implies a moderate sensitivity. If γ were higher, it would indicate a more pronounced impact of the repair effect on the repair cost. On the other hand, a lower γ would result in a less pronounced influence.

The effect of a repair activity, denoted as “ e_{rep} ”, indicates the measurable improvement in the condition of a structural component resulting from that specific repair action. In other words, it represents how significantly the repair operation improves the condition or quality of the specific component of the structure being repaired. The impact of a repair action e_{rep} can be expressed by considering the damage intensity η_{rep} after the repair has been completed:

$$e_{rep} = \frac{|\eta_i - \eta_{rep}|}{\eta_{0,5}} \quad (5.11)$$

Therefore, the expected total repair cost is:

$$C_{REP} = \sum_{j=1}^n (P(E_j) * \sum_{i=1}^{N_{insp}} \frac{C_{rep\ i,j}}{(1+r)^{T_{insp,i}}}) \quad (5.12)$$

Equation 5.12 considers a wide range of important factors, such as the various situations that the system might experience, the probabilities attached to those scenarios, the scheduling of inspections, and the inherent uncertainty in the process. When managing complex systems or structures, such as infrastructures, there are multiple paths or branches that these systems can follow. These paths correspond to various events that might occur, each with its own probability of occurrence $P(E_j)$. In parallel, inspections are carried out at different time intervals to assess the system's condition. The number of inspection cycles considered for the analysis is indicated by the index N_{insp} , where i stands for the various inspection cycles. Considering the repair costs associated with each event $C_{rep\ i,j}$ and the particular inspection cycle, Equation 5.12 sums up

these costs across all potential scenarios and inspection cycles. However, to make these future repair costs equivalent to their present value, a discounting factor “ r ” is employed. By summing up these discounted repair costs for all possible scenarios and inspection cycles, the equation provides a comprehensive projection of the expected total repair cost.

3.3 Failure Cost

Structures can deteriorate for a variety of reasons, including the natural aging of the structure, exposure to harsh environmental conditions, and the loads applied to it. Corrosion and fatigue are two common factors that can significantly reduce the resilience of concrete and steel structures. For reinforced concrete bridges, corrosion of the embedded reinforcement within the concrete is often recognized as the primary mechanism of deterioration (Chaker, 1992). Numerous researches have been dedicated to probabilistic service life predictions for deteriorating concrete bridges affected by corrosion (Enright and Frangopol, 1998; Li et al., 2005). In the case of steel structures, the degradation can be attributed to fatigue induced by various types of loading (Fisher et al., 1998). In some circumstances, fatigue-induced stress can cause unanticipated structural failures or crack formation, taking the steel structure temporarily out of service. The cost associated with a structural failure, denoted as the “failure cost” requires a thorough assessment that considers a wide range of factors. These factors include aspects like loss of human life, the inconvenience caused to users, and various other relevant aspects.

In this context, the Weibull distribution is used to model the probability of failure P_f . This distribution is chosen for its mathematical properties that make it suitable for representing the probability of failure over time for structures susceptible to gradual deterioration. Using the Weibull distribution allows estimating the probability of failure based on the intensity of damage, which is crucial for assessing the risks associated with structure deterioration. The probability of failure P_f is determined as follow:

$$P_f = \begin{cases} 0, & \eta_i \leq \eta_{min} \\ 1 - \left[\exp - \left(\frac{\eta_i - \eta_{min}}{\eta_{0,5}} \right)^\alpha \right], & \eta_i > \eta_{min} \end{cases} \quad (5.13)$$

The Weibull distribution includes several parameters; these parameters shape the distribution to fit the data. The exponent α determines how quickly the failure probability increases with the augmentation of the damage intensity η_i , The value η_{min} serves as a critical threshold. In cases where η_i is equal to or less than η_{min} , the probability of failure is set to zero, implying

that failure is not anticipated. This indicates that if the parameter η_i remains below a certain critical threshold η_{min} , the structure is considered safe and stable. Conversely, when η_i exceeds the value of η_{min} , the probability of failure is computed using the Weibull distribution (Equation 5.13). This mathematical expression is commonly employed to represent the likelihood of failure occurring as time progresses, particularly for structures that are susceptible to gradual deterioration.

As a result, the expected total failure cost C_{FAIL} is calculated by multiplying the cost of failure C_{fail} by the probability of failure over the structure's lifetime P_{fail} , which will be examined at a later point in the study (Equation 5.22). The failure cost represents the monetary loss due to a structural failure, and the expected total failure cost, C_{FAIL} can be expressed as:

$$C_{FAIL} = C_{fail} * P_{fail} \quad (5.14)$$

3.4 Expected total cost

The “expected total cost” is a way of quantifying the cost that a structure is expected to accumulate over its entire lifespan. This cost includes a variety of different factors that may have an impact on the financial aspects of maintaining the building from its construction through its eventual replacement. This concept is represented mathematically in Equation 5.15 as a sum of different individual cost components, each of these factors contributes to the overall financial burden associated with the structure, reflecting the various costs that need to be considered when evaluating its economic impact. These components are:

1. Initial Construction Cost C_{init} : which refers to the cost during the initial construction of the structure. This includes the cost of materials, labor, design and any other expenses directly related to the construction of the structure.
2. Inspection Cost C_{INSP} : which accounts for the financial outlay associated with routine assessments conducted to assess the condition of the structure. These inspections are crucial for identifying potential areas that require maintenance or repair.
3. Repair Cost C_{REP} : which appears when addressing necessary repairs due to damage, gradual deterioration, or other structural concerns that require correction. Repair cost cover the expenses associated with restoring the structure to its proper functionality and safety.

4. Failure Cost C_{FAIL} : which refers to the cost associated with a failure event that occurs to the structure. Failure costs can include charges for emergency repairs, replacements, addressing safety concerns, and any other costs resulting from unexpected structural failures.

The formulation of the expected total cost C_T as a sum of these components provides a comprehensive view of the financial implications of managing a structure over its entire life span. The expenses related to a structure extend beyond the construction phase to cover maintenance, inspections, repairs, and addressing failures. The annual total cost of the structure is used to determine the optimum maintenance management plan. It can be expressed as follow:

$$C_T = C_{init} + C_{INSP} + C_{REP} + C_{FAIL} \quad (5.15)$$

In order to effectively maintain and manage structures, a holistic approach to cost management and decision-making is essential. It underlines the complex nature of life-cycle costs and emphasizes how crucial it is to consider all pertinent cost aspects in order to make informed financial decisions.

4 Event Tree Analysis

To represent all the possible events associated with repair and non-repair actions, an event tree analysis is performed. An event tree analysis is a graphical representation used to map out all possible decisions in a sequential manner. The number of branches “ n ” in the event tree depends on the number of inspections $n = 2^{N_{insp}}$ where N_{insp} is the number of inspections conducted. Figure 5.2 depicts an example of event tree diagram representing two inspections throughout the structure’s life cycle ($N_{insp} = 2$), where P(NR) and P(R) represent actions for non-repair and repair, respectively. “ T_i ” stands for the inspection time, while “ P_{fj}^i ” denotes the probability of failure of the structure before each inspection. The fundamental idea presented in this study is that once any type of damage is detected during an inspection, it is immediately addressed through repair measures. This approach simplifies the analysis, as it eliminates the consideration of scenarios where detected damage might not be repaired. In this context, the probability of performing a repair after an inspection is linked to the likelihood of detecting a certain level of damage, denoted by the symbol “ η ”. This probability of repair after the first inspection is represented as P(R). The probability of not repairing after the first inspection P(NR) is simply the complement of P(R). In other words, it is the probability that repair is not

carried out after detecting damage during the first inspection. In addition, repair choices made after each successive inspection are influenced by prior decisions. For instance, whether or not the structure was fixed after the first inspection will affect the decision to repair or not after the second inspection. With an increase in the number of inspections denoted as N_{insp} , the count of branches in the event tree expands (see Figure 5.2). For each branch in the event tree, the probabilities of repair ($P(R)$) and non-repair ($P(NR)$) events are computed using specific formulas:

- $P(R)$ is determined using an equation involving the normal distribution function, which considers the deviation of the damage intensity η from a reference value $\eta_{0.5}$, normalized by its standard deviation (Equation 5.16).
- $P(NR)$ is the probability of a non-repair event occurring. It is calculated as the complement of the repair probability (Equation 5.17).

$$P(R) = \phi\left(\frac{\eta - \eta_{0.5}}{0.1 \eta_{0.5}}\right) \quad (5.16)$$

$$P(NR) = 1 - P(R) \quad (5.17)$$

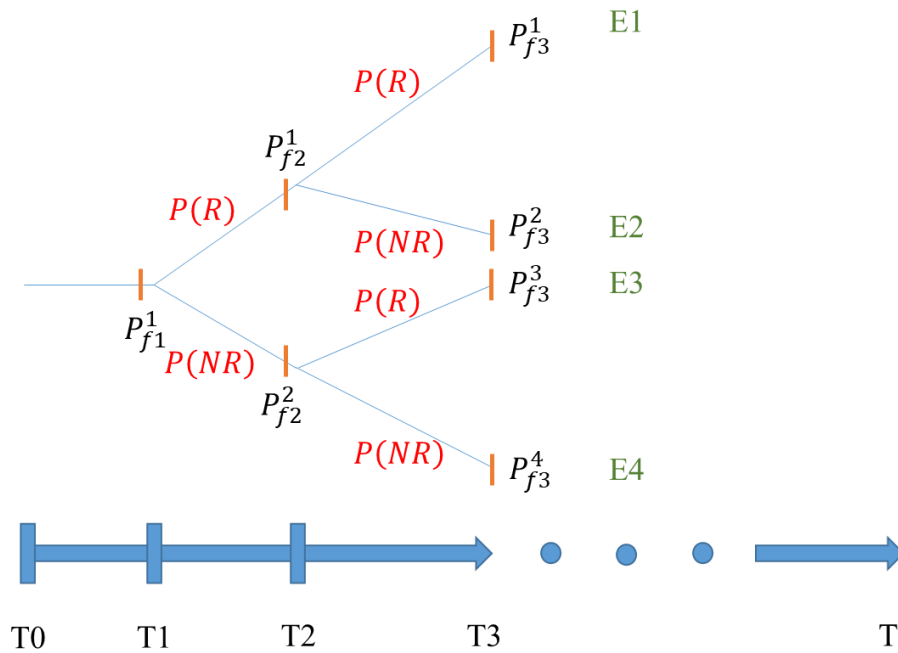


Figure 5. 2 Tree diagram corresponding to two inspections $N_{insp} = 2$

In this investigation, The events are all regarded as independent, the probabilities of the trajectories E1, E2, E3, and E4 occurring can be computed using the equations (5.18a, 5.18b, 5.18c, and 5.18d), as outlined in the work of (Frangopol et al., 1997) :

$$P(E1) = P(R) * P(R) \quad (5.18a)$$

$$P(E2) = P(R) * P(NR) \quad (5.18b)$$

$$P(E3) = P(NR) * P(R) \quad (5.18c)$$

$$P(E4) = P(NR) * P(NR) \quad (5.18d)$$

Each branch within the event tree holds three probabilities of failure: before the first inspection, before the second inspection, and at the end of the entire lifespan. In order to estimate the probability of failure for each branch, it is possible to consider a series system approach. For instance, for branch 1, this involves:

$$P_{f1} = (P_{f1}^1 \cup P_{f2}^1 \cup P_{f3}^1) \quad (5.19)$$

Where P_{f1}^1 is the probability of failure before the first inspection, P_{f2}^1 is the probability of failure before the second inspection, and P_{f3}^1 is the probability of failure at the end of the lifecycle. P_{f1} can be expressed using its marginal and joint probabilities:

$$P_{f1} = P_{f1}^1 + P_{f2}^1 + P_{f3}^1 - (P_{f1}^1 \cap P_{f2}^1) - (P_{f1}^1 \cap P_{f3}^1) - (P_{f2}^1 \cap P_{f3}^1) + (P_{f1}^1 \cap P_{f2}^1 \cap P_{f3}^1) \quad (5.20)$$

The solution for the equation above presents two limits. The lower limit assumes complete correlation, resulting in the expression: $P_{f1} \geq \max (P_{f1}^1, P_{f2}^1, P_{f3}^1)$

The upper limit, on the other hand, assumes no correlation among the probabilities, yielding the expression: $P_{f1} < 1 - [(1 - P_{f1}^1)(1 - P_{f2}^1)(1 - P_{f3}^1)]$

Following the approach outlined by (Frangopol et al., 1997), this study adopts the assumption that the failure probabilities before the first inspection, before the second inspection, and at the end of the lifecycle are entirely correlated. There are various reasons why total correlation between failure probabilities at different stages of a structure's lifecycle might be considered. Firstly, if environmental conditions and applied loads remain constant or evolve predictably, the cumulative effects of wear and deterioration may accumulate uniformly over time, leading to total correlation in failure probabilities. In addition, if repairs or interventions are carried out at various stages of the structure's lifecycle, this can influence the probability of failure at later

stages. For example, a repair made at an early stage may delay the onset of subsequent degradation, thereby creating a correlation between failure probabilities before and after the repair. Moreover, if certain parts of the structure are interdependent or share common failure mechanisms, this can result in a total correlation between failure probabilities at different times. For example, localized degradation in one component may affect the overall stability of the structure, thereby creating a correlation between failure probabilities at different stages. Furthermore, adopting an assumption of total correlation simplifies the model, facilitating its application and analysis.

As a result, the probability of failure for each individual branch is calculated using the equations:

$$P_{f1} = \max (P_{f1}^1, P_{f2}^1, P_{f3}^1) \quad (5.21a)$$

$$P_{f2} = \max (P_{f1}^1, P_{f2}^1, P_{f3}^2) \quad (5.21b)$$

$$P_{f3} = \max (P_{f1}^1, P_{f2}^2, P_{f3}^3) \quad (5.21c)$$

$$P_{f4} = \max (P_{f1}^1, P_{f2}^2, P_{f3}^4) \quad (5.21d)$$

Finally, the lifetime probability of failure of the structure, P_{fail} is computed by summing the products of the probability of failure for each branch P_{fj} and the probability of occurrence of each event $P(Ej)$:

$$P_{fail} = \sum_{j=1}^n P_{fj} * P(Ej) \quad (5.22)$$

5 Uniform interval inspection strategy

In the context of this study, the inspection strategy refers to the plan or schedule for inspecting a particular structure over its entire lifetime. Initially, this study begins with a simplified approach of conducting inspections, by limiting them to uniform time intervals. The structure under consideration is expected to have a total lifetime of 100 years, which falls between the lifespan of a common structure such as a building of around 50 years and of a bridge of around 150 years. In this context, the goal is to examine and evaluate 10 different inspection strategies. Each of these 10 inspection strategies likely involves conducting inspections at different time intervals. For instance, one strategy might involve inspecting the system every 5 years, another every 7 years, and so on. The purpose of considering multiple inspection strategies is to assess

how different inspection frequencies affect the overall effectiveness, cost, and reliability of maintaining the system over its expected 100-year lifetime.

This study consists of a parametric study involving variables such as: inspection quality, inspection cost, repair cost, and failure cost. Moreover, the impact of repairs on the reliability of the component and the influence of the time value of money are considered. This study is conducted based on the assumption of the following parameters:

- Life-cycle Time = 100 years
- Damage Rate = 40 MPa/year
- Damage intensity at which the NDT technique has a 50% of detection probability = 0.06 with a coefficient of variation of 0.1
- Annual discount rate = 0.02
- Initial Cost = 700 monetary units (M.U)
- Failure Cost = 50000 monetary units (M.U)
- Minimum and maximum inspection time intervals $t_{\min}=2$ and $t_{\max}=100$

In this context, the term N_{insp} represents the number of inspections that will be conducted throughout the service life of a structure. The study investigates a range of potential values for N_{insp} in order to determine the ideal number of inspections that would result in the most economical and successful maintenance approach for the structure. In other words, it aims to find the right balance between inspection frequency and maintenance cost to ensure the structure's longevity and minimize expenses. To find this optimal number of inspections, the objective is to consider various values of N_{insp} (from 1 to 10) and identify the value of N_{insp} that results in the smallest expected total cost. This value of N_{insp} represents the optimal number of inspections that would help minimize the overall life-cycle cost of the structure.

The results of the various estimated costs are shown in Figure 5.3 as a function of the number of uniform interval inspections. This analysis aims to determine the optimal inspection and repair strategy for the structure under consideration. This figure helps to identify the point at which a balance is achieved between the costs of inspections, repairs, and potential failures, resulting in the most efficient and cost-effective inspection and maintenance strategy for the structure. It is important to note that depending on the quantity of inspections performed N_{insp} , the behaviour of two different cost components varies in opposite directions. Firstly, the cost of repairs, referred to C_{REP} , increases as the number of inspections rises. This increase can be

attributed to the fact that inspections that are more frequent detect more damages, potentially requiring more repair actions to keep the structure in a good condition. Conversely, the expected cost of failures, denoted as C_{FAIL} , decreases as the number of inspections increases. This reduction occurs because more frequent inspections help prevent failures by identifying damage at an early stage, thereby reducing potential costs associated with failures. The intersection of repair costs and failure costs refers to the optimum inspection/repair strategy. At this point, the expected total cost, which considers inspection, repair and failure costs, reaches its minimum value. Figure 5.3 indicates that the optimal number of inspections over the entire lifespan of the structure, considering the values of the parameters presented above, is six. The lowest predicted total cost at this point shows that this inspection and repair strategy offers the optimal balance between maintenance costs and failure prevention.

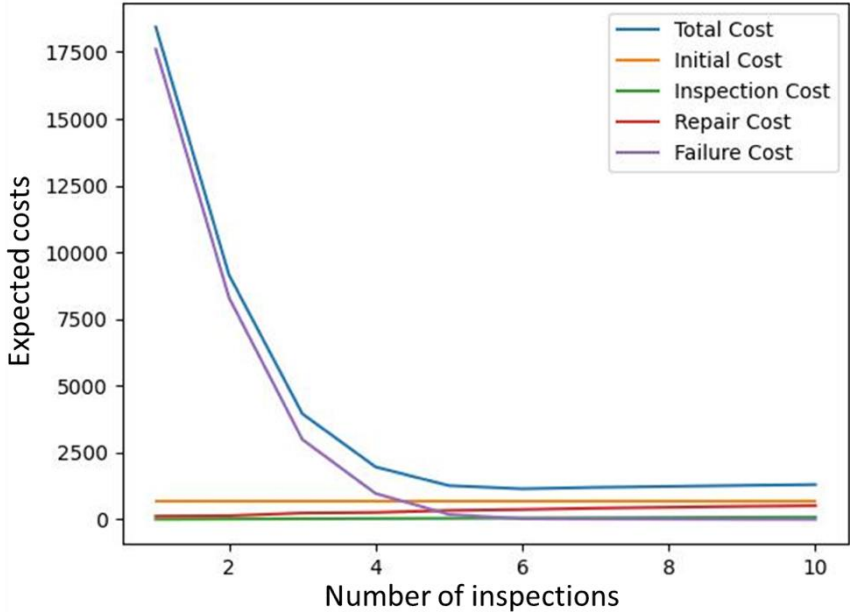


Figure 5. 3 The different expected costs as function of the number of uniform interval inspections

Figure 5.4 shows the specific event tree scenario with the highest likelihood of occurring in the context of performing six uniform inspections. In the context of this strategy, a specific order for inspecting and repairing is outlined. After performing the first two inspections, no repair actions are taken. This decision is based on a specific criterion: it is because the damage intensity η , which is being monitored during these inspections, has not yet reached a level that is high enough to be detectable or considered significant. In

other words, the damage has not yet reached a particular threshold η_{min} that would require repairs. The next four inspections are each followed by a repair action. This strategy outlines that if damage is found then a repair action will follow. If the damage is not found then the repair action will be postponed until the next inspection. Furthermore, in earlier researches, repairs were regarded as perfect, resulting in the restoration of the same initial properties of the structure. Nevertheless, in our study, the reliability of the structural component is improved after repair, although it does not fully return to the initial conditions.

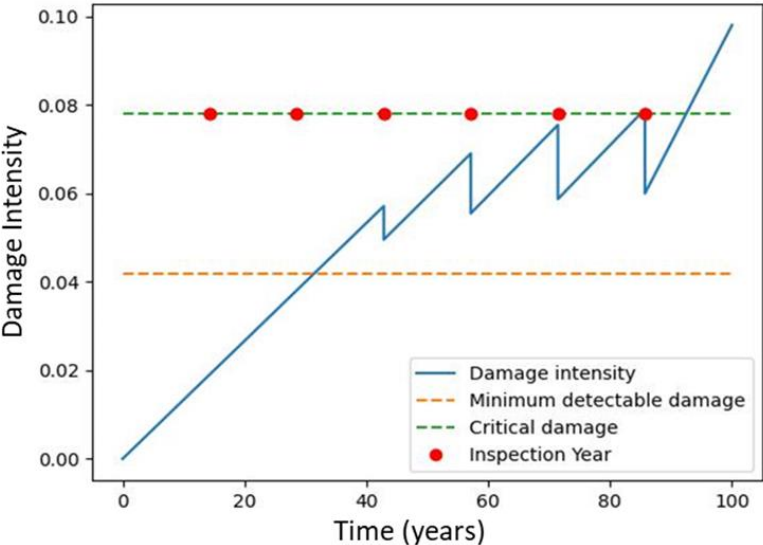


Figure 5. 4 Damage intensity as a function of optimum inspection/repair times (uniform inspections)

6 Nonuniform interval inspection strategy: introduction to the optimization problem

When it comes to optimizing the inspection and repair strategy, several key factors come into consideration. The total cost over the entire lifespan, also known as the life-cycle cost, the targeted lifetime reliability, inspection intervals, and the inspection quality must all be taken into consideration. Achieving the right balance between increased reliability and minimal expected total cost is a fundamental challenge. The primary objective of an optimal inspection and repair strategy is to minimize the total cost over the lifespan of a given structure while ensuring that this structure maintains an acceptable level of reliability throughout its intended service duration. Reliability over the lifespan is another key element to consider. It involves

determining how well the structure can maintain its performance and avoid failures throughout its lifespan. Increased reliability might require more rigorous inspections and repairs, leading to additional costs. On the other hand, a cost-saving approach could compromise long-term reliability and potentially result in unexpected costs related to failures.

