



Optimisation de l'intégration d'EnR et de batteries en soutien aux réseaux électriques existants intégrant une demande variable et incertaine

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Spécialité : Energétique et Thermique

Par

Sara FAKIH

Optimisation de l'intégration d'EnR et de batteries en soutien aux réseaux électriques existants intégrant une demande variable et incertaine

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Abstract

Due to the energy transition, worldwide electrical energy systems are subject to deep transformations in the energy production and distribution systems, illustrated by increased usage of decentralized renewable or zero-carbon emissions production units. In particular, electricity generation from renewable sources (hydro, wind, and solar PV) is on track to grow strongly around the world to meet the forecasted increase in global electricity demand and to fulfill the local authorities' commitments to energy transition policies. The hard prediction and control of these renewables increase the complexity of the electrical system planning process. To tackle these complexities, Electrical Power System Models (EPSM) for planning and operation optimization are developed.

In this thesis, a dynamic linearized AC-optimal power flow (DLOPF) model is developed based on a successive linear programming resolution approach of the AC OPF model. In the first step of the work, the DLOPF model enables the identification of the need for power production for each bus of the grid on an hourly basis by using the concept of virtual generators. This information helps generate and assess interesting scenarios of renewable energy and storage unit deployment. This methodology is tested on a case study of an undersized network in the context of increasing electricity demand.

In a second step, based on the DLOPF model coupled with an optimization stage, an EPSM is developed following a bi-level approach. This model optimizes the size and planning of Renewable Energy Sources (RES) and Battery Energy Storage (BES) while taking into account cost minimization and carbon constraints. The upper level implements a Particle Swarm Optimization (PSO) model and the lower level the DLOPF. The PSO sizes and identifies the placement of the BES systems and DLOPF places and sizes RES in a spatial-temporal framework. This combination helps to dispatch power generation and storage in a network in the context of increasing demand, avoiding the need to reinforce the grid.

Finally, an Uncertainty Analysis (UA) coupled with a Sensitivity Analysis (SA) is used to assess the impact of demand uncertainty (due to its unpredictable variability) at each bus on the EPSM and the proposed grid performance indicators.

Keywords: Energy planning, Bi-level optimization, Dynamic linearized OPF, Electrical network, Renewable energy sources, Battery energy storage, and sensitivity analysis

Résumé

En raison de la transition énergétique mondiale, les systèmes d'énergie électrique sont soumis à un ensemble de transformations profondes des systèmes de production et de distribution d'énergie illustrées par l'utilisation accrue d'unités de production décentralisées renouvelables ou à faible émission de carbone. En particulier, la production d'électricité à partir de sources renouvelables (hydraulique, éolienne et solaire photovoltaïque) est en passe de croître fortement dans le monde pour répondre à l'augmentation prévue de la demande mondiale d'électricité et aux engagements des collectivités dans leurs politiques de transition énergétique. Cependant, la prédiction et le contrôle rigoureux de ces énergies renouvelables augmentent la complexité du processus de planification du système électrique. Pour faire face à ces complexités, des modèles de systèmes d'alimentation électrique (EPSM) pour la planification et l'optimisation de l'exploitation sont développés.

Dans cette thèse, un modèle dynamique linéarisé AC-Optimal Power Flow (DLOPF) est développé sur la base d'une approche de résolution de programmation linéaire successive du modèle AC OPF. Dans la première étape du travail, le modèle DLOPF permet d'identifier le besoin de production d'électricité pour chaque bus du réseau sur une base horaire, en utilisant le concept de générateurs virtuels. Ces informations permettent de générer et d'évaluer des scénarios de déploiement d'énergies renouvelables et d'unités de stockage. Cette méthodologie est testée dans le cas d'un réseau sous-dimensionné dans un contexte d'augmentation de la demande d'électricité.

Dans un second temps, le modèle DLOPF est couplé à une étape d'optimisation pour proposer un EPSM suivant une approche bi-niveau. Ce modèle optimise la taille et la planification des sources d'énergie renouvelables (RES) et du stockage d'énergie par batterie (BES) tout en tenant compte de la minimisation des coûts et des contraintes d'émissions carbone. Le niveau supérieur utilise un modèle d'optimisation par essaims de particules (PSO) et est responsable du dimensionnement et du placement des BES. Le niveau inférieur (DLOPF) place et dimensionne les RES dans un cadre spatio-temporel en considérant les résultats du niveau supérieur. Cette combinaison permet de répartir la production et le stockage d'électricité dans un réseau dans un contexte d'augmentation de la demande, en évitant le renforcement le réseau.

Enfin, une analyse d'incertitude couplée à une analyse de sensibilité est utilisée pour évaluer l'impact de l'incertitude de la demande (due à sa variabilité imprévisible), à chaque bus, sur les résultats de l'EPSM et les indicateurs de performance du réseau proposés.

Mots-clés: Planification énergétique, Optimisation à deux niveaux, OPF linéarisé dynamique, Réseau électrique, Sources d'énergie renouvelables, Stockage d'énergie par batterie, analyse d'incertitude et de sensibilité

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Résumé Substantiel

I. Introduction générale

Contexte environnemental

En 2021, plus de 15 événements météorologiques extrêmes ont été enregistrés [1]. Parmi ceux-ci, les inondations qui ont touché l'Allemagne, la France et d'autres pays européens [2]. Ces catastrophes météorologiques ont mis en évidence les risques d'un changement climatique non contrôlé et ont provoqué la misère pour des millions de personnes dans le monde entier. Aujourd'hui, 90 % de la population mondiale respire un air pollué, ce qui entraîne plus de 5 millions de décès par an [3]. L'humanité ne pourra probablement pas empêcher la Terre de se réchauffer, au moins temporairement 1.5°C au-dessus des niveaux préindustriels, selon le dernier rapport du Panel intergouvernemental des Nations Unies sur le changement climatique (IPCC) [4]. Ainsi, des actions agressives visant à réduire les émissions de gaz à effet de serre et à extraire le carbone de l'atmosphère pourraient limiter le réchauffement futur de la planète. Cependant, le rapport du IPCC indique que le coût des sources d'énergie renouvelables (EnR), telles que les éoliennes et les panneaux solaires photovoltaïques (PV), a considérablement baissé au cours de la dernière décennie [5]. Ceci, ajouté à des actions de planification énergétique appropriées, facilitera leur intégration dans le mix énergétique mondial et contribuera à atténuer le réchauffement de la planète. D'où la nécessité de la transition énergétique.

Transition énergétique

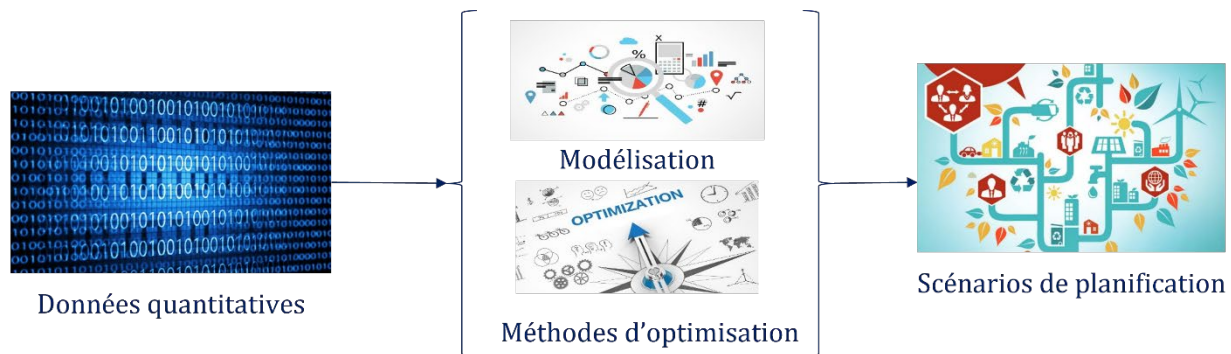
La transition énergétique est le changement des techniques de production vers une production renouvelable, une sobriété énergétique et une meilleure efficacité énergétique des systèmes. Elle consiste à passer des combustibles fossiles (pétrole, gaz et charbon) et des systèmes de production non renouvelables à un système plus économique basé sur des sources d'énergie décarbonée et renouvelables telles que le soleil (énergie solaire), le vent (énergie éolienne), l'eau (énergie hydraulique) ainsi que la terre (géothermie). Cela concerne toutes les activités humaines, et notamment le **secteur électrique**, car il occupe une place centrale dans les systèmes énergétiques modernes par la diversité de ses usages.

Pilotables électrique doit intégrer une production accrue provenant de sources renouvelables : ces sources sont difficilement prévisibles, fortement variables et faiblement pilotables. En plus, l'augmentation de la demande en électricité aboutit à un déséquilibre entre l'offre et la demande. La transition énergétique débute par une démarche territoriale qui nécessite des schémas directeurs, des feuilles de route, des projets plan climat-air-énergie territorial (PCAET), etc. Cette transition implique une diversité d'acteurs comme les autorités organisatrices de la distribution d'électricité (AODE), les gestionnaires du réseau, les consommateurs et les producteurs. La transition énergétique est généralement accompagnée par une transition numérique via la donnée qui comporte à la fois des données propres aux acteurs et des données exogènes. La nécessité d'évaluer l'impact de la demande sur la production en identifiant les voies d'un développement à long terme du secteur énergétique exige une planification énergétique.

Planification énergétique

La planification énergétique est le processus par lequel les stratégies d'investissement, les politiques et les objectifs nationaux ou régionaux sont définis sur la base d'une analyse quantitative des scénarios du secteur énergétique. Des modèles de planification énergétique (EPSM) sont développés. Ces modèles de planification énergétique permettent de prendre des décisions sur : la localisation, le dimensionnement et le pilotage des systèmes par une analyse technico-économique. Comme le montre la Figure 1, les EPSM sont des modèles numériques qui utilisent des données quantitatives pour leurs calculs. Ce processus demande une modélisation du système énergétique et des méthodes d'optimisation pour définir des scénarios de planification qui satisfont les contraintes définies au moindre coût.

Figure 1: Différentes étapes de planification énergétique



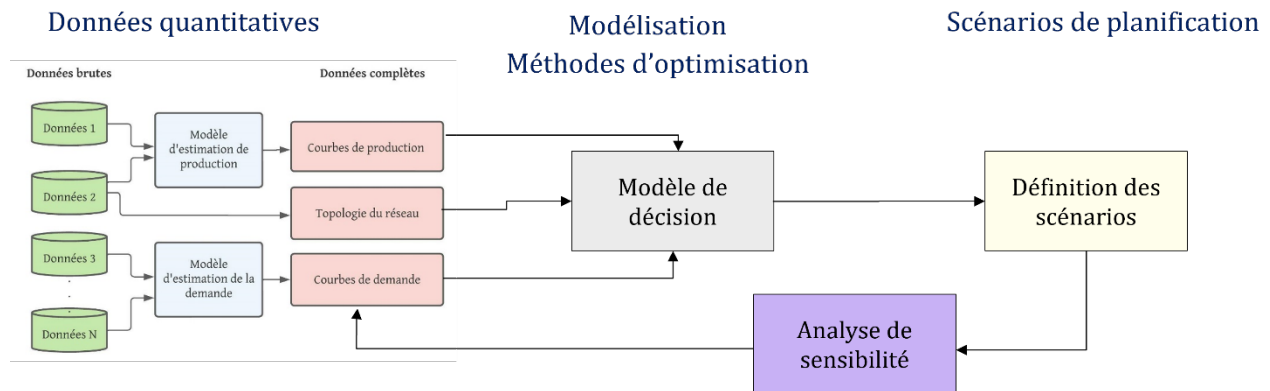
II. Problématique et objectifs du travail de thèse

L'approche de planification énergétique proposée dans le cadre de la thèse est présentée dans la Figure 2. En premier temps, des données brutes sont collectées en entrée des modèles d'estimation de la production et de la demande afin de produire des données complètes (e.g. courbes de production et de demande). Ces données complètes font l'entrée du modèle de décision basé sur la modélisation et les méthodes d'optimisation dans le but de définir des

scenarios de planification. Les questions scientifiques autour desquelles la thématique de la thèse se présente sont les suivantes :

1. Quelles solutions pour la modélisation du réseau dans une perspective d'analyse de l'intégration et du stockage des EnR en tenant compte des caractéristiques du réseau?
2. Quelles stratégies d'optimisation à mettre en œuvre ?
3. Comment l'incertitude de la demande influe-t-elle sur la planification énergétique ?

Figure 1: Approche de planification énergétique



L'objectif principal est de développer un outil de simulation, de modélisation et d'optimisation de l'intégration des EnR et du stockage dans le réseau électrique existant. Ce modèle considère tous les paramètres d'opération du réseau électrique. Pour cela, à travers une modélisation optimale des flux de puissance, des stratégies de planification et d'exploitation du réseau électrique sont explorées au cours de cette thèse. En plus, ce travail vise à étudier l'analyse de sensibilité de l'incertitude de la demande électrique sur les scénarios énergétiques proposés.

Données quantitatives : Estimation de la demande

La demande d'électricité augmente dans de nombreux pays en raison de l'augmentation de la population. Elle varie pour chaque pays en fonction des conditions climatiques, du contexte économique, social et culturel, etc. La charge électrique totale du système est généralement calculée et connue, et de nombreuses données sur les consommations historiques sont disponibles. À court terme, la charge électrique peut être estimée pour déterminer l'engagement des unités de production, mais pour la planification de la production, une prévision à plus long terme est nécessaire [6].

Les modèles de prévision de la charge estiment une courbe d'énergie annuelle qui inclut la demande de pointe annuelle. Ces modèles dépendent généralement de la disponibilité des données en provenance de plusieurs sources et bases de données. Et par suite, ils sont donc sensibles à la qualité hétérogène des données d'entrée et peuvent donc présenter des

incertitudes. Cela vaut la peine d'étudier l'effet des incertitudes sur la qualité des scénarios de planification définis.

Dans cette thèse, une partie de l'estimation de la demande est faite en utilisant un modèle de prévision de charge qui s'appelle MOSAIC, ce dernier utilise des données d'entrée (base de données logement, équipements électriques, etc.) dont la qualité hétérogène conduit à des courbes non-exactes qui contiennent des incertitudes. Les incertitudes sont donc à caractériser afin de faire des études de sensibilités des modèles EPSM.

Modélisation et méthodes de décision : Modèle de décision

Le dimensionnement et le placement optimaux des énergies renouvelables et des dispositifs de stockage nécessitent des outils et des méthodes d'optimisation rapides et précis qui reflètent bien les technologies d'EnR, de stockage, ainsi que le système électrique (dont la stabilité du réseau) et de la faisabilité économique. Ces outils permettent d'obtenir des solutions techniquement réalisables et facilitent l'intégration des futurs systèmes.

Un nombre considérable d'études utilisent des méthodes d'optimisation pour analyser le fonctionnement, la planification du système électrique [7] et l'optimisation du placement et du dimensionnement des énergies renouvelables et du stockage. Elles ont pour but de minimiser le coût total du système électrique [8] en positionnant de manière optimale les énergies renouvelables [9]. Il faut à la fois optimiser la capacité des systèmes (dimensionnement) et la coopération entre les unités de production et de stockage dans le système énergétique intégré (pilotage) afin d'améliorer les performances du système [10], etc. Concernant la modélisation détaillée des réseaux, l'OPF (Optimal Power Flow) est reconnu comme l'outil le plus adapté [11] et peut être utilisé pour modéliser aussi bien les systèmes de distribution que de transmission, en incluant les utilisateurs finaux et les générateurs, tout en respectant les contraintes du réseau. L'OPF a de nombreuses applications dans le secteur de la planification de l'énergie (ex : intégration optimale des EnR [12], [13], contrôle économique optimal de la gestion de la charge avec un système de stockage d'énergie [14]).

Comme les modèles traditionnels de flux de puissance [15], l'OPF détermine le courant, la tension et la puissance injectée dans un réseau de distribution électrique. Cependant, l'OPF cherche à minimiser les pertes ou le coût de production en répartissant de manière optimale la production des systèmes électriques connectés au réseau. Dans le travail présenté dans cette thèse, un algorithme OPF linéarisé et étendu pour effectuer une analyse multi-période est développé. L'analyse multi-période est importante en présence de variables dépendant du temps, comme les dispositifs de stockage qui nécessite une modélisation dynamique.

Analyse d'incertitude et analyse de sensibilité

Les modèles de prévision de la charge sont utilisés pour prédire les comportements futurs de la demande qui serviront d'entrée au modèle de planification optimale. L'efficacité de ce type de modèle dépend en amont des aspects stochastiques de la demande (comportements, occupation des bâtiments, etc.), et en aval de la précision et de la fiabilité de ses résultats. Ainsi, lorsqu'elle se propage dans le modèle, toute incertitude dans les entrées d'un modèle due à un manque de connaissances, peut rendre sa sortie incertaine. Il est donc crucial de comprendre l'étendue des impacts de l'incertitude en utilisant l'analyse d'incertitudes et de savoir si celles-ci ont un effet significatif ou mineur sur les résultats finaux. Par conséquent, il est nécessaire de disposer de techniques robustes et rigoureuses qui peuvent fournir des informations quantifiables sur l'impact de l'incertitude des données d'entrée (ici la variabilité de la demande) sur les sorties du modèle.

Les techniques d'analyse de sensibilité (AS) intègrent un ensemble de méthodes qui visent à identifier les paramètres d'entrée les plus importants entraînant la variabilité des résultats du modèle.

Dans cette thèse, des macro-paramètres décrivant la variabilité des courbes de demande sont définis. Les incertitudes de ces macro-paramètres de la demande sont quantifiées et analysées. La sensibilité des indicateurs économiques et techniques de sortie du modèle à la variabilité de ces macro-paramètres (et sur les scénarios de planification énergétiques) est étudiée en utilisant une méthode de régression (Pearson).

III. Structure générale de la thèse

Ce travail est présenté en six chapitres :

1. Le **premier chapitre** présente une introduction générale sur l'état d'urgence climatique, la transition énergétique ainsi que l'importance des stratégies de planification énergétique. L'introduction présente de plus le positionnement de la problématique traitée et les objectifs du travail.
2. Le **chapitre 2** présente une étude de la littérature récente relative aux modèles de planification et de pilotage des systèmes d'énergie électrique (EPSM) basés sur des méthodes d'optimisation. La revue de littérature couvre les modèles de planification et d'opération ainsi que les méthodes de dimensionnement et les indicateurs utilisés dans ces modèles. De même, plusieurs approches et travaux sur les incertitudes des EPSM sont ensuite présentées. Cette synthèse bibliographique débute par la présentation des méthodes de prévision de la charge, des méthodes de caractérisation et d'analyse des incertitudes et arrive à la revue de la littérature des méthodes d'analyse de sensibilité et de leur application aux modèles énergétiques.

Ce chapitre compare les caractéristiques des différents EPSM au regard des dernières parties concernant l'approche EPSM proposée dans cette thèse. Les modèles existants utilisent des méthodes de dimensionnement et des indicateurs d'évaluation différents en fonction de leur type (planification, exploitation) et du réseau visé (transmission, distribution). La plupart des modèles existants dans la littérature n'incluent pas le réseau de distribution. Les modèles présentés sont largement basés sur des méthodes d'optimisation non-linéaires et/ou heuristiques ce qui augmente le temps de simulation surtout en ajoutant les composantes temporelles pour rendre le modèle dynamique. Il est donc nécessaire de disposer d'un modèle qui combine la planification et l'exploitation. Ce modèle doit être basé sur une approche linéaire et dynamique pour couvrir une durée définie et visualiser le comportement du réseau à chaque pas de temps. Ce modèle doit utiliser une méthode de dimensionnement qui considère divers indicateurs d'évaluation, qui soit adapté à différentes échelles de réseau (distribution et transmission), et qui permette une analyse de sensibilité globale.

3. Le **chapitre 3** présente l'approche générale de l'EPSM proposé pour répondre aux limitations discutées dans le chapitre précédent. L'EPSM proposé peut optimiser à la fois la planification et le pilotage du réseau électrique. Il couvre les deux types de réseaux (distribution et transmission). Le modèle général comprend un algorithme d'optimisation hybride à deux niveaux basés sur un modèle PSO méta-heuristique en niveau supérieur et un modèle de flux de puissance optimal en niveau inférieur pour effectuer la planification et le pilotage simultanément, tout en intégrant les sources d'énergie renouvelables (EnR) et le stockage d'énergie par batterie (BES). Deux indicateurs différents sont choisis ici : l'indicateur économique en minimisant le coût actualisé de l'énergie, et l'indicateur environnemental pour minimiser les émissions de gaz à effet de serre CO₂ en utilisant la méthode ε -contrainte. Pour l'optimisation des opérations, contrairement à la plupart des modèles qui utilisent l'OPF, le modèle développé inclut un AC-OPF en linéarisant les équations pour assurer une solution globale optimale, qui est utilisée par le niveau inférieur du modèle. Le modèle développé permet d'établir des solutions de planification comprenant le dimensionnement et la localisation des EnR et des BES, par une modélisation physique du réseau détaillé et en considérant la demande à chaque pas de temps pendant la période ciblée. Pour les cas où le potentiel de production est insuffisant pour assurer l'équilibre, une solution est garantie avec la considération de nouveaux éléments inclus dans notre approche appelés générateurs virtuels.

La structure générale du modèle EPSM est abordée dans le chapitre 3. Les détails du modèle à deux niveaux, y compris leurs équations (fonctions objectifs et contraintes) et les méthodes d'optimisation utilisées pour les résoudre y sont détaillés. Enfin, la linéarisation du modèle OPF est vérifiée en comparant les résultats à ceux obtenus à partir d'une référence non linéaire.