The inspection interval plays a crucial role in the optimization strategy. Too many inspections can lead to excessive costs, while overly long intervals might allow damage to increase before being detected, potentially leading to more expensive repairs or even catastrophic failures. In addition, careful planning of repairs, using appropriate materials, is essential to maintain the structure's durability. By considering costs throughout the lifespan, aiming for acceptable reliability, and selecting appropriate inspection and repair intervals, it is possible to ensure that structures remain safe and functional during their intended service duration.

Although regular inspection intervals are more practical and manageable, considering nonuniform time intervals may result in lower costs and improved efficiency. Introducing nonuniform time intervals might require more sophisticated planning and data analysis, but the potential benefits in terms of cost savings, improved reliability, and better resource allocation make it a compelling strategy to consider. The lifetime optimization procedure for nonuniform inspection intervals involves determining the ideal number of inspections N_{insp} and the most favorable timing for conducting inspections and repairs.

The objective of the optimization here is to minimize the total cost over the lifespan of the structure (Equation 5.23). It involves finding the best combination of inspection and repair intervals that results in the lowest total cost.

$$\begin{aligned} \text{Minimum } C_T &= C_{init} + C_{INSP} + C_{REP} + C_{FAIL} \\ \text{Subject to } t_{min} &\leq t_i \leq t_{max} \\ \sum_{i=1}^{N_{insp}} t_i &\leq T \end{aligned} \tag{5.23}$$

Where T is the life-cycle of the structure, $t_i = T_i - T_{i-1}$ is the time interval between the inspections $i - 1$ and i . t_{min} and t_{max} are the minimum and maximum inspection time intervals. In this study, it is assumed that the lifetime of the structure is 100 years. The first constraint ensures that the time intervals between inspections t_i fall within a specified allowable range (t_{min} and t_{max}). It makes sure inspections happen at the right times, not too often and not too rarely, thus achieving a harmonious balance between safety and cost-efficiency. The

second constraint ensures that the sum of intervals between inspections does not exceed the total lifespan of the structure.

The aim of this study is to determine the most effective long-term strategy by solving a complex optimization problem, which is represented by Equation 5.23. This optimization problem considers various factors that impact the lifetime of the studied structure. First, it accounts for the quality and effectiveness of different inspection techniques used to assess the condition of the system. Additionally, it considers all possible repair options based on an event tree. The intensity of the damage is also considered, as it can influence the choice of repair. Moreover, the concept of the time value of money is considered, this means that the future costs are adjusted to their present value.

Similar to the approach taken with uniform inspection intervals (Section 5), the process of finding the optimal number of inspections denoted as N_{insp} involves solving an optimization problem (Equation 5.23) for various values of N_{insp} . The purpose of this process is to identify the number of inspections that results in the most efficient and cost-effective maintenance strategy.

Both Figure 5.5 and Figure 5.6 present key insights into the optimal inspection and maintenance strategy associated with nonuniform time intervals. Figure 5.5 illustrates the different costs while varying the number of lifetime inspections, providing a clear comprehension of how the presented costs evolve as the number of inspections changes. First, the cost of inspection is influenced by both the equipment's quality and the inspection method employed. Since the inspection is relatively inexpensive, the inspection cost has little effect on the total cost. On the other hand, repair cost is determined by the maintenance plan. This means that the timing and scheduling of maintenance activities can significantly influence the cost associated with repairs. However, the total expected cost is dominated by the expected losses due to structural failure. When expected cost of failure is included in the analysis, it is possible to find the optimal balance between safety and economy. Enhancing the overall safety level leads to an increase in most cost terms, but the expected cost of failure decreases.

Drawing a comparison between Figures 5.3 and 5.5, it becomes evident that the optimal strategy involving nonuniform inspection intervals offers a more cost-effective solution. It results in a lower expected total cost of 1061.3 M.U in contrast to 1146.6 M.U for uniform intervals (i.e. a difference of 8%). This improved solution is achieved by conducting a reduced number of inspections (three instead of six), performed later in the service life of the structure (at 61, 74

and 84 years) as opposed to the previously identified inspection times (14, 29, 43, 57, 71, and 86 years). The decision to conduct inspections later in the life of a structure is based on several factors aimed at optimizing maintenance strategies. By deferring inspections until later stages, a more accurate assessment of long-term structural stability and performance can be achieved. Potential issues that may not manifest in the early stages of the structure's life can be better identified and addressed. Additionally, delaying inspections reduces overall costs associated with maintenance activities and allows resources to be directed towards addressing critical damages. Furthermore, as structures age, certain degradation mechanisms may become more pronounced, leading to more predictable patterns of deterioration, making it easier to anticipate and address specific types of damage.

The effectiveness of the nonuniform inspection strategy is demonstrated through its ability to offer a more cost-efficient solution while conducting fewer inspections at specific time intervals. Table 5.2 presents the optimal inspection schedules and the expected total lifetime costs associated with varying the number of inspections conducted at nonuniform time intervals. The purpose of this table is to assist in decision-making regarding the timing and frequency of inspections for the structure. To achieve a minimum total cost of 1061.3 M.U, the optimal strategy for inspections is to conduct them at the following times during the lifetime of the structure: 61 years, 74 years, and 84 years.

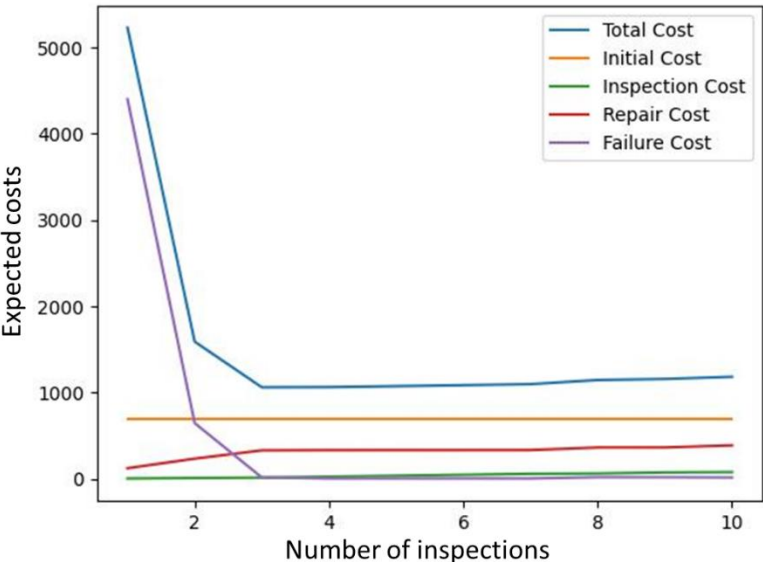


Figure 5. 5 The different expected costs as function of the number of nonuniform interval inspections

Table 5. 2 The optimum inspection times, and the expected total lifetime costs for different numbers of inspections associated with nonuniform time intervals

Number of inspections	Optimum Inspection Times (years)										Total Cost
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	
1	73.8										5228.8
2	69.1	78.8									1590.5
3	61	74.6	84.2								1061.3
4	33.1	60.3	73.5	86.8							1063.5
5	31.8	33.8	60.3	73.5	86.5						1074.7
6	30.5	32.5	34.5	60.3	73.5	85.7					1086.1
7	29	31	33	35	60.3	73.5	85.2				1097.9
8	28.5	31.5	33.5	35.5	61.8	75.7	81.8	83.8			1145.8
9	27.5	29.5	31.5	33.5	35.5	61.7	75.6	81.9	83.9		1157.8
10	26.5	28.5	30.5	32.5	34.5	60.2	74.8	80.2	82.2	84.2	1183.6

The most efficient and cost-effective strategy is illustrated in Figure 5.6. This strategy involves three inspections and corresponding repairs, strategically conducted at specific intervals throughout the service life of the structure, at 61, 74, and 84 years. In this case, the necessity for inspection arises when the structural parts or components approach or exceed the maximum critical value of damage intensity η_{max} . The rationale behind this approach is to ensure that inspections are not performed too frequently, which could result in unnecessary costs. Instead, inspections are timed to take place when the damage has reached a critical stage. This strategy optimizes efficiency and cost-effectiveness by minimizing both the frequency of inspections and the risk of missing significant damage that could compromise structural integrity. The deduction drawn from this thorough analysis is that the nonuniform inspection strategy yields favorable outcomes, notably achieving a minimum expected total cost of 1061.3 M.U.

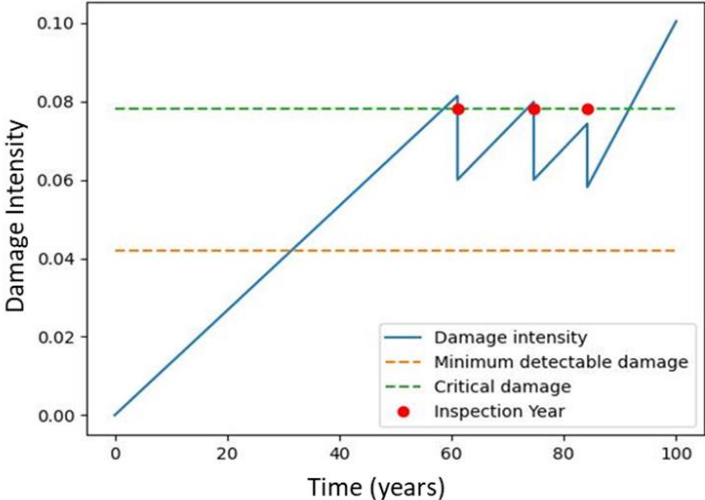


Figure 5. 6 Damage intensity as a function of optimum inspection/repair times (nonuniform inspections)

7 Parametric study on the optimization variables

A parametric analysis is introduced in the case of uniform and nonuniform inspection intervals in order to assess the impact of each variable on the determination of the optimal number of inspections. The parametric analysis conducted here highlights the intricate relationships among several variables, including the damage rate, the quality of nondestructive techniques, the annual discount rate, and the cost associated with failures. All of these factors influence the selection of the most effective and affordable inspection strategy. Finding a balance point where the reliability of the structure is assured, the frequency of inspections is minimized, and the associated costs are effectively managed is the ultimate goal of this study. Finding this equilibrium is a challenging task that varies depending on the specific conditions and variables used. It highlights the importance of adapting the approach to each specific situation, recognizing that what's effective in one case may be very different in another due to the interaction of several aspects.

Table 5.3 provides an overview of the variables that have been considered and studied in the parametric analysis. Each of these variables plays a crucial role in determining the optimal inspection intervals and maintenance strategy for the structure in question. The importance of evaluating these variables lies in the ability to make informed decisions regarding inspection strategies. In the subsequent analysis, when examining the effect of each parameter on the optimal number of inspections, it is important to note that the parameter under consideration is

the one that varies, while the other parameters are kept constant. This approach enables us to isolate the individual effect of each parameter on the optimal inspection strategy and understand how each variable influences the overall outcome.

Table 5. 3 Variables considered in the parametric study

Studied variables	Considered values
Damage Intensity (quality of NDT)	0,04 – 0,05 – 0,06 – 0,07 – 0,08
failure cost	5000 – 10000 – 20000 – 50000
Damage rate (MPa/year)	30 – 35 – 40 – 45 – 50
Annual net discount rate	0,02 – 0,05 – 0,08 – 0,1

7.1 The influence of damage rate on the optimal number of inspections

In order to illustrate the impact of different damage rates on the number of inspections, we have considered five damage rates, as indicated in Table 5.3. The influence of damage rate is presented in Figure 5.7, it can be observed that the greater damage rate is, the more inspections will be performed over the component's lifetime. For example, the optimal number of lifetime inspections for damage rates of 30 MPa/year, 40 MPa/year, and 50 MPa/year is four, six, and eight, respectively, for uniform inspection intervals. This indicates that as the damage rate accelerates, a higher frequency of inspections becomes necessary to effectively manage the associated risks and costs. Moreover, Figure 5.7 provides a comprehensive comparison between two distinct scheduling approaches: uniform and nonuniform time intervals. Interestingly, regardless of the specific damage rate examined, the nonuniform time intervals consistently demonstrate better optimization. This approach requires fewer lifetime inspections compared to the uniform inspection strategy. These results underscore the cost-effectiveness and efficiency of nonuniform inspection schedules in various damage rate scenarios.

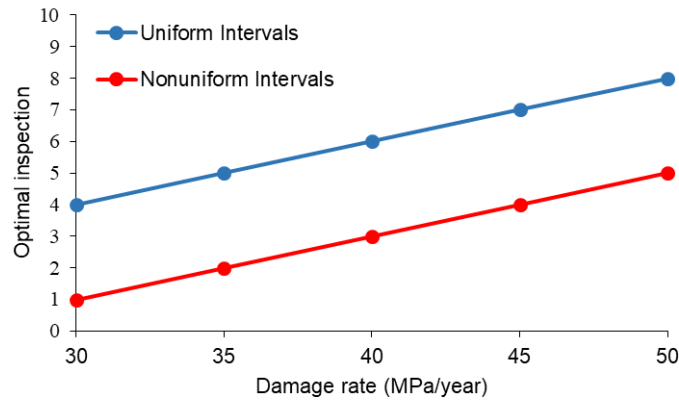


Figure 5. 7 Optimum number of inspections as a function of damage rate

7.2 The influence of the quality of the NDT technique on the optimal number of inspections

In general, visual inspection is often considered more cost-effective when compared to the use of NDT tools and equipment for conducting inspections. However, visual inspection requires a higher threshold of damage intensity $\eta_{0.5}$ in order to be consistently reliable in detecting damage. In simpler terms, visual inspection may not be very good at detecting small or non-surface defects. Conversely, when employing NDT techniques to assess the intensity of damage, the cost of inspection tends to be higher than that of visual inspection. The reason for this higher cost is that NDT techniques can detect smaller amounts of damage compared to what can be seen visually. In theory, $\eta_{0.5}$ should be smaller when using a high-quality NDT tool, because it is able to identify smaller-scale damage that might go unnoticed during visual inspections.

The quality and accuracy of the NDT technique employed for inspection play a large role in determining the optimal inspection and repair strategy. This effect is illustrated in Figure 5.8 using five different damage intensity. When a high-quality NDT technique is used (low level of damage intensity), it results in a reduction in the number of lifetime inspections required. From Figure 5.8, it is evident that when employing a high-quality technique, the optimal number of inspections decreases from 9 to 4, in the case of uniform interval inspections. This highlights the importance of investing in precise and reliable inspection methods to optimize maintenance efforts and minimize unnecessary inspections.

It is important to make informed and well-considered decisions when it comes to the selection of inspection methods. A very high level of sensitivity in the inspection method is necessary in some circumstances, in order to detect even the smallest damage. Conversely, in some cases, a basic assessment can be sufficient. In this case, the level of precision required is not as critical,

and a simplified approach often yields satisfactory results without the necessity of employing more advanced, and usually more expensive, inspection equipment. The choice of inspection method must align with both the budget constraints and the specific level of damage detection required for a given situation. Moreover, these findings underscore the cost-effectiveness and efficiency of adopting nonuniform inspection schedules, regardless of the inspection quality.

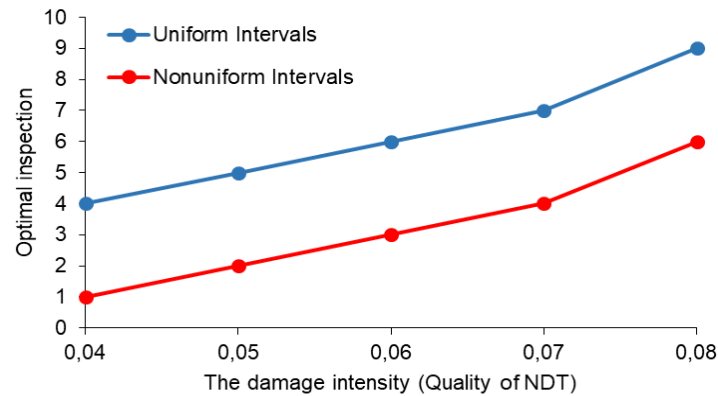


Figure 5. 8 Optimum number of inspections as a function of the quality of NDT

7.3 The influence of the failure cost on the optimal number of inspections

It is important to consider the effect of failure when choosing the optimal number of inspections to perform throughout the lifespan of a structure. Beyond the direct effects on the structure itself, the consequences of failure are extensive. Direct losses cover a wide range of concerns, including operational disruptions (reduced productivity, missed deadlines, and delayed projects), environmental damage (arising from environmental degradation due to the failure), and, most importantly, injury or loss of human life. Indirect losses hold equal significance, as they can affect other sectors reliant on the goods or services supplied by the impacted structure.

Failure cost, which accounts for the financial repercussions of a structural failure, should be calculated by taking numerous factors into consideration, including loss of life, reconstruction expenses, and the inconvenience caused to users, among other relevant factors (Allen C. Estes and Frangopol, 2005). Therefore, achieving a rational estimation of the failure cost is essential. It ensures that the inspection and monitoring strategy is aligned with the actual consequences associated with structural failures, ensuring both safety and cost-effectiveness in the management of critical infrastructure.

Figure 5.9 presents the optimal number of inspections with respect to the failure cost. The optimum number of lifetime inspections is 5 when cost of failure is 10000, for uniform intervals. Under the same conditions when the cost of failure is 50000 the optimum number of

inspections is 8, in the case of uniform interval inspections. Consequently, a higher failure cost leads to a solution requiring more inspections. Moreover, if we examine Figure 5.9 closely, it offers a comprehensive comparison between the uniform and nonuniform inspection intervals. The nonuniform approach requires fewer inspections over the structure's lifespan in comparison to the uniform strategy, regardless of the specific failure cost under consideration.

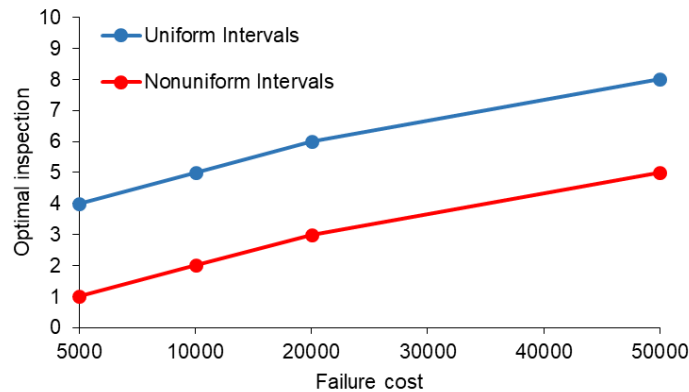


Figure 5. 9 Optimum number of inspections as a function of the failure cost

7.4 The influence of the annual net discount rate on the optimal number of inspections

The work of (Thoft-Christensen and Sørensen, 1987) already highlighted the importance of considering the annual discount rate in optimization studies. Figure 5.10 further validates this idea by demonstrating that, beyond its role as a financial metric, the annual discount rate takes into account the time value of money and the broader economic context. It affects the present value of future costs and benefits associated with inspections, thus playing an important role in shaping the optimal inspection strategy. A higher discount rate has a significant impact on the nature of the optimal inspection plan. A higher discount rate, by lowering the present value of future benefits, makes the cost of inspections relatively more significant when compared to these discounted future benefits. Consequently, to make the inspection cost more justifiable in present value terms, the optimal plan tends to recommend inspections that are more frequent. For example, considering an inspection cost of \$1000, the future benefit of this inspection, preventing a major failure, might be valued at \$5000 a year from now. If we apply a higher discount rate, the present value of that future benefit decreases, making the \$1000 inspection cost more significant. As a result, the optimal plan may suggest performing inspections more frequently to increase the perceived value of these future benefits.

Figure 5.10 illustrates the optimal number of inspections in relation to the annual discount rate “ r ”. In other words, it shows how variations in the discount rate have an impact on the suggested inspection frequency. These findings align with the research of (Thoft-Christensen and Sørensen, 1987), underscoring the significance of the annual discount rate as a critical factor in optimization studies. A higher annual discount rate influences the optimal number of inspections required over the component's lifespan. For instance, let us consider Figure 5.10, when the discount rate changes from 0.02 to 0.1, there is a notable effect on the number of inspections. In the scenario of uniform inspection intervals, the number of inspections increases from 4 to 8. Similarly, for nonuniform inspection intervals, the number of inspections increases from 1 to 5. Furthermore, when comparing the two strategies (nonuniform vs. uniform), the nonuniform approach consistently results in fewer inspections throughout the structure's lifespan. Regardless of the annual discount rate being considered, the difference in the number of inspections between the two approaches remains consistent.

Overall, the annual discount rate seems to be an important factor in the optimization study, as it also influences the determination of the optimal number of inspections in the life cycle of the component. Consequently, its inclusion in optimization studies ensures that the resulting inspection plans align with both economic considerations and the long-term sustainability of the structure.

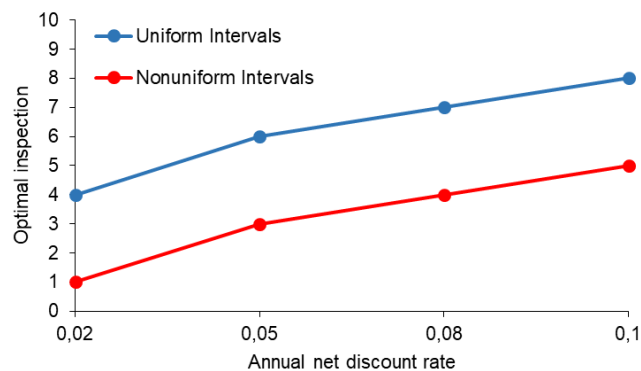


Figure 5. 10 Optimum number of inspections as a function of the annual net discount rate

8 Conclusion

A conceptual framework has been introduced to facilitate the design of life-cycle costs for deteriorating concrete structures with a focus on reliability. In this framework, the case study revolves around a reinforced concrete bridge susceptible to damage. If we consider the possibility that the reinforcing steels reach states of plasticity, it is important to note that the initially mentioned conceptual model may not be suitable for this scenario. The models

describing material behavior, especially for steel in a plastic phase, need adjustment, possibly employing nonlinear models. In addition, failure criteria should be revisited to accommodate mechanisms linked to steel plasticity, and optimization strategies should be adapted to manage the challenges posed by steel plasticity in lifecycle management.

This work shows the efficiency of minimizing the expected total life-cycle cost in order to find the optimal inspection\repair strategy of structures that deteriorate over time. To achieve this, the study employed an event tree model, which provides a systematic way to arrange and evaluate the repair possibilities. The results were obtained using two different strategies: one using uniform inspection time intervals, where the optimization is limited to the number of inspections, and the other using nonuniform inspection time intervals, where both the number of inspections and the time intervals are optimized. The analysis considered several critical factors, including the quality of inspection methods, exploration of all available repair options, the impacts of damage on structural reliability, and the influence of the time value of money.

Firstly, the inspection strategy was restricted to uniform time intervals, considering the number of inspections N_{insp} to be given. The optimization problem was solved for all values of N_{insp} and then the value that produces the smallest expected total cost is considered as the optimal number of inspections. Subsequently, nonuniform inspection intervals were considered, introducing a dynamic aspect to the process. In this approach, the optimization of the structure's lifetime aims at minimizing the total expected cost over the structure's lifespan. In this context, the timing and frequency of inspections are no longer fixed but are instead based on the specific requirements of the structure. Regarding the optimization strategy, the optimal nonuniform inspection/repair strategy is more cost-effective and requires fewer lifetime inspections/repairs than that based on uniform intervals.

A parametric study on the optimization variables was also preformed, and important results were obtained. With a higher cost of failure, the optimal solution involves an increased number of inspections and repairs, resulting in a higher overall cost. Furthermore, as the quality of the inspection method improves, the optimal number of inspections also increases. In addition, the numerical results demonstrate an increase in the optimal number of inspections as the damage rate rises. Finally, it is essential to consider the net annual discount rate, as it also affects the determination of the optimal number of inspections. The findings show that each of the parameters involved can be considered when determining the optimal number of inspections to

perform throughout the component's lifespan. When reliable and precise input data for these factors are available, the methodology described within this context offers real potential.

Overall, the methodology developed in this study has the capability to integrate economic considerations such as cost-effectiveness, and safety concerns such as ensuring structural integrity and preventing failures.

Chapter Six: Conclusions and Perspectives

Enhancing the precision of structural performance assessment and prediction via effective use of nondestructive data enables timely and well-suited maintenance interventions. This, in turn, can result in a decrease in both the failure cost and the expected maintenance expenses for deteriorating structural systems. The existing nondestructive assessment approach involves the use of nondestructive measurements conducted at several test locations within the structure. Subsequently, cores are extracted from selected locations for compressive tests to establish a relationship known as the “conversion model” between the compressive strength and NDT measurements. This conversion model serves as a tool to estimate the strength value at each test location based on the corresponding NDT value. Improving the reliability and credibility of nondestructive assessments necessitates addressing and minimizing uncertainties through a precise understanding and management of their contributing factors. This research focused on the identification and strategic control of factors that can be adjusted to improve the precision of assessments. Consequently, the principal aim is to conduct a thorough examination of the existing assessment methodologies and provide valuable recommendations to enhance the dependability of in-situ strength assessments.

Chapter 2 offered a comprehensive literature review on assessing concrete strength by integrating nondestructive testing techniques with core sampling. The investigation program's design, focusing on core drilling and NDT, was emphasized as a fundamental process to accurately determine concrete strength. The significance of Rebound Hammer and Ultrasonic Pulse Velocity in concrete strength assessment was thoroughly discussed, including principles, devices, methodologies, and influencing factors. The significance of combining Rebound Hammer and Ultrasonic Pulse Velocity methods was extensively discussed. The chapter addressed accuracy and precision in concrete strength estimation, emphasizing the need for a robust and informed assessment process. Various model identification approaches, including the multiple regression method and calibration approaches were explored. The limitations of the current approaches in effectively assessing strength variability were confirmed. Consequently, the second focus of this thesis was on proposing an innovative model identification approach, denoted as the “multi-objective” approach. The objective was to

provide a deeper and more comprehensive understanding of the behavior of concrete by not only predicting the mean strength but also capturing the variability.

The main objective of Chapter 3 revolved around the analysis and comparison of two model identification approaches, aiming to evaluate concrete strength. This assessment was conducted by combining NDT methods (SonReb) and using Monte Carlo simulations to consider the uncertainties in NDT measurements and the variability of concrete properties. The experimental dataset used in this study was derived from an extensive nondestructive testing program and coring operation conducted on structural elements of an existing building. Given the constraints posed by the limited quantity of actual experimental data, synthetic simulations were conducted. As the data were analyzed, it became clear that the multiple linear regression approach (the mono-objective method) and the multi-objective approach both show correct estimates of the mean strength. Nevertheless, the analysis underscored that evaluating strength variability is notably more challenging than assessing mean strength. The limitations revealed by the multiple regression approach in precisely assessing the variability of concrete strength, highlight the critical need for the multi-objective approach to effectively evaluate both mean strength and variability of concrete. Moreover, the multi-objective approach outperformed the mono-objective approach in terms of relative errors, showing a better alignment of predicted strengths with true strengths. The outcomes emphasized the significant impact of the number of test locations on the accuracy of concrete strength evaluation. Thus, through strategic selection of an appropriate number of test locations distributed across the structure or building, the assessment gains a higher level of representativeness regarding the overall concrete strength attributes. In this context, the multi-objective approach shows a clear advantage in terms of estimating concrete strength with lower variability and higher precision, especially when dealing with a small number of cores. Overall, the most effective strategy for designing a testing program appeared to involve a well-balanced combination of NDT techniques and the multi-objective optimization approach.

In Chapter 4, a methodological strategy was introduced, representing a notable advancement in improving the precision and accuracy of concrete strength assessment within structural elements. This approach has been rigorously validated through an empirical investigation carried out in a real case study. The primary focus of this investigation was to address two critical aspects: the sampling process and the combination of two nondestructive testing techniques, Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV). The analysis conducted in this chapter aimed to quantify the collective impacts of various factors, including

the progressive increase in the number of core samples, the implementation of the different sampling strategies, the application of both bi-objective and multi-objective approaches, and the use of single or combined NDT methods. The objective of this chapter was to assess different core sampling methods through Monte Carlo simulations, with the goal of identifying the most efficient approach for achieving a more accurate representation of the entire spectrum of concrete strength. The outcomes demonstrated that the different sampling plans result in a more accurate estimation of mean strength, significantly decreasing the margin of error when compared to the random coring method. Moreover, when UPV and RH testing methods are combined, the results from employing random coring and those derived from conventional sampling techniques showed a noteworthy similarity. Therefore, there is a connection between the possible advantage of using the different sampling plans and the additional benefit of combining nondestructive testing methods. In the other hand, the results of assessing strength variability using the bi-objective and multi-objective approaches provided acceptable results when applying random sampling. It is worth mentioning that the introduction of alternative sampling plans did not improve the assessment of strength variability. This study is challenging because of the complex interactions between the advantages of the different sampling procedures and the benefits of using robust model identification methods, such as the bi-objective and multi-objective approaches. In addition, the study recommended variance sampling as a promising alternative for reducing inherent uncertainties in the assessment process. Variance sampling showed robust strength estimation with low prediction errors compared with the other sampling plans. This sampling method, based on specific conditions, does not involve any extra costs, requiring only a preliminary nondestructive testing investigation before concluding the choice of core sample locations.

The last chapter introduced a robust conceptual framework aimed at enhancing the design of life-cycle costs for deteriorating concrete structures, emphasizing the important aspect of reliability. In this framework, the case study revolves around a reinforced concrete bridge susceptible to damage. The research demonstrated the efficiency gained by minimizing the total life-cycle cost to derive the most optimal inspection and repair strategy for structures degrading over time. Two distinct strategies were explored: one focusing on uniform inspection time intervals, optimizing the number of inspections, and the other using nonuniform inspection time intervals, where both the number of inspections and the time intervals were optimized. Inspection intervals play a crucial role in the optimization strategy. Too frequent inspections can lead to excessive costs, while too long intervals may allow damage to worsen, potentially

resulting in more expensive repairs or catastrophic failures. The study aimed to find the optimal strategy by minimizing the total cost over the structure's lifespan. This involved determining the optimal number of inspections, the optimal timing for inspections, and the associated costs. The analysis comprehensively considered essential factors, including the quality of inspection methods, consideration of all available repair options, the implications of damage on structural reliability, and the influence of the time value of money. The application of an event tree model offered a systematic and structured approach to assess and evaluate various repair possibilities. The research indicated that varying inspection schedules might be a better cost-saving approach compared to regular ones. It suggests conducting fewer inspections at specific times to save money while still ensuring safety. Furthermore, a thorough parametric study of optimization variables was performed, revealing interesting results. Notably, when the potential cost of failure is higher, there is a greater requirement for frequent inspections and repairs, ultimately resulting in a higher overall cost. Moreover, an improved quality of inspection technique leads to a higher optimal number of inspections, and this number increases even more when damage rates are higher. The net annual discount rate also proved to be important in deciding the best number of inspections. A higher discount rate, by lowering the present value of future benefits, makes the cost of inspections relatively more significant when compared to the discounted future benefits. Consequently, to make the inspection cost more justifiable in present value terms, the optimal plan tends to recommend inspections that are more frequent. In summary, considering these elements allows for more informed choices when it comes to selecting the best inspection strategy.

The significant advantage of the methodology developed in this work lies in its simplicity, requiring only a custom-developed calculation code, making it easily accessible and applicable in various engineering settings. However, the main limitation of these statements is that they are based on a specific case study. All the data were collected within a well-defined context, including a specific range of concrete strength and a particular level of precision in the NDT test results. This precision in the NDT test results is a critical parameter, as it can vary depending on the context of each situation, which has a big impact on the process of identifying the model parameters. To obtain more general and robust conclusions, it is recommended to compare our findings with those obtained from other on-site experimental databases. This would provide a better understanding of how different levels of precision in NDT tests and concrete strength ranges can affect the validity of conversion models in various contexts. Future research can also expand on the findings by considering other nondestructive techniques, such as the combination

of Rebound Hammer, Ultrasonic Pulse Velocity, and Resistivity. The idea behind combining these techniques is to take advantage of their individual benefits in order to provide a more comprehensive assessment of the concrete structure. The analysis of the various NDT combinations (SonReb, SonRes, 2R, S2R) will allow for assessing the minimum number of cores required for a desired confidence level, revealing the most optimal combination. Furthermore, with the continuous advancement of technology, there is an increasing focus on structural health monitoring systems, which provide ongoing assessments of the structure's condition. Perspectives could include integrating the research's findings into such monitoring systems for ongoing assessment and maintenance. Big data and predictive analytics empower engineers to make informed decisions based on data rather than relying solely on traditional schedules or visual inspections. By collecting a vast amount of data from sensors, monitoring devices, and historical records, professionals can gain a comprehensive understanding of a structure's condition. Another angle to consider involves optimizing specific NDT measurement locations and quantities within a limited inspection budget to evaluate overall structural condition, thus bridging the gap between safety, economics, and efficiency in concrete assessment. The optimization of NDT measurement locations involves identifying critical areas or components within a concrete structure. These areas might be more susceptible to damage or degradation due to various factors, such as environmental conditions or structural loads. By focusing inspection efforts on these critical locations, the approach helps mitigate risks effectively while considering the cost-effectiveness. Through the optimization program, the approach can reduce inspection expenses while maintaining the essential level of assessment.

INTRODUCTION GÉNÉRALE

1. Problématique

Plusieurs constructions, dont les ponts, les tunnels, les barrages et les bâtiments, sont réalisées en utilisant le béton comme principal matériau de construction. Le béton est reconnu pour sa bonne résistance et sa durabilité, en faisant un choix idéal pour la construction de structures qui doivent résister à divers problèmes structurels et environnementaux au fil du temps. De plus, le béton est une option rentable en raison de la disponibilité et de l'accessibilité de ses matières premières, y compris le ciment, les granulats et l'eau. De plus, la malléabilité du béton permet aux architectes de concrétiser leurs visions créatives. Cependant, le vieillissement des structures en béton armé nécessite un examen approfondi des propriétés des matériaux en raison du manque d'informations sur les caractéristiques mécaniques des matériaux de construction d'origine. En conséquence, mener une campagne expérimentale devient impératif pour évaluer l'état et les performances d'un bâtiment en béton armé existant.

Tout au long de leur cycle de vie opérationnel, les structures subissent un déclin progressif de leurs performances en raison de divers facteurs environnementaux (Liu et Frangopol, 2006). Pour garantir la sécurité et prolonger la durée de vie opérationnelle de ces structures en détérioration, des recherches approfondies ont été consacrées à l'établissement d'approches rentables de maintenance (Estes et Frangopol, 2001 ; Frangopol et al., 1997 ; Garbatov et Guedes Soares, 2001 ; Kong et Frangopol, 2003). Cela implique une modélisation précise des charges appliquées, une prédiction précise du comportement structurel, une estimation précise des coûts de gestion et de maintenance dans le temps, ainsi que la formulation de solutions bien calibrées (Liu et Frangopol, 2006). Améliorer la précision dans l'évaluation et la prédiction des performances structurelles, grâce à l'utilisation appropriée des techniques du contrôle non destructif, conduit à des interventions de maintenance optimales et bien chronométrées. Les méthodologies explorées dans cette étude sont universelles et peuvent être appliquées à un large éventail de structures affectées par diverses formes de dégradation.

Parmi les différentes propriétés mécaniques et physiques du béton, la résistance à la compression revêt une importance immense dans la conception des éléments structuraux et dans le calcul de leur capacité de charge. Lors de la construction de nouvelles structures, le contrôle qualité est essentiel pour garantir que le béton satisfait aux normes spécifiées et respecte toutes les réglementations pertinentes. De plus, en cas d'incertitudes concernant la qualité du béton

dans un nouveau projet de construction, il devient essentiel d'évaluer la résistance à la compression in situ. De plus, lorsque la fonction prévue d'une structure change, la résistance du béton doit être réévaluée afin de déterminer précisément la capacité de la structure selon les spécifications mises à jour. De même, évaluer la résistance du béton est important lors de l'évaluation des dommages résultant du feu, de la fatigue, des surcharges ou des dégradations environnementales. Enfin, à mesure que nos efforts pour améliorer la résilience des bâtiments contre les tremblements de terre continuent de croître, il devient impératif de réaliser des évaluations précises de la résistance du béton dans les structures existantes. Ceci est crucial pour garantir une sécurité et une fiabilité structurelles optimales.

Il existe plusieurs méthodes de test disponibles pour estimer la résistance in situ du béton. Le carottage est une méthode directe couramment utilisée à cette fin, mais il présente des inconvénients significatifs. Le carottage peut être techniquement difficile dans certains cas, voire impossible dans d'autres, compromettant potentiellement la stabilité de la structure. Le deuxième problème est bien sûr économique, car le nombre de carottes augmente considérablement le coût des tests. Par conséquent, explorer des méthodes non destructives pour évaluer l'état des structures existantes offre une meilleure alternative à la fois sur le plan économique et technique. Les méthodes non destructives sont largement utilisées pour évaluer la résistance du béton in situ (Alwash, 2017 ; Breyse, 2012 ; Breyse et al., 2019). Ces méthodes présentent plusieurs avantages tels que la simplicité, la rapidité et la rentabilité par rapport au test sur carotte. Elles offrent également une couverture plus large de la structure et permettent l'accès à des informations supplémentaires. Cela inclut des informations sur la variabilité spatiale des propriétés du béton et l'identification de zones homogènes au sein de la structure. Cependant, elles ne mesurent pas directement la résistance in situ. Elles mesurent plutôt d'autres propriétés, ensuite la résistance à la compression est déduite d'un modèle de corrélation entre les propriétés mesurées et la résistance.

Une limitation significative entravant l'utilisation efficace des résultats des tests non destructifs et des mesures de résistance sur carotte est la focalisation principale des normes actuelles (Comité ACI 228, 2003 ; EN 13791, 2007) sur les protocoles de mesure individuels. Malheureusement, elles sont souvent insuffisantes pour offrir des directives complètes sur la manière de mener un programme d'investigation (Breyse, 2012 ; Breyse et Martínez-Fernández, 2014). Par exemple, les normes existantes ne fournissent pas suffisamment de détails sur des aspects essentiels tels que le plan d'échantillonnage, qui inclut la détermination des positions spécifiques pour l'extraction des carottes. De plus, elles ne spécifient pas la

quantité de mesures NDT nécessaires pour atteindre un niveau de confiance ou de précision souhaité dans l'évaluation. En outre, ces directives ne fournissent pas d'aperçus utiles sur les approches d'identification de modèles et sur l'efficacité de la combinaison de plusieurs méthodes NDT pour une évaluation plus robuste. Ce manque d'orientation complète peut présenter des défis pour les ingénieurs visant à concevoir et exécuter des programmes d'évaluation efficaces et fiables.

Ces observations montrent qu'un programme d'investigation plus approfondi est nécessaire pour prendre en compte ces problématiques et atteindre le niveau de précision souhaité dans l'évaluation de la résistance. Ainsi, pour pallier les limites détectées, la méthodologie existante se concentre sur l'élaboration d'un modèle de conversion spécifique adapté à la combinaison de techniques CND. Ce modèle est développé en utilisant une approche multi-objectifs, en intégrant les données issues à la fois des tests destructifs et non destructifs. La résistance à la compression est ensuite évaluée à l'aide du modèle développé à des emplacements spécifiques où les valeurs des mesures non destructives sont disponibles pour le béton considéré. La stratégie d'évaluation offre une flexibilité, exigeant des décisions cruciales quant à la quantité de prélèvements et la combinaison de techniques non destructives adéquates, ainsi que des décisions essentielles concernant le choix de la meilleure stratégie d'inspection et de réparation pour les structures en dégradation, en mettant l'accent sur leur fiabilité. La planification de la gestion des structures en détérioration peut être formulée comme un problème d'optimisation, impliquant la prise en compte de plusieurs indicateurs de performance tels que la fiabilité, la disponibilité, les indices de sécurité, ainsi que les coûts.

2. La portée de ce travail

Dans le cadre des constructions existantes, plusieurs situations telles que la rénovation, la modification, les changements d'utilisation ou des événements tels que les incendies ou les tremblements de terre exigent souvent une évaluation approfondie de la résistance du béton au sein de la structure. Cette évaluation est indispensable pour parvenir à une compréhension précise et globale de la capacité structurelle du bâtiment (Comité ACI 228, 2003). Évaluer et améliorer la résistance in situ est une étape importante pour garantir la sécurité structurelle et la résilience contre d'éventuelles dégradations. Une évaluation du modèle de croissance des dommages peut servir d'outil précieux pour évaluer la diminution de la résistance d'une structure en béton soumise à un environnement agressif. En effet, une compréhension complète des mécanismes de détérioration est fondamentale. En outre, grâce à l'analyse du cycle de vie,

nous pouvons évaluer systématiquement les impacts du processus de détérioration, des actions de maintenance et de réparation sur les performances et la durée de vie des structures (Liu et Frangopol, 2006 ; Moan, 2005).

Dans les applications pratiques, les principaux repères d'évaluation comprennent la résistance moyenne à la compression, le module de Young et la résistance caractéristique à la compression. Bien que la résistance moyenne à la compression représente un paramètre fondamental, le module de Young est également important pour les évaluations structurelles. Le module de Young peut être estimé indirectement à partir de la résistance à la compression en utilisant des relations empiriques (Aladejare et al., 2021 ; Vu et al., 2021). En outre, un autre aspect clé de cette stratégie d'évaluation réside dans la détermination de la résistance caractéristique. Ce paramètre dépend à la fois de la résistance moyenne et la variabilité de la résistance à la compression (Alwash, 2017 ; Breyse et al., 2019). De plus, lorsque la résistance du béton varie considérablement ou que différentes sections de la structure présentent des compositions ou qualités distinctes, les normes telles que celles du (Comité ACI 228, 2003 ; EN 13791, 2007) recommandent de subdiviser la structure examinée en plusieurs zones de test. Dans cette étude, on suppose que chaque ensemble de données utilisé pour l'analyse appartient à une seule région de test. Cette recherche met l'accent sur l'estimation des valeurs de la résistance locale, de la résistance moyenne et de la variabilité de la résistance du béton. En estimant soigneusement ces paramètres, il est possible de déterminer précisément à la fois la résistance caractéristique et le module de Young. Cela peut aider à fournir aux ingénieurs des données essentielles pour prendre des décisions éclairées concernant la conception, la sécurité et les performances globales des structures.

L'évaluation de la résistance du béton au sein d'une structure peut être effectuée en prélevant directement des carottes. Néanmoins, cette approche peut être coûteuse et n'est pas toujours autorisée en raison de la dégradation structurelle qu'elle peut entraîner. Ainsi, les méthodes de contrôle non destructif offrent une solution partielle en proposant une alternative rapide, économique et reproductible (Ali-Benyahia et al., 2019 ; Alwash, 2017 ; Bień et al., 2015 ; Facaoaru, 1969). Les méthodes non destructives, telles que le scléromètre, le radar, les essais d'émission acoustique, la thermographie et les ultrasons, sont largement utilisées dans le domaine du génie civil et de la construction pour évaluer la résistance in situ du béton (Jones, 1962 ; McCann et Forde, 2001 ; Verma et al., 2013). Cependant, dans le cadre de cette recherche, l'attention est portée sur deux méthodes spécifiques : le test du rebond et le test par ultrasons. La sélection de ces deux méthodes repose sur divers facteurs, principalement leur

utilisation étendue dans l'évaluation des structures en béton armé. Leur popularité dans l'industrie de la construction est due à leur praticité, leur efficacité et leur fiabilité. Le scléromètre permet une estimation rapide et directe de la résistance du béton en mesurant le rebond résultant d'un impact, ce qui le rend adapté aux évaluations sur site. D'autre part, le test par ultrasons utilise des ondes ultrasonores pour évaluer les propriétés du béton, offrant une manière non invasive d'inspecter la qualité et l'intégrité du béton. La technique SonReb suggère de combiner les deux méthodes pour pallier leur faible fiabilité lorsqu'elles sont utilisées individuellement. Depuis plusieurs années, ce concept a été introduit dans le but d'améliorer le processus d'évaluation en évitant de dépendre uniquement d'une seule méthode CND (Ali-Benyahia et al., 2019, 2017 ; Breysse et al., 2008 ; Sbartaï et al., 2018). Pour combiner la mesure du rebond et celle des ultrasons, de nombreux modèles empiriques multiparamétriques ont été proposés dans la littérature sous forme linéaire, puissance, exponentielle ou polynomiale (Bensaber et al., 2023 ; Craeye et al., 2017 ; Cristofaro et al., 2020 ; Qasrawi, 2000). Cependant, il est important de noter que ces modèles ne représentent pas précisément le béton spécifique examiné. Cela souligne la nécessité d'établir de nouveaux modèles pour chaque situation différente, basés sur une approche robuste d'identification des modèles.