4. Le **chapitre 4** développe un modèle OPF linéarisé et dynamique (DLOPF) pour générer des scénarios et les résultats de l'EPSM détaillés dans le chapitre 3. Pour évaluer les performances de l'EPSM dans le contexte d'un réseau existant et d'une demande évolutive, deux applications différentes sont présentées dans ce chapitre. La première utilise uniquement le DLOPF sans la partie métaheuristique. DLOPF est appliqué à l'étude d'un cas de référence IEEE de 30 bus pour simuler le comportement du réseau en l'état sans EnR en premier temps. Une solution réalisable est garantie même dans le cas de l'insuffisance des générateurs existants, grâce à l'intégration des générateurs virtuels. Ces générateurs virtuels sont supposés possibles sur tous les nœuds pour pouvoir identifier les points du réseau en déficit de production et essayer de proposer des scénarios d'intégration d'EnR et de stockage. Plusieurs scénarios d'intégration d'EnR et de batteries sont ainsi simulés et comparés.

Les résultats obtenus montrent la capacité de l'outil DLOPF à cartographier le comportement spatio-temporel des générateurs, des énergies renouvelables, du réseau et des BES dans le réseau. Le fait de savoir comment l'énergie est répartie dans le réseau et les branches dans lesquelles elle transite permet de mieux compléter le système sans renforcement des lignes. Les indicateurs de performance (facteur de charge individuel, facteur de charge global, etc.) étudiés dans les cinq scénarios considérés, utilisables dans un processus de décision (planification énergétique), montrent l'intérêt de l'approche en termes d'efficacité énergétique et économique.

Dans une deuxième application, le modèle EPSM à deux niveaux PSO-DLOPF est appliqué à la fois pour le dimensionnement des énergies renouvelables et des batteries de stockage. Le chapitre commence par une introduction qui présente les données d'entrée utilisées dans les différentes applications.

Les résultats obtenus à partir de l'EPSM montrent la capacité du modèle à planifier et à piloter le réseau, en plaçant et en dimensionnant de manière optimale les EnR et les BES, tout en respectant les contraintes liées aux émissions de carbone et en minimisant le LCOE. Ce modèle à deux niveaux souligne par ailleurs l'importance du stockage et de sa conception en termes de spécifications des batteries. Cependant, l'obtention de ces résultats requière un temps de calcul important du fait de l'utilisation de méthodes métaheuristiques (40 heures par scénario).

C'est pourquoi le chapitre suivant propose un cadre pour l'analyse de sensibilité en utilisant un EPSM plus rapide à partir du modèle à deux niveaux (niveau haut PSO et niveau bas DLOPF), en considérant de manière simplifiée le dimensionnement des batteries (sans tenir compte des détails des spécifications des batteries : durée et puissance de charge).

5. Les chapitres précédents montrent que l'EPSM est un outil puissant pour concevoir efficacement les EnR et les BES afin de réaliser la planification et le pilotage énergétique des systèmes. Cependant, l'EPSM est sensible aux incertitudes due à la variabilité de la demande, en particulier ses composantes stochastiques

(comportements, occupations, usages des équipements, ...). Une autre source d'incertitude est due à la qualité des données utilisées en entrée des modèles de demande (données souvent reconstituées à partir de bases de données ouvertes et/ou désagrégées à partir de ratios généraux).

L'existence de ces incertitudes peut affecter la qualité des résultats du modèle dans le processus de planification et potentiellement conduire à des solutions sous-optimales. Il convient donc de qualifier ces incertitudes et la sensibilité des modèles développés précédemment. Le **chapitre 5** présente donc un cadre méthodologique pour l'étude des incertitudes dans le modèle EPSM. Les entrées du modèle considérées dans cette partie du travail sont les courbes de demande extraites du modèle de prévision de la charge MOSAIC (hors du cadre de la thèse) ; les incertitudes sont d'abord caractérisées par l'identification des lois de distribution de la demande à chaque pas de temps (loi gamma dans le cas étudié). Les paramètres de cette loi ($\Gamma(\alpha_t, \beta_t)$) sont ensuite déterminés pour chaque pas de temps et utilisés pour générer un ensemble de séries temporelles de charges utilisées pour mener l'analyse de sensibilité. Pour chaque courbe, un ensemble de macro-paramètres (Puissance max, variances, énergie totale, etc.) décrivant ces courbes de demande sont définis et représentés afin d'étudier l'effet de ces caractéristiques sur les scénarios générés.

Les cas générés sur la base des courbes de demande d'entrée sont utilisés pour exécuter l'EPSM sur un réseau de distribution de 14 bus [16] afin de créer différents scénarios de planification et étudier l'effet des incertitudes sur la variabilité des scénarios obtenus. En plus des macro-paramètres d'entrée, plusieurs indicateurs de sortie (indicateurs économiques et techniques du réseau) sont définis pour mener l'analyse d'incertitude et effectuer l'analyse de sensibilité.

Ce chapitre utilise un modèle EPSM pour effectuer une analyse d'incertitude et de sensibilité. Les résultats montrent que les incertitudes ont des effets importants sur les sorties du modèle notamment la saturation du réseau dans les branches. Le paramètre qui a le plus d'impact est la demande totale d'énergie pendant la période de forte demande (hiver). Cela fait de ce paramètre un paramètre essentiel dans le dimensionnement des EnR, BES et donc dans la planification du réseau.

6. Le dernier **chapitre 6** résume les principaux résultats et observations qui sont discutés dans les chapitres précédents. Il met également en évidence les limites et les possibilités de compléter et d'améliorer le modèle et la méthodologie développés dans cette thèse. En outre, des pistes de recherche techniques pouvant être suivies en utilisant l'outil comme plateforme sont identifiées.

IV. Contributions et résultats principaux de la thèse

Les principales contributions sont résumées comme suit :

- Évaluation de l'importance des modèles de flux de puissance optimaux (OPF) par une étude bibliographique pour le développement de modèles de systèmes d'énergie électrique dans le contexte de la planification et de l'opération des réseaux électriques.
- Développement d'une méthodologie pour la simulation du fonctionnement du réseau par la localisation et l'estimation du manque de production afin d'établir des scénarios d'intégration des EnR et du stockage pour la planification énergétique, en soutien d'un réseau existant.
- Développement d'un modèle complet à deux niveaux incorporant un outil méta-heuristique en complément de l'OPF pour le dimensionnement et le placement optimaux simultanés des EnR et des batteries dans les réseaux existants, en intégrant les indicateurs économiques et d'émission de CO₂.
- Démonstration de la capacité du modèle à gérer un équilibre dynamique entre l'offre et la demande tout en optimisant les variables de dimensionnement et de pilotage (indicateurs économiques et d'émission de CO₂).
- Développement d'une étude pour la caractérisation et l'analyse des incertitudes de la demande et analyse de sensibilité des modèles développés à ces incertitudes dans le cadre de la planification énergétique via les réseaux de distribution électriques.

V. Perspectives de la thèse

Les principales perspectives sont résumées comme suit :

- Le modèle DLOPF pourra être couplé avec des méthodes d'aide à la décision multicritère, des modèles de demand side management pourront être utilisés ainsi que ce modèle peut inclure les autoconsommations individuelles et/ou collectives.
- Le modèle bi-niveau PSO-DLOPF pourra être développé pour décider sur le choix entre plusieurs technologies de batteries avec une prise en compte du cyclage. Des indicateurs de qualité de service réseau pourront être inclus.
- Dans l'Analyse de sensibilité, une prise en compte de davantage des paramètres incertains (coûts, efficacité, émissions, etc.) pourrait être considérée ainsi qu'une Analyse de sensibilité globale qui intégrerait une propagation des incertitudes sur toutes les étapes de planification.

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Nomenclature

Abbreviations and acronyms

EPSM	Electrical power system model
AC	Alternating current
DC	Direct current
OPF	Optimal power flow
DLOPF	Dynamic linearized optimal power flow
PV	Photovoltaic
WT	Wind turbines
PSO	Particle swarm optimization
CG	Classic generator
VG	Virtual generator
RES	Renewable energy sources
BES	Battery energy storage
O&M	Operation & Maintenance
LCOE	Levelized cost of energy
PDF	Probability density function
UC	Uncertainty characterization
UA	Uncertainty analysis
SA	Sensitivity analysis
VPI	Voltage profile Improvement
DSM	Demand side management
NLP	Non-linear programming
GA	Genetic Algorithm
LCA	league championship algorithm
EP	Evolutionary programming
ABC	Artificial Bee Colony
AI	Artificial Intelligence
MILP	mixed-integer linear programming
DLMP	Distribution Locational Marginal Price
SLP	Successive linear programming
LWOPF	line-wise optimal power flow
HS	harmony search
MOPSO	multi-objective particle swarm optimization
DP-RET	dynamic programming region elimination technique

TAC	Total Annual Cost
ACS	Annualized Cost of System
NPV	net present value
LCC	Life Cycle Cost
COE	Cost of Energy COE
PBP	payback period
TCC	total capital cost
TIC	total investment cost
CE	carbon emission
CFOE	carbon footprint of energy
GHG	greenhouse gas
EE	embodied energy
LPSP	loss of power supply probability
LOLP	loss of load probability
LSA	Local Sensitivity Analysis
GSA	Global Sensitivity Analysis
OAT	One at a time
MC	Monte-Carlos
VB	Variance based
PFA	Power flow analysis
REH	Renewable energy share
GLF	Global load factor
ILF	Individual load factor

Variables

P	Active power [MW]
Q	Reactive power [MVar]
S	Apparent power [MVA]
V	Voltage [V]
I	Current [A]
F	Objective function
D	Storage duration
p	p-value
C / J	Total operational/investment cost by production
Γ	Total cost by category
CC	Capital Cost
A	Installed surface of PV [m ²]
R	Ratio of installed WT capacity [MW]
v	Voltage magnitude
θ	Phase angle
G/B	Real/imaginary part of the admittance matrix
g/b	Conductance/susceptance of a branch
ϵ	Variables added to guarantee voltage positivity
E	Active energy level in the BES
X	Population for PSO
Δ_F	Normalized objective function approximation error between two successive iterations
Δ_{tol}	Tolerance for the objective function approximation error
Pr	Proportion factor

ve / xe	Particle velocity /position in the PSO
pe / ge	experience by itself / group's experience PSO

Parameters

C	Elementary operational cost
J	Elementary investment cost
O	Elementary O&M cost
$\mathbb{C}$	Elementary cost coefficient TAC
LT	Lifetime
ls	Lifetime of the overall system
En	CO ₂ emissions
Ta	CO ₂ emissions constraint [%]
α / β	Storage cost constants for BES investment cost calculation
r	Discount rate of the project
η	Battery efficiency
n	Number of segments needed to linearize branch flow limits
li	Group of lines for the branches' flow limits
ra	Random parameters between 0 and 1
w	inertia weight in PSO
a	Acceleration in PSO

Indices and sets

$\mathcal{N}$	Set of buses, $i, j \in \mathcal{N}$
$\mathcal{T}$	Set of all times, $t \in \mathcal{T}$
$\mathcal{B}$	Set of batteries
Nb	Number of batteries
$c / u / s / w$	Indices of buses with CG/VG/PV/WT
k	Iteration number in DLOPF
L	Iteration number in PSO
ll / ul	Lower level/Upper level
inv	Investment
$o\&m$	Operation and maintenance
op	Operational
d	Particle index in PSO
e	Case index

Upper-scripts

cg / vg	Classic generator/virtual generator
pv / wt	Photovoltaic/wind turbines
b	BES index
l	Load index at a bus
c	Charge index of the storage system
d	Discharge index of the storage system
p / q	Active/reactive power
max	Maximum value for the upper limit
cgT	Total produced by classic generators
inj	Injected at the bus
$best$	Best experience of parameter in PSO

Chapter 1: Introduction

1.1 Background

In 2021, more than 15 extreme weather events were recorded [19]. Among them, the widespread flooding across Germany, France and other European countries in July [20]. These weather disasters highlighted the risks of unmitigated climate change and brought misery to millions around the world. Today, 90% of the world's population breathes polluted air, leading to over 5 million premature deaths yearly [21]. Humanity probably isn't going to prevent Earth from at least temporarily warming 1.5°C above pre-industrial levels, according to the latest report from the United Nations Intergovernmental Panel on Climate Change (IPCC) [22]. Thus, aggressive actions to curb greenhouse-gas emissions and extract carbon from the atmosphere could limit future global warming. However, The IPCC report indicates that Renewable Energy Sources (RES), such as Wind Turbines (WT) and Photovoltaic (PV) solar panels, have dropped significantly in cost over the past decade[23]. This, added to proper planning actions, will facilitate their integration into the worldwide energy mix and contribute to mitigate global warming.

1.1.1 Transition of the electrical network

A pathway toward transforming the global energy sector from fossil-based to zero-carbon RES fosters energy transition policies [24]. The energy transition is the change in energy generation techniques and energy consumption. It's about a shift from fossil fuels (oil, gas and coal) and non-renewable production systems towards a more economical and renewable system based on decarbonized and renewable energy sources such as the sun (solar power), wind (wind power) and water (hydraulic power). This covers all human activities, especially the electric sector, as it occupies a central place in modern energy systems by the diversity of its uses.

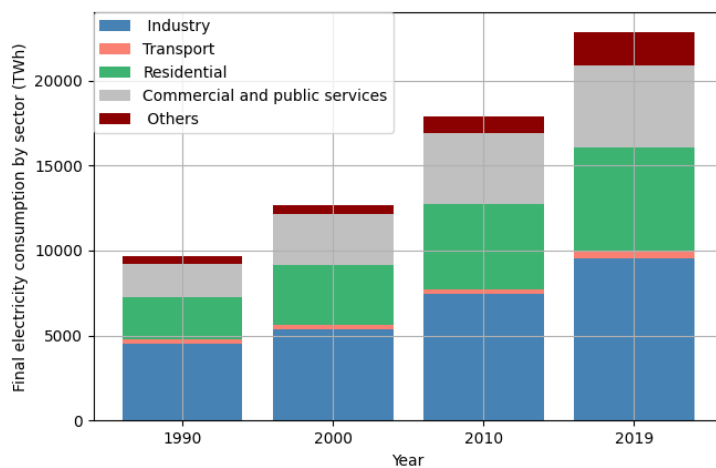


Figure 1–1: World electricity final consumption by sector, 1990-2019 (data taken from IEA [7])

Electricity is crucial for various essential sectors (Industry, transport, residential, commercial, etc. as shown in Figure 5–1. This means that the increase in total electricity consumption between 1990 and 2019 (from 9701 TWh to 22847 TWh) is due to increases in the various abovementioned sectors (Figure 5–1). However, this evolution of electricity consumption is not similar between the different sectors. The smallest variation compared to the others is marked at 42% for the transport sector, which already occupied only a minor part of the total consumption (1.8%). For the others, a variation of 52.7% is noticed for the industry, 58.5% for the residential, 59.8% for the commercial, and it arrives at 75.6% for the other sectors cumulated. And therefore, the worldwide electricity demand is going through a significant expansion and growth (500 TWh/year [25]), which makes it responsible for 22% of the final energy consumption in the world in 2019 [26]. This growing demand is one of the main reasons behind the increase in global CO₂ emissions of the power sector. Hence, the 6.9% increase in CO₂ emissions from the electricity between 2020 and 2021 is due to 5.9% of growth in electricity demand in 2021 [27]. This comes back to the call for Coal-fired power plants upon to meet half of the increase in global electricity demand in 2021. These emissions reached a record of 36.3 Gt in 2021 [28]. Therefore, an energy transition is essential to guarantee a future with easy access to decarbonized and high-quality electricity¹ [30] without compromising the environment. This transition affects the way electricity is produced, delivered, and utilized. Transmission and distribution grids are no longer only receptors of electrons from power lines but also, at times, supplying electrons to them [31]. With this transition, stabilizing power flows in electric grids has become more complex due to the hard prediction and control of distributed and intermittent renewables such as solar panels and wind turbines [30].

The energy transition scenarios

As stated by the International Renewable Energy Agency (IRENA) [32], “ *The energy transition is a pathway toward transformation of the global energy sector from fossil-based to zero-carbon by the second half of this century. At its heart is the need to reduce energy-related CO₂ emissions to limit climate change*”.

IRENA says that urgent actions are required on a global scale to achieve de-carbonization and that while energy transition is already underway in many parts of the world, more needs to be done. In fact, the penetration of RES, such as solar and wind, is increasing thanks to the higher requirements of worldwide governments to achieve goals related to emission reduction and energy independence [33].

¹ High quality electricity is generally meant to express the quality of voltage and/or the quality of current [29].

Renewables generated up to 26.3 % of worldwide global electricity generation in 2019, as presented in Figure 1–2 (16% hydropower, 5.3% wind, etc.) [34], and is expected to rise up to 45% by 2040 [35]. Most of the increase will likely come from solar, wind power, and hydropower [36].

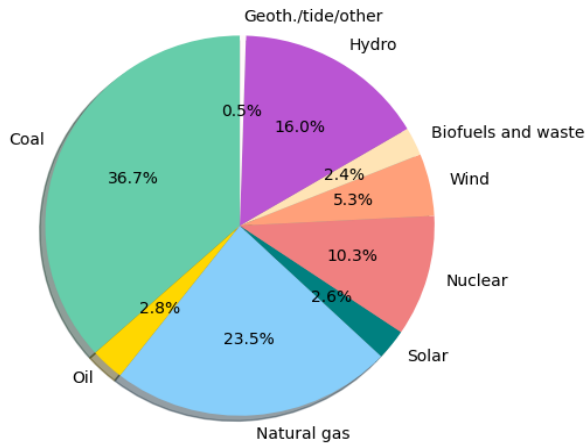


Figure 1–2: World gross electricity production by source, 2019 (data taken from IEA [25])

Several long-term scenarios are presented in the World Energy Outlook (WEO) [3]. These scenarios illustrate the choices that face the world’s decision-makers in the run-up to the crucial 27th Conference of the Parties (COP27). These scenarios set targets for CO₂ emissions until 2050. The WEO report presents 4 different scenarios with their corresponding CO₂ targets more or less optimistic, as depicted in Figure 1–3, where a gap between scenarios’ expectations is shown. The Net Zero Emissions (NZE) by 2050 sets out a strict but feasible path for the global energy sector to achieve net zero CO₂ emissions by 2050, where the Stated Policies Scenario (STEPS) estimates a return to similar emissions in 2050 to those of 2021 (34 Gt CO₂) with a slight increase then a drop between these two periods.

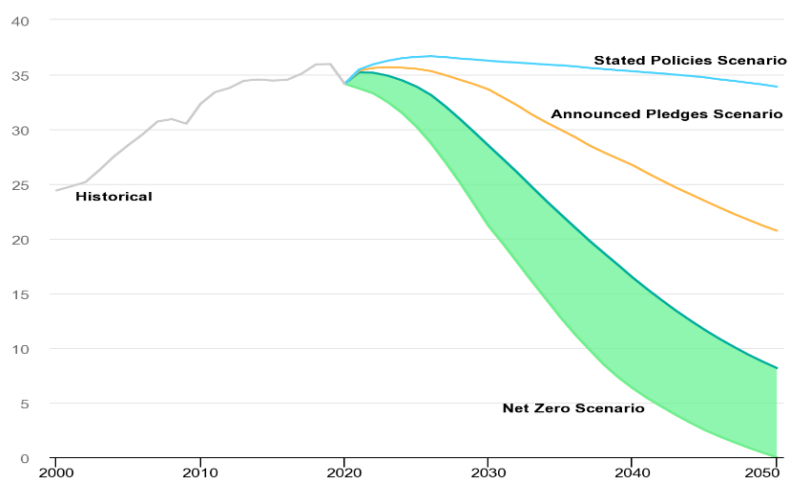


Figure 1–3: CO₂ emissions (Gt CO₂) in the WEO-2021 scenarios, 2000-2050 [37]²

The expected transformations in these scenarios rely heavily on the electricity sector, so an energy transition is narrowly focused on the electricity sector, which requires a significant increase in investment in generation and networks. Renewable energy is set to become the foundation of power systems around the world. Over the next decade, the commitments announced will lead to an expansion of renewables fast enough to keep up with the growth in electricity demand and reduce the need for fossil fuels in electricity [37]. The share of renewables is expected to increase to about 77% in 2050 in the NZE, where 69.1% are essentially wind turbines (35.5%) and solar panels (33.6%) as shown in Figure 1–4. By comparing Figure 1–4 to Figure 1–2, a disappearance of several sources of production is noticed. These sources are known to have high CO₂ emission factors (Coal, oil, etc.).

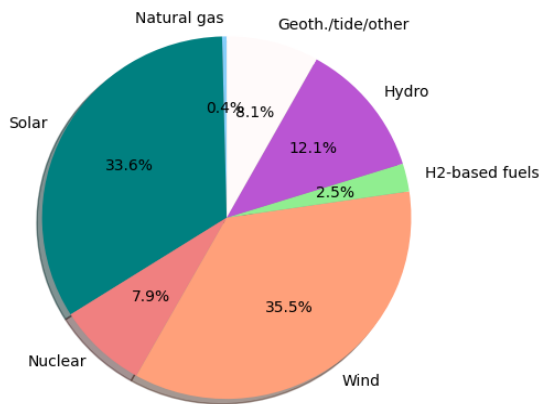


Figure 1–4: Expected electricity generation by technology in 2050 for the Net-Zero Emissions by 2050 scenario (data taken from [38])

1.1.2 The French electric power system

The full development of the electrical power system in France has been an arduous task over the last hundred years. France's electrical power system evolution began between 1880 and 1990. The three stages of power system development include initial electrification, expansion of the system to supply end users, and finally, ensuring the power supply quality [30].