Pour évaluer la qualité de l'estimation de la résistance du béton par des méthodes non destructives, cette étude s'appuie sur une vaste campagne d'inspection impliquant des tests de rebond et ultrasons, ainsi que des carottages, réalisés sur des éléments structuraux d'une construction existante, comprenant des poteaux et des poutres. Environ 100 ensembles de triplets de données (100 mesures de résistance sur carotte et 100 mesures de tests non destructifs) sont collectés pour cette étude. En raison du nombre limité de données expérimentales, des simulations synthétiques sont également effectuées. Pour générer cet ensemble de données synthétiques, nous utiliserons la technique de simulation de Monte-Carlo. Cette méthode permet de générer un ensemble diversifié d'échantillons aléatoires caractérisés par des distributions de probabilité connues. Nous effectuerons également une analyse statistique approfondie des données et des performances du modèle pour quantifier l'impact de divers facteurs. Ces facteurs comprennent le nombre de carottes utilisées pour l'étalonnage, l'approche d'identification du modèle, l'utilisation efficace d'une combinaison de deux techniques du CND et la mise en œuvre des différentes stratégies d'échantillonnage.

Dans le dernier chapitre, un cadre complet est développé pour aborder divers aspects, notamment l'optimisation probabiliste, la fiabilité, les incertitudes liées à la propagation des dommages et aux méthodes d'inspection, le modèle de détérioration, les coûts attendus du cycle

de vie et les tests non destructifs. L'objectif de ce programme est de trouver la planification optimale d'inspection et de maintenance des structures en détérioration. La méthodologie utilisée dans cette étude est spécifiquement utilisée pour analyser les structures de ponts subissant des dommages. Cependant, il est important de noter que ces approches peuvent être appliquées à tout type de structure subissant diverses formes de détérioration. Il est également important de noter que les actions de maintenance dépendent du résultat de l'inspection. Si des dommages sont détectés, il est crucial d'appliquer la maintenance dès que possible. Cependant, dans la pratique, le manque de ressources financières peut rendre plus difficile l'application immédiate de la maintenance après la détection des dommages. Il convient de noter que dans cette étude, la décision d'initier une réparation après la détection des dommages est basée sur la probabilité.

3. Objectif et méthodologie générale de recherche

L'objectif principal de cette thèse est de mener une analyse approfondie de l'évaluation non destructive, visant non seulement à estimer la résistance du béton au sein de la structure, mais également à évaluer et caractériser la qualité de cette estimation. Une revue exhaustive de la littérature sur l'évaluation de la résistance du béton par la combinaison de techniques du CND en conjonction avec des tests sur carottes est proposée. La portée et l'importance du scléromètre et du test par ultrasons dans l'évaluation de la résistance du béton sont largement discutées, couvrant les principes, les dispositifs et les facteurs affectant les résultats des tests. De plus, la fiabilité des résultats obtenus via ces méthodes CND est considérée, et les normes appropriées sont citées pour assurer les pratiques de test.

Lors de l'évaluation du béton in situ, la nécessité de prédire sa résistance devient primordiale en raison de la variabilité inhérente dans la composition des mélanges de béton. Cela nécessite le développement de modèles empiriques établissant une relation entre les mesures non destructives et les caractéristiques du béton au sein de la structure. L'objectif principal de cette thèse tourne autour de l'analyse et de la comparaison de la qualité de l'estimation en utilisant diverses approches d'identification de modèle. Cette évaluation vise à analyser à la fois la résistance moyenne et la variabilité de la résistance du béton en combinant des méthodes CND, en utilisant à la fois des données synthétiques et des données expérimentales. Notre travail couvrira également des contributions originales dans la conception d'un programme de test optimal. Ce programme implique une combinaison de techniques CND et une approche

d'optimisation multi-objectifs afin de prédire à la fois la résistance moyenne et la variabilité de la résistance du béton.

De plus, cette étude comprend une évaluation approfondie de l'efficacité de diverses méthodes d'échantillonnage proposées. L'objectif est de fournir des orientations sur le choix de l'emplacement le plus approprié pour l'extraction des carottes. En examinant rigoureusement les différentes approches d'échantillonnage, l'étude vise à améliorer la précision et l'efficacité du processus d'extraction des carottes, contribuant ainsi à des résultats plus fiables et précis dans l'évaluation de la résistance du béton. De plus, l'analyse menée dans le cadre de cette étude vise à quantifier les impacts collectifs découlant de divers facteurs. Ces facteurs comprennent le nombre de carottes collectées, l'approche d'identification de modèle utilisée, la mise en œuvre des différentes stratégies d'échantillonnage et l'utilisation de techniques CND individuelles ou combinées.

Cette thèse propose également un cadre conceptuel pour simplifier le calcul des coûts du cycle de vie des structures en dégradation, en mettant l'accent sur l'amélioration de leur fiabilité. Dans cette optique, l'étude de cas concerne un pont en béton armé susceptible de subir des dommages. Cette étude se concentre sur la diminution graduelle de la rigidité, mesurée par le module de Young, au fil du temps. L'utilisation des techniques non destructives est donc nécessaire en raison de la nature des dommages. Cette étude met en évidence l'efficacité de la minimisation du coût total attendu du cycle de vie pour trouver la stratégie optimale d'inspection/réparation des structures se détériorant avec le temps. L'analyse des coûts couvre tous les éléments contribuant au coût total du cycle de vie de la structure. Pour ce faire, l'étude utilise un modèle d'arbre d'événements, qui offre une méthode systématique pour organiser et évaluer les possibilités de réparation. De plus, l'analyse prend en compte plusieurs facteurs critiques, notamment la qualité des méthodes d'inspection, l'impact du taux d'endommagement sur la fiabilité structurelle, l'impact du coût attendu d'une défaillance structurelle et l'influence du taux d'actualisation annuel net. La méthodologie développée dans cette étude a la capacité d'intégrer des considérations économiques telles que la rentabilité et des préoccupations de sécurité telles que garantir l'intégrité structurelle et prévenir les défaillances. La thèse actuelle suivra la méthodologie de recherche présentée dans la Figure 1.1.

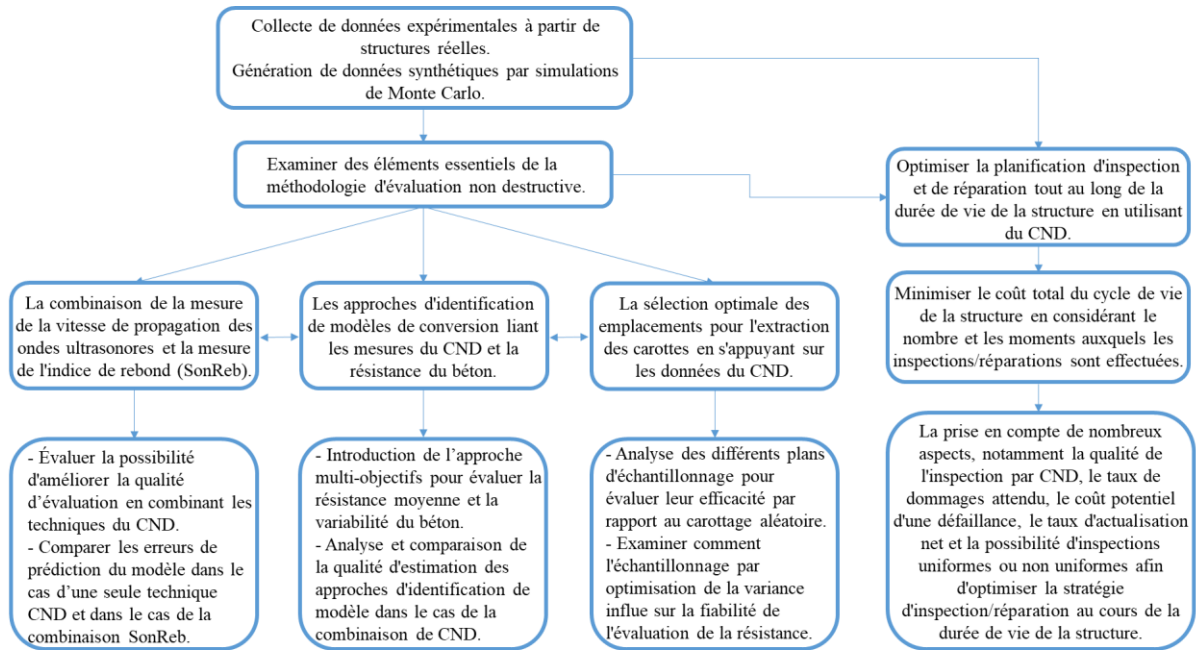


Figure 1. 1 Méthodologie générale de recherche

CONCLUSIONS ET PERSPECTIVES

Optimiser la précision de l'évaluation et de la prédiction des performances structurelles grâce à une exploitation efficace des données non destructives permet des interventions de maintenance appropriées et ponctuelles. Cela pourrait également conduire à une réduction à la fois des coûts liés aux défaillances et des dépenses de maintenance attendues pour les systèmes structurels en dégradation. L'approche actuelle d'évaluation non destructive implique l'utilisation de mesures non destructives réalisées à plusieurs emplacements de test au niveau de la structure. Ensuite, des carottes sont extraites de certains emplacements pour des tests de compression afin d'établir une relation connue sous le nom de « modèle de conversion » entre la résistance à la compression et les mesures CND. Ce modèle de conversion sert d'outil pour estimer la valeur de résistance à chaque emplacement de test en fonction de la mesure CND correspondante. Améliorer la fiabilité et la crédibilité des évaluations non destructives nécessite de traiter et de réduire les incertitudes grâce à une compréhension précise et une gestion des facteurs qui y contribuent. Cette recherche s'est concentrée sur l'identification et le contrôle stratégique des facteurs pouvant être ajustés pour améliorer la précision des évaluations. Par conséquent, l'objectif principal est d'examiner minutieusement les méthodologies d'évaluation existantes et de fournir des recommandations précieuses pour renforcer la fiabilité des évaluations de la résistance in situ.

Le chapitre 2 a proposé une revue exhaustive de la littérature sur l'évaluation de la résistance du béton en intégrant des techniques de tests non destructifs avec des prélèvements de carottes. La planification du programme d'investigation, se concentrant sur le carottage et les techniques du CND, a été soulignée comme une étape essentielle pour déterminer précisément la résistance du béton. L'importance du scléromètre et du test par ultrasons dans l'évaluation de la résistance du béton a été largement discutée, incluant les principes, les appareils et les facteurs influents. De plus, la pertinence de combiner les deux tests a été examinée en détail. Le chapitre a abordé la précision dans l'estimation de la résistance du béton, mettant l'accent sur la nécessité d'un processus d'évaluation robuste et précis. Diverses approches d'identification de modèles, y compris la méthode de régression multiple et les approches de calibration, ont été explorées. Les limites des approches actuelles dans l'évaluation efficace de la variabilité de la résistance ont été confirmées. Par conséquent, le deuxième objectif de cette thèse était de proposer une nouvelle approche d'identification de modèles, désignée comme l'approche « multi-objectifs ».

L'objectif était d'approfondir la compréhension du comportement du béton en prédisant non seulement sa résistance moyenne, mais également sa variabilité.

L'objectif principal du chapitre 3 porte sur l'analyse et la comparaison de deux approches d'identification de modèles visant à évaluer la résistance du béton. Cette évaluation a été menée en combinant des techniques du CND (SonReb) et en utilisant des simulations de Monte Carlo pour prendre en compte les incertitudes des mesures du CND et la variabilité des propriétés du béton. Le jeu de données expérimentales utilisé dans cette étude provient d'un programme étendu de tests non destructifs et d'opérations de carottage réalisés sur des éléments structurels d'un bâtiment existant. Compte tenu des contraintes liées à la quantité limitée de données expérimentales réelles, des simulations synthétiques ont été réalisées. L'analyse des données a révélé que la régression linéaire multiple (méthode mono-objectif) ainsi que l'approche multi-objectifs ont produit des estimations précises de la résistance moyenne. Néanmoins, l'analyse a souligné que l'évaluation de la variabilité de la résistance est nettement plus difficile que l'évaluation de la résistance moyenne. Les limites révélées par l'approche de régression multiple dans l'évaluation précise de la variabilité de la résistance soulignent la nécessité de l'approche multi-objectifs pour évaluer efficacement à la fois la résistance moyenne et la variabilité du béton. En outre, l'approche multi-objectifs a dépassé l'approche mono-objectif en termes d'erreurs relatives, démontrant une meilleure correspondance entre les résistances estimées et les résistances réelles. Les résultats ont souligné l'impact significatif du nombre d'emplacements de test sur la précision de l'évaluation de la résistance du béton. Ainsi, grâce à la sélection stratégique d'un nombre approprié d'emplacements de test répartis dans la structure ou le bâtiment, l'évaluation gagne un niveau de représentativité supérieur en ce qui concerne les caractéristiques de la résistance du béton. Dans ce contexte, l'approche multi-objectifs présente un avantage clair en termes d'estimation de la résistance du béton avec une variabilité moindre et une précision plus élevée, particulièrement lorsque peu de carottes sont utilisées. Dans l'ensemble, la stratégie la plus efficace pour concevoir un programme de tests semble impliquer une bonne combinaison de techniques CND et de l'approche multi-objectifs.

Au quatrième chapitre, une stratégie méthodologique a été présentée, marquant une avancée significative pour améliorer la précision et l'exactitude de l'évaluation de la résistance du béton dans les éléments structurels. Cette approche a été rigoureusement validée grâce à une enquête empirique menée dans le cadre d'une étude de cas réelle. L'objectif principal de cette investigation était de traiter deux aspects critiques : le processus d'échantillonnage et la combinaison de deux techniques du CND, le scléromètre et le test par ultrasons. L'analyse

réalisée dans ce chapitre vise à quantifier les impacts collectifs de différents facteurs, incluant l'augmentation progressive du nombre de carottes, la mise en œuvre des différentes stratégies d'échantillonnage, l'application des deux approches bi-objectifs et multi-objectifs, ainsi que l'utilisation des méthodes CND individuelles ou combinées. L'objectif de ce chapitre était d'évaluer différentes méthodes d'échantillonnage à travers des simulations de Monte Carlo, dans le but d'identifier l'approche la plus efficace pour obtenir une représentation plus précise de l'ensemble des valeurs de résistance du béton. Les résultats ont démontré que les différents plans d'échantillonnage permettent une estimation plus précise de la résistance moyenne, réduisant significativement la marge d'erreur par rapport au carottage aléatoire. De plus, en combinant les deux méthodes de test non destructives, les résultats obtenus par le carottage aléatoire et ceux issus de l'échantillonnage basé sur les mesures du CND ont présenté des similitudes marquées. Ainsi, il existe une corrélation entre l'avantage potentiel de l'utilisation des divers plans d'échantillonnage et le bénéfice supplémentaire de la combinaison des méthodes du CND. En revanche, les résultats obtenus de l'évaluation de la variabilité de la résistance en utilisant les approches bi-objectifs et multi-objectifs se sont révélés acceptables lors de l'application de l'échantillonnage aléatoire. Il convient de mentionner que l'introduction des plans d'échantillonnage alternatifs n'a pas amélioré l'évaluation de la variabilité de la résistance. Cette étude présente une complexité résultant des interactions subtiles entre les avantages des diverses procédures d'échantillonnage et ceux issus de l'application des méthodes d'identification de modèle efficaces, telles que les approches bi-objectifs et multi-objectifs. En outre, l'étude a recommandé l'échantillonnage par optimisation de la variance comme une alternative prometteuse pour réduire les incertitudes inhérentes au processus d'évaluation. L'échantillonnage par optimisation de la variance a montré une estimation robuste de la résistance avec de faibles erreurs de prédiction par rapport aux autres plans d'échantillonnage. Cette méthode d'échantillonnage, basée sur des conditions spécifiques, n'implique aucun coût supplémentaire, ne nécessitant qu'une enquête préliminaire de tests non destructifs avant de conclure le choix des emplacements des échantillons pour le carottage.

Le dernier chapitre a introduit un cadre conceptuel visant à améliorer la conception des coûts du cycle de vie des structures en béton en dégradation, mettant l'accent sur l'aspect important de la fiabilité. La recherche a illustré l'efficacité de la minimisation du coût total du cycle de vie pour définir la stratégie optimale d'inspection et de réparation des structures en dégradation progressive. Deux approches distinctes ont été étudiées : l'une axée sur des intervalles d'inspection uniformes, optimisant le nombre d'inspections, et l'autre utilisant des intervalles

d'inspection non uniformes, optimisant à la fois le nombre d'inspections et les intervalles de temps entre les inspections. Les intervalles d'inspection jouent un rôle crucial dans la stratégie d'optimisation. Des inspections trop fréquentes peuvent entraîner des coûts excessifs, tandis que des intervalles trop longs pourraient aggraver les dommages, pouvant potentiellement entraîner des réparations plus coûteuses ou des défaillances catastrophiques. L'étude vise à trouver la stratégie optimale en minimisant le coût total sur la durée de vie de la structure. Cela implique de déterminer le nombre optimal d'inspections, le moment optimal pour les inspections et les coûts associés. L'analyse a pris en compte de manière exhaustive des facteurs essentiels, notamment la qualité des méthodes d'inspection, les options de réparation disponibles, les implications des dommages sur la fiabilité structurelle et l'influence de la valeur temporelle monétaire. L'usage d'un modèle d'arbre d'événements a permis une approche méthodique et structurée pour évaluer et examiner différentes options de réparation. Les conclusions de l'étude ont suggéré que des calendriers d'inspection variables pourraient représenter une stratégie plus économique que des calendriers réguliers. De plus, une étude paramétrique approfondie des variables d'optimisation a été réalisée, révélant des résultats intéressants. Notamment, lorsque le coût potentiel de la défaillance est plus élevé, il est nécessaire de réaliser des inspections et des réparations plus fréquentes, entraînant finalement un coût global plus élevé. De plus, une meilleure qualité de la technique d'inspection conduit à un nombre d'inspections plus élevé, et ce nombre augmente encore davantage lorsque le taux de dommage est plus élevé. Le taux d'actualisation annuel net s'est également avéré important pour déterminer le nombre d'inspections optimal. Un taux d'actualisation annuel élevé diminue la valeur actuelle des bénéfices futurs, accentuant ainsi l'importance relative du coût des inspections par rapport à ces bénéfices actualisés. Ainsi, afin de justifier davantage le coût des inspections en termes de valeur actuelle, le plan optimal suggère des inspections plus fréquentes. En résumé, prendre en compte ces éléments permet de faire des choix plus éclairés lorsqu'il s'agit de sélectionner la meilleure stratégie d'inspections et réparations.

Le principal avantage de la méthodologie développée dans ce travail réside dans sa simplicité, nécessitant uniquement un code de calcul personnalisé, ce qui la rend facilement accessible et applicable dans divers contextes d'ingénierie. Cependant, la principale limite de ces affirmations réside dans leur fondement sur une étude de cas spécifique. Toutes les données ont été collectées dans un contexte bien défini, impliquant une plage spécifique de résistance du béton et un niveau particulier de précision dans les résultats des tests CND. Cette précision dans les résultats des tests CND est un paramètre critique, car elle peut varier en fonction du contexte

de chaque situation, ce qui a un impact considérable sur le processus d'identification des paramètres du modèle. Pour obtenir des conclusions plus générales et robustes, il est recommandé de comparer nos résultats à ceux obtenus à partir d'autres bases de données expérimentales sur site. Cela permettrait de mieux comprendre comment différents niveaux de précision dans les tests du CND et de résistance du béton peuvent affecter la validité des modèles de conversion dans divers contextes. Des recherches futures pourraient également élargir les conclusions en tenant compte d'autres techniques non destructives, telles que la combinaison du scléromètre, du test par ultrasons et de la résistivité. L'idée derrière la combinaison de ces techniques est de tirer parti de leurs avantages individuels afin de fournir une évaluation plus complète de la structure en béton. L'analyse des différentes combinaisons de CND (SonReb, SonRes, 2R, S2R) permettra d'évaluer le nombre minimum de carottes requis pour un niveau de confiance souhaité, révélant la combinaison la plus optimale. En outre, avec l'avancée continue de la technologie, il existe un intérêt croissant pour les systèmes de surveillance de l'état des structures, qui fournissent des évaluations continues de l'état de la structure. Les perspectives pourraient inclure l'intégration des résultats de la recherche dans de tels systèmes de surveillance pour une évaluation et une maintenance continue. Les big data et l'analyse prédictive permettent aux ingénieurs et aux équipes de maintenance de prendre des décisions informées basées sur les données, plutôt que de dépendre exclusivement des calendriers traditionnels ou des inspections visuelles. En collectant une vaste quantité de données à partir de capteurs, de dispositifs de surveillance et d'archives historiques, les professionnels peuvent acquérir une compréhension complète de l'état d'une structure. Un autre angle à considérer implique l'optimisation des emplacements et des quantités de mesures CND dans le cadre d'un budget d'inspection limité pour évaluer l'état global de la structure, comblant ainsi l'écart entre la sécurité, la rentabilité et l'efficacité dans l'évaluation du béton. L'optimisation des emplacements de mesures CND implique d'identifier les zones ou composants critiques au sein d'une structure en béton. Ces zones peuvent être plus susceptibles d'être endommagées ou dégradées en raison de divers facteurs, tels que les conditions environnementales ou les charges structurelles. En concentrant les efforts d'inspection sur ces emplacements critiques, cette approche aide à atténuer efficacement les risques tout en tenant compte de la rentabilité. Grâce au programme d'optimisation, l'approche peut réduire les dépenses d'inspection tout en maintenant le niveau d'évaluation requis.

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APPENDIX (A)

This appendix includes our published paper:

Kouddane, B., Sbartai, Z.M., Alwash, M., Ali-Benyahia, K., Elachachi, S.M., Lamdouar, N., Kenai, S., 2022. Assessment of Concrete Strength Using the Combination of NDT—Review and Performance Analysis. *Applied Sciences* 12, 12190.

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Review

Assessment of Concrete Strength Using the Combination of NDT—Review and Performance Analysis

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Abstract: This paper presents a review on combining NDT techniques, such as rebound hammer and ultrasonic pulse velocity, for assessing concrete compressive strength. These methods, though being favorably not invasive and easy to be extended to a larger number of elements, are affected by many contingency factors. The SonReb technique suggests combining the two methods to partially offset their low reliability if considered separately. For years, this concept was introduced in order to improve the evaluation compared with the use of one NDT. In order to combine the ultrasonic pulse velocity and rebound hammer, many empirical, multiparametric models were proposed in the literature as linear, power, exponential, or polynomial. However, the variety of these models emphasizes that they can give a correct strength prediction only for the particular cases that they are derived for. Therefore, to assess concrete on site, the strength should be predicted using a calibration procedure due to the variability of existing concrete mixes. This paper presents a brief outline of the key aspects of strength assessment, including the different approaches used to build the SonReb model and a calibration procedure for assessing concrete strength. A comparison study between the different approaches is proposed, and a performance analysis using Monte Carlo simulations is discussed. Finally, the estimation capacity of the existing model identification approaches is investigated, and the effect of the “trade-off” is analyzed for different random sampling with varying the number of cores.

Keywords: NDT; NDE; concrete evaluation; concrete strength; combination

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1. Introduction

The on-site diagnosis of concrete is an essential issue for engineers in order to take the correct decision about the condition of an existing structure [1]. Nondestructive evaluation (NDE) covers two main objectives of concrete diagnosis, namely, the estimation of concrete mechanical properties or the assessment of durability indicators (porosity, depth of carbonation, water content, etc.). Nondestructive techniques (NDT), such as rebound hammer ultrasonic, impact echo, or electrical resistivity, play an important role in any investigation program since they allow for the gathering of information about the quality and durability of concrete without damaging it. The more-evaluated property of concrete is the compressive strength, which is important for the assessment of the mechanical capacity of the evaluated structure [1,2].

The main challenge in using NDT assessment is that the NDT measurements cannot give directly compressive strength. In fact, the NDT result is often a physical parameter, such as the velocity for the ultrasonic pulse velocity technique or the rebound index for

the rebound hammer technique [3,4]. In several cases, theoretical relationships between the concrete compressive strength and the parameters measured by NDT are unknown. Consequently, empirical relationships' "conversion models" are usually identified for this purpose. There are several procedures to identify the conversion models. The most widely used is the regression approach that is based on the least-squared method. Another possibility is the calibration approach generally used for on-site evaluation [5]. The calibration approach is based on the modification of an existing model (from the literature or standards) for the concrete under consideration. In addition, innovative methods, such as machine learning methods [6–8], can be used to identify the relationship between the NDT measurement and compressive strength, but their application on a real structure is limited by the wide variation of concrete mixes [7]. The literature provides many conversion models (linear, power, exponential, polynomial, etc.). It is then necessary to mention here that there is no general conversion model that can be applied for all concretes on real structures. Therefore, the identification of a new model or calibration of an existing model for concrete under consideration is essential [8].

For years, the concept of combining two NDT techniques has been studied. The most famous one is called SonReb. It is the combination between the ultrasonic pulse velocity technique and the rebound hammer technique in order to evaluate the concrete compressive strength. This combination has been the focus of many laboratories and on real-structure studies aiming to improve the quality of assessment. The interest in this combination is the inversed sensitivity of ultrasonic pulse velocity and rebound hammer to water content. In fact, ultrasonic pulse velocity is increased in wet concrete, while rebound number is reduced compared to the case of dry concrete [9]. Consequently, the conversion model that correlates the concrete strength to ultrasonic pulse velocity or rebound index can be false if water content variation is not controlled. Therefore, these two indicators should be evaluated simultaneously, so they are decoupled. The way to do this can be the combination of the two techniques. However, the method that consists of combining NDT is promising only if the additional costs due to combination are compensated by an improvement in the reliability of assessment [10].

Many researchers have presented their results related to the application of the SonReb method. Cristofaro has used a large database to check the effectiveness of the available prediction models and to propose new relationships, which are very effective for predicting the concrete strength of Italian RC buildings made in the latter decades of the 20th century [11]. Diaferio has taken advantage of an extensive experimental campaign in order to calibrate a huge number of conversion models by varying the setup conditions and the considered number of data [12]. Another methodology has been proposed by Ali-Benyahia in order to improve the precision of the assessment quality of concrete strength in an existing structure. The analysis quantified the combined effects of increasing the number of cores, the conditional coring option, and the use of single or combined NDT methods [13]. However, since the regression methods have shown less accuracy in concrete-strength predictions, new techniques, such as Artificial Neural Network ANN, have been employed to capture the relationship between NDT parameters and concrete mechanical characteristics. The results obtained from the work of Bonagura et al. indicate the excellent estimation potential of a multilayer feed-forward neural network trained with a back propagation error algorithm in the evaluation of concrete compressive strength [14].

Knowing the reliability of assessment is therefore necessary to make a decision about improving the quality of diagnosis or the cost. Moreover, it is interesting to see whether the combination process gives a better evaluation or not. It is important to note that due to many factors, there is not a consensus regarding the efficiency of SonReb compared to using a single NDT. In fact, as reported by Alwash, the combination of pulse velocity and rebound hammer techniques is not always efficient, and this efficiency depends on the quality of NDT measurements (uncertainty) and the number of samples or cores [15]. As reported in some research works, the quality of concrete affects the reputability of the rebound hammer method [16].

This paper presents a review of the combination of NDT techniques using SonReb for the assessment of concrete strength. First, the method is described, and different calibration approaches from the literature are presented. The efficiency of the SonReb method is discussed regarding the use of the RMSE index. In addition, the necessity for identification or calibration of a model for the concrete under evaluation is considered. The performance of the SonReb method is also analyzed by using Monte Carlo simulation, and the trade-off effect is presented. Several conclusions and recommendations are provided regarding the use of the SonReb NDT combining method.

2. Combining NDT Techniques Using the SonReb Method for Concrete-Strength Evaluation

2.1. Identification of Conversion Models for the Case of the Combination of NDT Techniques

For the case of combining NDT techniques, in order to identify a conversion model, the process is mainly a mathematical approach. It is based on the solution of a multivariate mathematical system. The existing approaches for identifying the conversion models can be classified into two main groups: classical approaches (regression analysis) and machine learning approaches (neural networks, support vector machine, etc.). In this paper, only SonReb using a bivariate regression approach is presented.

2.2. Bivaried Regression Model for the SonReb Method

Instead of using a single NDT technique with cores for assessing the concrete strength, the NDT techniques can be used in combination (in addition to the cores). This combination, called SonReb, is the most used combination method for assessing the concrete compressive strength in laboratory and on real structures. This method combines the ultrasonic pulse velocity technique and the rebound hammer technique in order to assess the concrete compressive strength.

The theoretical principle of combination is that when two or more NDT techniques are affected inversely by an influencing factor, combining these techniques can reduce or eliminate this effect and, as a result, improves the reliability of strength estimation [6]. As an example, there is the effect of the concrete moisture condition which produces an increase in pulse velocity and a decrease in rebound number when it increases. However, the benefit of this improvement in reliability resulting from using the combination of NDT techniques should be assessed against the additional time, cost, and complexity of using this combination.

Two RILEM Technical Committees (7 NDT and 43 CND) played an important role in the development of the SonReb method. TC 43 recommendations [17] provided a procedure to establish isostrength curves for a reference concrete (concrete has the materials and composition from a particular region or country for which the curves are devoted). For different concrete compositions, correction factors are used for this purpose. When the composition is unknown (as is the case for old structures), the correction factor should be estimated using cores extracted from the structure under investigation [17]. This methodology can have a major limit because in several cases, information about concrete mix are unknown, and the correction of the result in this case is impossible.

In fact, the isostrength curves represent specific conversion models that correlate the concrete strength with NDT values (pulse velocity and rebound number). The monogram is not unique and many other versions were developed by researchers all around the world (see examples [18–20] for isostrength curves, [19,20] for isorebound number curves, and [21] for isopulse velocity curves).

The variety of these isocurves emphasizes that they can give a correct strength prediction only for the particular cases that they are derived for. Therefore, to assess concrete on site, the strength should be predicted using a model derived for the concrete under consideration.

For this reason, the last RILEM recommendations (249 ISC) give more methodological information about how the structure can be investigated, how the models can be identified, and how the model can be calibrated on site [22]. The recommendations focus on a new flowchart that describe all steps from NDT measurements up to mean strength and error evaluation. It also gives important recommendations about the estimation of the number of cores to be extracted and their positions in the structure by using NDT results that can capture concrete-strength variability.

The evaluation of concrete strength using the SonReb method is similar to that for a single NDT. It includes carrying out the NDT measurements, extracting cores (random or using specific methodology as proposed by RILEM 249 ISC), establishing a model using the dataset (pulse velocity V , rebound number R , compressive strength f_{core}) values, and estimating strength at any test location by applying V and R values (corresponding to this test location) in the identified/calibrated model. We will focus in this paper on how to build the SonReb model, how it can be calibrated, and how the performance can be evaluated.

2.2.1. Types of Models

For combining the pulse velocities and rebound numbers with cores, different model forms have been considered by researchers, such as bilinear, double power, exponential, polynomial, and other miscellaneous forms. In the study presented by [23], Breyse gathered about 69 models from the literature. Table 1 shows several models derived by different researchers.

A possibility promoted by some researchers, see for examples [24,25], is to combine (in addition to NDT measurements) several concrete characteristics (water-to-cement ratio, aggregate-to-cement ratio, admixture content, concrete density, age, etc.) in the model. However, the main drawback of this type of model is the need to know the concrete characteristics as inputs in the model, while they usually remain unknown in old structures. Therefore, in this study, models with only NDT measurements as the inputs are considered.

Table 1. Some models derived by different researchers in order to estimate strength using combined rebound hammer and pulse velocity techniques.

Model (f_{cest} in MPa, V in km/s)	Title 2
$f_{cest} = 8.630V + 1.416R - 51.581$	[26]
$f_{cest} = 7.695 * 10^{-11} V^{2.6} R^{1.4}$	[17,27]
$f_{cest} = e^{0.446V + 0.048R}$	[28]
$f_{cest} = 0.67 e^{0.72V + 0.04R}$	[29]
$f_{cest} = 0.42 R^{0.63} e^{0.58V}$	[30]
$f_{cest} = -173.04 + 4.07V^2 + 57.96V + 1.31R$	[31]
$f_{cest} = -21.1 + 1.24R + 0.058V^4$	[32]
$f_{cest} = -76.30 + 0.17 V^{0.4} R^{0.7}$	[33]
$f_{cest} = (R/(3.64 + 0.023R - 0.56V))^2$	[34]
$f_{cest} = 44.8V + 0.77R - 194$	[35]
$f_{cest} = 1.974 e^{0.000542V + 0.01605R}$	[36]
$f_{cest} = 0.01174V + 0.37R - 28.44$	[18]
$f_{cest} = 10^{-4.251} V^{1.281} R^{0.686}$	[36]

The power form is the most widely used one in the literature, and it is written as follows:

$$f_c = a \times V^b \times R^c \tag{1}$$

where a , b , and c are the model parameters to be identified. The least squares minimization [37] can be used to derive the values of the model parameters; however, it is necessary to

first put the model in a linear form using the logarithmic transformation. Consequently, Equation (1) becomes:

$$\ln f_c = \ln a + b \times \ln V + c \times \ln R \quad (2)$$

As an example, the SonReb model provided by [23] is $f_c = 1.15 \times 10^{-10} V^{2.6} R^{1.3}$. The graphical representation of this model is shown in Figure 1. From this figure, the compressive strength corresponding to any values of V and R can be evaluated (for example, for $V = 3800$ m/s and $R = 40$, the compressive strength $f_c = 30$ MPa).

It is necessary to note here that this model and each one of the models presented in Table 1 were identified from experimental work on a specific concrete, which explains the variability in the values of the model parameters from one model to another. Generally, the identification of the SonReb model for a specific concrete requires a dataset of NDT measurements (V and R) and compressive strengths f_c from a destructive test on samples. This dataset (V , R , and f_c) is used to identify the model parameters, and, consequently, the identified model can be used to assess the compressive strength within the concrete for which this model is derived. If this model is used to assess the compressive strength within another concrete, the calibration of this model is very important. The principles of calibration will be discussed later.

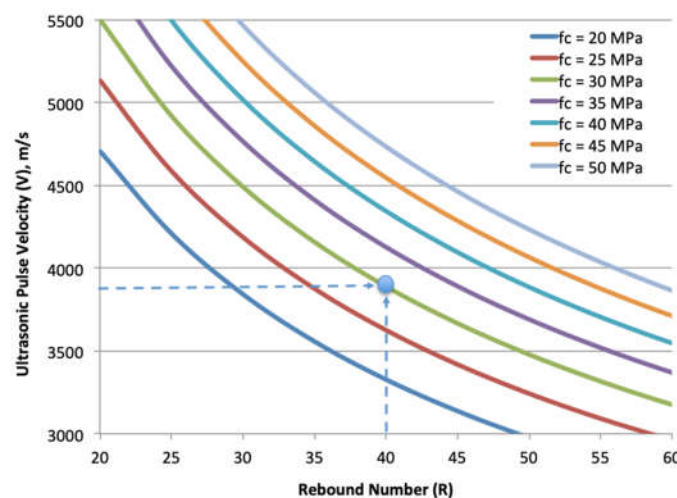


Figure 1. Graphical representation of the SonReb model using Equation (1) [7].

2.2.2. Efficiency of the SonReb Method

The SonReb method is widely used in real practice; however, until now, there has been no general agreement about the efficiency of this method (i.e., whether the use of ultrasonic and rebound hammer techniques together is more efficient than the application of only one of these two techniques). Some studies indicate that using the SonReb method leads to a better assessment of the compressive strength [19,38]. However, other studies did not find an important improvement in the quality of assessment when using the SonReb method [39,40].

In real practice, to study the efficiency of the SonReb method, the coefficient of determination r^2 for the case of combination is compared with r^2 values that correspond to cases of single NDT techniques. Table 2 compares r^2 values obtained from using SonReb with the values obtained from using the ultrasonic pulse velocity technique only (single V) or rebound hammer only (single R) and for several datasets selected from the literature. It is clear that, for each dataset, the value of r^2 for SonReb is always greater than the corresponding values for the cases of single V and single R . However, from the principles of statistics, adding a new term to the model (as is the case for SonReb) will increase the

value of r^2 [41]. As a result, the coefficient of determination is a misleading indicator about the efficiency of SonReb. Table 2 also shows the values of the RMSE (root mean square error) calculated at the prediction stage, i.e., for the part of dataset that was not used in the model identification (fitting stage). From these values, it is clear that for some datasets, the minimum errors are obtained from using a single NDT technique, while for other datasets, the minimum errors are provided by the SonReb method. This indicates that the combination is not always efficient. Furthermore, [42] has studied the efficiency of the SonReb method using synthetic datasets and highlighted that the efficiency of SonReb depends on the qualities of the two techniques combined (in other words, the uncertainties of measurements) and on the number of samples or cores used in the model identification process.

In summary, the SonReb method is not always efficient, and its efficiency is affected by factors such as the quality of pulse velocity and rebound hammer measurements, the number of samples/cores used in the model identification, and probably the concrete quality (strength, variability, moisture variation, etc.). To analyze the efficiency of SonReb, it is necessary to do so at the prediction stage and not at the fitting stage. This consists of splitting the data in two groups, one for fitting models and the second for testing the model (prediction on data not used for fitting). Moreover, to deepen the analysis of the efficiency, it is important to compare the cost of the SonReb with that of using a single technique in order to derive conclusions that are more realistic.

Table 2. Analyzing the efficiency of SonReb.

Ref	Dataset Size	r^2			RMSE (MPa)		
		Model-Fitting Stage			Prediction Stage		
		Single V	Single R	Combined V + R	Single V	Single R	Combined V + R
[43]	23	0.64	0.23	0.70	3.9	5.3	4.6
[44]	18	0.27	0.31	0.43	2.5	2.5	3.5
[45]	18	0.57	0.78	0.84	6.8	4.9	6.2
[46]	16	0.79	0.68	0.92	8.2	9.2	5.8
[47]	14	0.81	0.88	0.97	3.6	2.2	1.6
[18]	80	0.51	0.83	0.87	10.1	5.6	6.5

$$RMSE = \sqrt{\sum_{i=1}^{NC} (f_{core\ i} - f_{cest\ i})^2 / NC} \quad (3)$$

where $f_{core\ i}$ is the true in situ strength, $f_{cest\ i}$ is the estimated compressive strength, and NC is the number of cores.

3. Calibration of Conversion Models for the Case of Combination of NDT Techniques

3.1. Objective and Aim of Calibration

As both V and R are influenced by many factors (i.e., aggregate type, moisture, cracks, carbonation, etc.), calibration is needed for more accurate strength evaluation. Instead of identifying the conversion models, as described in the previous section, for assessing concrete in the existing structures, conversion models from standards or laboratory studies or those provided in the literature can be tested for this purpose. However, since there is no universal model, which can be applied for all concrete, these models, can only be used for the cases from which they are derived, and the application of these models to any other case needs a prior calibration step. The objective of the calibration process of an existing model is to modify it to the concrete under consideration.

3.2. Methods of Calibration

Different methods can be applied in order to calibrate an existing conversion model. These calibration methods differ in their simplicity and accuracy. We present here several calibration methods:

3.2.1. Shifting Factor Method (Δ -Method)

The method of calibration by shifting (Δ -method), in which the model f is calibrated by shifting it by a calibration constant Δ , i.e., the calibrated model becomes $f + \Delta$. The constant Δ is calculated from the values of indicators and observables measured at some points within the concrete under consideration. The calibration by the shifting method is easy to carry out and inexpensive. However, the parameter Δ cannot correct or modify the conversion model to include the effects of all influencing parameters. Moreover, it does not modify the model sensitivity coefficients (i.e., if the model is linear, then the calibration has no effect on the slope "sensitivity coefficient") which may lead in some cases to serious errors. The concept here is to shift the uncalibrated prior model by a coefficient Δ ,

$$f_{cest}(x) = f_{c\ uncal}(x) + \Delta \tag{4}$$

The coefficient Δ is calculated as in the following steps:

- (a) Use the uncalibrated prior model to calculate the estimated strength at each core location $f_{c\ uncal\ i}$, then
- (b) Calculate the shifting factor Δ

$$\Delta = \sum_{i=1}^{NC} (f_{core\ i} - f_{c\ uncal\ i}) / NC = (\bar{f}_{core} - \bar{f}_{c\ uncal}) \tag{5}$$

Figure 2 shows the scatter diagram with an uncalibrated model selected from the literature and the calibrated models that result from using the two calibration methods (k -method and Δ -method).

3.2.2. Multiplying Factor Method (k -Method)

In this method, the conversion model f is multiplied by a calibration constant k in order to produce a calibrated model $k \times f$. As in the previous method, the calibration constant k is calculated from the available data on the concrete under consideration. In contrast to the calibration method by shifting, the present method modifies all coefficients of the conversion model.

The principle comes to update an uncalibrated prior model by a coefficient k to produce a calibrated model,

$$f_{cest}(x) = k \times f_{c\ uncal}(x) \tag{6}$$

where $f_{c\ uncal}$ is the estimated compressive strength calculated from the selected uncalibrated prior model. The coefficient k is calculated as in the following steps:

- (a) Calculate the mean value of core strengths,
- (b) Use the uncalibrated prior model to calculate the estimated strengths at core locations and then take the mean of these values,
- (c) Calculate the calibration factor.

$$k = \bar{f}_{core} / \bar{f}_{c\ uncal} \tag{7}$$

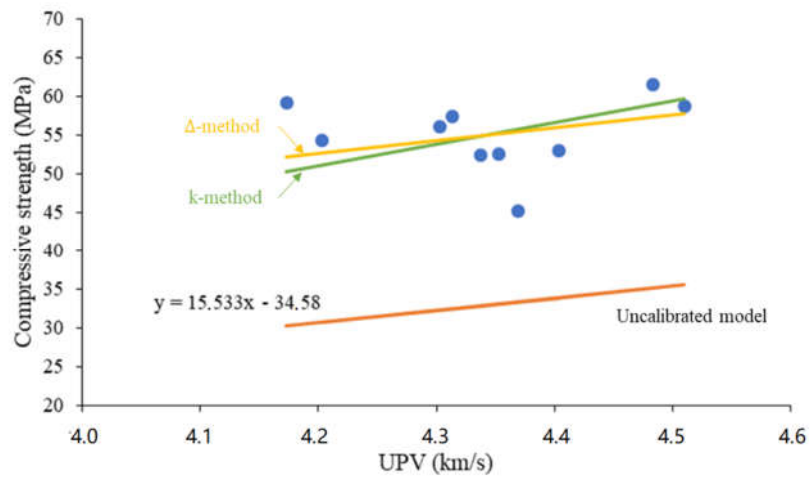
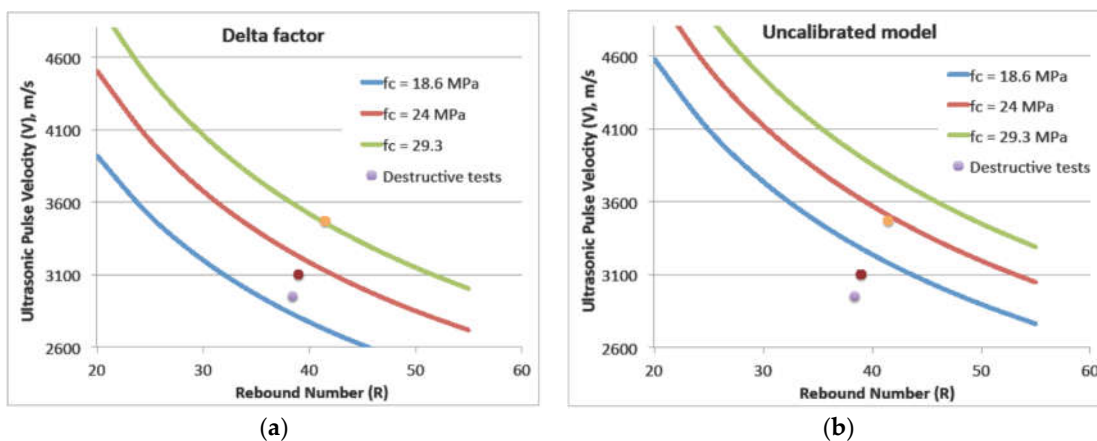


Figure 2. Scatter diagram of the $(x_{f_{core}})$

pairs with models obtained by the calibration approach.