An electrical network is a set of energy infrastructures that enable the flow of electrical energy from the production plants to the final consumers of electricity. This transfer is divided into three essential parts (Production - Transmission - Distribution).

² IEA, CO₂ emissions in the WEO-2021 scenarios, 2000-2050, IEA, Paris <https://www.iea.org/data-and-statistics/charts/co2-emissions-in-the-weo-2021-scenarios-2000-2050>, IEA. License: CC BY 4.0

1.1.2.1 Production

Electricity production in France is mainly generated by thermal power plants that use different energy sources: nuclear (69%) or fossil fuels (7%). Today, a growing variety of RES is used to produce electricity (hydraulic (13%), photovoltaic (3%), wind turbines (7%), etc.) [39].

1.1.2.2 Grid infrastructure

The transmission and distribution systems constitute the two main primary electric grid structures for the current architecture of the power system. These two systems are interconnected to transit electricity from centralized production sources to end-use clients while maintaining power quality, minimizing operational costs and reducing losses. Multiple voltage levels are used in the transmission and distribution systems connected via transformers at various stages to achieve this goal. The transformers are used to step down voltages to a level accessible for residential, commercial and industrial consumers. A representation of the electric system, including production, transmission, distribution, end-users and their interconnections, is shown in Figure 1–5.

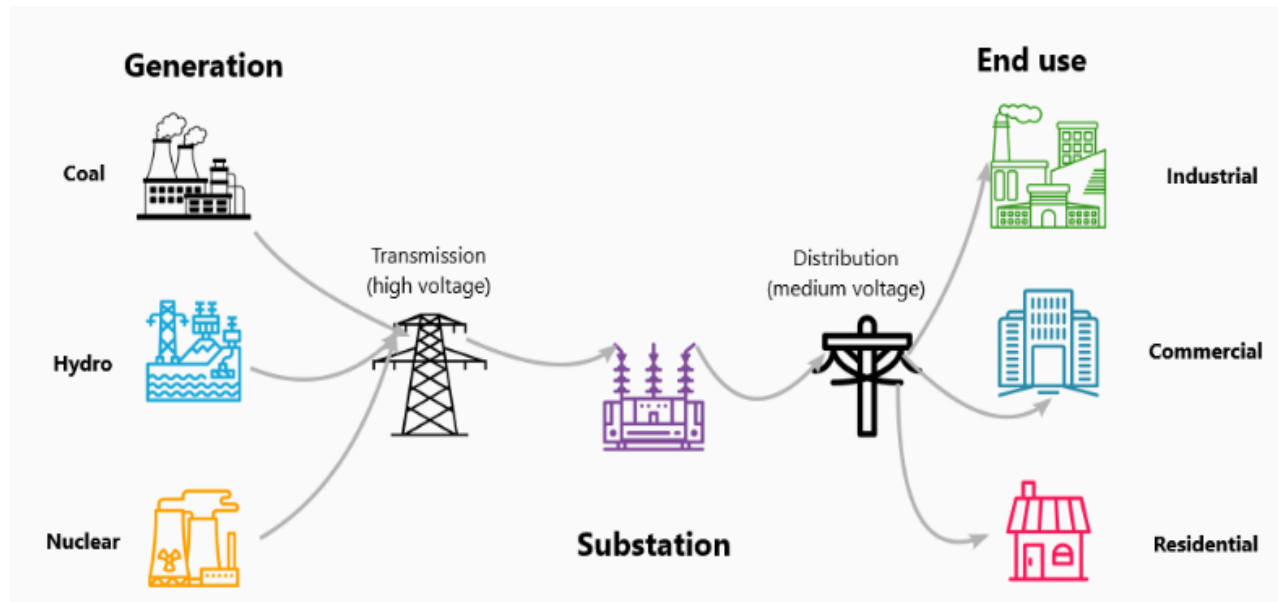


Figure 1–5: Elements of electrical power grid

Transmission

The transmission system comprises high-voltage transport lines (400 kV or 225 kV) connected to medium voltage (90 kV and 63 kV – repartition network). Some industrial clients are connected directly to the medium voltage transmission network. Other transformers called secondary substations are used to lower the voltage to the distribution level (less than 50 kV – standard IEC 60038) to which most commercial and residential customers are connected. The transmission system in France is managed by RTE [40].

Distribution

The electric distribution system is the lower voltage system; it distributes electrical energy on a local scale from the distribution points to most end-use customers: individuals, small and medium-sized businesses, etc. The distribution network is divided into two voltage levels: medium voltage HTA (less than 50 kV – standard IEC 60038) and low voltage BT (less than 1 kV – standard IEC 60038), with the standard connection voltage of most customers being 230 V. An HTA/BT substation is a local ensuring the connection between the medium and the low voltage network. The distribution system in France is mostly (95%) managed by Enedis [41].

1.1.3 Energy planning strategies

Energy planning is the process by which national or regional investment strategies, policies, and goals are defined based on quantitative analysis of energy sector scenarios. This process is often reinforced by energy system modeling [7]. Consequently, energy planning models (EPMs) are developed. This development started in the late 1950s but increased after the oil crisis of the 1970s in a reflection of the recognition of the impact of external political events on global and local energy supply [8]. It was necessary to assess the interconnections between the energy sources' supply and demand by identifying pathways for the long-term development of the energy sector [9].

EPMs play an essential role in developing the energy sector at global, national and regional levels by enabling informed decision-making about when, where, and how to invest in the energy sector. Nevertheless, given that some two-thirds of global Green House Gases (GHG) emissions come from the heat, electricity, and transportation sectors, the integration of the environmental aspects of energy demand and supply within EPMs became crucial, providing a comprehensive image of the interrelationships between energy, environment, and climate change [42].

EPMs are numerical models and utilize quantitative data for calculation. Thus, some essential elements could be defined to develop an EPM, which are the keys to differentiations between the models. The elements include the type, temporal and spatial resolution, scope and timeframe of the input and output variables regarding the nature of the data and the models' objectives. Optimization methods are frequently in EPMs to find planning scenarios that satisfy the defined constraints with the least-cost.

1.2 Problem statement

1.2.1 Planning strategies for electrical systems

The electric power grid is one of France's oldest and most well-developed structures. Therefore, all electrical generation planning is performed within the framework of modifying the existing system. The electrical planning strategy must find an investment schedule considering the current investment price, for example, the lifetime of the investment, the timing of the proposed investment concerning

the long-term investment strategy, etc. The process should start with an electricity load demand forecasting, followed by an evaluation to determine where and when additional generation is needed. Then, optimal capacity expansions are selected based on economic considerations and environmental target scenarios.

1.2.1.1 Increasing demand and load forecasting

Electricity demand is growing across many countries as the population increases. It varies for each country based on climate conditions, political strategies, social and cultural context, etc. The total system load is generally well-known, and much historical data is available. In the short term, the load can be forecasted accurately to determine generation units' commitment, but for generation planning, a longer time horizon forecasting is needed [43].

Load forecasting models estimate an annual load forecast energy curve (kilowatt-hours) that includes the annual peak demand (kilowatts). These models are generally dependent on data availability.

1.2.1.2 Integration of decentralized generation

The question is which type of generation technology (PV, WT or other) would make the most significant economic and environmental contribution to the system. This is resolved by combining an analysis of investment costs with an analysis of production costs and CO_2 emission targets. The type and the number of units that could be added in each geographical zone are predefined by the planners regarding the area's types (urban or rural), the installable surfaces, etc.

For the connection of decentralized generators, the procedure used by Enedis includes the verification of short circuit security, harmonics produced by the generator, perturbations of the communication system with safety components, maximum line capacity study, fluctuation in voltage profile, and indicating a set maximum possible current injected by the generator [44]. Thus, these regulations should be included in an electric planning model as grid constraints.

1.2.1.3 Storage

The intermittence nature of the RES and their dependence on the weather is a challenge associated with their integration into the power system. The storage systems are added to minimize the RES's curtailment and mitigate their congestion problems. Battery Energy Storage (BES) units absorb energy during periods when electricity production exceeds demand and discharge the electricity in the opposite case. When attempting to optimize a whole system, optimal sizing and location of BES need to be found considering synergy and coordinated operation of decentralized RES with the storage devices.

1.2.2 OPF analysis for planning and operational tools

The optimal sizing and placement of renewables and storage devices induce the necessity for fast and accurate optimization tools and methods that optimize the network and systems deployment while

considering the network's stability and economic feasibility. This allows for obtaining technically feasible solutions and facilitates the control and operation of such future systems [45].

A considerable number of studies use optimization methods for analyzing power system operation, planning [46] and optimizing the placement and sizing of renewables and storage, aiming to minimize the total cost of the power system [47], to optimally locate renewables [48], to optimize both the capacity and cooperation between production and storage units in the integrated energy system to improve the performance of the system [49], etc. However, to focus on the detailed modeling of networks, Optimal Power Flow (OPF) is recognized to be the most adapted tool to solve such analyses [50] and can be used to model the distribution and transmission systems with end-users and generators while respecting grid constraints. OPF has wide applications in the power planning sector [51].

Like traditional power flow models [52]–[54], OPF determines current, voltage and injected power in an electrical distribution grid. However, OPF seeks to minimize losses or the cost of generation by optimally dispatching the generation of electrical systems connected to the network. Moreover, an OPF algorithm can be extended to perform multi-period analysis. The multi-period analysis is important in the presence of time-dependent variables such as storage devices.

1.2.3 Uncertainty analysis and Sensitivity analysis

Load forecasting models are used to predict future demand behaviors to be used as input for the optimal planning model. Any model's worth depends on how accurate and reliable its output is. Thus, when propagated through the model, any uncertainty in a model's inputs owing to a lack of knowledge can also make its output uncertain. Therefore, it is crucial to understand the extent of uncertainty's impacts using uncertainty analysis and whether it has a significant or minor effect on the final results. Formerly, there is a need for robust and rigorous techniques that can provide quantifiable information about the impact of uncertainty on model outputs.

Sensitivity Analysis (SA) technics incorporate a set of methods that aim to identify the most important input parameters driving the model output variability in addition to the non-influential parameters whose uncertainty can be safely ignored.

1.3 Thesis work objectives

The main objective of this thesis is to develop a simulation, modeling and optimization tool that considers all the electrical network's operating parameters. For that, through optimal power flow modeling, strategies for planning and operations for the electrical network will be explored during this thesis. The main contributions are summarized as follows:

- Evaluation of the importance of optimal power flow models for the development of electrical power system models in the context of planning and operations of electrical grids

- Development of a methodology for the simulation of the grid's operation through locating and estimating the lack of production to support the definition of scenarios of RES and BES integration for energy planning
- Development of a full bi-level model incorporating meta-heuristic tool in addition to the OPF for the simultaneous optimal sizing and placement of RES and BES in existing networks concerning economic and CO2 emission indicators.
- Demonstration of the model's capacity in handling dynamic supply-demand equilibrium while optimizing economic and CO2 emission indicators.
- Development of a framework for the demand uncertainties characterization and analysis using the developed models for electrical planning in a distribution network.

1.4 Structure of the thesis

The present research aims to develop and present a novel model for electrical planning that would support energy transition to more sustainable energy. This work is presented in six chapters presented by Figure 1–6. The literature review conducted for this research is presented in Chapter 2;; the methodology followed in the present study is detailed in Chapter 3;; the results obtained using different optimization strategies are presented and discussed in Chapter 4;; the results of uncertainty and sensitivity analysis are presented and discussed in Chapter 5;; Chapter 6: concludes the present research and opens some perspectives.

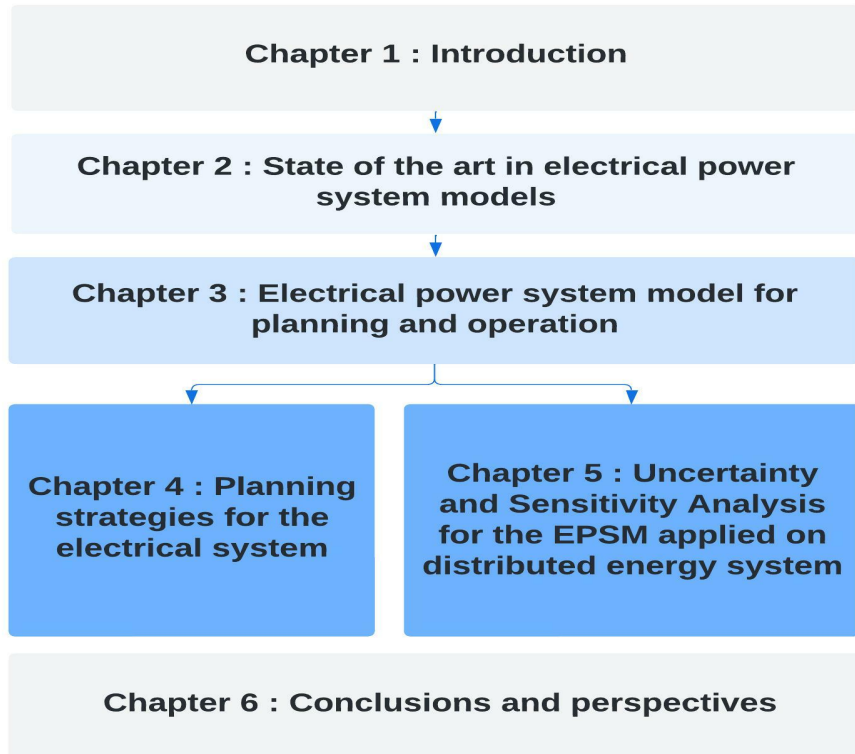


Figure 1–6: Thesis structure

Chapter 2: State of Art in Electrical Power System Models

2.1 Introduction

This chapter represents a survey of recent literature related to the electrical power system planning and operation models (EPSM) based on optimization methods. It ranges from the planning and operational models to the sizing methods and indicators used in these models. Studies of the uncertainties of EPSM are then presented. This begins with the presentation of load forecasting methods, uncertainty characterization and analysis methods and arrives at the literature review of sensitivity analysis methods and their application to energy models.

2.2 Electrical power system planning and operation optimization models

The purpose of developing Electrical Power System Models (EPSM) is to enable optimal system planning and operation [55]. EPSMs are used to analyze and evaluate system performance and review important system operations such as generation/load balance, line capacities and voltages. The nature, level of detail and software tools (programming language, optimization method, etc.) used for the development of the EPSM depend on the system itself, the phenomena involved and the targeted objectives of the study. This allows one to assess the impact of future growth patterns on the power system's reliable operation and find optimal solutions for planning [56] and operation[57]. The optimization models formed in the context of an electrical power grid are categorized regarding their optimization objectives, decision variables and study horizons into two main Groups: *planning* [58] and *operation models* [59]. Both categories are compared in Table 2-1 and detailed in the following parts.

Table 2-1: Electrical power system modeling methods

EPSM	Planning	Operation
Purpose of use	To study the influence in a long-term of power sector policies and technology organization on the energy mix [55].	To study in a short-term the effect of the dynamic of the generation, energy conversion and storage systems on the grid's operation [55]
Optimization objectives	- Minimize total system cost [60], [61], [62] - Voltage profile improvement [63], [64] - Minimization of power losses [59], [65]	- Minimization of the total generation cost [66], [67] - Maximization of grid stability against transient effects [68] - Minimization of emissions [69] - voltage profile improvement indices [66], [70]
Time horizon	Months / Years	Minutes/hours
Model output	- System lifetime energy supply - Annual fuel consumption - greenhouse gas emissions	- Minutes and hourly power flow - Generation and storage capacity dispatch

Software packages	• Generation costs • Generation and storage capacity dispatch	• Losses • Fuel consumption • Short-term emissions
	NEMS [60] – LEAP[71]– TIMES [61] – MARKAL [72], REMix [62] etc.	PowerFactory [73] – MATPOWER [74] – System optimizer (ABB), etc.

2.2.1 Planning models: Design-based models

EPSMs are mostly developed for optimal sizing or/and placement. The main purpose is to ensure that the system will continue to meet energy demand by upgrading the system [75]. Planning is sometimes oriented to long-term optimization using a monthly or annual time horizon, as shown in Table 2-1. EPSM can be formulated as a single or multi-objective optimization model. The typical planning issues are the followings: The first issue is the power generation mix selection and sizing that aims to achieve high cost-effectiveness and low environmental impact. The second issue is the sitting problem, including power source allocation with the objective of low power losses. The third is the network topology reconfiguration performed to reduce load imbalances, satisfy voltage profile requirements and minimize losses [76]. The voltage profile improvement (VPI) is adapted in planning models by varying RES penetration levels affecting the voltage profile and voltage deviation [77]. Voltage profile improvement VPI is used as the optimal placement index using voltage penalty functions as in [78]. The total cost minimization is commonly targeted in the planning models like for the optimal allocation of PV/BES in Lim et al.[79] and also in the common used planning software packages (NEMS[60] –LEAP[71]– MARKAL[72], REMix[62], etc.). Some tasks are applied in energy planning models to help achieve the objectives. Demand side management (DSM) is one of the tasks used to balance the value of the load with the available generation [80] and to improve the current generation and distribution of electricity while reducing the production cost [79]. Another task to help in the optimization of planning objective is the economic dispatch used in [11] and [12] based on a cost function that choose the appropriate energy mix able to reduce electricity costs. The expected outputs from an EPSM planning model are the total generation cost, gas emissions, generation and storage capacities and dispatch in addition to energy supply and fuel consumption.

Most of the EPSMs are classified as bottom-up models based on a detailed description of the technical components of the energy system [83]–[85]. The existing commercial planning software packages are cited in Table 2-1. The most common bottom-up software are TIMES [61], MARKAL [72] and MESSAGE [86] for national or regional geographic scales in a yearly timeframe. The spatial resolution detail is essential for renewables regarding their economic potential and generation cost that depend on their location [83]. However, the abovementioned planning energy system models (e.g., TIMES) are decoupled from power transmission and distribution system analysis. Therefore, many important constraints, such as voltage magnitude, phase angle and active/reactive power balances, are not considered [87].

2.2.2 Operational models: Optimal power flow models

Operational EPSMs are developed to ensure a power balance between supply and demand, to determine active/reactive power and economic dispatch and to study the effect of changes in the generation systems on the grid's operation. It is a short-term power system model with finer time resolution (hours or minutes). In this case, voltages, phase angles, and active and reactive power are considered. The operational models aim to reduce the total generation cost [88], minimize emissions [69], and maximize grid stability against transient effects [68]. Moreover, operational models aim to improve the voltage profile [66], [70]. Thus, the active/reactive injected power are optimized by analyzing their impact on voltage profiles as done in [89]. In other works [90], operational models are developed to maximize network benefits using Demand side management. In this case, the operational EPSM can be useful in determining the optimal allocation of demand-side resources. The expected outputs from operational models are the dynamic power flow, transport or distribution losses, generation cost in addition to emissions. The used time steps range from minutes to one hour.

Some of the existing software are listed in Table 2-1. This concerns unit commitment, economic dispatch, Alternating Current (AC) load flow analysis and Optimal Power Flow (OPF) [55]. The most common problem used for operational EPSM, including optimization, is the Optimal Power Flow (OPF). OPF problem considers operational variables (active and reactive power generation levels at a bus, voltage magnitudes and angles for each bus, etc.). The problem includes the power flow equations as equality constraints. The inequality constraints have the grid's safety constraints, such as maximum apparent power in the lines and acceptable voltage magnitudes and angle ranges.

2.2.2.1 Optimal power flow

The first OPF problem was introduced in 1962 by Carpentier [91] with a nonlinear programming (NLP) formulation [92], which can accurately describe the behavior of the power system. OPF includes an objective function that must be optimized (maximized or minimized). In general, the OPF schedule the power system decision variables in an optimal manner that simultaneously satisfies the power flow equality constraints and other technical inequality constraints (e.g., acceptable ranges of voltage magnitudes and angles and maximum apparent power). The resulting optimization problem is typically non-convex with mixed integer variables. The following Table 2-2 resume the OPF properties and specifications.

Table 2-2: Overview of OPF specifications

Extended OPF versions	• Static OPF: It optimizes the objective function at a given time • Dynamic OPF: It covers multiple time periods • AC OPF: It represents AC power networks • DC OPF: It doesn't consider reactive power • Etc.
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Solution categories	• Local optimum: a point where the objective function value is smaller/greater than at nearby points but possibly greater/smaller than at a distant point. Nonlinear and non-convex problems have many local optima. • Global optimum: a point where the function value is the best (smaller/greater) solution than at all other feasible points.
Variables	• Independent: optimization variables (e.g., active/reactive power, voltages, etc.) / The number of optimization variables determines the solution space dimensions • Dependent (state variables): calculated based on optimization variables results.
Constraints	• Active/reactive power constraints: equilibrium between power generation and loads and grid losses, on the other hand. • Voltage magnitudes (V) constraints: lower and upper voltage security limits • Voltage angle (θ) constraints: lower and upper operating limits on voltage angles • Other constraints: maximum apparent power in branches, operational constraints related to storages and other producers (PVs, WTs, etc.)
Objective functions	• Single objective (e.g., Active power generation cost [13]) • Multi-objective (e.g., Active/reactive generation cost and carbon emissions [97])
Solution methods (Detailed in the next section)	• Conventional (mathematical) • Heuristic

2.2.2.2 Solution methods for OPF

Numerous OPF formulations have been developed, and many OPF solution methods have been proposed [98], [99], each with specific mathematical characteristics and computational requirements. The existing solution methods for OPF are categorized into two main groups: Conventional and non-conventional approaches.