4. Case of the SonReb Method

To calibrate SonReb conversion models, any one of the two approaches (i.e., Δ -method or k-method) presented above can be applied. In this section, an example of the calibration of the SonReb model is presented; the two calibration methods were applied on datasets collected from the literature [23]. These datasets consist of ultrasonic pulse velocity and rebound hammer measurements carried out on an existing structure. Firstly, the results of using the SonReb model without calibrations are shown in Figure 3a. If one compares the concrete strength estimated by the SonReb model with the values obtained from destructive tests, see Figure 3a; it is clear that the uncalibrated model is unable to assess the strength with a good precision (here, the mean absolute error of 6.2 MPa is found). However, when the model in Figure 3a is calibrated by applying the Δ -method (Figure 3b) or the k-method (Figure 3c), the reliability of assessment is improved. The strengths estimated after calibration were compared with the measured strengths, as shown in Figure 3d. From this figure, it is obvious that the errors are reduced to 1.2 MPa for both the Δ -method and the k-method.



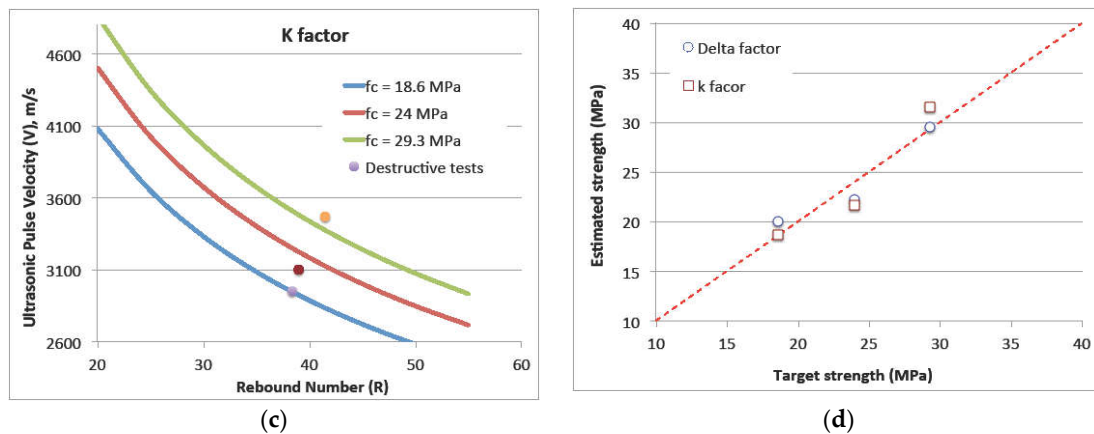


Figure 3. In situ case study of using the calibration methods on the SonReb model (a) uncalibrated model, (b) calibration by Δ -method, (c) calibration by k-method, (d) the error of calibration of the two methods (shifting and multiplication) [7].

5. Performance of the Evaluation Using Monte Carlo Simulations

In real practices, after the in situ measurements and strength testing in laboratory, these results are used to identify/calibrate a conversion model between the NDT measurements and concrete strengths. This methodology can be affected by some factors, such as the number of cores and the uncertainty of NDT measurements. To take into account these effects, recent works [24,48] proposed to simulate the methodology using the Monte Carlo method.

The model calibration is based on a random selected number of test results or number of cores (NC). The process of strength estimation goes first through the identification step and then the prediction step. The strength estimation in the identification step is based on the NC of the test results or cores chosen for the calibration. On the other hand, the strength estimation in the prediction step is based on a number NT-NC of test results, where NC is the number of test or cores used to identify the model and NT is the total number of test locations or tested samples for NDT measurements.

After the random selection of NC from NT test locations, the regression analysis is used to identify three linear models corresponding to three cases: using pulse velocity method V, using rebound hammer method R, and using combined method (V + R). Each identified model is used to estimate the local strength, which is used to calculate the estimated mean strength \bar{f}_{cest} , the estimated strength standard deviation (strength variability) $s(f_{cest})$, and errors [42].

The figure below shows three Fitting Error Curves (FEC) and Prediction Error Curves (PEC) corresponding to three cases (single technique V, single technique R, and combination of V + R).

From Figure 4, the following can be noted:

- The fitting error RMSEfit increases as NC increases. This is rational because the number of points to be fitted using a model having a fixed number of parameters is increased.
- The other interesting observation is about the points with RMSEfit = 0 when NC = 2 for the case of a single technique and NC = 3 for the case of combination of NDT techniques. This means that when NC is equal to the number of model parameters, the model parameters can be identified without any fitting error, but the prediction error is very large, i.e., the models have poor predictive ability. This discrepancy must be pointed out, since a very low number of cores is a common practice.
- The prediction error exhibits an adverse pattern to that of fitting error, since it decreases while NC increases by increasing NC.

- For each of the three cases (V and R measurements alone or in combination), the difference between the FEC and PEC decreases as NC increases.
- For all cases, the error of prediction starts stabilisation after six cores. After nine cores, there is no significant improvement in the strength prediction. Therefore, no core is needed after this number.

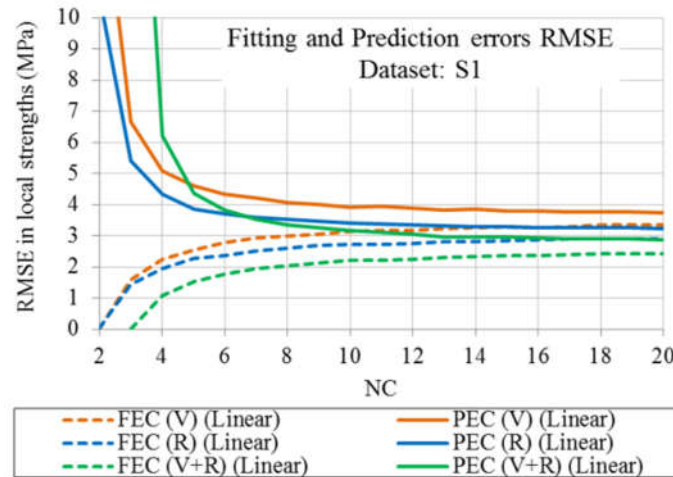
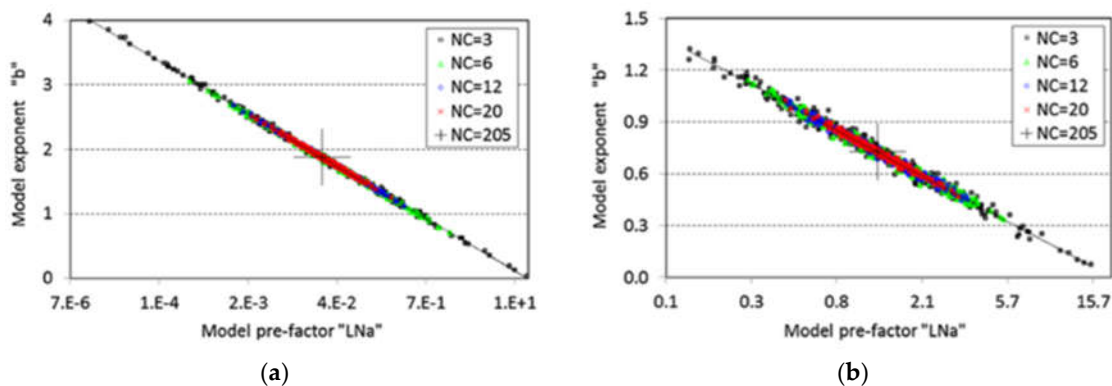


Figure 4. Fitting and prediction errors (FEC and PEC) as a function of NC resulting from analyzing the in situ dataset S1 [40].

6. Relationship between the Statistical Parameters of the Model “Trade-Off effect”

Based on the dataset of [40] composed of triplet of V , R , and f_{core} , the trade-off effect is analyzed on the SonReb method. In order to analyze the model calibration quality, and to study the effect of calibration on the model parameters, the number of cores (NC) that are subject to calibration is varied between the minimum number of 3 cores and a maximum of 20 cores. This procedure is repeated 10,000 times for each number of cores in order to study the stability of the repetitive process. From each repetition, a model with its own statistical parameters is estimated. This set of parameters varies from one repetition to another. The relationship between models’ parameters is called “trade-off”. This effect has only been studied for the single NDT method [23]. The authors reported that the relation between the two parameters of all the models having the same form from the literature is linear. On a large experimental database [13], similar results are presented, as can be seen in Figure 5. This figure presents the results for both R and V measurements. The colours indicate the number of cores used for calibration. It can be seen that increasing NC allows one to decrease the variation range of the parameters “a” and “b”.



(a)

(b)

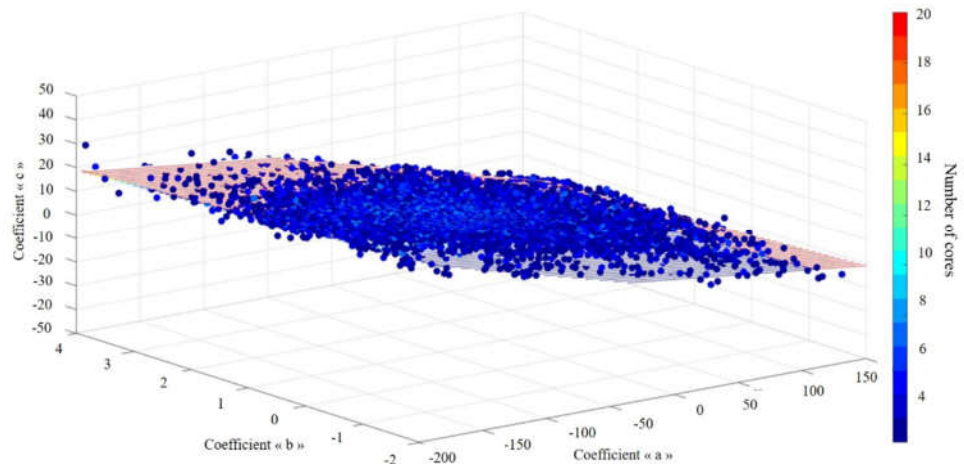
Figure 5. Trade-off between model parameters (for 300 iterations) with single methods for different numbers of NC [40]. (a) R test results, power model, $b = f(LNa)$, (b) V test results, exponential model, $b = f(LNa)$.

Regarding the SonReb method, this effect has not been studied. For this reason, in this paper, the same dataset from [48] that is composed of on-site measurement of 205 triplet V , R , and f_c from a reinforced concrete building was used.

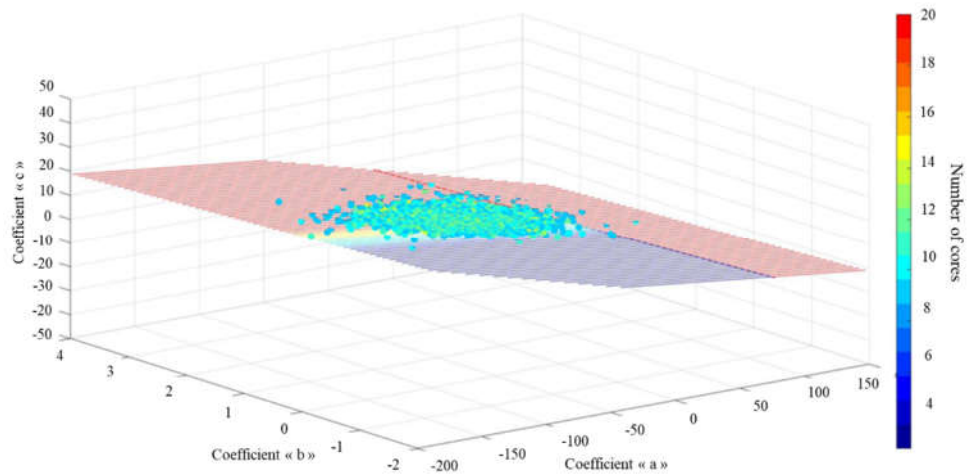
From this database, the SonReb method was tested by calibration. Figure 6 illustrates the trade-off between the statistical parameters “a”, “b”, and “c” of the multivariable model for the combination of rebound and ultrasonic pulse velocity. Furthermore, this trade-off is then analyzed for different NC with 10,000 repetitions for each given number.

For a given NC, each repetition (randomly chosen) has its own model and its own parameters (a, b, and c), which are different from one simulation to another. It is noticed that all the parameters (a_i , b_i , and c_i) of the repetitions ($i = 1$ to 10,000) for a given NC are on the same plane ($c_i = f(a_i, b_i)$). Moreover, it is also noticed that even if NC is varied, the sets (a_i , b_i , and c_i) always remain on the same plane. Dispersion of the sets is decreased by as much as the NC increases. Figure 6 confirms that, in an appropriate reference frame, the parameters a, b, and c of a multivariable model are related by a linear relationship.

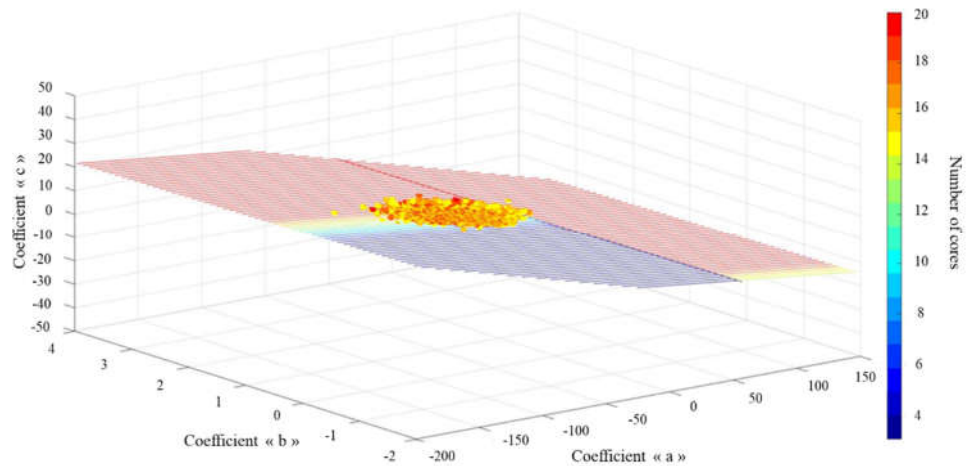
It is clearly shown in Figure 6 that the variation of the NC slightly influences the values of the parameters a, b, and c of the 10,000 repetitions of each NC. These values become closer to the parameters of the whole population model (N) as the NC increases. Moreover, the variation of the NC has a significant influence on the degree of dispersion (standard deviation) of the parameters a, b, and c of each NC.



(a) Relation between SonReb model parameters; the number of cores varies from 3 to



(b) Relation between SonReb model parameters; the number of cores varies from 9 to 14



(c) Relation between SonReb model parameters; the number of cores varies from 15 to 20

Figure 6. Effect of the trade-off as a function of the NC number.

7. Conclusions

This paper discusses the issues of combining NDT methods in order to assess the concrete compressive strength from a literature point of view. The method is presented, and the mathematical concept is discussed. Even with the combination of NDT, the conversion models identified for a specific concrete cannot be applied for other concretes without calibration procedure. This paper discusses the performance of SonReb and the two methods of calibration (Δ -method and k-method) from a statistical point of view by using Monte Carlo simulation.

In real practice, in order to study the efficiency of combination, the coefficient of determination r^2 of the model derived for the combination of NDT techniques is compared with those corresponding to the models established from using these techniques separately. In fact, r^2 can be a misleading indicator about the efficiency of combination and may lead to wrong conclusions. Thus, assessing the model prediction capability by using RMSE is an efficient way to decide whether using combined techniques is better than using a single NDT technique.

Using a combination of rebound hammer and ultrasonic pulse velocity techniques with cores for assessing the concrete strength is a common practice. However, there is no consensus about the efficiency of this combination. Some researchers found that it yields results that are more reliable, while others did not find a significant improvement in the concrete assessment by combining methods. A general conclusion about the efficiency of combination methods cannot be provided because it depends on the quality of assessment provided by each specific combination in comparison with what corresponds to the use of only one NDT. Therefore, there is not a general conclusion on the efficiency of SonReb. In fact, for each investigation on a real structure, the evaluation of SonReb efficiency is recommended. This can simply be performed by comparing the RMSE of the prediction from SonReb with the one from a single method (UPV, Rebound, or other method).

Calibration of SonReb on cores taken from structures is very important. The use of a direct model without calibration can lead to wrong evaluation of concrete strength. A shifting method can be applied for the calibration of some models, but its use can over- or underestimate concrete strength. The use of a multiplying factor or a new regression is more efficient.

The use of a prediction dataset for the evaluation of model performance is mandatory. In fact, it is the only way to give realistic information about the predictive capacity of the identified/calibrated model.

Monte Carlo simulation is powerful for evaluating the uncertainty of the SonReb evaluation of concrete compressive strength.

As for the case of one NDT method, SonReb results from the analysis of the trade-off effect demonstrate that the model parameters are correlated linearly, and the number of cores influences the dispersion.

The minimum number of cores is about six to seven cores for stable results. The use of more than nine cores does not significantly improve the quality of the evaluation.

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APPENDIX (B)

This appendix includes our published paper:

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New multi-objective optimization to evaluate the compressive strength and variability of concrete by combining non-destructive techniques

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ABSTRACT

Concrete compressive strength is one of the most important parameters in the evaluation of the mechanical performance of reinforced concrete structures. The recent methodology for assessing concrete strength in an existing structure involves integrating Non-Destructive Testing (NDT) techniques, such as Rebound Hammer measurement and Ultrasonic Pulse Velocity measurement, with destructive sampling measurements to establish a conversion model that correlates mechanical strength with non-destructive measurements. The conversion model is then used to estimate the local value of strength at each location of non-destructive measurements and thus to represent the spatial variability. Despite successfully identifying the compressive mean strength through this methodology, there remains significant uncertainty regarding the variability of compressive strength. The goal of this study is to propose a new model identification approach based on multi-objective optimization to predict the compressive strength of concrete and its variability, based on the combination of NDT measurements. Monte Carlo simulations are carried out to check the performance by taking into account the uncertainty of NDT measurements and the variability of concrete. For this purpose, a large dataset of experimental and simulated data of both destructive and non-destructive tests is used. The conclusions drawn from the synthetic data will be compared with the results obtained on the experimental dataset in order to test the efficiency of the proposed methodology. This study shows the principle of the optimization methodology and the first results of its effectiveness in predicting compressive strength including its variability. The findings indicate that the multi-objective method is efficient in determining the mean strength compared to other approaches. Furthermore, by employing the multi-objective approach, engineers and researchers can attain enhanced accuracy in estimating the variability of concrete. Simultaneously, they can optimize the number of core samples, leading to improved efficiency, cost-effectiveness, and minimized impact on concrete structures.

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1. Introduction

Non-Destructive Testing (NDT) is increasingly used to evaluate the state of existing reinforced concrete structures [1,2]. The development of methods and data processing for a better evaluation of building materials has been the subject of extensive research [1–4]. Rebound hammer (RH) and Ultrasonic Pulse Velocity (UPV) techniques are often used to evaluate concrete characteristics and estimate compressive strength in the laboratory and in situ [3,4]. Several factors, including the aggregate, water/cement ratio, moisture, and others, have an impact on this ultrasonic pulse velocity [5]. In another hand, the rebound hammer technique is performed through the device called sclerometer (Schmidt Hammer Rebound). It is based on the principle that the rebound of an elastic mass depends on the hardness of the concrete surface. There are many factors that affect the rebound number, such as the moisture content of the concrete, the surface smoothness, the nature of the coarse aggregate, the age of the concrete, the size and shape of the concrete, and the rigidity of the concrete specimen [6].

For years, correlating concrete strength (f_c) simultaneously with Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV), which is the origin of the SonReb method, has been tested in many research works [1–12]. The idea of combining the Rebound Hammer technique with Ultrasonic Pulse Velocity measurement (SonReb method) is based on a reasonable assumption that the use of two NDT methods, affected by different physical properties of concrete correlated to strength, could decrease uncertainties according to Facaoaru [7]. Numerous research papers have been published since the late 1970s based on the calibration of models in order to assess the mechanical strength of concrete using SonReb [8,9]. In 1993, RILEM NDT4 also suggested using the combination of NDT techniques to evaluate the concrete compressive strength [10]. However, the SonReb approach is considered promising, but only if the additional cost is offset by improved diagnostic quality. The combination of NDT techniques also includes the limitations of each individual technique. In fact, the quality of an evaluation can be affected by several factors: the characteristics of the concrete being studied, the variability of properties in the concrete, and measurement errors.

The assessment methodology of NDT combination is similar to a single NDT technique. It includes performing the NDT measurements, extracting the samples, building a model using the dataset (UPV, RH and compressive strength values) and finally estimating the strength at any test location using the conversion model.

In addition, to combine the ultrasonic pulse velocity and rebound hammer, different forms of model were considered by several researchers. It is important to note that these models were derived from experimental measurements on different concretes; this explains the variety of the models' parameters. Many of them have been calibrated upon data related to compressive tests of cubic concrete samples or cylindrical concrete samples prepared in laboratory, while other ones have been calibrated on data related to compressive tests of cores extracted from existing buildings. When classifying prediction models, it is important to take into account the nature of the correlation between the independent variables and concrete strength. In fact, models have been classified as either linear (LN), exponential (EXP) or power (PW). However, using a general (universal) model between concrete strength and NDT measurements for assessing a real structure leads to unreliable estimations and calibration is mandatory [11]. In real practice, there are two possibilities for calibration: multiplying factor method, and shifting factor method [12].