- Conventional (mathematical) methods: They include Newton-Raphson [100] and Gauss-Siedel [101] numerical methods used to solve nonlinear programming [102] (objective

function and/or constraints are nonlinear), the Simplex resolution method used to solve linear programming [103] (objective function and constraints are totally linear), gradient methods [104], interior point method [105] and decoupling method[106], etc.

- Heuristic methods: They include the Genetic Algorithm (GA) [51]-[52], gravitational search algorithm (GSA)[109], league championship algorithm (LCA)[110], evolutionary programming (EP) [111], Particle Swarm Optimization (PSO) [112], Artificial Bee Colony (ABC) [113]and Miscellaneous Artificial Intelligence (AI) methods (e.g., Simulated Annealing (SA) technique [114]), etc.

The conventional methods are totally mathematical based and used to solve different-size OPF problems. Therefore, conventional methods suffer many shortcomings in solving the OPF problem [115]. Firstly, it is not possible to use them in practical systems because of their nonlinear characteristics; they cannot guarantee global optimality. Most of them can guarantee reaching an optimal solution, but the global optimum can be guaranteed only for LP problems as they are convex by nature [116]. Secondly, heuristic methods show superiority over conventional methods regarding problem handling (how the method deals with constraints, discrete variables and uncertainties), computational complexity and multi-objective optimization performance [117]. Still, they cannot guarantee to reach optimal global solutions.

Optimizing a grid consisting of a considerable number of buses leads to a high-dimensional problem and a high calculation burden. Using nonlinear OPF algorithms requires simplification strategies while conserving accuracy [30]. To overcome this challenge, linear programming (LP) formulations of OPF problems can be used [103]. These formulations are advantageous as they allow the use of well-developed LP solution methods, e.g., Simplex Method. In addition, they efficiently handle the inequality constraints like voltage and angles limits at all nodes with excellent convergence properties. Moreover, these methods ensure efficient treatment of inequality constraints, fast recognition of problem reliability, speed, infeasibility and excellent convergence properties. Also, the convex LP formulations guarantee a global optimal solution [50].

Since the LP approach is suitable for an optimal global solution, grid operators used approximate solution techniques based on LP and mixed-integer LP (MILP) to solve the DCOPF with loss factors. The DCOPF approach oversimplifies the physical problem (uses constant voltage, ignores reactive power, assumes small voltage angle differences and supposes resistances to be much lower than the reactance). DCOPF is acceptable if the ratio (resistance over reactance) of electrical lines is less than 0.25 and the voltage profile is flat [118]. However, DCOPF approximations are not accurate enough for operation algorithms in the context of distribution grids. Since DCOPF is based on a linear assumption about losses in the lines and does not consider reactive power flows, it is not appropriate for modeling distribution grids where losses and reactive power play an important role. In fact, reactive power transit in the distribution system can affect the voltage profiles.

Moreover, the voltage profile could not be considered flat for the transmission grid. The transmission grid's losses depend on the transmitted active and reactive power flow [119]; neglecting the reactive

power leads to underestimating the transmission losses. For all these reasons, applying the OPF model for both distribution and transmission networks requires efforts to incorporate all physical and operational constraints in ACOPF formulations.

To solve the ACOPF, conventional and heuristic methods are used. Among them are the equations linearization approaches. For example, the proposed approach by Alsaç et al. [104] takes advantage of the loose coupling between V and θ . It shows weakness in the over-solicited grids and in cases where losses are high. It also shows voltage magnitude violations. In contrast, coupled methods that keep the coupling between variables (between V and θ) respect bus voltage limits and reactive power requirements and can take fewer iterations [103]. A coupled method was applied by Franco et al. [120] using least-squares regression to obtain a non-iterative linear approximation of the ACOPF in terms of voltage components. However, this non-iterative approach ignores numerous physical constraints, especially reactive power and branch limits. It is only applicable to small networks. Taylor series expansions are used to derive the linear approximation [121], [122], [123], where the reactive power and voltages are considered. For the distribution network, linearized OPF formulations are developed by Yuan et al.'s [29] using the distribution Locational Marginal Price (DLMP) formulation on grids with only radial topology.

Linearized models deviate from the original model according to several criteria, such as voltage levels and angles and apparent power in the branches. They are also usually applicable to specific topologies or grid types. To overcome these limitations and expand the applications to more topologies, iterative approaches are used. Whereas some iterative approaches can be found in the literature that aims to solve linear models iteratively, like in [95], where Castillo et al. built an OPF model based on the “IV-ACOPF” formulation. This method includes significant approximation and penalty factors affecting the solution performance. Furthermore, high-quality initial points may not be available in the first few iterations, possibly making this approach's approximation error relatively large. In Mohamed et al. [124], a line-wise optimal power flow (LWOPF) formulation is developed using line-wise power balance equations and solved with the successive linear programming (SLP) technique. SLP exhibits simple and fast solutions. Zehar et al. [125] show the performance of SLP solutions in the environmental context to reduce emissions. It was also used by Yang et al. [126], who proposed a linearized OPF model based on the quasi-linear relationship of $P - \theta$ (power- voltage angle). This model considers the square of voltage magnitude, creating the benefit of a linear relationship between power and voltage magnitudes. The quadratic apparent branch flow limits were linearized using piecewise linearization for the power limits including a process to recover the AC feasibility. This method includes some approximations (assuming conditions for well-conditioned transmission systems $\theta \approx 0$, etc.). All these works use linear OPF solutions regarding the targeted configurations in centralized networks that do not incorporate distributed energy sources. The problem is further complicated when renewable energy sources and independent power producers are present in the system [127]. The problem's complexity due to RES units is mostly affected by the existence of economic physical and technical constraints relates to the production systems. Thus, the objective function accounts not only for the operation cost of the conventional units but also for RES.

Furthermore, the constraints related to the extracted power from RES are integrated in addition to the storage related constraints.

2.2.3 Design and operational models' combination

The increasing application of smart grids with the recent developments on EPSM has broken the limits of the typical horizon of the classic planning and operation problems, allowing some of their corresponding optimization tasks to merge [128], [129]. A new category of models appears; these models enable the automation of several issues, ranging from operational issues such as active & reactive power dispatch (OPF), unit commitment, etc., to network planning, including RES and BES allocation, allowing them to be carried out simultaneously. This new category of models allows for the efficient integration of RES and grid operation.

This can be done with the expansion of the OPF models to accomplish the planning at the same time. In order to extend the OPF model to cover multiple time periods, a dynamic optimal power flow (DOPF) is proposed in [94]. The optimal power generation dispatch across a network is solved using DOPF to meet the demand during a given timeframe. It models 'intertemporal' technologies (e.g., energy storage) and effects (e.g., flexible demand, generator ramping limitations). Several studies using DOPF can be found in the literature [130]–[133]. This comprises a study of DOPF for load reduction in an electricity market [134], a study of multi-period optimization method to suggest the optimal placement and usage of renewables and storage systems [135] and a study on optimal dispatch of active and reactive power while including wind power and energy storage [136]. In these studies [134]–[136], nonlinear OPF formulations were applied, which is time-consuming and often technically difficult to solve. This highlights the importance of developing fast and robust methods for solving nonlinear, large-scale and dynamic optimization problems. Few works have addressed the linear OPF formulation in a dynamic approach. Cargarian et al. [137] did, but they used DC-OPF for their dynamic smart electric grid study, which applies only to limited cases (for secondary sector grids that includes the industrials).

Moreover, the increasing practical applications on smart grids with the increasing integration of RES in power grids has led to the search for new applications (e.g., virtual power plants, BES, electric vehicles, etc.). The introduction of additional variables related to these applications leads to complex combinatorial optimization problems involving many highly coupled variables and constraints. This raises many critical challenges that can be successfully addressed using metaheuristic optimization methods [76]. These models could be combined with OPF models to cover the planning and operational objectives.

2.3 Methods for RES and BES integration

2.3.1 Sizing methods

The problem of optimal sizing of RES and BES in an EPSM was solved using various methods in the literature [138]. These methods can be classified in three main groups: *Traditional methods*, *Artificial Intelligence (AI) methods* and *Hybrid methods*.

Traditional methods are relatively simple and have certain requirements to characterize the problems. Traditional methods include probabilistic methods (e.g., the approach developed by [139] based on convolution technique using probability density function to assess the long-term performance of hybrid PV-WT system, another probabilistic method is developed in [140] to provide an optimal sizing for a grid-connected to a wind-hydrogen system), the probabilistic methods considers changes in meteorological data only (e.g., ambient temperature, wind speed, solar irradiation). Iterative methods are also attributed to traditional methods (e.g., the population-based optimization algorithm proposed in [141] to minimize the Levelized cost of hydrogen production and the energy transfer loss, another approach is used in [142] to co-optimize the configuration of PV arrays and batteries). Iterative methods research results demonstrated that they are more effective than the Genetic Algorithm (GA) in some cases [143], but they generally cannot optimize some essential parameters for the system (e.g., PV panel inclination angle, WT installation height, WT sweep area) [144].

AI algorithms can solve nonlinear and complex problems, and deals with intermittent problems of wind/solar power and with incomplete data [145]. Thus, Particle Swarm Optimization (PSO) is attributed to AI used by Maleki et al. [146] to optimally size a hybrid multisource system PV-WT-BES) in addition to the harmony search methods (HS) [147] etc. The Genetic algorithm (GA) is also attributed to AI methods (used, for example, by Yang et al. [148] to optimize the configuration of a hybrid PV/WT system with BES with the objective of minimizing the total cost); the most used AI algorithms in the literature are GA and PSO [138] where PSO has been commonly used by taking advantage of its high efficiency and probability in reaching global optima [147]. In Xu et al. [149], PSO, GA and annealing method (SA) were compared to validate a better performance for PSO compared to other methods. AI algorithms may tend to reach a local optimum, so global optimality is not guaranteed.

Each method from the above-mentioned traditional and AI methods has its weaknesses and limitations. To deal with these limitations, *hybrid methods* have been proposed. Hybrid methods combine two or more methods and have become the mainstream computational methods due to their effectiveness in combining the advantages of different methods. Examples of hybrid methods: The multi-objective particle swarm optimization (MOPSO) developed to optimally design the hybrid PV/diesel/battery in a ship's power system [150], the dynamic programming region elimination technique (DP-RET) defined in [151] for the optimal sizing and management of lithium-ion batteries for PVs and the bi-level GA programming approach to optimize the BES sizing and operations in Ma

et al. [152]. Hybrid methods show high accuracy and fast convergence speed compared to GA and artificial bee colony (ABC).

Integrating RES in an operation model with a full grid description is represented in the literature where the OPF models are used e.g., in [153]. Still, they did not consider the dynamic behavior of the network. In (Li et al.[154]), a deep reinforcement learning-based approach is applied to dynamically search for the optimal operating point to integrate renewables into the distribution network. The spatial-temporal frame is considered in this approach, and the OPF is formulated into a multi-objective optimization problem. The proposed algorithm is accompanied by graphical information of the distribution network where the network's buses are interrelated in temporal and spatial views for spatial-temporal graph information extraction. This method considers the spatial-temporal frame but is computationally burdensome and applies to a limited number of renewable sources.

2.3.2 Evaluation indicators for sizing RES and BES

To start a system design, several indicators can be used independently or in combination to create one or more objectives prior to the optimization step. These indicators are Economic, environmental and reliability indicators:

- Economic indicators

In this case, the EPSM optimization process aims to find a feasible solution to meet the load while optimizing an economic indicator. Economic indicators combine different costs such as capital costs (purchase, installation, etc.), operation and maintenance costs, the purchase cost of energy flows consumed by the production systems, etc.

The economic indicators frequently used in the literature are the followings:

- 1- The Total Annual Cost (TAC) is the sum of the annual capital cost and the system's annual maintenance and operation cost. The annual capital cost is converted from the initial capital cost using the capital recovery factor (function of the interest rate and the number of years in the system lifespan). Minimizing the TAC is used in [155] to optimize the number of PVs, WTs and BES.
- 2- The Annualized Cost of System (ACS) is the sum of the annual capital cost, annual maintenance cost and annual replacement cost of the system. Minimizing the ACS is adopted in [156] to size the PVs and the BES capacity.
- 3- The net present value (NPV) is the difference between the present discounted values of incomes and the discounted present costs through the useful lifetime of the system. NPV is minimized in [157] to optimize Croatia's hydro-PV-WT-battery energy system planning.
- 4- The Life Cycle Cost (LCC) is the sum of the NPVs of the capital costs, operation and maintenance (O & M) costs, replacement costs in addition to the net present value of salvage value. Minimizing the LCC for PV panels area, number of WTs, etc., is applied in [158]–[160].

- 5- The Cost of Energy COE expresses the cost per unit of generated energy. COE is the ratio of ACS to total energy production. The minimization of COE is applied to design a pumped hydro storage-wind system island in Spain [161].
- 6- The Levelized Cost of Energy LCOE measures lifetime costs divided by energy production. The lifetime cost includes the capital cost of constructing the project, the price of fuel, O & M costs, as well as decommissioning costs. LCOE calculates the cost per unit of energy produced. LCOE is used in TIMES [61], LEAP [71], [162] and [163], etc., for the purposes of energy planning and RES placement.

Other economic indicators also exist, such as payback period (PBP) [164], unit generation cost [165], total capital cost (TCC) [166], total investment cost (TIC) [167], return on investment, internal rate of return, etc.

Among these indicators, LCOE is considered one of the most important decision indicators and is popular in the literature on renewable energy technologies [168]. Since it gives the actualized total cost per unit of generated energy, it is widely used for technology comparison between energy scenarios [169].

- Environmental indicators

The main reason for RES incorporation is to reduce the environmental pollution caused by fossil fuels in addition to sustainable use of resources. Fossil fuels release significant quantities of carbon and sulfur dioxide. Hence, environmental indicators must be considered in the optimization design of EPSM. The most used environmental indicator is carbon emission (CE) which evaluates the carbon emissions over a period of time [170]. CE is presented in about 70% of the cases summarized in the review study of Lian et al. [138] (e.g., in [155], [158]). Another indicator is the carbon footprint of energy (CFOE) [171], which represent the collection of carbon dioxide emissions from a system. It is used to quantify the greenhouse gas emissions per kilowatt-hour of electricity generated during the system's lifetime. The life cycle assessment (LCA) [172] refers to greenhouse gas (GHG) emissions. LCA evaluates the environmental factors and potential impacts related to the different phases of the hybrid system components (production, supply and transportation). Moreover, the embodied energy (EE) [173] refers to the non-consumed energy during the use of an energy system. It is the energy required for all activities related to the production process. Environmental indicators include also fuel consumption [162], fuel emissions [172] and life cycle emissions [174], etc.

- Reliability indicators

The unpredictable weather and climate conditions affect power generation resulting in difficulty in finding a reliable power supply. The reliability indicators are used to evaluate the system's ability to meet the load demand. In the literature, different indicators are presented. The loss of power supply probability (LPSP) is considered in [175], [176]; it is defined as the percentage of power supply that's not able to satisfy the load demand and is currently considered the most popular index to evaluate

reliability. Another indicator is the loss of load probability (LOLP), used in [177], for example, and is defined as the ratio of total energy deficit during a time period etc.

The existing models in the literature could be separated into mono-objective and multi-objective models. The mono-objective models are focused on only one indicator (e.g., Minimizing the total cost of the system in [178], etc.), while the multi-objective models combine two or more indicators from different categories (e.g., minimizing LCOE and CE in [163], etc.).

Multi-objective sizing models

Multi-objective models that use two or more indicators are solved differently in the literature. In some, several objectives are included in the main objective function, which depends on the model and the algorithm used. The multi-objective optimization methods are usually employed with decision methods like Multi-Criteria Decision Analysis (MCDA) to enhance the process of decision-making in a problem based on various objectives and criteria. An example is the decision support tools developed in [179] for selecting optimal water treatment technologies in India based on multi-objective optimization and MCDA. In others, a single objective function is used with an epsilon-constraint (ε – constraint) method for the remaining objectives. The ε – constraint method generates single objective subproblems by turning objectives into constraints. The upper-bound of these constraints is given by the vector ε and, and by varying it, the exact Pareto front can theoretically be generated. The ε – constraint method is one of the classical methods to deal with multi-objective optimization problems. In this method, one objective will be used as the objective function, and the other objectives will be the constraints that depend on the epsilon value, which is a boundary of the objective. This method is used for energy planning scenarios in [180] to constraint the CO_2 emissions while the main objective function is minimizing the investment and operational costs. This method is faster compared to MCDA if the problem is bi-objective.

2.4 Uncertainty in electrical planning models

EPSM is a powerful tool for effectively designing RES and BES to perform energy planning and operation. However, it is prone to uncertainty. It returns to the existence of time-dependent aspects that introduce uncertainty to the planning process. These time-dependent aspects are the followings:

- Human behavior that makes forecasts of future energy demand sensitive to uncertainties
- Renewable energy intermittency and the future climate
- Errors in forecasts of fuel prices, investment costs, etc.

The existence of uncertainties in the planning process can affect the quality of the model's outcomes and leads potentially to sub-optimal solutions. Thus, it is recognized that the success of energy system planning depends critically on the consideration of uncertainties and their impacts.

2.4.1 Load forecasting models

Accurate estimations of future energy consumption are crucial for decision-makers to better plan production and distribution systems' future design and operation [181]. Different models were used in the literature for load forecasting [182], [183]. The traditional regional or national electricity demand and their hourly profile have been based on analysis of historical patterns and forecasted by scaling up the current electrical load (e.g. [184], [185], etc.). But the future electricity system will be affected by newly available technologies (e.g., electric vehicles) and new sector demands for energy services that are difficult to detect based on historical load patterns [186]. Thus, it is important to study trends among end-users where new technologies and flexibility resources are emerging. The most common approaches are divided into two types with respect to their input data: top-down and bottom-up approaches. Top-down models attribute energy consumption to the total housing park according to its characteristics [187]. Whereas bottom-up approaches are developed by aggregating either simulated stochastic individual load profiles or average load profiles. From these models, the model presented in [188] provides an hourly load curve for residential customers from a few dwellings to a large area (1000 customers). The existing load forecasting models are classified in the literature based on different features. In Barbier et al. [187], load forecasting methods are classified relatively to their elementary spatial scale of simulation, which means the minimum level of spatial aggregation the model can provide as output. Six different models classes are identified in [187]: 1- models based on the aggregate consumption of a zone [189], 2- Models based on consumption by customer type [190] (*It is the electrical consumption of different customers of the same type: residential, tertiary, industrial*), 3- Models based on consumption per use for a specified zone [191] (*electrical consumption of a specific use or device in a defined zone*), 4- Models based on consumption by type of customer (residential, industrial, tertiary) and by use [192] (*It is the consumption of one type of device but only for a certain type of customer*), 5- Models based on consumption per customer [193] (*A customer's electrical consumption is that which is measured at his electric meter (e.g., linky) to make short-term electricity consumption forecasts for individual customers*), 6- Models based on consumption per device to which bottom-up residential models belong. The literature presents models of electrical load forecasting at all levels of aggregation. Still, only bottom-up models based on consumption per device can produce scenarios that are not based on statistical trends in electricity consumption. However, this type of model is mostly developed in the residential sector [187]. The tertiary sector, is subject of less literature, as there is much less data available in addition to the diversity of its uses [194]. Indeed, the operation of the non-residential sector is more centralized and there is a specific interest in the reduction of the energy consumed and a greater number of regulations [195].

The literature shows a lack of models capable of simulating non-traditional scenarios (scenarios with specific uses), learning power consumption data by area and modeling all customer classes. The challenge comes from the lack of precise data on large-scale energy consumption. This is changing in recent years with the large amounts of data that are now available. The use of smart and connected meters such as the “linky” meter in France that measure electricity consumption in time steps of a few

minutes. In addition, the Internet of Things (IoT) is used for real-time monitoring and measurement of energy data.

Other types of models are based on knowledge from data sources (uses of the areas, surface, occupation, etc.) that are not based on historical data. Among them, the new model developed by Enedis, named “Modèle de Simulation et d’Analyse de l’Impact de la Charge sur le réseau (MOSAIC)”. This model uses a bottom-up electric load curve simulator [196]. MOSAIC allows to assess of the impacts on the electrical grid of different city-development scenarios in France at different time scales through the demand curves estimation for each scenario.

Since load forecasting models are generally designed to estimate future energy demand, they rely on long-term expectations for the parameters influencing the load profile (e.g., temperatures, number of residents, etc.). Therefore, they are likely to give estimations of low accuracy [197]. Uncertainty in demand estimation introduces additional complexity alongside network design, including RES sizing and placement, BES dimensions, etc. This can influence the design process that combines technical, economic and policy aspects. Under such conditions, it is crucial to understand how uncertainty affects the optimal design and to identify the most influential uncertain parameters [180].

2.4.2 Uncertainties characterization

An EPSM requires a considerable collection of input data, such as demand curves from load forecasting models, RES production curves, economic parameters of RES and BES, etc. Studying the impact of each of these inputs on the EPSM outputs requires the first quantification of the uncertainties of these inputs. The quantitative description of the input uncertainties is defined as “uncertainty characterization (UC).” UC consists in selecting the model’s uncertain parameters and assigning a mathematical description to their uncertainty.