Despite the importance of evaluating strength variability, it has received very little attention. It should be noted that the term "variability" primarily corresponds to the standard deviation, which is the most relevant parameter for describing dispersion. Recent work of Alwash et al. [13] has developed a new bi-objective method able to assess variability with better accuracy than conventional methods (regression analysis or calibration methods). The main limitation of this method is that it does not allow combining two NDT techniques to assess strength and its variability. For this reason, this article proposes to answer this problem by introducing a new method based on multi-objective optimization for predicting both mean and variability of compressive strength when at least two NDT methods are used (RH and UPV here).

In this paper, the dataset collecting the results of synthetic and experimental data is presented in Section 2. Various model identification approaches are analysed to compare their effectiveness in evaluating both the mean strength and variability of concrete strength (Section 3). Finally, in Section 4, the proposed models are validated on both synthetic and experimental database.

2. Synthetic data and experimental program

2.1. Synthetic data

Due to the limited number of experimental data, synthetic simulations were performed, allowing the control of some parameters such as the effect of humidity and measurement uncertainty. The synthetic data is generated using Monte Carlo simulation, which is a well-established technique for generating random samples based on known probability distributions. The simulation incorporates probability distribution functions to generate random values for input variables. The correlation between input (strength and moisture content with their mean and standard deviation values) and output (UPV and RH) variables is based on empirical models developed in previous studies, ensuring that the generated synthetic data reflects realistic relationships between variables [14]. The advantage of such an approach is to build a synthetic database in order to simulate different configurations and therefore to evaluate the quality of the methodology. The simulation's primary steps are:

- 1) Definition of the simulation input variables and their domains,
- 2) Generation of random values for the input variables using the appropriate probability distribution function,
- 3) The output variables are determined by establishing the correlations between the inputs and outputs and performing the necessary computations.

- 4) Reiteration of the simulations in order to account for the sampling effect. Since the simulation involves generating random values for the input variables based on probability distribution functions, repeating the simulations multiple times helps to account for this randomness and provides a more robust estimate of the model's performance.

We consider as input variables of the simulation, the in-situ strength as well as the moisture content, with the following mean and standard deviation values respectively: $\bar{f}_{ist} = 25 \text{ MPa}$, $s(f_{ist}) = 2 \text{ MPa}$, $\bar{S}_R = 75\%$, $s(S_R) = 2.25\%$. Those specific mean and standard deviation values for in-situ strength and moisture content were selected to ensure that the synthetic dataset covers a range of realistic scenarios. By using representative values that align with typical concrete properties and environmental conditions, the objective is to create a dataset that reflects real situations.

The true in-situ concrete strength f_{ist} is generated by assuming a normal distribution $N(\bar{f}_{ist}, s(f_{ist}))$. The truncated normal distribution, $N(\bar{S}_R, s(S_R))$ with $0 \leq S_R \leq 100\%$, is used to generate the values for the degree of saturation S_R . A truncated normal distribution is similar to a normal distribution but it is bounded within a specific range. This allows for the generation of degree of saturation values that fall within a defined range of practical values observed in concrete structures. This distribution can avoid extreme values.

In order to correlate the inputs with the true in-situ ultrasonic pulse velocity V_t and true in-situ rebound number R_t , synthetic models were developed in Ref. [14]:

$$V_t = V_{ref} (f_{ist}/f_{cref})^{1/bf} (S_R/S_{Rref})^{1/bs} \quad (1)$$

$$R_t = R_{ref} (f_{ist}/f_{cref})^{1/cf} (S_R/S_{Rref})^{1/cs} \quad (2)$$

The reference values are $R_{ref} = 40$, $V_{ref} = 4000 \text{ m/s}$, $S_{Rref} = 85\%$ and $f_{cref} = 40 \text{ MPa}$.

The strength sensitivity exponents' bf and cf in equation (1) and equation (2) have been respectively taken equal to 4.90 and 2.10. The humidity sensitivity exponents' bs and cs have been respectively taken equal to 7.14 and -3.33 [15].

Moreover, random errors are added to the generated true in-situ values (R_t , V_t and f_{ist}) in order to obtain the simulation outputs:

$$V = V_t + \varepsilon_V \quad (3)$$

$$R = R_t + \varepsilon_R \quad (4)$$

$$f_c = f_{ist} + \varepsilon_f \quad (5)$$

The magnitude of these errors are obtained by assuming a normal distributions with zero-mean $N(0, sd_V)$, $N(0, sd_R)$ and $N(0, sd_f)$, the standard deviations represent the within-test variability of the measurements (see Table 1). The possible range of within-test variability has been widely documented in the literature [14,16,17].

In order to produce a synthetic dataset, the data simulation process outlined in Fig. 1 must be repeated a number of times equal to the total number of test locations (dataset size) in the synthetic structure. Each repetition of the process generates the outputs (V , R and f_c) corresponding to a single test location.

The cumulative distribution functions of core strength is illustrated in Fig. 2, it provides an understanding of the overall strength distribution corresponding to the synthetic dataset. The mean strength is 24.9 MPa and the variability is 2.52 MPa. Similarly, the cumulative distribution of NDT measurements is illustrated in Fig. 2; it shows the distribution of measurements obtained through Rebound Hammer and Ultrasonic Pulse Velocity corresponding to the synthetic dataset. The Rebound Hammer data exhibits an average value of 32.93 units and a variability of 2.09 units. The Ultrasonic Pulse Velocity exhibits an average value of 3.53 km/s and a variability of 0.09 km/s.

2.2. Experimental data

The experimental dataset is a large auscultation and coring campaign on structural elements of a building existing since 2004 and undergoing demolition [18]. The project in question is designed for administrative use and is part of a factory composed of two reinforced concrete buildings. Non-destructive evaluations of rebound hammer and ultrasonic pulse velocity measurements were applied on the structural elements (columns and beams). In parallel, compressive tests of the sampled cores were also performed. The building is composed of two blocks with different floors (R + 1 and R + 2). Approximately 155 structural elements (columns and beams), distributed over the two blocks, were subjected to NDT tests, with a number of two to three test locations selected on each element. 145 elements were sampled from the two blocks, yielding a total of 205 cores. These samples were assessed by NDT and compressive tests. The NDT tests were performed on test locations of 15 cm × 10 cm using RH type N, C181 model and also an ultrasound type E46 with transducers of 50 mm diameter and 54 kHz frequency. The diameter of the core samples obtained from the structural elements is nominally 75 mm. First, the cores were subjected to surface grinding by sawing and then to the measurement

Table 1
The within-test standard deviation according to measurements quality levels.

	High Quality (HQ)	Average Quality (AQ)	Low Quality (LQ)
sd_V	50 m/s	100 m/s	200 m/s
sd_R	1 unit	2 units	4 units
sd_f	1 MPa	1.5 MPa	2 MPa

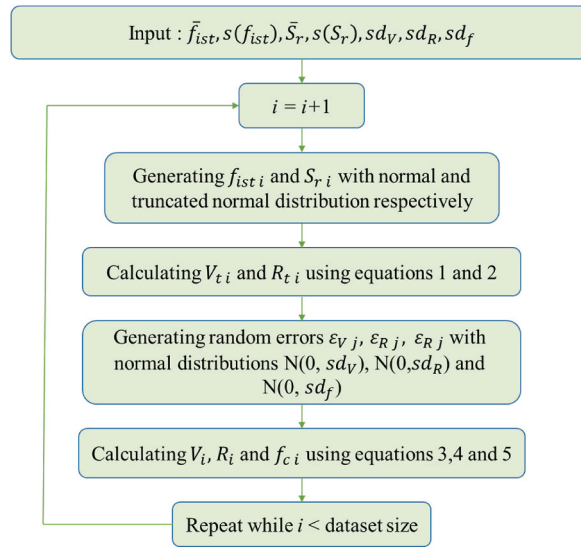


Fig. 1. Generating dataset using synthetic simulation.

density (ranging from 2.07 to 2.33 kg/dm³). The rebound test result corresponding to each core is the median value of the set of measurements expressed as a whole number [19]. The cores have been compressed under an applied load to failure with a loading rate of 0.5 MPa/s.

Fig. 3 offers valuable insights into the strength and NDT measurement characteristics of the experimental dataset. The experimental data has a mean strength of 25.98 MPa with a variability of 10.18 MPa. The Rebound Hammer data has an average value of 36.38 units and a standard deviation of 6.43 units. On the other hand, the Ultrasonic Pulse Velocity data exhibits an average value of 3.9 km/s with a standard deviation of 0.5 km/s. In addition, synthetic data and experimental data were plotted on the same figure to facilitate a direct comparison between them.

3. Strength assessment using combination of non-destructive techniques

In this section, a new model identification approach is introduced, namely multi-objective optimization. Additionally, parametric multi-variable regression method (mono-objective approach) is presented and can be more easily implemented. The purpose of this paper is to evaluate the prediction level of the multi-objective approach by comparing the predicted compressive strength, determined from NDT measurements, with the actual compressive strength obtained through destructive testing of cores.

3.1. Mono-objective approach using multiple regression (SonReb method)

The regression approach used for a single NDT technique as an independent variable can be expanded to include multiple NDT techniques as independent variables. Thus, the resulting regression model that can be employed to approximate the strength is:

$$f_c = a + b_1x_1 + b_2x_2 + \dots + b_nx_n + \epsilon \tag{6}$$

The parameters $(a, b_1, b_2, \dots, b_n)$ are obtained through least squares minimization [20]. The equation above can also be written in matrix form or more compactly:

$$Y = X \times A \tag{7}$$

where A is the model parameters matrix, X is the design matrix which includes NDT measurements and Y is the response vector namely the compressive strength.

To get the parameters of the model we are looking for, we have to invert the equation or the matrix system. This inversion can be done by the method of least squares for example, but also by the calculation of the inverse matrix.

The commonly used model for combining UPV and RH for strength evaluation is SonReb method proposed from many decades. Various types of models were proposed as linear, exponential or power (Table 2). Those models were derived from experimental measurements conducted on different types of concrete. Using a general model between concrete strength and NDT measurements for assessing a real structure leads to unreliable estimations and calibration is mandatory [13]. In real practice, there are two possibilities for calibration: multiplying factor method, and shifting factor method as presented in the review of combining NDT techniques for strength evaluation [21].

3.2. Multi-objective approach

The multiple objective optimization problems have been receiving growing interest from researchers with various background

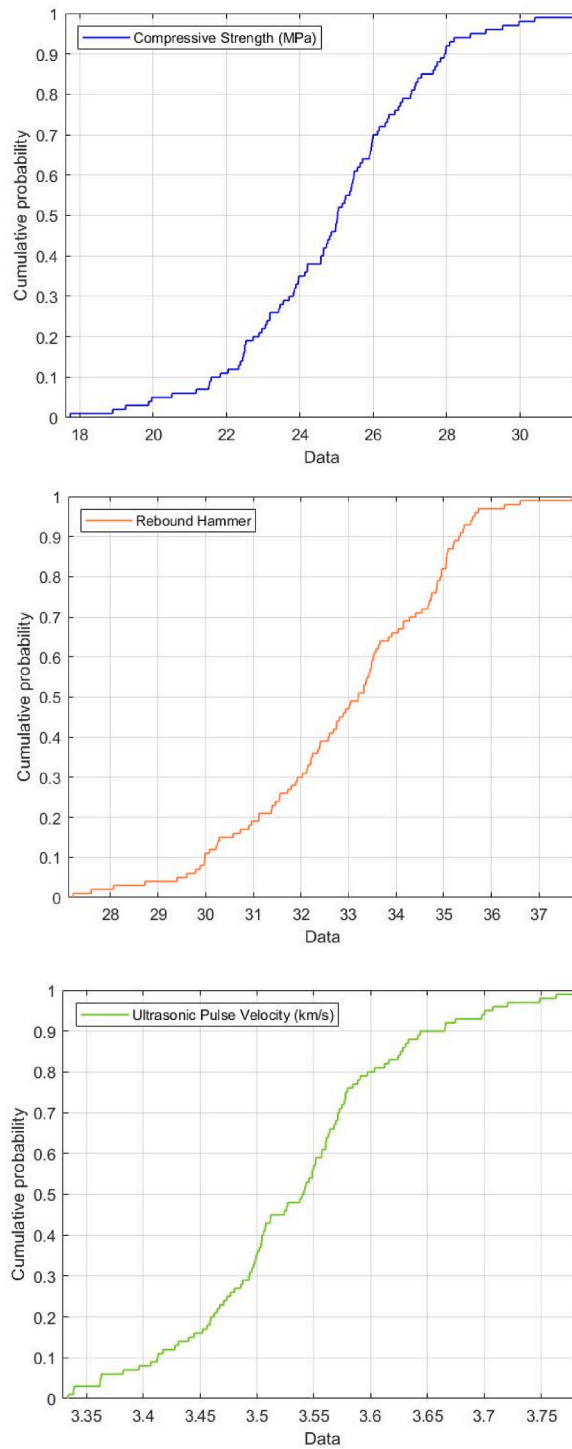


Fig. 2. Cumulative distribution of core strength and NDT measurements corresponding to the synthetic dataset.

[33]. The growth in research on multi-objective optimization during the 1990s was propelled by the realization that numerous real-world applications need the fulfilment of multiple objectives at the same time [34]. The formalization of an optimization program includes the same steps whatever the techniques required later for the analysis:

- 1) The definition of the problem and the identification of the variables, in our case it is to identify the parameters of the conversion model,

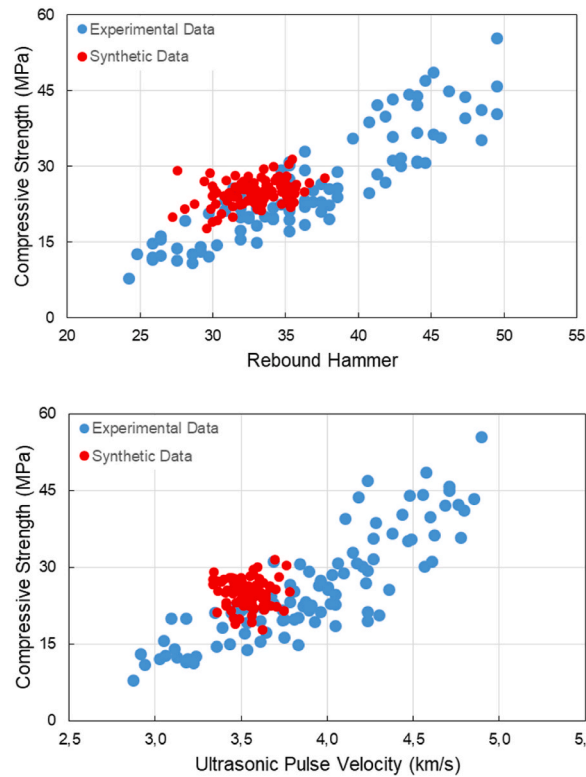


Fig. 3. Clouds of NDT measurements and compressive strength for experimental and synthetic dataset.

Table 2

Models developed by different researchers to estimate the strength of concrete.

Linear model	Exponential model	Power model
$F_c = 8.63V + 1.416R - 51.581$ [22]	$F_c = 7.695 \times 10^{-11} V^{2.6} R^{1.4}$ [23]	$F_c = e^{0.446V + 0.048R}$ [24]
$F_c = 17.13V + 0.866R - 62.684$ [25]	$F_c = 1.15 \times 10^{-10} V^{2.6} R^{1.3}$ [14]	$F_c = 0.67e^{0.72V + 0.04R}$ [26]
$F_c = 5.0614V + 1.532R - 39.57$ [27]	$F_c = 0.00153 \times 0.611V^3 R^3$ [28]	$F_c = 1.974e^{0.000542V + 0.01605R}$ [29]
$F_c = 44.8V + 0.77R - 194$ [30]	$F_c = 0.00004 \times V^{0.80840} R^{1.88148}$ [31]	
$F_c = 0.01385V + 0.26511R - 34.51583$ [32]	$F_c = 10^{-4.251V + 1.281R} R^{0.686}$ [29]	
$F_c = 0.01174V + 0.37R - 28.44$ [7]	$F_c = 9.27 \times 10^{-11} V^{2.6} R^{1.4}$ [10]	

- 2) The formulation of the objective functions,
- 3) The formulation of the constraints, when they exist.

The multi-objective approach used in the assessment methodology involves an optimization procedure that focuses on minimizing three objective functions to assess the mean strength and its standard deviation with NDT. The used functions are the root mean square error (RMSE), the relative error on the mean (RME), and the relative error on the standard deviation (RSE). The aim of the last function is to reduce the error associated with the evaluation of the variability of concrete compressive strength.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N_c} (f_{c\ est\ i} - f_{c_i})^2}{N_c}} \tag{8}$$

$$RME = \frac{|\bar{f}_{c\ est} - \bar{f}_c|}{\bar{f}_c} \tag{9}$$

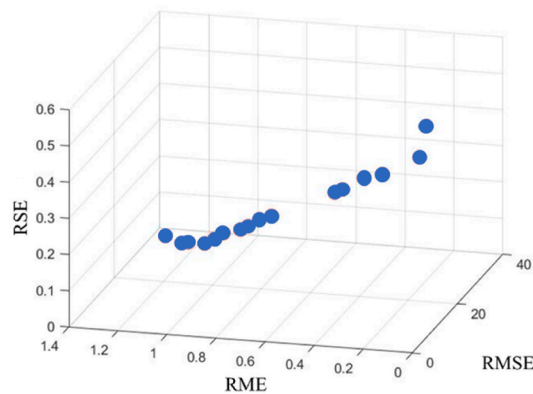
$$RSE = \frac{|s(f_{c\ est}) - s(f_c)|}{s(f_c)} \tag{10}$$

Using three errors as objectives in the multi-objective optimization problem allows for a more comprehensive evaluation of the performance of the model and provides a better trade-off analysis between different aspects of the model's accuracy. The root mean square error provides an indication of how well the model's predictions align with the observed data. The relative error on the mean evaluates how well the model captures the central tendency of the data. The relative error on the standard deviation assesses how well the model captures the variability or dispersion of the data.

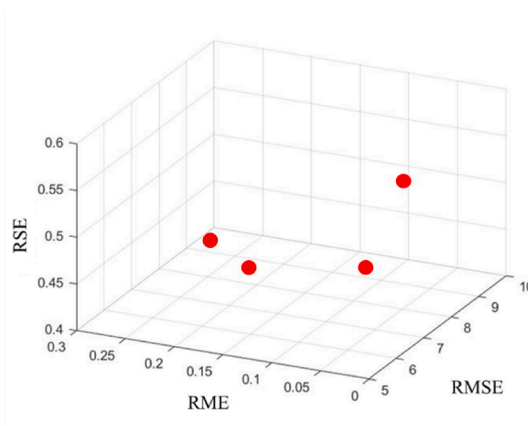
Multi-objective algorithms are designed to discover policies that achieve satisfactory trade-offs among the various objectives of a task. A good compromise can be defined in terms of Pareto front dominance [35], which allows comparison of solutions to a multi-objective problem as shown in Fig. 4a. In this study, a high-performance multi-objective algorithm known as the NSGA-II is used to find the Pareto optimal solutions [36]. Genetic algorithm uses the concept of survival of the fittest to produce more desirable individuals in subsequent evolutionary of the population. At each generation, the objective function value of each individual in the population is calculated. The new generation of candidate solutions is then used in the next iteration of the algorithm. Generally, the algorithm ends when a maximum number of generations has been produced or a satisfactory fitness level has been reached for the population.

The NSGA-II algorithm is built upon the principle of Pareto dominance. In multi-objective optimization, this dominance relationship allows for the comparison and ranking of solutions based on their objective values. NSGA-II places a strong emphasis on maintaining diversity within the population. This is achieved through a combination of selection, crossover, and mutation operations. By employing a technique called “non-dominated sorting,” solutions are divided into different “fronts” based on their Pareto dominance relationships. NSGA-II uses a binary tournament selection operator to select individuals for the mating process. In each tournament, two individuals are randomly selected, and their dominance relationship is evaluated. The individual with higher dominance is selected as a parent for reproduction. Moreover, this algorithm employs a simulated binary crossover operator, which enables both exploration and exploitation of the search space. The simulated binary crossover operator mixes the genetic information of parents while maintaining diversity among solutions. NSGA-II incorporates a mutation operator to introduce random changes within the offspring population. It also integrates an elitism mechanism to preserve the best solutions discovered so far across generations. This preserves high-quality solutions and prevents premature convergence of the algorithm. These key concepts and operations constitute the foundation of the NSGA-II algorithm. By adhering to these principles, NSGA-II aims to efficiently search for Pareto optimal solutions by maintaining diversity and effectively balancing the exploration and exploitation of the search space.

The parameters of genetic algorithms are set as follows: maximum generation is 600, population size is 50, function tolerance data is 0.0004 and constraint tolerance data is 0.001. As the number of generation increases, the individuals in the population get closer



a) Before imposing constraints on the decision variables



b) After imposing constraints on the decision variables

Fig. 4. Pareto front a) before and b) after imposing constraints on the decision variables.

together and approach the minimum point. The termination tolerance for the objective function was set to 10^{-6} . Parameters were estimated with lower bounds equal to zero, the termination tolerance for the parameter estimates was also taken equal to 10^{-6} .

The Pareto set in Fig. 4a represents the set of optimal solutions in the multi-objective optimization problem, considering no constraints. Each point represents a trade-off between the root mean square error (RMSE), the relative error on the mean (RME), and the relative error on the standard deviation (RSE), and there is no point that dominates the others in terms of the three objectives. In the other hand, assuming we have additional constraints: that RMSE should not exceed 10 MPa and both RME/RSE should not exceed 1 MPa. In this case, the Pareto set comprises only four points.

4. Results and discussions

4.1. Analysing the model identification approaches

In this section, the predictive ability of different approaches is investigated, namely mono-objective and multi-objective optimization for the case of combined NDT techniques. For this purpose, two main sources of data are used in this study: synthetic and experimental datasets.