Different parameters are treated as uncertain in different domains and similarly, the methods to characterize their uncertainty vary in the literature. In most cases, uncertainty characterization is done for economic parameters, including investment costs and resource prices, as in Pye et al. [198], where uncertainties are represented using triangular distributions between upper and lower bounds estimated from the literature. The same uncertainties are considered in Lythcke-Jørgensen et al.[199] where $\pm 25\%$ of cost variations are assumed, and uniform distributions are attributed. Energy price uncertainties are also quantified by defining ranges in Majewski et al. [200]. Statistical theory is adopted in some studies using Probability Density Functions (PDF) as in Dubuis et al. [201], like normal, uniform and beta distributions used to specify the uncertainty as in [202]. To rely on statistical theory, the data must be sufficiently present to define the distribution parameters that characterize them.

Another uncertain aspect addressed in the literature is renewable energy production, i.e., the total amount of available energy that can be used during a defined period of time, including temporal variation. Due to their variable nature, intermittent and variable issues are frequently associated with solar and wind energy. Their variability is characterized and considered in the design processes to

adapt the design to shortages and surpluses of produced energy. PDF is the most applied approach to characterize renewables production profiles [203], including normal distribution [204], beta [205] and uniform distribution [206], etc. In these cases, patterns are treated as independent random variables. Moreover, to consider the autocorrelation between successive time steps, autoregressive time series models [207] were adopted in other studies in addition to artificial neural networks [208]. Carbon factor uncertainty was seldom treated in the literature. For the LCA electricity CO₂ factor, a uniform distribution is assigned in [209] and normal distribution in [210]. In Moret et al. [197], a detailed method is developed for the ranges of varying definitions for the uncertain parameters (demand, energy efficiencies, costs, etc.) in energy planning models.

The main function of EPSM is to satisfy the energy requirements of all consumers. Energy demand patterns result from interaction among multiple factors like the number of residences, building characteristics, occupancy schedules and occupant behavior, weather conditions, etc. The uncertainty associated with all these factors makes load forecasting or energy demand models highly uncertain. Not recognizing and addressing the uncertainty of energy demand can lead to a lack of adequate generation capacity and, therefore, an inability to meet energy demand. The approaches adopted in the literature to address uncertainties in energy demand patterns can be classified into two main types:

- Total demand uncertainty: this type of uncertainty characterization is applied to the demand patterns directly measured or extracted from the load forecasting models. To assign uncertainty on energy demand profiles. The most commonly used approach is applying PDF to each time step of the demand time series, like normal distribution [211], uniform distribution [212], etc. In Ekren et al. [213], for each individual hourly time step of the electricity demand data, a distribution is attributed separately (normal, beta, gamma, triangular, exponential, etc.)
- Model-based uncertainty: Load forecasting models are used to generate an hourly profile of energy demands. In this case, uncertainty is assigned to the input parameters of the load forecasting tool and is propagated to obtain a series of demand patterns. The model-based uncertainty approach is applied in the literature for different types of demand patterns. In [203], using a building performance simulation tool, the thermal response of buildings is modeled against varying conditions; the uncertainties are attributed to the following input parameters: building material properties, occupancy patterns, usage of lighting, hot water services, ventilation, weather and climate parameters, etc. Probability distributions are attributed to these parameters (normal, triangular, etc.), and the distribution parameters are then estimated. Thousands of profiles are then extracted and represented in the form of probability distribution to sample them to generate random energy demand profiles for the following study steps. The same approach is applied for MOSAIC in [214], where the input variables are distributed into four types: quantitative continuous (local height, coefficient of performance for heater, temperatures, etc.), qualitative binary (e.g., presence of air conditioner or not), quantitative discrete (e.g., number of occupants) and qualitative nominal

(e.g., thermal performance level). The parameters are classified to define their variability ranges then probability density distributions are attributed to continuous variables. Multiple demand patterns are then extracted from MOSAIC. This thesis treats the total demand uncertainty characterization for the extracted curves.

2.4.3 Uncertainty analysis

Uncertainty Analysis (UA) is used to investigate the variability of the model's output given uncertain input parameters. In energy planning models, UA allows examining how the optimal design output varies in response to various uncertain inputs (costs, demand, etc.). If the model results remain the same when different values of input parameters are used, the model output can be called robust. In the opposite case, if a wide range of results is obtained, the impact of uncertainty is significant, and the uncertain model response should be quantified.

Methods used for uncertainty analysis can be divided into probabilistic and non-probabilistic methods. Probabilistic approaches are based on rigorous probability theory and are used when sufficient data is available. The non-probabilistic approaches are developed to cope with a lack of information or data.

In the literature, the Monte Carlo (MC) method is the most widely used method to study the UA of model outputs. It is a sampling-based simulation method. This technique consists of the propagation of random samples of the uncertain parameters through the model to obtain the uncertain response of the model. In MC analysis, the input parameters are first characterized by their respective distribution functions. Each variable's sample of the corresponding distribution is drawn to produce a set of vectors. A set of values of model output is then produced. Then, the average output, standard variation, confidence bounds, etc., could be calculated to perform the uncertainty analysis [215]. MC analysis for UA is used for energy carrier price uncertainty in Kienzle et al. [216] for the optimal dispatch of an energy system and in Movrotas et al. [217] for optimal distributed energy system design. MC simulations are also performed in [199], considering uncertainties in investment costs and CO₂ emissions rate. Analytical approaches have also been developed to directly identify the model's variance from its form [218]. The main disadvantage of the MC method is the large number of function evaluations needed to reach convergence, which results in a high computational cost that can be reduced using sampling techniques.

Thus, several sampling technics have been used to obtain the combinations of input variable values from Probability Density Function (PDF). Among them is the Random Sampling Method that selects random samples from PDF. This method is used in [219] to estimate electricity and gas consumption variations using the Crystal ball software. However, this method requires a large number of samples for convergence [220]. Another used sampling method is the Latin Hypercube Sampling (LHS); LHS is a stratified sampling method that divides the range of every input variable into N segments with equal probability. This method requires a smaller sample size than the random sample method for the same statistical accuracy. LHS is combined with the MC method in the uncertainty analysis study in [221] to develop a meta-model for building performance analysis. However, the sample size is

recommended to be ten times the number of variables. Still, this size may be inadequate for UA when complicated non-linear relationships exist in the model between inputs and outputs. An example of a Non-probabilistic uncertainty propagation method is the interval analysis [222]. Interval analysis is the simplest non-probabilistic method. It assumes that an interval that consists of real numbers bounded by a lower and upper number. In this method the resulting outputs cannot be interpreted as a probabilistic distribution but as output interval bounds. This method is the most suitable for the cases where the UA study is not based on the input uncertain parameters but on the features characterizing these parameters. Thus, if the input parameters are time series data, the UA study will be based on the features describing these input parameters (e.g., total, maximum, variances, etc. that are not attributed to PDFs) and the output parameters. This analysis is performed using interval analysis.

2.5 Sensitivity analysis

2.5.1 Sensitivity analysis theory and methods

Uncertainty Analysis is usually followed by Sensitivity Analysis (SA). Frequently, there is confusion between the two analyses. The goal of (parameter-driven) SA is to determine the importance of the input parameters regarding their influence on model output variability. SA can serve several useful purposes, such as simplifying the models, establishing priorities for research, etc. In particular, they allow for determining which model input variables contribute the most to a given output quantity of interest, which ones have no influence, and which ones interact within the model. SA techniques are usually divided into Local Sensitivity Analysis (LSA) and Global Sensitivity Analysis (GSA).

Local sensitivity analysis: LSA measures the effect of input parameters on model output by varying one model parameter at a time while all other parameters remain fixed at their nominal point. LSA is the most straightforward SA approach, also called “one-at-a-time” (OAT) analysis. LSA is only informative around the calculation point, so it doesn’t cover the whole input parameter space. Moreover, using OAT ignores the interaction effects among factors, as these would require simultaneous input variation. These gaps have been addressed with the development of GSA.

Global sensitivity analysis: Contrarily to the LSA, GSA extends the scope of investigation of uncertain parameters from the base point to the entire space of input parameters, thus allowing the study of interactions between parameters. GSA contains a series of different methods that are applicable in other contexts.

Before starting a sensitivity analysis study, it is necessary to clearly specify the objectives [220]. The different purposes are identifying and prioritizing the most influential inputs, determining the non-influential inputs, etc. Many surveys were published to facilitate the selection of the appropriate method [223] - [224]. The one presented in the following Table 2-3 is adapted from Loos [225]. This synthesis summarizes SA techniques within an applicative methodological framework.

In table2-3, the existing methods are classified into three main groups (screening, measures of importance and deep exploration of the model behavior) with respect to their main tasks. The number of model evaluations is then attributed to each existing group of methods in terms of a number of input parameters (d). There is a huge difference between methods regarding the needed evaluations' number. "Screening" methods require fewer evaluations than "measure of importance" methods and those for "deep exploration of model behavior." In addition to the objective, selecting an appropriate SA method depends on its complexity (monotone, linear, etc.) and the regularity of the model (interactions, continuous, etc.).

Table 2-3: Synthesis of sensitivity analysis methods. (d: number of input parameters)

Methods Group	Screening			The measures of importance			Deep exploration of the model behavior	
Main Task	Coarse sorting of the most influential inputs from a large number			Quantitative sensitivity indices			measure the effects of inputs over their total range of variation	
Existing Methods	Very large screening [226]	Plan of experiences [227]	Morris method [215]	Linear regression [228]	Statistical tests [229]	Variance-based VB [230] (Sobol)	Smoothing methods [231]	Metamodels-based SA [232]
Examples	- Supersaturated plans - Group screening - Sequential bifurcations	- Full factorial design - R3 (resolution plan three) - OAT (one at a time) - R4 (resolution plan four) - Fractional factorial design	Elementary Effects (EE)	- Pearson regression coefficient SRC - Partial correlation coefficient PCC - Spearman - Standard regression coefficient on rows SRRC - Partial correlation coefficient on rows PRCC	- Common averages - Common variances - Common locations	- Based on MC - Based on quasi-MC	- Moving averages - Kernel methods - Local polynomials - Smoothing splines	- Polynomial chaos expansions - Gaussian processes
Number of Model simulations (d: number of input parameters)	d	d:2d	2d:10d	10d	10d	100d: 1000d	10d:100d	10d:100d
Complexity/Regularity of The Model	Monotone / Without interactions	Linear Monotone/ Interactions	Non-monotone / Discontinuous	Linear	Non-monotone / Continuous	Non-monotone / discontinuous	Non-monotone / discontinuous	Non-monotone / continuous or discontinuous

2.5.2 Sensitivity analysis applied to energy models

In the current energy models, SA methods are integrated since they are valuable supports to any modeling effort. Table 2-4 reviews applications of sensitivity analysis in energy models.

Table 2-4: Review of application of sensitivity analysis to energy models

Reference	Method(s)	Parameters	Output(s) indicators
Kattan and Ruble [233]	LSA	Fuel prices	Energy price
Mian et al. 2016 [234]	EE, MC	Cost, efficiencies, interest rate, temperatures	Cost
Lythcke-Jørgensen et al. 2016 [199]	EE	fuel price, inv. cost, emissions	Net present value, Global warming potential
Moret et al. 2017 [197]	Two stages EE - VB	Energy prices, inv. Costs, losses, etc.	Total annual cost, investment decision
Mavromatidis et al. 2018 [180]	Two-stages EE – VB	Energy demand, solar patterns, inv. & operation costs	System cost
Sadeghi et al 2020 [235]	LSA	Demand, wind speed	Life cycle cost, loss of power supply probability
Luerssen et al. 2021 [236]	Two-stages EE – VB	PV efficiency, discount rate, battery lifetime, cooling load, Battery CAPEX, etc.	Levelized cost of storage
Ma et al. 2022 [152]	LSA	Investment budget, power loss rate, power cost, capacity cost	Reduction of WT/PV curtailment costs, reduction of thermal unit cost, peak shaving, rated power, rated capacity
Li et al. 2022 [237]	Two-stages EE – VB	Energy prices, efficiencies, electricity demand, interest rate, etc.	Annual cost, installed capacity

The reviewed works are classified according to three criteria: the used methods, uncertain parameters and the output indicators. The analysis reveals that LSA methods are widely used [172, 174, 91] where uncertain input parameters are varied in OAT while keeping the other parameters fixed at their nominal values. However, GSA considers the effects associated with the interaction among different uncertain inputs and the sensitivity is evaluated over the entire range of each input factor [238]. The EEs method developed by Morris [239] lies in between. It is an efficient way of screening a model to identify non-influential parameters, as demonstrated by Lythcke-Jørgensen et al. [199] and Mian [234]. For the application of GSA in the energy models, the adoption of a two-stage method is proposed in different studies [138, 139, 175, 176]. The two-stage GSA method allows for dealing with the large number of uncertain parameters typically found in energy planning models (e.g., costs, demand, solar patterns, etc.): the first stage (Morris EEs method) performs an efficient screening of the model and highlights non-influential parameters; the second stage (Sobol variance-based methods) offers a ranking of the influential

parameters. Applying a two-stage approach facilitates considering a large number of parameters in the analysis of energy models.

2.6 Summary

This chapter discusses state of the art in electrical power system planning and operational models. Table 2-5 compares the features of various EPSM regarding the last parts concerning the EPSM approach proposed in this thesis. The existing models use different sizing methods and evaluation indicators depending on their type (planning, operation) and targeted network (transmission, distribution).

Hence there is a need for a model that combines planning and operation (2.2), uses a hybrid sizing method (2.3.1) with various evaluation indicators (2.3.2), is targeted to different network scales and allows a global sensitivity analysis.

Table 2-5: Summary of some methods for EPMS

Ref	Type		Network level	Network constraints	Sizing methods	Evaluation sizing indicator(s)	Sensitivity Analysis
	Planning	Operational					
REMix [62]	✓		Transmission	-	Hybrid: Linear/Mixed-integer	Economic (NPV)	
LEAP [71]	✓		Transmission	-	Heuristic	Economic (NPV, LCOE) Environmental (GHG)	
MARKAL/TIMES [61]	✓		Transmission	-	Linear	Economic (NPV, LCOE)	
MATPOWER [74]		✓	Transmission or distribution networks	P, Q, V, θ	-	-	
PLEXOS [240]	✓	✓	Transmission		Hybrid: Linear/Mixed-integer	Economic (NPV)	
Moret [238]	✓		Transmission	-	MILP	Economic and environmental performance indicators (PIs)	✓
Thesis proposed method	✓	✓	Transmission or distribution networks	P, Q, V, θ	Hybrid: Meta-heuristic/linear	Economic (LCOE) + Environmental (CE)	✓

Chapter 3: Electrical Power System Model for Planning and Operation

3.1 Introduction

This chapter presents the general approach of the novel EPSM proposed to address the limitations discussed in the previous chapter. The proposed EPSM can optimize the planning and operation of the electrical grid. This covers both types of networks (distribution and transmission), where most of the existing models in the literature do not include the distribution network. The general framework includes a hybrid bi-level optimization algorithm based on a meta-heuristic PSO model and an optimal power flow model to perform the planning and operation simultaneously while integrating Renewable Energy Sources (RES) and Battery Energy Storage (BES). Two different indicators are chosen here: the economic indicator by minimizing the Levelized cost of energy, and the environmental indicator to minimize CO₂ emissions using ε -constraint. For operation optimization, unlike most models that use OPF, this model includes an AC-OPF by linearizing the equations to ensure an optimal global solution for the lower level. The developed model can return planning results, including RES and BES dimensions and localizations, with the detailed grid and producers' behavior at each time step during the targeted period. For the cases where the production potential is insufficient to ensure equilibrium, a solution is guaranteed with the new elements included in our approach called virtual generators.

The general structure of the EPSM model is discussed in the following section. The details of the bi-level model, including their equations (objective functions and constraints) and optimization methods used to solve them are then detailed in this chapter.

3.2 General structure proposed planning and operation of EPSM

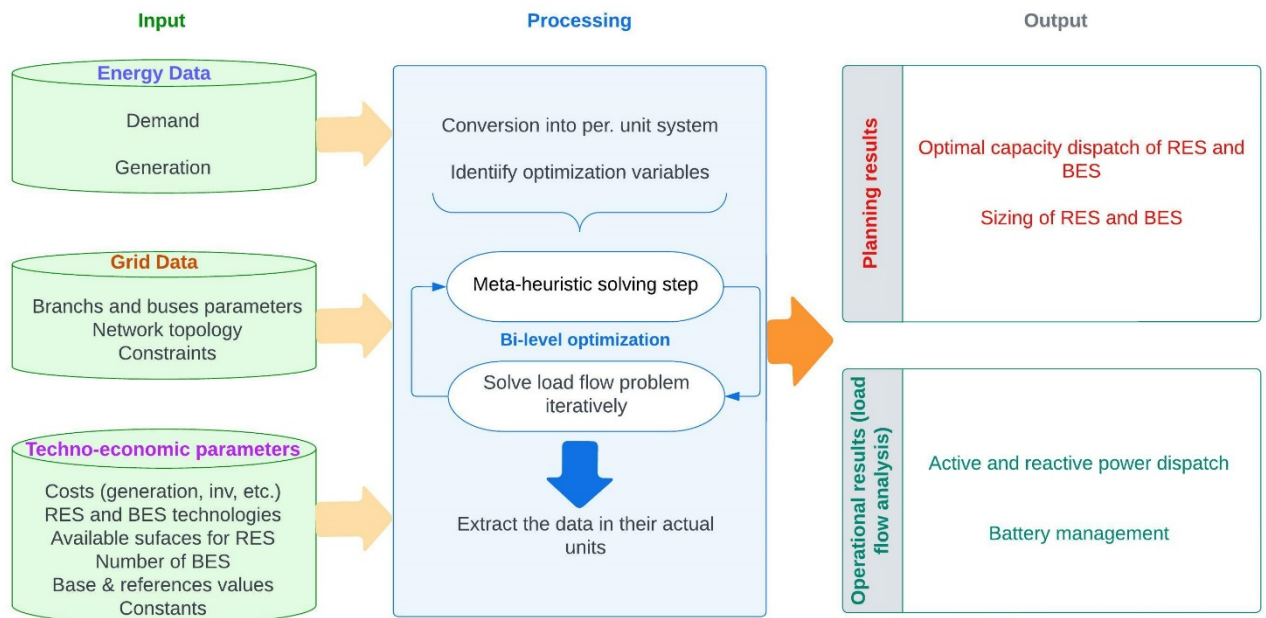


Figure 3–1: Structure of the proposed EPSM

The general structure of the developed EPSM in this Ph.D. is presented in Figure 3–1. It has three main parts: Input, processing and outputs. The input part is where data is collected and needed to

construct the optimization model. Regarding the energy data, the demand profiles should be simulated in addition to the maximum installed energy technologies (generators, RES, etc.). The network specifications or grid data include the network topology and type (transmission or distribution) in addition to the physical parameters and constraints (voltage magnitudes, voltage angles and power branch limits, etc.) describing the grid. Additional information like techno-economic parameters is also required, including costs, constants, the available areas for RES installations, etc.

The processing is where the extracted input data are used to formulate a *bi-level optimization model*. The approach is based on the combination of two types of optimization models: the first one is non-linear and the second one is also non-linear but can be linearized around an operating point. In the lower level, the CO_2 emissions are restricted using ε -constraints.

In terms of solution, the first one is solved using a meta-heuristic method and the second one is solved by successive linear optimizations. The identified optimization variables are then calculated and extracted in their actual units to the output part. The output part shows the details of the obtained planning and operation results.

Bi-level optimization model

The bi-level optimization model is described in Figure 3–2. The upper-level designs and allocates BES by minimizing the Levelized Cost of Energy (LCOE) using the PSO method. In each PSO iteration, the upper-level layer transfers the batteries' sizes and locations to the lower-level layer. This latter uses a Dynamic Linearized OPF (DLOPF) to make optimal planning and operational decisions, such as the size and location of RES and optimal dispatch of energy production and storage over the simulated period. This decision is made by also minimizing the LCOE in the network. Only the Battery cost is excluded from the lower-level optimization since the battery sizes and locations are known and constant in each Upper-level iteration. The details of both levels are explained in the following sections.