A simulator was created to carry out the analysis in the current study. The main algorithm of this simulator is depicted in the flowchart in Fig. 5. The first step in the simulation process is choosing the dataset (NDT measurements and strengths from destructive tests) that will be used throughout the subsequent stages. Identifying the test locations is necessary for organizing any on-site research program in order to perform NDT measurements. To assess the quality of model calibration and identify its parameters, the number of cores (NC) is varied between the minimum number of 3 cores and a maximum equal to 20 cores. The samples selected for each NC number are chosen among the 100 cores (population). The next step is to develop a conversion model between NDT data and concrete strengths. After identifying each model, the local strengths are evaluated, and subsequently, the mean estimated strength $\bar{f}_{c\ est}$, the variability of estimated strength $s(f_{c\ est})$ and relative errors are calculated. The prediction error is calculated from the differences between the estimated local strengths and the corresponding true in-situ strengths. The simulator is designed to repeat the simulation a certain number of times (NI = 10,000) in order to get stabilized results. Therefore, after NI repetitions, the results for each dataset, each identification approach and each NC value were:

- the average value and standard deviation of the estimated concrete strengths, $\bar{f}_{c\ est}$ and $s(f_{c\ est})$ respectively;
- Standard deviation values for the NI mean strength and concrete variability, $s(\bar{f}_{c\ est})$ and $s(s(f_{c\ est}))$
- Relative errors and root mean square errors.

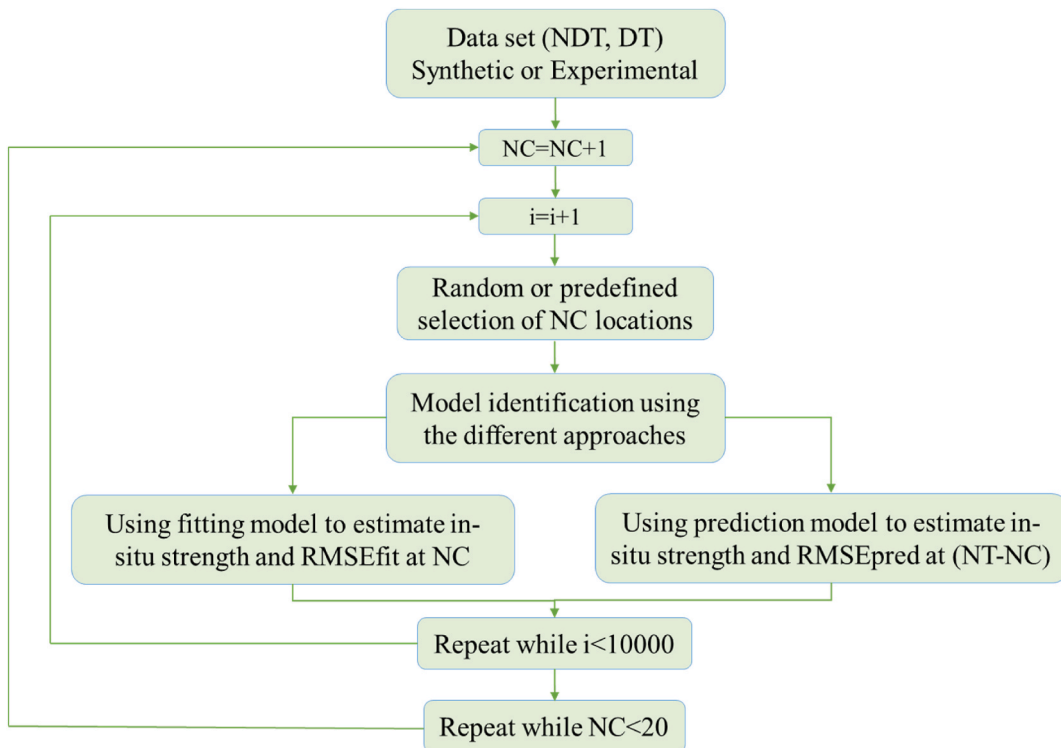


Fig. 5. The assessment strategy using Monte Carlo simulation.

4.1.1. Results of simulated data

Fig. 6a displays $\bar{f}_{c\ est}$ values as a function of NC values, for the two identification approaches (mono or multi-objective optimization) when using synthetic dataset, while Fig. 7a depicts the $s(f_{c\ est})$ values. Both figures also feature reference lines (in red) representing the mean strength or concrete strength variability values corresponding to the synthetic dataset. Relative errors in mean strength and strength variability are given in Figs. 6b and 7b respectively.

According to Fig. 6, the mean strength of concrete can be accurately estimated through the effective use of both multi-objective approach and the existing mono-objective method (Multiple Linear Regression approach). Additionally, enhancing the value of NC can notably improve the efficacy of these estimations.

Based on Fig. 7, it is evident that the multi-objective approach is the only method capable of accurately estimating the true reference value of concrete strength variability. While the mono-objective method fails to account for the true concrete variability and raising NC does not noticeably improve the predictive ability.

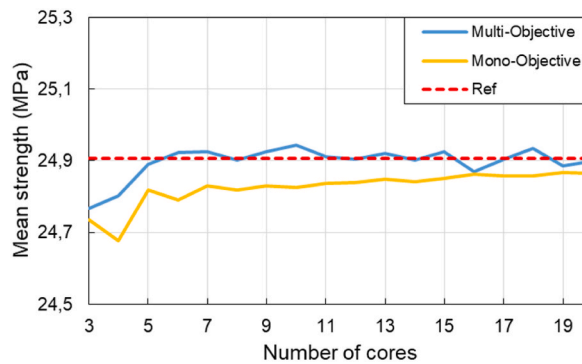
In addition, having an insufficient number of test locations can lead to less reliable estimates of the mean strength and variability. Conversely, increasing the number of test locations allows for a more comprehensive assessment, capturing a wider range of variations in concrete strength.

4.1.2. Results from experimental data

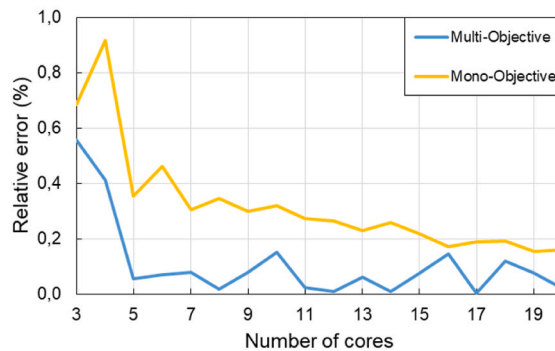
To assess the validity of the multi-objective approach compared to the mono-objective approach, Figs. 8 and 9 display the ultimate outcomes attained through using mono-objective and multi-objective approaches, when using in situ dataset. The figures offer a comparison among the identification approaches under consideration, in terms of mean estimated strength $\bar{f}_{c\ est}$, the variability of estimated strength $s(f_{c\ est})$, and relative errors.

By using multi-objective optimization, it becomes possible to obtain a model with high predictive quality. This means that the model is capable of providing accurate estimations of both mean strength and concrete strength variability. In contrast, using a mono-objective approach (Multiple Linear Regression approach), which considers only one objective at a time to assess the concrete strength, is less efficient (Figs. 8a and 9a). Moreover, the degree of error in the mono-objective approach depend on the number of cores used. Using a small number of cores can limit the accuracy of the mono-objective approach in estimating the concrete mean strength and variability (Figs. 8b and 9b).

In summary, multi-objective optimization provides a more comprehensive and accurate approach to estimate both the mean

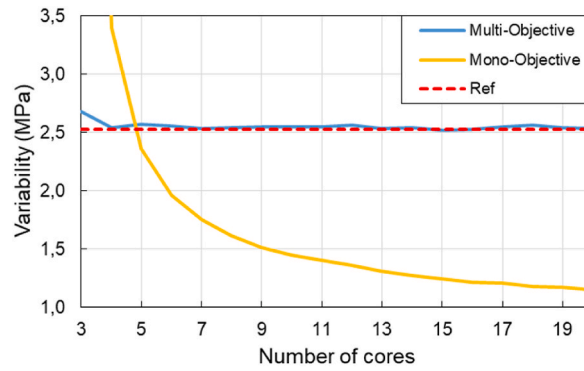


a) Mean strength

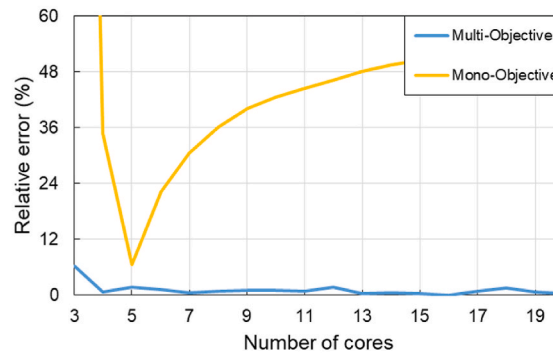


b) Relative errors

Fig. 6. Predicting a) the mean strength and b) relative errors of mean strength, using the Mono-Objective and Multi-Objective approaches (synthetic data).



a) Strength variability



b) Relative errors of strength variability

Fig. 7. Predicting a) strength variability and b) relative errors of concrete variability, using the Mono-Objective and Multi-Objective approaches (synthetic data).

strength and variability of concrete strength. The mono-objective approach, on the other hand, may be less efficient and prone to larger relative errors, especially when the number of cores is limited.

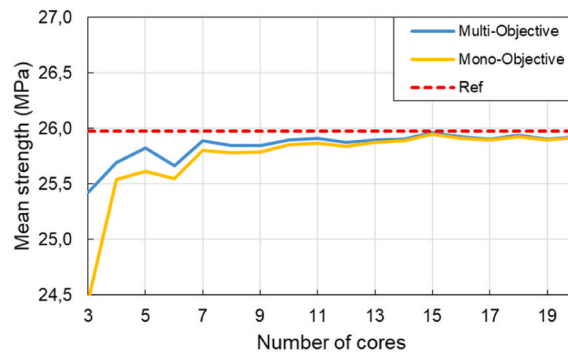
4.2. Evaluation of the accuracy of strength and variability estimation

For further analysis of results, the cumulative distribution functions (CDF) are displayed. For the case of synthetic data and for each NC value, a series of 10,000 values of $\bar{f}_{c\ est}$ and a series of 10,000 values of $s(f_{c\ est})$ were plotted in terms of cumulative distribution function CDF. However, the figures only display the curves that correspond to particular NC values (NC = 3, 10). On both figures (Figs. 10 and 11), the red vertical line represents the real value of concrete mean strength and variability ($\bar{f}_{c\ Ref} = 24.91$ MPa and $s(f_{c\ Ref}) = 2.52$ MPa). The assessment quality is higher when the CDF curve is closer to the red line.

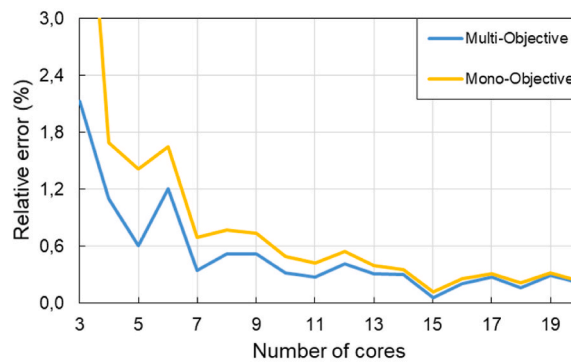
In a perfect scenario (with no dispersion), CDF curves would match the red line. Nevertheless, because there are sources of uncertainty, some scatter is unavoidable and could be reduced. As one can see in our case, the scatter decreases as NC increases. Moreover, the reduction in the scatter appears remarkable in the case of using multi-objective approach. The outcome is different for the assessment of strength variability shown in Fig. 11, using the mono-objective approach. Increasing NC actually minimizes scatter but does not ensure convergence to the genuine in-situ value. On the other hand, the CDF curves associated with the multi-objective method, shown in Fig. 11, present a significant reduction in scatter on both sides and a trend to converge, more slowly than for mean strength (Fig. 10), towards in-situ value as NC grows. This finding confirms that the multi-objective approach, as previously shown, provides a reliable solution to improve the concrete variability assessment.

4.3. Studying the effect of combining NDT techniques on the assessment strategy

The aim of combining NDT techniques is to improve the quality of assessment. The efficiency of combination studied herein is limited to the case of combining the Rebound Hammer and Pulse Velocity. To evaluate whether the quality of assessments can be improved by combining NDT techniques, it is necessary to compare the model's fitting and prediction capacity (i.e., fitting and prediction error) for the proposed combination with those determined for each NDT technique used independently. In what follows, we retain the three approaches: bi-objective for single NDT, mono-objective and multi-objective for the combination of NDT techniques. Table 3 shows the average values of RMSEfit and RMSEpred for each case, obtained by repeating the simulation NI times (NI =



a) Mean strength



b) Relative errors

Fig. 8. Predicting a) mean strength and b) relative errors of mean strength, using the Mono-Objective and Multi-Objective approaches (experimental data).

10,000).

Table 3 highlights a comparative analysis between the values of identification and prediction errors for the case of single and combined techniques. It is shown here that the combination of NDT techniques is potentially effective in obtaining low identification and prediction errors but only when the multi-objective approach is taken into account or when the number of cores exceed seven. By comparing the values of identification and prediction errors for combined techniques while using mono-objective and multi-objective approaches, Table 3 provides insights into the relative performance of the multi-objective approach.

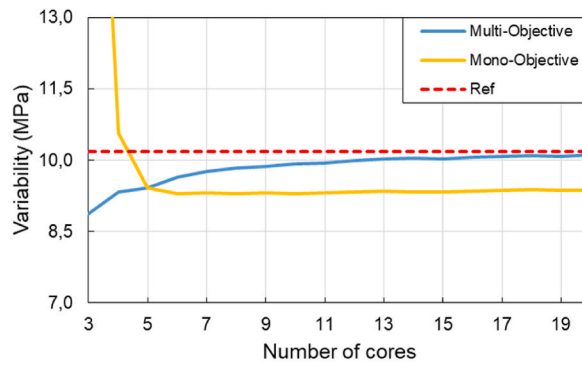
In addition, it is obvious that identification and prediction errors of Pulse Velocity technique are significantly higher than that corresponding to Rebound Hammer technique. Since the effects of the sources of uncertainty other than the measurement uncertainty are the same (the same concrete, sample size, NC, etc.) on both techniques. Therefore, the difference between RMSE of pulse velocity technique and rebound hammer technique is mainly due to measurements uncertainty (the quality of measurements).

5. Conclusions and perspectives

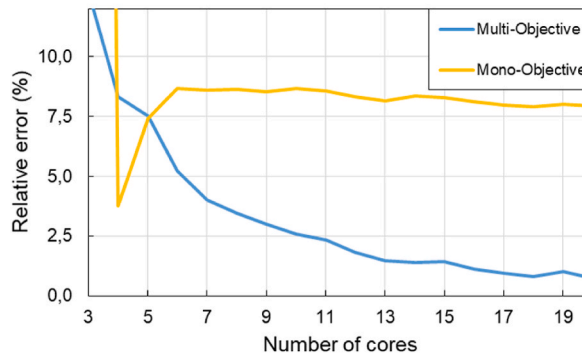
The aims of this project were mainly concerned with the analysis and comparison of the estimation quality of the model identification approaches for the evaluation of the mean strength and the variability of concrete strength in the case of combining NDT methods, on synthetic data and a real case study. Based on the aforementioned results, it was shown that multi-objective optimization is highly relevant for evaluating both the mean strength and variability of concrete. The findings of these analyses also highlight the significant impact of the number of test locations on the accuracy of concrete strength evaluation.

The primary objective of this study is to investigate methods for enhancing the assessment of concrete strength in buildings. The most effective approach for designing a testing program appears to involve a well-balanced combination of NDT techniques and the multi-objective optimization approach. This integrated methodology offers a reliable means of assessing the in-situ variability of concrete strength. By considering multiple objectives simultaneously, it captures the trade-offs between mean strength and variability, leading to a comprehensive and accurate evaluation. Moreover, the study emphasizes the significance of the number of test locations in the evaluation process. By strategically choosing an adequate number of test locations throughout the structure or building, the evaluation becomes more representative of the overall concrete strength characteristics. This enables a more robust analysis and a better understanding of the concrete's performance, enhancing the reliability of the assessment.

In summary, the multi-objective approach offers a more comprehensive estimation of variability by considering multiple objectives



a) Strength variability



b) Relative error

Fig. 9. Predicting a) strength variability and b) relative errors of concrete variability, using the Mono-Objective and Multi-Objective approaches (experimental data).

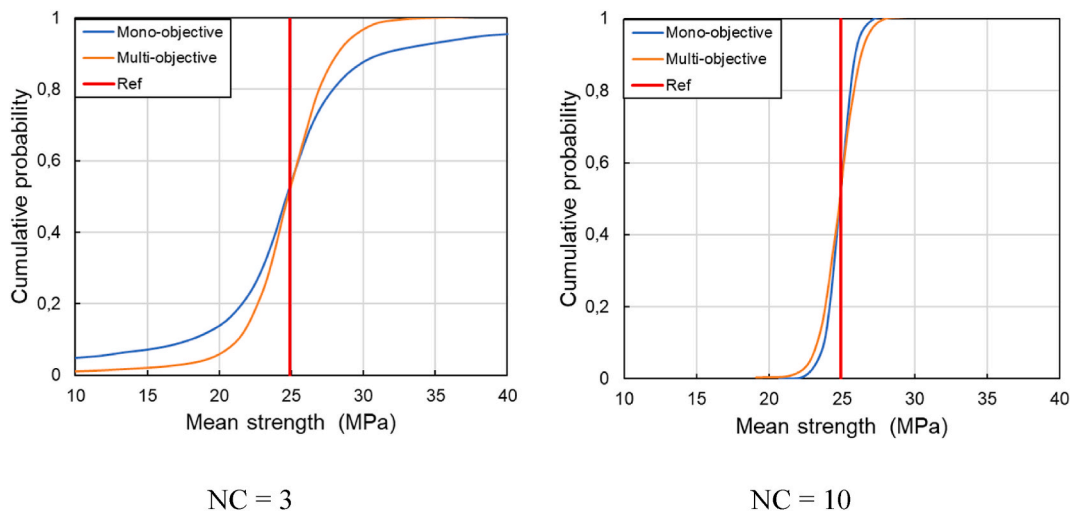


Fig. 10. CDF curves of mean strength using Mono-Objective approach and Multi-Objective approach (synthetic data).

simultaneously. It also facilitates the reduction of core samples required by optimizing the sampling strategy, thereby improving efficiency and reducing costs while maintaining the desired level of quality.

Overall, the developed methodology offers a practical tool for engineers and researchers to enhance the assessment of concrete strength in practice. It provides a reliable and efficient approach that combines NDT techniques and multi-objective optimization,

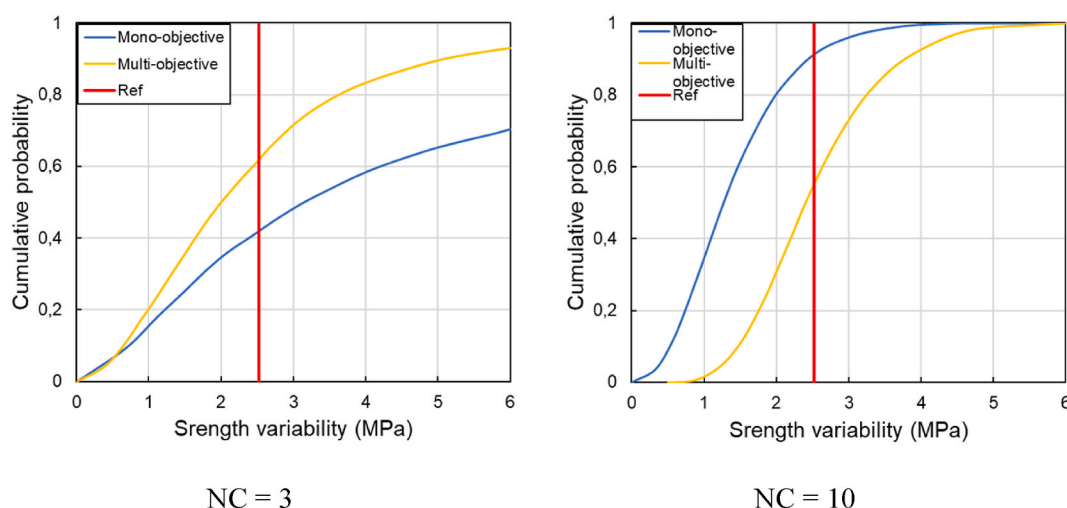


Fig. 11. CDF curves of concrete variability using a) Mono-Objective approach and b) Multi-Objective approach (synthetic data).

Table 3

Fitting and prediction errors as a function of the number of samples resulting from the experimental database analysis.

Number of cores NC	Fitting errors RMSEfit (MPa)				Prediction errors RMSEpred (MPa)							
	RH	UPV	SonReb	Multi-objective	SonReb	Mono-objective	RH	UPV	SonReb	Multi-objective	SonReb	Mono-objective
3	2,35	2,70	2,22		0,01		7,68	8,70	5,55		24,03	
5	3,50	4,01	3,08		2,15		5,96	6,72	4,97		5,93	
7	3,93	4,49	3,41		2,75		5,57	6,25	4,75		4,97	
9	4,15	4,73	3,58		3,04		5,38	6,08	4,62		4,66	
11	4,30	4,89	3,67		3,21		5,29	5,96	4,54		4,47	
13	4,38	5,01	3,73		3,32		5,23	5,89	4,44		4,34	
15	4,46	5,11	3,79		3,42		5,17	5,85	4,40		4,28	
17	4,50	5,14	3,80		3,46		5,14	5,83	4,36		4,22	
20	4,56	5,21	3,85		3,55		5,11	5,76	4,31		4,16	

enabling an accurate evaluation of mean strength and variability. By adopting this methodology, professionals in the field can improve their understanding of concrete performance, make informed decisions, and ensure the integrity and safety of structures. The significant advantage lies in the fact that this methodology requires only one tool, a custom-developed calculation code, which engineers can easily generate and implement, making it easily accessible and applicable in various settings.

5.1. Perspectives

More samples from other existing buildings could be gathered for future research for additional examination. Other non-destructive techniques can also be combined as electrical resistivity. Further work is to study the effect of conditional selection of test locations, which may improve the quality of the assessment. Different sampling plans of core locations are being studied and multi-objectives optimization will be used for the identification of conversion model in the case of combining NDT techniques.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data availability

Data will be made available on request.

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