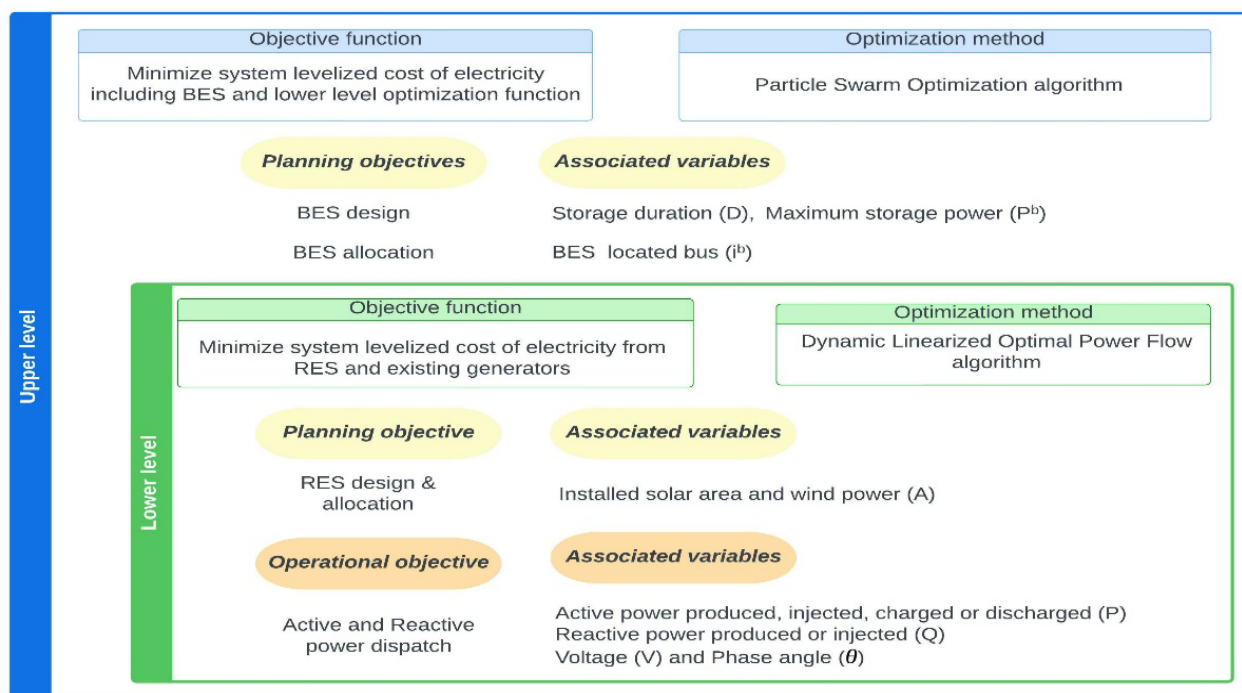


Figure 3-2: Bi-level optimization model

3.3 Upper-level model

The planning tasks at each level are depicted in Figure 3-3. The optimization problem parameters are first defined. These conditions include the existing branches, demands and classic generators in the grid. The possible areas for PVs and WTs are also part of the optimization problem parameters in addition to the number of available batteries to be added. The RES (PVs + WTs) are first localized in the lower-level model. Then, based on the initial conditions, the BES is added to the grid in the upper-level model where RES exists.

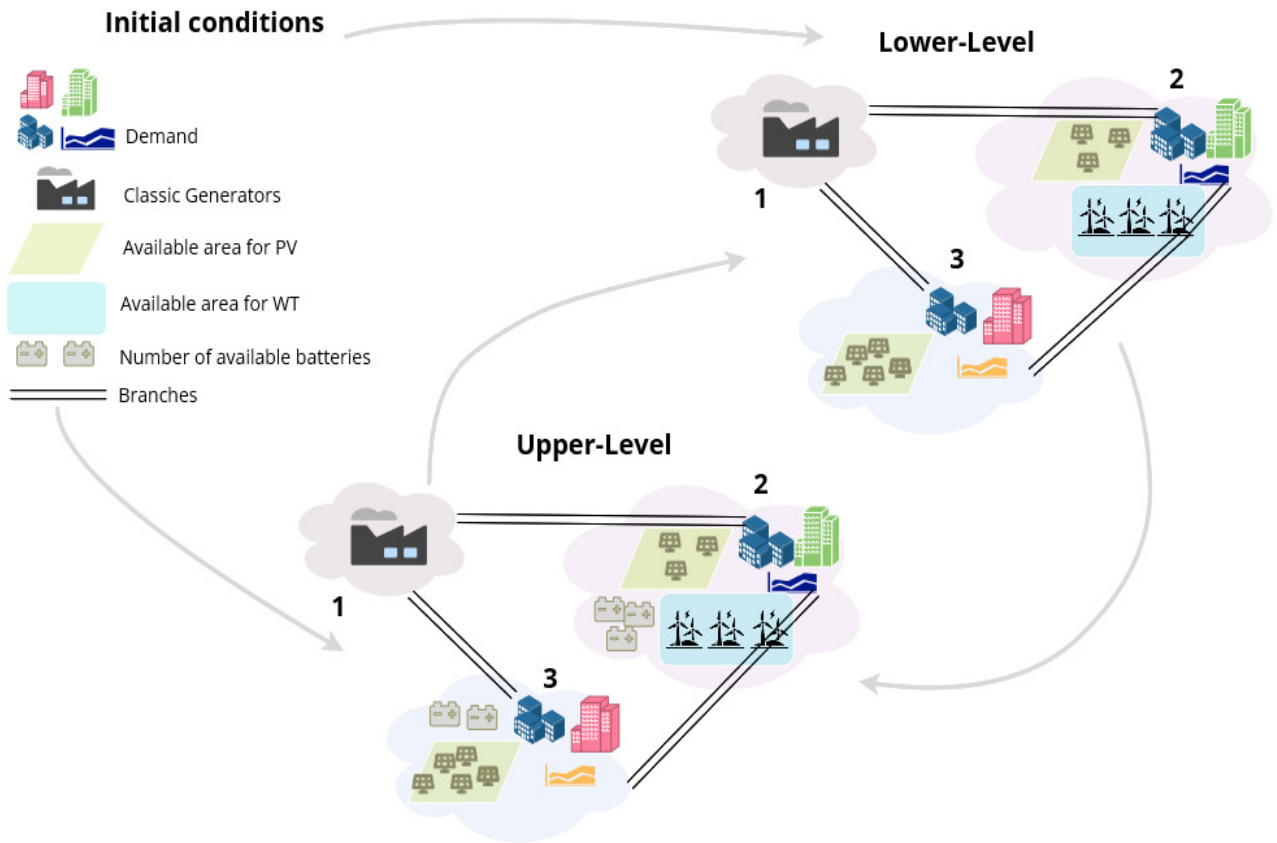


Figure 3-3: Planning tasks at each level

3.3.1 Batteries cost estimation

Since the main planning objective of the upper-level is the minimization of LCOE cost for the BES (Figure 3-2), the BES design must be subjected to a defined cost function in terms of specific design elements. These latter are:

- Power capacity of the battery (P^b): also called rated power capacity, is defined as the total possible instantaneous discharge capability of the BES system. In other words, it is the maximum rate of discharge that the BES system can achieve, starting from a fully charged state (in kW or MW).
- Energy capacity (E^b) (or storage capacity): It is the maximum amount of stored energy (in kWh or MWh).
- Battery storage duration (D): the amount of time during which the storage can discharge at its power capacity before exhausting its energy capacity. For example, a battery with $P^b = 1$ MW and $E^b = 4$ MWh will have a storage duration of 4 hours.

To model the investment cost function for BES, the relation between the different design elements (P^b and E^b) should be accomplished with their related capital costs. A cost projections study for 2-, 4- and 6-hour duration batteries is performed in [241] using a method called the mid-cost

projection. The resulting graph from the study (Figure 3–4) presents the corresponding capital cost (CC^b) in (\$/Kw).

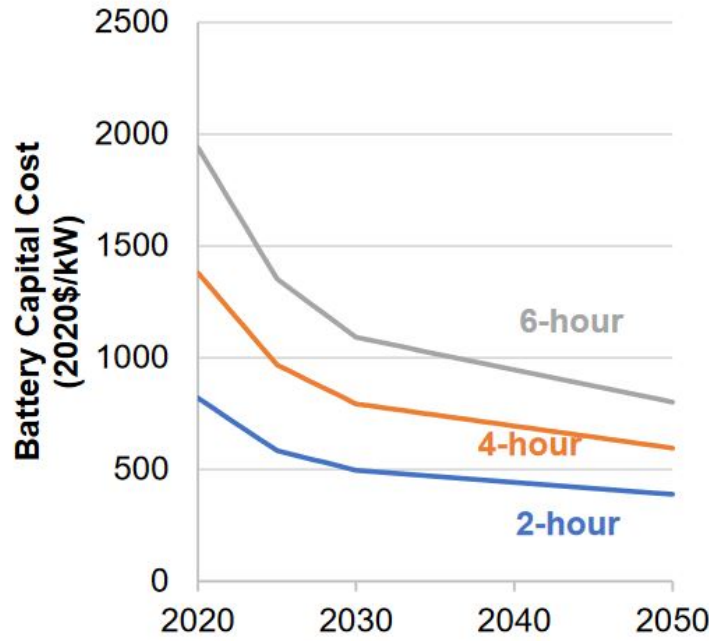


Figure 3–4: Cost projections for 2-, 4- and 6-hour duration for lithium-ion batteries (\$/kW) [241]³

Based on this graph, a specified year is fixed to find a correlation between the different storage durations and capital costs at each time. A linear regression is done for the year 2022 to build Eq. (3-1) where α and β are respectively the slope and the intercept of the trend line, D is the storage duration.

$$CC^b \left(\frac{\$}{kW} \right) = \alpha \times D \text{ (hours)} + \beta \quad (3-1)$$

The BES investment cost (J^b) is then performed using Eq.(3-2) where P^b is the power capacity.

$$J^b (\$) = CC^b \left(\frac{\$}{kW} \right) \times P^b (kW) \quad (3-2)$$

³ Reprinted with permission from the National Renewable Energy Laboratory, <https://www.nrel.gov/docs/fy21osti/79236.pdf>, accessed November 4, 2022.

3.3.2 Upper-level objective function

To find the optimal placement and sizing of BES, the model aims to optimize the *Levelized Cost of Energy (LCOE)*, including total investment, production, maintenance, and operations (O&M) costs. The objective function in Eq. (3-3) is the LCOE of the system with BES defined by:

- The BES cost is calculated by multiplying the total produced energy over the life span of the overall system (ls) by the ratio of the BES investment cost ($\mathcal{I}^b$) and the BES lifetime (LT^b). This product is divided by the sum of demand ($P_{i,t}^l$) (in all buses ($\mathcal{N}$)/ i : bus index $\in \mathcal{N}$) for the defined period ($\mathcal{T}$) in years / t : time index $\in \mathcal{T}$) over a function of the discount rate of the project (r).

- The optimized Levelized cost (F_{ul}) includes the RES installation and maintenance costs in addition to the energy production from classical energy sources. This latter is optimized in the lower-level optimization problem where optimal placement and sizing of RES and optimal energy production and storage dispatch are achieved. The optimization variables are written in **bold** in the document's equations.

$$\min F_{ul} = \min \frac{\mathcal{I}^b \cdot \left(\frac{ls}{LT^b}\right)}{\sum_{i=1}^{\mathcal{N}} \sum_{t=1}^{\mathcal{T}} \frac{P_{i,t}^l}{(1+r)^t}} + \min (F_{ll}) \quad (3-3)$$

Eq.(3-4) determines the investment costs of BES ($\mathcal{I}^b$) as detailed in the section 3.3.1. $\mathbf{P}_{i_j^b}^b$ and $\mathbf{D}_{i_j^b}$ values are limited by respectively the upper bounds of the batteries power ($P_{i_j^b}^{b,max}$) and the maximum storage durations $D_{i_j^b}^{max}$ stated by eq (3-5)). The optimization variables $\mathbf{i}_j^b$ belongs to a set of batteries $\mathcal{B}$ that contains a maximum number of batteries (Nb). Each index $\mathbf{i}^b$ belongs to one of the buses candidates for the placement of BES. The maximum batteries energies $E_{i_j^b}^b$ are calculated by eq.(3-6) in terms of $\mathbf{D}_{i_j^b}$ and $\mathbf{P}_{i_j^b}^b$ for each BES located at the node $\mathbf{i}_j^b$ where

$$\mathcal{I}^b = \sum_{i_j^b \in \mathcal{B}} (\alpha \cdot \mathbf{D}_{i_j^b} + \beta) \cdot \mathbf{P}_{i_j^b}^b \quad \mathcal{B} = \{\mathbf{i}_j^b\} \quad j = 1 : Nb \quad (3-4)$$

$$S.t \begin{cases} 0 \leq \mathbf{P}_{i_j^b}^b \leq P_{i_j^b}^{b,max} \\ 0 \leq \mathbf{D}_{i_j^b} \leq D_{i_j^b}^{max} \end{cases} \quad (3-5)$$

$$E_{i_j^b}^{b,max} = \mathbf{D}_{i_j^b} \cdot \mathbf{P}_{i_j^b}^{b,max} \quad (3-6)$$

In summary, the optimization variables of the upper-level are the followings: $\mathbf{D}_{i^b}$, $\mathbf{P}_{i^b}^b$ and $\mathbf{i}^b$.

3.3.3 Optimization method: Particle Swarm Optimization

The upper-level model contains nonlinear equations describing the nonlinear battery cost. To solve this optimization problem, synchronous Particle Swarm Optimization (PSO) is used. PSO is a population-based and gradient-free metaheuristic algorithm that attempts to discover the global solution of an optimization problem by simulating the social behavior of animals, such as bird

grouping. PSO was originally invented in 1995 by Eberhart and Kendy [242]. In the PSO algorithm, each feasible solution is a particle specified by a vector containing all the optimization variables. Particles have memory and thus retain some of their previous states. There is no restriction for the particles to share the same point in the search space, but their individuality is protected. The motion of each particle is the composition of two weighted influences and an initial random velocity: sociality, the tendency to move to the previous best position of the neighborhood, and individuality, the tendency to return to the last best position of the particle. PSO algorithm uses a multidimensional real-valued space as a search space and objective function values. The particles fly through the n -dimensional domain space of the function to be minimized in this case. The state of each particle is represented by its position $(xe_{d1}, xe_{d2}, \dots, xe_{dN})$ and its velocity $ve_d = (ve_{d1}, ve_{d2}, \dots, ve_{dN})$. The states are then updated using the following equations: Eq. (3-7) and Eq.(3-8).

$$ve_d^{L+1} = Ww^L \cdot ve_d^L + a_1 \cdot ra_1^L \cdot (pe_{best_d}^L - xe_d^L) + a_2 \cdot ra_2^L \cdot (ge_{best}^L - xe_d^L) \quad (3-7)$$

$$xe_d^{L+1} = xe_d^L + v_d^{L+1} \quad (3-8)$$

The velocity update Eq. (3-7) contains the three components whose weights are tuned using three parameters. The first parameter is the acceleration constant a_1 which is used to control how much the particle heads toward its personal best position (momentum component). The second is the inertial constant (Ww^L), which controls how much the particle remembers its previous velocity. The third is the acceleration constant a_2 which controls how much the particle heads toward the swarm's best-ever position (social component). ve_d^L is the d^{th} dimension in iteration L and xe_d^L is for the d^{th} particle position. ra_1 and ra_2 are random variables between 0 and 1. The inertia weight Ww^L starts from an initial value $Ww^0 \geq 0$ and decreases during the iterations $w^{L+1} = \mu \times w^L$. pe_{best}^L and ge_{best}^L are the best positions achieved so far by a particle and its L (here $L = 100$) times and the dimension d of their respective position and the swarm of its most optimal position [146]. The algorithm is running as follows:

Step 1. A group of particles (here D_{ib} , P_{ib}^b and i^b) is randomly initialized in the search space

Step 2. Each particle makes use of its memory (containing pe_{best} : best experience by itself and ge_{best} : group's best experience) and flies through the search space to obtain a better position than its current one

The position of each particle in that space is achieved using Eq. (3-7) and Eq.(3-8)

3.4 Lower-level optimization model

3.4.1 Power flow analysis

A power flow study is a steady-state analysis that aims to determine a system's current, voltages, and real and reactive power flow under given load conditions. Power Flow Analysis (PFA) is an important tool used by power engineers for planning power systems.

3.4.1.1 Bus classification

A bus is a node connected by one or various transmission lines, generators and loads. In a PFA, every bus is related to 4 elements:

- Voltage's magnitude (V)
- Phase angle of voltage (θ)
- Active power (P)
- Reactive power (Q)

Two of these elements are specified and the remaining two should be calculated. The buses are classified depending on the two known elements that have been specified. The three different buses categories are presented in the following Table 3-1 and illustrated by Figure 3-5:

Table 3-1: Bus classification

Bus type	Variables			
	P	Q	V	θ
Generator (P-V)	Known	Unknown	Known	Unknown
Load (P-Q)	Known	Known	Unknown	Unknown
Slack	Unknown	Unknown	Known	Known

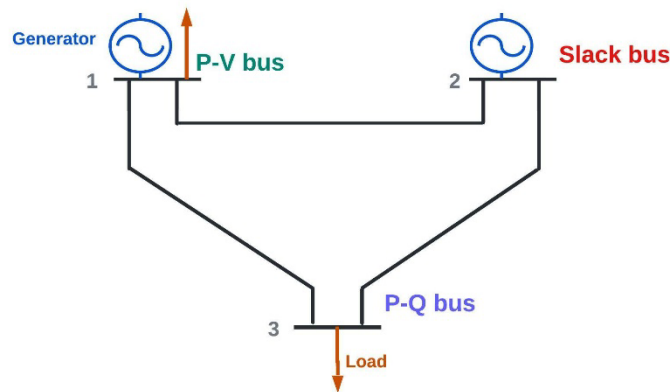


Figure 3-5: 3-bus system for load flow calculation

(a) Generator bus (P-V)

This bus is connected to a generator (substation, generator, PV, WT, etc.) unit (bus number 1 in Figure 3-5). Generators can supply active power and supply or absorb reactive power within certain limits. Often, limits are given to the reactive power values depending on the characteristics of each unit (PV, Wind Plants, etc. [243]). The known variables are P and V and the unknown are Q and θ .

(b) Load bus (P-Q)

The consumption of electrical energy is the result of all sectors of economic life: industries, services, and households. It takes many different forms: synchronous and asynchronous motors,

heating appliances, etc. The real and reactive power supply to a power system is defined to be positive, while the power consumed in a power system is defined to be negative. The consumer power is reached at this bus (bus number 3 in Figure 3–5). The known variables are P and Q and the unknown are V and θ .

(c)

Slack bus

It is used as a reference bus to meet the power balance condition (bus number 2 in Figure 3–5). A slack bus is usually a generating unit that can be adjusted to take what is needed to ensure power balance. The known variables on this bus are V and θ and the unknowns are P and Q .

3.4.1.2 Power flow analysis method

Numerical analysis, including the solution of simultaneous algebraic equations, forms the basis for solving performance equations in computer-aided power system analyses, such as for load flow analysis [244].

The first step in load flow analysis is to form the Y-bus admittance using the input data from the transmission line and transformer. The nodal equation of a power system using a Y-bus can be written as follows Eq. (3-9):

$$I = Y_{Bus} \cdot V \quad (3-9)$$

For $\mathcal{N}$ bus system, the nodal equation can be written in a generalized form as shown in Eq.(3-10).

$$I_i = \sum_{j=1}^{\mathcal{N}} Y_{ij} \cdot V_j \quad \text{for } i = 1, 2, 3, \mathcal{N} \quad (3-10)$$

The complex power delivered to bus i is given by Eq.(3-11) and Eq.(3-12) (with I_i^* : the complex conjugate of the per-unit current injected at the bus i , V_i^* : the complex conjugate of the per-unit voltage at bus i)

$$P_i + jQ_i = V_i I_i^* \quad (3-11)$$

$$I_i = \frac{P_i - jQ_i}{V_i^*} \quad (3-12)$$

Substituting for I_i in terms of P_i & Q_i , the equation gives

$$\frac{P_i - jQ_i}{V_i^*} = V_i \sum_{j=1}^{\mathcal{N}} y_{ij} - \sum_{j=1}^{\mathcal{N}} y_{ij} V_j \quad (3-13)$$

The above equations are usually solved using iterative techniques to solve the load flow problem, such as Gauss-Seidel, Newton Raphson, fast decoupled load flow, etc. [245].

3.4.2 Optimization problem formulation

The generating power in our approach is supposed to be extracted from different production sources to satisfy the demand at each time step, as depicted in Figure 3–6.

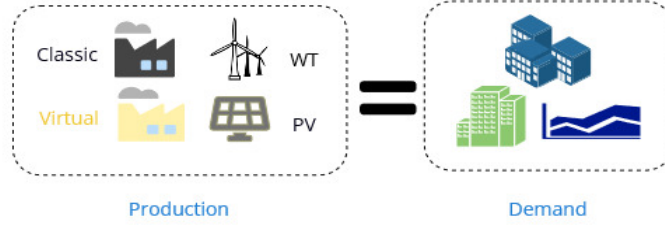


Figure 3-6: Different types of production sources

The *Producers* are formed by: Classic Generators (CG) that can be either centralized power generators or transmission substations at grid connection points between two different voltage levels. Producers can also be renewable energy sources: Photovoltaic (PV) solar systems and wind turbines (WT). Other producers called “*virtual generators*” are introduced, as shown in Figure 3–6. These new elements have a generation cost significantly higher than real generators (CG, PV, WT) and have two roles:

- 1) They guarantee the existence of a feasible solution for each time step.
- 2) They serve as an indicator for the production deficit on the corresponding node.

The *consumers* are either direct consumers or distribution substations between two different voltage levels.

3.4.2.1 Objective function

The lower-level optimization model aims to minimize the LCOE of the production system. This corresponds to the LCOE of the whole system, excluding BES cost, which is determined at the upper-level optimization and constant during the lower-level optimization.

The objective function is presented by Eq. (3-14). Where:

- Γ_{inv} (Detailed in Eq.(3-15)) is the sum of the investment costs for the PVs (J^{pv}) and WTs (J^{wt}). For the investment costs, the installed area of PVs is an optimization variable A^{pv} and is multiplied by the investment cost (I^{pv}) (eq. (3-16)). The continuous designed variable R^{wt} defines the ratio of installed power capacity to a maximum installable capacity ($R^{wt_{max}}$) of local wind energy. R^{wt} multiplied by the investment cost (I^{wt}) eq. (3-17)
- Γ_{op} is the total actualized operational costs represented by Eq. (3-18) where the C^{cg} is the actualized operational cost of CGs and C^{vg} is the actualized operational cost of VGs. As solar and wind power are clean energy sources, their corresponding operational costs (C^{wt}, C^{pv}) have very low values. The total operational cost for CGs (C^{cg}) is given by eq. (3-19) where both the sum of active (P^{cg}) and reactive (Q^{cg}) produced power are multiplied by their corresponding costs ($C^{cg,p}$ for active and $C^{cg,q}$ for reactive). Similar to Eq.(3-19), Eq.(3-20) gives the *virtual generation cost* (C^{vg}). In each bus, virtual generators have generation costs significantly higher than other generators (both $C^{vg,p}$ and $C^{vg,q}$). The total operational costs of WTs (C^{wt}) and PVs (C^{pv}) are represented

respectively by Eq.(3-21) and Eq.(3-22). Γ_{op} is variable according to the energy consumed.

- Actualized operation and maintenance cost $\Gamma_{o\&m}$ is given by Eq.(3-23). It is dependent on the sizing of WTs, PVs and the existing CGs. and their O&M costs (O^{wt}, O^{pv}) in addition to the existing CGs maintenance costs (O^{cg}) multiplied by the total installed power of CGs (P^{cgT}). This cost is a fixed cost for the year regardless of the amount of production.

$$\min F_{ll} = \min \frac{(\Gamma_{op} + \Gamma_{o\&m}) + \Gamma_{inv}}{\sum_{i=1}^N \sum_{t=1}^T \frac{P_{i,t}^l}{(1+r)^t}} \quad (3-14)$$

Such that

$$\Gamma_{inv} = J^{wt} + J^{pv} \quad (3-15)$$

$$J^{pv} = \sum_{s=1}^{N^{pv}} I^{pv} \cdot A_s^{pv} \quad (3-16)$$

$$J^{wt} = \sum_{w=1}^{N^{wt}} I^{wt} \cdot R_w^{wt} \quad (3-17)$$

$$\Gamma_{op} = C^{cg} + C^{vg} + C^{wt} + C^{pv} \quad (3-18)$$

$$C^{cg} = \sum_{t=1}^T \sum_{c=1}^{N^{cg}} \frac{C^{cg,p} \cdot P_{c,t}^{cg} \cdot \Delta t + C^{cg,q} \cdot Q_{c,t}^{cg} \cdot \Delta t}{(1+r)^t} \quad (3-19)$$

$$C^{vg} = \sum_{t=1}^T \sum_{i=1}^{N^{vg}} \frac{(C^{vg,p} \cdot P_{i,t}^{vg} \cdot \Delta t + C^{vg,q} \cdot Q_{i,t}^{vg} \cdot \Delta t)}{(1+r)^t} \quad (3-20)$$

$$C^{wt} = \sum_{t=1}^T \sum_{w=1}^{N^{wt}} \frac{C^{wt} \cdot P_{w,t}^{wt} \cdot \Delta t}{(1+r)^t} \quad (3-21)$$

$$C^{pv} = \sum_{t=1}^T \sum_{s=1}^{N^{pv}} \frac{C^{pv} \cdot P_{s,t}^{pv} \cdot \Delta t}{(1+r)^t} \quad (3-22)$$

$$\Gamma_{o\&m} = \frac{\sum_{i=1}^T (O^{pv} \cdot A^{pv} + O^{wt} \cdot R^{wt} + O^{cg} \cdot P^{cgT})}{(1+r)^t} \quad (3-23)$$

3.4.2.2 Node's energy power constraints

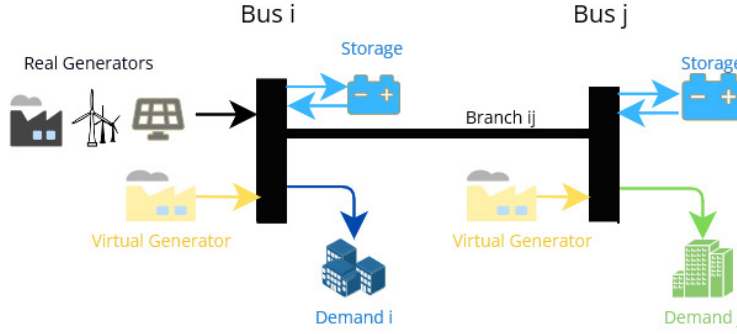


Figure 3-7: Two connected buses in the grid

To guarantee the equilibrium at each bus, the power injected in the bus must be equal to the power extracted for it. Figure 3-7 shows the inlet and outlet power types for an example of two connected buses. Thus, Eq. (3-24) expresses each bus's active power equilibrium concept illustrated in Figure 3-7. The left terms parameters are the active power extracted from real generators, including classic generators (P_i^{cg}), PVs (P_i^{pv}) and WTs (P_i^{wt}), the extracted power from virtual (P_i^{vg}) generators in addition to the discharging power variable (P_i^d). The right-side elements are the active power demand (P_i^l), the active power P_i^{inj} injected to the network at bus $i/i \in \mathcal{N}$ (where $\mathcal{N}$: set of buses) and the active charging power in the battery (P_i^c). In the reactive power case, the same equilibrium concept is expressed in Eq.(3-25) without considering the battery reactive power variable (battery's power factor equal to 1). Since this model is dynamic, all the optimization variables are time-dependent. For the sake of simplicity, the time dependence notation is dropped in all equations except for the battery balance Eq.(3-33).

$$\sum_{i \in \mathcal{N}} P_i^{cg} + P_i^{pv} + P_i^{wt} + P_i^{vg} + P_i^d = P_i^l + P_i^{inj} + P_i^c \quad i \in \mathcal{N} \quad (3-24)$$

$$\sum_{i \in \mathcal{N}} Q_i^{cg} + Q_i^{vg} = Q_i^l + Q_i^{inj} \quad i \in \mathcal{N} \quad (3-25)$$

3.4.2.3 Network constraints

- The active (P_i) and reactive (Q_i) power injected to the network are expressed by Eq.(3-26) and Eq.(3-27)(3-43). G_{ij} and B_{ij} are real and imaginary parts of the network's admittance matrix.

$$P_i = \sum_{j=1}^{\mathcal{N}} (v_i v_j G_{ij} \cos \theta_{ij} + v_i v_j B_{ij} \sin \theta_{ij}) \quad (3-26)$$

$$Q_i = - \sum_{j=1}^{\mathcal{N}} (v_i v_j B_{ij} \cos \theta_{ij} - v_i v_j G_{ij} \sin \theta_{ij}) \quad (3-27)$$

- Branches' flows equations are usually expressed in their general form as follows in Eq.(3-35) and Eq.(3-37):

$$P_{ij} = (v_i^2 - v_i v_j \cos \theta_{ij}) g_{ij} - v_i v_j b_{ij} \sin \theta_{ij} \quad (3-28)$$

$$Q_{ij} = -(v_i^2 - v_i v_j \cos \theta_{ij}) b_{ij} - v_i v_j g_{ij} \sin \theta_{ij} \quad (3-29)$$

The constraints of the active and reactive branch's flow are those for apparent power flowing in the grid branches (T). The quadratic Eq.(3-39) limits the apparent allowable power ($S_{ij,max}$) by a circle area with radius $|S_{ij}|^{max}$, to avoid overloading using the active flowing power P_{ij} between two buses (i and j) and the reactive flowing power Q_{ij} in the branches.

$$(P_{ij,k})^2 + (Q_{ij,k})^2 \leq S_{ij,max}^2, \quad i, j \in T \quad (3-30)$$

- The voltage at each bus is limited regarding the acceptable ranges related to the network level type (transmission or distribution). The voltage constraints are given by Eq.(3-31).

$$V_{min} \leq V \leq V_{max} \quad (3-31)$$

- The voltage angle θ is bounded by minimum and maximum values, as shown in (3-32).

$$\theta_{min} \leq \theta \leq \theta_{max} \quad (3-32)$$

3.4.2.4 Energy storage constraints

The active energy level in the batteries at the time of t ($E_{i,t}^b$) is calculated using the state of charge Eq.(3-33), where the energy stored in the battery is updated at each time step based on the energy level from the previous time step ($E_{i,t-1}^b$), the power stored $P_{i,t}^c$ or discharged $P_{i,t}^d$ from the battery in the current time step. These variables are bounded in Eq.(3-34) and Eq.(3-35) by the power capacity of the BES (P_i^b) calculated in the upper level. η^c and η^d represent respectively the charge and discharge efficiencies. The state of charge is bounded by the maximum stored energy in the BES calculated in the upper level (Eq.(3-36)). The time step is considered one hour ($\Delta t = 1h$).

$$E_{i,t}^b = E_{i,t-1}^b + \eta^c P_{i,t}^c \Delta t - P_{i,t}^d \Delta t / \eta^d \quad (3-33)$$

$$0 \leq P_{i,t}^c \leq P_i^b \quad (3-34)$$

$$0 \leq P_{i,t}^d \leq P_i^b \quad (3-35)$$

$$0 \leq E_{i,t}^b \leq E_{i,t}^{b,max} \quad (3-36)$$

3.4.2.5 Power generation constraints

The active $P_{c,t}^{cg}$ and reactive $Q_{c,t}^{cg}$ power extracted from classic generators is limited by zero and the maximum power of the existing generators in the network (Eq.(3-37)-(3-38)). The active $P_{i,t}^{vg}$ and reactive $Q_{i,t}^{vg}$ power for virtual generators are also bounded by zero and fixed maximum values usually close to those for classic generators (Eq.(3-39)(3-40)).

A^{pv} is bounded by the available surface area to install PVs ($A^{pv\max}$) Eq.(3-41), which corresponds to the maximum installed surface based on unitary PV production PV_t Eq.(3-42).

R^{wt} is bounded by $R^{wt\max}$ (Eq.(3-43)) which corresponds to the maximum exploitable power based on unitary WT production WT_t (eq. (3-44)). Actual PV and WT hourly production ($P_{s,t}^{pv}$ and $P_{w,t}^{wt}$) are bounded by time dependent available powers ($P_{s,t}^{pv\max}$ and $P_{w,t}^{wt\max}$) as detailed in Eq.(3-45) and Eq.(3-46). These available powers are calculated using Eq.(3-42) and Eq.(3-44) where PV_t and WT_t extracted from meteorological data and represent the unitary PV and WT power production, respectively, without curtailment.

$$0 \leq P_{c,t}^{cg} \leq P_c^{cg\max} \quad \forall c \in [0, \mathcal{N}^{cg}] \quad (3-37)$$

$$0 \leq Q_{c,t}^{cg} \leq Q_c^{cg\max} \quad \forall c \in [0, \mathcal{N}^{cg}] \quad (3-38)$$

$$0 \leq P_{i,t}^{vg} \leq P_i^{vg\max} \quad \forall i \in [0, \mathcal{N}^{vg}] \quad (3-39)$$

$$0 \leq Q_{i,t}^{vg} \leq Q_i^{vg\max} \quad \forall i \in [0, \mathcal{N}^{vg}] \quad (3-40)$$

$$0 \leq A_s^{pv} \leq A_s^{pv\max} \quad \forall s \in [0, \mathcal{N}^{pv}] \quad (3-41)$$

$$P_{s,t}^{pv\max} = A_s^{pv} \cdot PV_t \quad (3-42)$$

$$0 \leq R_w^{wt} \leq A_w^{wt\max} \quad \forall w \in [0, \mathcal{N}^{wt}] \quad (3-43)$$

$$P_{w,t}^{wt\max} = R_w^{wt} \cdot WT_t \quad (3-44)$$

$$0 \leq P_{s,t}^{pv} \leq P_{s,t}^{pv\max} \quad \forall p \in [0, \mathcal{N}^{pv}] \quad (3-45)$$

$$0 \leq P_{w,t}^{wt} \leq P_{w,t}^{wt\max} \quad \forall w \in [0, \mathcal{N}^{wt}] \quad (3-46)$$

3.4.2.6 Carbon emissions constraints

$$\sum_{t=1}^T \sum_{i=1}^{\mathcal{N}} En^{cg} \cdot P_{c,t}^{cg} \leq En^{cgT} \cdot Ta \quad (3-47)$$

Only CGs are supposed to emit CO₂ while producing energy. Minimizing the total CO₂ emissions is a second objective function considered for the RES and BES design following the ε -constraint method [246]. For this reason, an additional constraint is added to the problem (Eq.(3-47)). This constraint imposes an upper limit to the CO₂ emissions called emission constraint. Ta is a CO₂ emission cut-off factor selected by the system designer and varied to obtain various designs that achieve different carbon performances. En^{cgT} is the total CO₂ emissions calculated over the

selected period in case of 100% of power is extracted from classic generators. The CO₂ emissions are calculated by the product of $P_{c,t}^{cg}$ and En^{cg} which is the carbon emission factor of classic generators.

3.4.2.7 Optimization variables

The optimization variables of the lower level are categorized as:

- Planning variables: A^{pv}, R^{wt}
- Operation variables: $P^{pv}, P^{wt}, P^{cg}, P^{vg}, Q^{cg}, Q^{vg}, V, \theta, P^c, P^d, E^b$

3.4.3 Description of the iterative solution method

The linear OPF algorithm uses a linearization of the AC OPF equations to optimize generator dispatch and to determine the optimal value for every parameter defining each bus in a network. Those parameters include active and reactive power inputs, voltage, phase angles and battery storage levels. They also involve the active and reactive power flows that circulate in each branch between two nodes subject to the loading constraints of the network branches. The optimization process is based on *Yang et al.*'s methodology [126], which uses an iterative optimization approach. Linear optimization is first performed around an initial approximation (start point). After the resolution, a new operating point is found and used to update the results. This procedure is repeated iteratively until reaching convergence. This approach is upgraded in this work by adding equations for virtual generators and energy storage in desired buses to allow a dynamic simulation of the network.

3.4.3.1 Active and reactive power injections

Power flow equations are usually expressed in their general nonlinear form as follows:

$$P_i = \sum_{j=1}^N (v_i v_j G_{ij} \cos \theta_{ij} + v_i v_j B_{ij} \sin \theta_{ij}) \quad (3-48)$$

$$Q_i = - \sum_{j=1}^N (v_i v_j B_{ij} \cos \theta_{ij} - v_i v_j G_{ij} \sin \theta_{ij}) \quad (3-49)$$

Where P_i and Q_i are the active and reactive power injected into the network and G_{ij} and B_{ij} are real and imaginary parts of the network's admittance matrix.

These equations are linearized given initial guess values (e.g., default values (1,0)) to the voltages and phase angles (v_i^0, θ_i^0) and updated at each iteration k . In the linearization procedure, θ and v^2 are considered as independent variables, and cosine and sine functions are linearized using their first-order Taylor series expansion as follows:

$$\sin \theta_{ij} \approx S_{ij,k}^1 \theta_{ij} + S_{ij,k}^0 \quad (3-50)$$

$$\cos\theta_{ij} \approx h_{ij,k}^1 \theta_{ij} + h_{ij,k}^0 \quad (3-51)$$

$$s_{ij,k}^1 = \cos\theta_{ij,k}, \quad s_{ij,k}^0 = \sin\theta_{ij,k} - \theta_{ij,k} \cdot \cos\theta_{ij,k} \quad (3-52)$$

$$h_{ij,k}^1 = -\sin\theta_{ij,k}, \quad h_{ij,k}^0 = \cos\theta_{ij,k} + \theta_{ij,k} \cdot \sin\theta_{ij,k} \quad (3-53)$$

Then, the following mathematical transformation (3-54) is used to extract a linear expression that can accurately represent $v_i \cdot v_j$.

$$v_i \cdot v_j = \frac{1}{2} (v_i^2 + v_j^2 - (v_i - v_j)^2) = \frac{v_i^2 + v_j^2}{2} - \frac{v_{ij}^2}{2} \quad (3-54)$$

v_{ij}^2 is then linearized in (3-55) to define a new term $v_{ij,L}^s$:

$$v_{ij}^2 \cong 2 v_{ij,k} \cdot v_{ij} - v_{ij,k}^2 \cong 2 \frac{v_{i,k} - v_{j,k}}{v_{i,k} + v_{j,k}} (v_i^2 - v_j^2) - v_{ij,k}^2 = v_{ij,L}^s \quad (3-55)$$

The linear approximation given in (3-55) can lead to negative values, which contradicts the fact that v_{ij}^2 determines the influence of the difference in voltage magnitudes on the losses. In order to guarantee the positive values of v_{ij}^2 , ϵ_{ij} variables are added and the new inequality constraints are added to the optimization problem [126]:

$$2 \frac{v_{i,k} - v_{j,k}}{v_{i,k} + v_{j,k}} (v_i^2 - v_j^2) - v_{ij,k}^2 + \epsilon_{ij} \geq 0 \quad \text{with } \epsilon_{ij} \geq 0 \quad (3-56)$$

ϵ_{ij} are penalized (multiplied by very high coefficients) in the objective function to guarantee their positivity.

Injected active and reactive powers are then calculated around a known solution (v_i^k, θ_i^k) using linearized Eq.(3-57) and Eq.(3-58):

$$P_i = \sum_{j=1}^N \left[G_{ij,k}^p \frac{v_i^2 + v_j^2}{2} + B_{ij,k}^p (\theta_{ij} - \theta_{ij,k}) - G_{ij,k}^p \frac{v_{ij,L}^s}{2} \right] \quad i \in \mathcal{N} \quad (3-57)$$

$$Q_i = \sum_{j=1}^N \left[-B_{ij,k}^q \frac{v_i^2 + v_j^2}{2} + G_{ij,k}^q (\theta_{ij} - \theta_{ij,k}) - B_{ij,k}^q \frac{v_{ij,L}^s}{2} \right] \quad i \in \mathcal{N} \quad (3-58)$$

Where:

$$G_{ij,k}^p = (G_{ij} \cdot h_{ij,k}^0 + B_{ij} \cdot s_{ij,k}^0) + (G_{ij} \cdot h_{ij,k}^1 + B_{ij} \cdot s_{ij,k}^1) \theta_{ij,k} \quad (3-59)$$

$$B_{ij,k}^p = (G_{ij} \cdot h_{ij,k}^1 + B_{ij} \cdot s_{ij,k}^1) v_{i,k} \cdot v_{j,k} \quad (3-60)$$

$$B_{ij,k}^Q = -(G_{ij} \cdot s_{ij,k}^0 + B_{ij} \cdot h_{ij,k}^0) - (G_{ij} \cdot s_{ij,k}^1 - B_{ij} \cdot h_{ij,k}^1) \theta_{ij,k} \quad (3-61)$$

$$G_{ij,k}^Q = (G_{ij} \cdot s_{ij,k}^1 - B_{ij} \cdot h_{ij,k}^1) v_{i,k} \cdot v_{j,k} \quad (3-62)$$

3.4.3.2 Branches' flows equations:

Branches' flows equations are usually expressed in their general nonlinear form as follows in Eq.(3-63) and Eq.(3-64):

$$P_{ij} = (v_i^2 - v_i v_j \cos \theta_{ij}) g_{ij} - v_i v_j b_{ij} \sin \theta_{ij} \quad (3-63)$$

$$Q_{ij} = -(v_i^2 - v_i v_j \cos \theta_{ij}) b_{ij} - v_i v_j g_{ij} \sin \theta_{ij} \quad (3-64)$$

Using the same approximations as for power injections, the linear equations for branch flows are deduced in (3-65) and (3-66), and the parameters are calculated in (3-67) to (3-70).

The active and reactive powers flow in the branches can be calculated to facilitate the addition of a maximal apparent power constraint to the branches:

$$P_{ij} = g_{ij} \cdot v_i^2 - g_{ij,k}^p \cdot \frac{v_i^2 + v_j^2}{2} - b_{ij,k}^p (\theta_{ij} - \theta_{ij,k}) + g_{ij,k}^p \frac{v_{ij,L}^s}{2} \quad (3-65)$$

$$Q_{ij} = -b_{ij} \cdot v_i^2 + b_{ij,k}^q \cdot \frac{v_i^2 + v_j^2}{2} + g_{ij,k}^q (\theta_{ij} - \theta_{ij,k}) + b_{ij,k}^p \frac{v_{ij,L}^s}{2} \quad (3-66)$$

Where:

$$g_{ij,k}^p = (g_{ij} \cdot h_{ij,k}^0 + b_{ij} \cdot s_{ij,k}^0) + (g_{ij} \cdot h_{ij,k}^1 + b_{ij} \cdot s_{ij,k}^1) \theta_{ij,k} \quad (3-67)$$

$$b_{ij,k}^p = (g_{ij} \cdot h_{ij,k}^1 + b_{ij} \cdot s_{ij,k}^1) v_{i,k} \cdot v_{j,k} \quad (3-68)$$

$$b_{ij,k}^Q = -(g_{ij} \cdot s_{ij,k}^0 + b_{ij} \cdot h_{ij,k}^0) - (g_{ij} \cdot s_{ij,k}^1 - b_{ij} \cdot h_{ij,k}^1) \theta_{ij,k} \quad (3-69)$$

$$g_{ij,k}^Q = (g_{ij} \cdot s_{ij,k}^1 - b_{ij} \cdot h_{ij,k}^1) v_{i,k} \cdot v_{j,k} \quad (3-70)$$

3.4.3.3 Branches' flow limits

The inequality constraints are based on the limits of the apparent power flowing in the grid branches (T). A quadratic Eq.(3-71) limits the apparent allowable power ($S_{ij,max}$) by a circle area with radius $|S_{ij}|^{max}$, to avoid overloading using the active flowing power P_{ij} between two buses (i and j) and the reactive flowing power Q_{ij} in the branches.

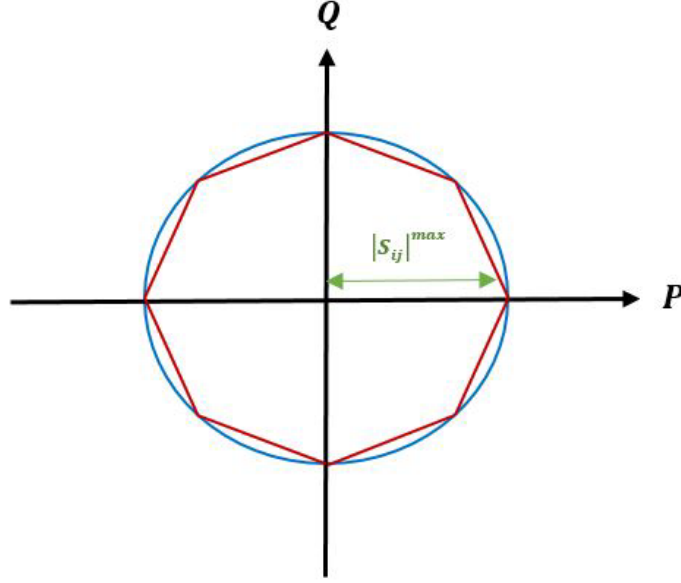


Figure 3-8: Piecewise linear approximation of a circle

$$(P_{ij,k})^2 + (Q_{ij,k})^2 \leq S_{ij,max}^2, \quad i, j \in T \quad (3-71)$$

To linearize this equation, a piecewise linear modeling is used to approximate the circle area presented in Figure 3-8 by an n -sided polygon region that is formed by a group of lines given by Eq.(3-72). Therefore, the nonlinear equation is transformed into n linear equations. In this approach, a higher number of sides 'n' leads to a more accurate solution but with more computational burden [123].

$$\left(\sin\left(\frac{360 * l}{n}\right) - \sin\left(\frac{360}{n}(l-1)\right) \right) Q_{ij} - \left(\cos\left(\frac{360 * l}{n}\right) - \cos\left(\frac{360}{n}(l-1)\right) \right) P_{ij} - S_{ij}^{max} * \sin\left(\frac{360}{n}\right) \leq 0 \quad (3-72)$$

3.4.3.4 Stop criterion

The development of the DLOPF model is based on a formulation of LOPF adapted for the use of transmission or distribution networks. The load profiles are used as input data covering the targeted period. Modeling of network architecture and constraints are required, along with the definition of boundaries (lb and ub) of the output solution. The objective function uses true values, and the use of virtual power is strongly penalized.

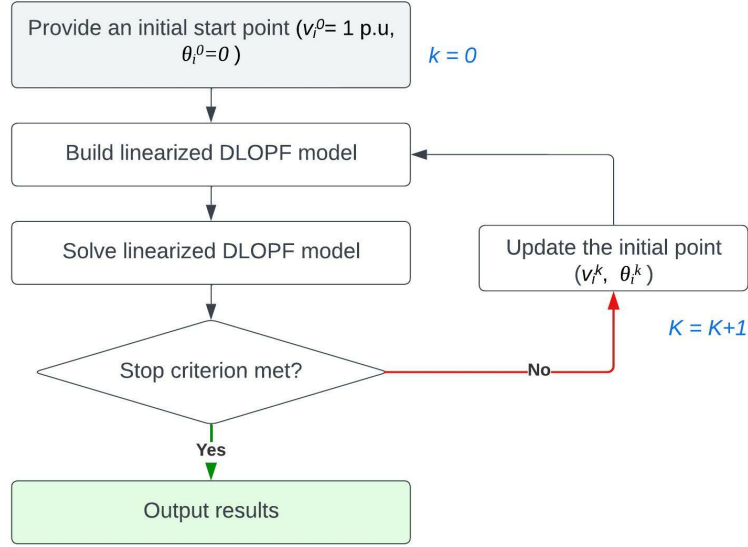


Figure 3-9: Flowchart of the proposed DLOPF algorithm

All these conditions must be initialized to solve the problem with a single optimization procedure summarizing all time periods achieving a global optimal solution. The flowchart of Figure 3-9 represents the resolution process. Given a flat start point ($v_i^0 = 1 \text{ p.u.}$, $\theta_i^0 = 0$), the DLOPF model is built and solved, which leads to new voltages and angle values that are used to update the solution. The number of iterations is not fixed; the process is repeated until the stop criterion is reached. This criterion is defined as the deviation of objective function between two successive iterations ($k - 1$ and k) due to the approximations using the following equation:

$$\Delta_F = \left| \frac{F^k - F^{k-1}}{F^k} \right| \quad k \in [1, 2, \dots] \quad (3-73)$$

When $\Delta_F < \Delta_{tol}$, the stop criterion is satisfied.

3.5 Bi-level model flow chart

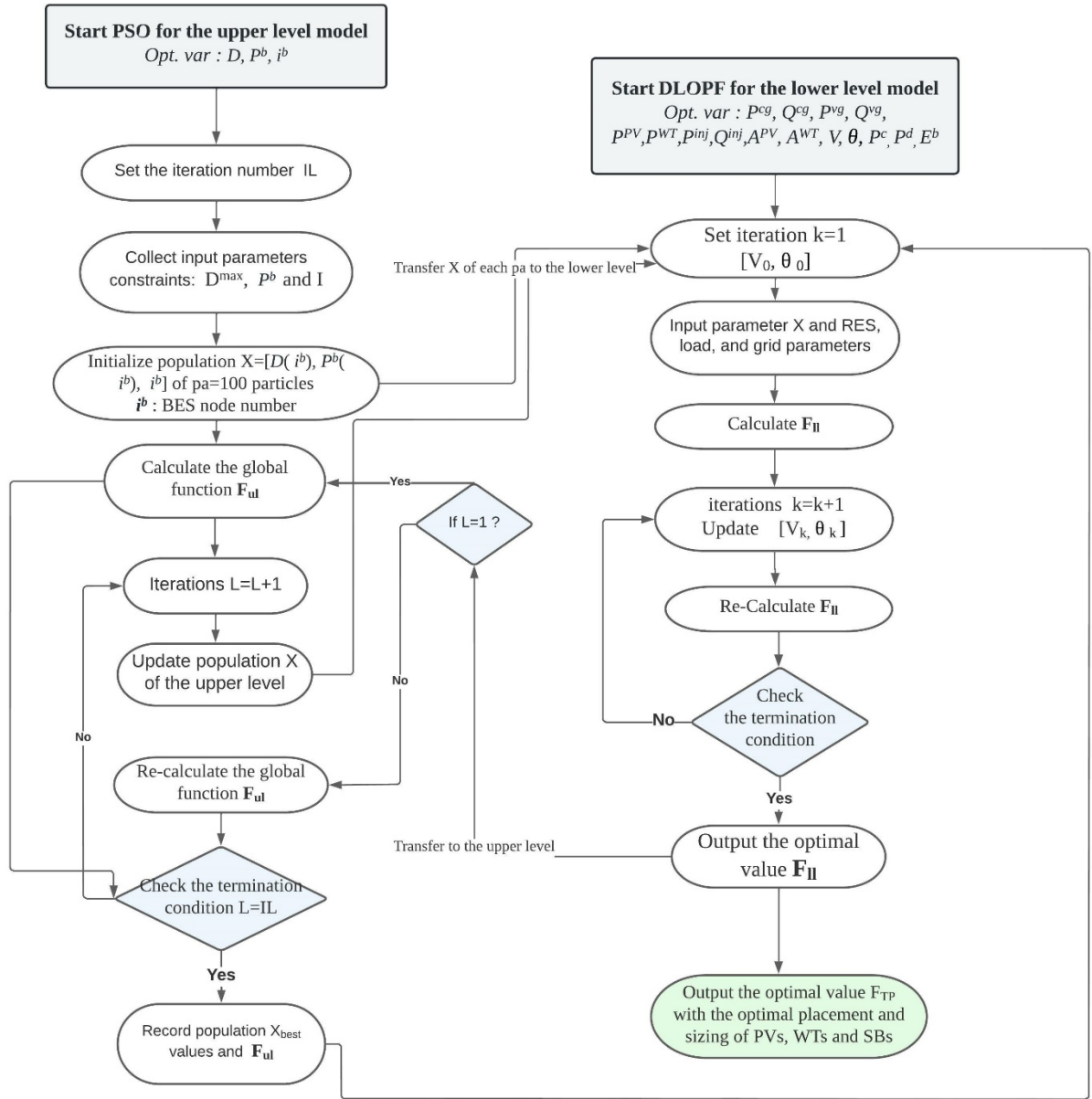


Figure 3-10: Flowchart of the bi-level optimization model

The overall structure of the proposed PSO-DLOPF model is shown by the flowchart of Figure 3-10 and explained as follows:

- Step 1. Set the iteration number for the upper-level model, collect input parameters boundaries, initialize population X as the solution of the upper-level model and obtain BES location, duration and power from X . Transfer X to the lower-level model.
- Step 2. Collect relevant data, input grid parameters and load data. Initialize the values of V_0 and θ_0 . The design BES information X is transmitted to the lower-level model as known parameters. Calculate F_{ll} for the first iteration.

- Step 3. Update the lower-level iteration by updating V_k and θ_k according to the results of the first iteration. Then recalculate F_{ll} .
- Step 4. Evaluate the termination condition based on eq. (3-73) to determine whether a stopping criterion is achieved. If the criterion is reached, the recorded optimal value is passed back to the upper-level model to calculate the upper-level objective function value.
- Step 5. Increase the number of iterations $L = L + 1$. Update the upper-level population X and transfer the updated population from the upper to the lower-level model to repeat steps 2-4.
- Step 6. Increase the number of iterations $L = L + 1$; if the stopping criterion is met, exit the loop to stop the iteration.
- Step 7. Transfer the values of X_{best} to the lower level to obtain the optimal values corresponding to the proposed design.

3.6 Validation of the linearized method

The development of the bi-level optimization model started with a linearization of the OPF to obtain the linearized OPF. This model is validated first, then the dynamic simulation is performed by adding the time variable to obtain DLOPF, and the upper-level is added to get PSO-DLOPF.

To ensure the linearized model's accuracy (LOPF), a validation is made using the Matpower benchmark reference model that uses the power flow equations in their nonlinear forms [247]. The same specifications defined in Matpower for the 'Case30' [248] are used. This 'Case30' is shown in Figure 3-11 and is formed by 30 buses, including 6 generator buses (P-V) and 21 load buses (P-Q). The branches' details are described in Appendix A.

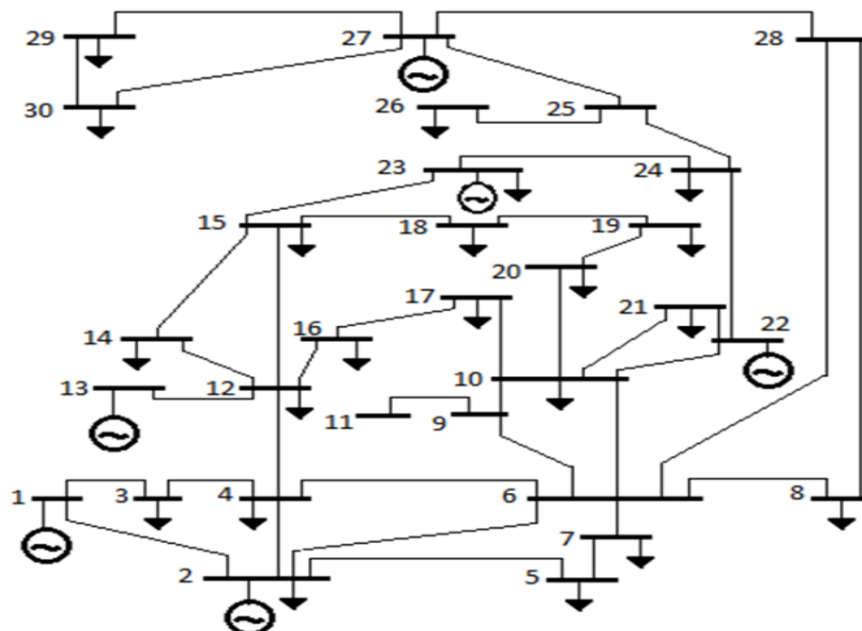


Figure 3-11: IEEE-30 bus system

Optimization with the LOPF is first done on the 'Case30' model. Then, the resulting values of active and reactive power and voltages are used as input data of Matpower model in its simulation mode.

The values of generated active/reactive power, transmitted active/reactive power in the branches, the voltage levels and the phase angles obtained from LOPF and Matpower are extracted. The results of active power generated and transmitted are shown respectively in Figure 3-12 and Figure 3-13. The results are totally consistent for the active generated (P^g) and transmitted power (P^{inj}) and variate with a small accepted amounts for the voltage levels (Figure 3-14) and phase angles (Figure 3-15).

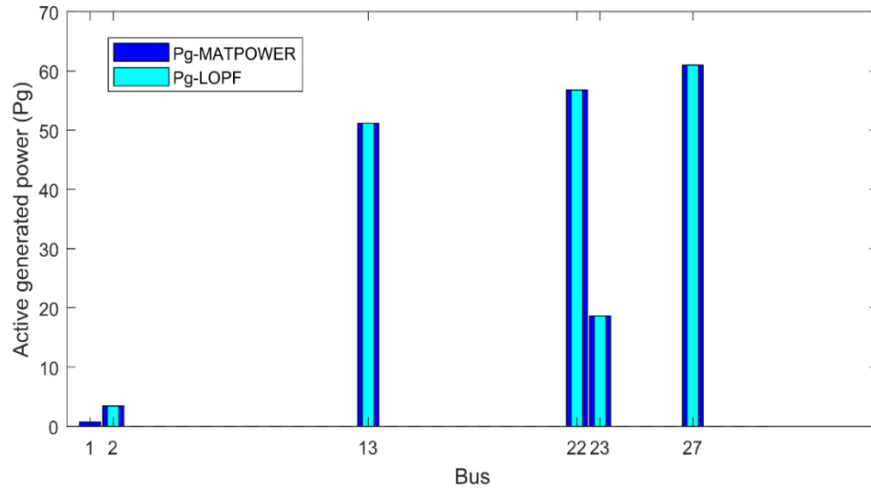


Figure 3-12: Generated active power (MW)

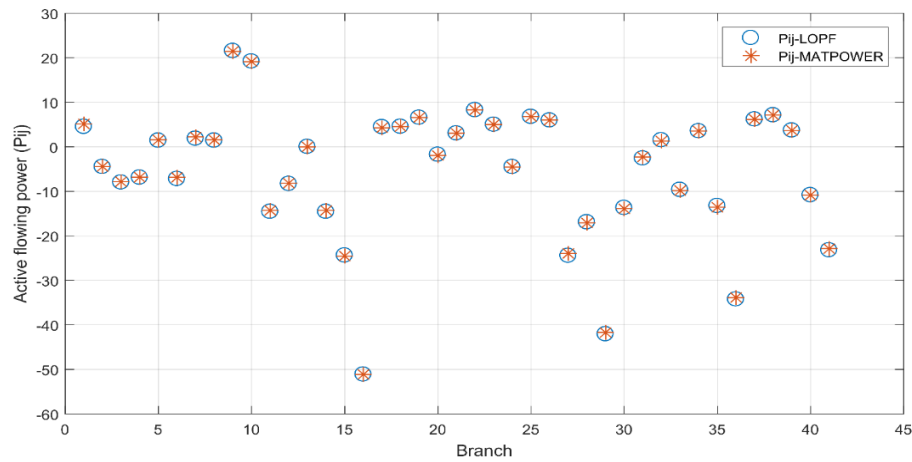


Figure 3-13: Transmitted active power in the branches (MW)

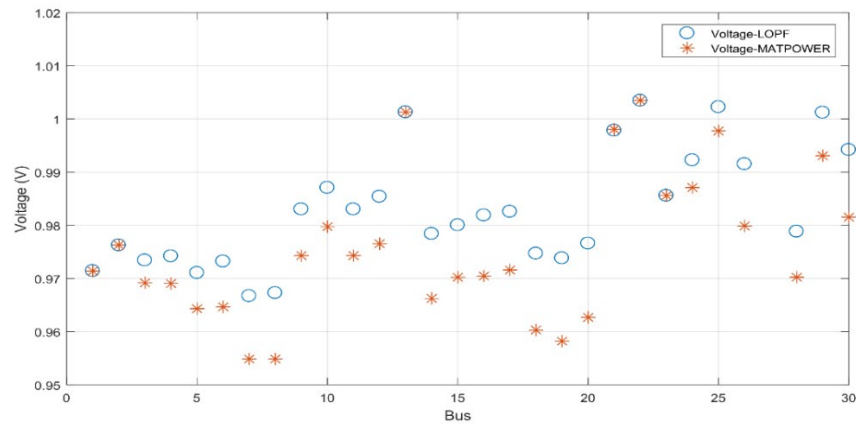


Figure 3-14: Voltage level (per.unit)

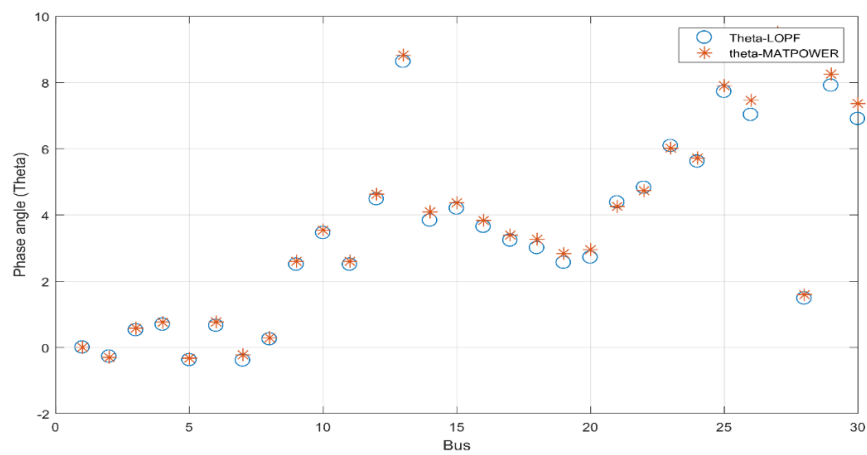


Figure 3-15: Phase angles (degree)

In addition to the graphical validation, the *Root Mean Square Errors (RMSE)* is calculated for all the operational parameters as listed in Table 3-2.

Parameters	RMSE (LOPF-Matpower)
P^g	0.01 kW
Q^g	1.02 kVAr
P^{inj}	0.22 kW
Q^{inj}	1.5 kVAr
θ	4.61 degree
V	0.0089 V

Table 3-2: RMSE values

The RMSE results show that the linearized model gives accurate values in the active power parameters (generated and transmitted) and voltages with negligible RMSE values (0.01 KW, 0.22

KW, 0.0089 V). Higher rates of RMSE are obtained for the reactive parameters (generated and transmitted) and phase angles (1.02 kVar, 1.5 kVar and 4.61 degrees). All the RMSE values are minor and accepted, confirming the linearized model's good accuracy.

3.7 Summary

This chapter presents the general structure of the EPSM model developed in this thesis. The description of the bi-level approach follows it. Then, the procedures that are used to formulate and solve the equations of the PSO-DLOPF problem are discussed. Finally, the linearization of the OPF model is verified by comparing the results to those obtained from a nonlinear reference. The following chapter elaborates on a DLOPF model to generate scenarios and the results of the EPSM detailed in this chapter.

Chapter 4: Planning Methodologies for the Electrical System

4.1 Introduction

To evaluate the performances of the EPSM in the context of an existing network and evolving demand, two different applications are presented in this chapter. The first one uses only the DLOPF without the metaheuristic part. DLOPF is applied to the 30-bus case study to simulate the grid behavior with integrated renewables based on the virtual generator results. Then, in the second application, the bi-level EPSM is applied for both the sizing and dimensioning of renewables and storage batteries. The chapter starts with an introduction to present the input data used in the following parts. In addition to a brief summary that describes the following applications.

4.2 Case study

4.2.1 Renewable energy technologies considered

The following case studies consider renewable generation, such as wind and solar PV. The electricity produced from such technologies is considered as locally generated. Since simulations are time-dependent, the generation output from these renewable energy sources is simulated using HOMER [168] for wind generation based on available wind data speed and HelioScope [249] for solar PV generation based on available solar radiation in a specific location.

4.2.1.1 Solar resources

HelioScope is used in this work to simulate solar array output for a specific location under technological, architecture and environmental assumptions. The global simulated Model components considered in HelioScope are the followings: System model, Module model and Environmental Model. The system model includes inverters, combiners, wires, and distributed electronics. The system model calculates all the electrical relationships and models field output for a given time under a given set of assumptions. The module model includes a single-diode model, PVSyst diode model, photocurrent calculation, Reverse Saturation Current, shunt resistance calculation and temperature model. The environmental model includes meteorological data (solar angles), irradiance calculations, and near shading. The output power produced for a test field for a specific time slice is calculated. This calculation is then performed for each hour over a given year, allowing us to identify the total annual production.

In this study, we start by choosing the location coordinates (Nantes-France). In the selected location, the global hourly irradiation data specific to this area is extracted by HelioScope from meteonorm [250] and presented in Figure 4–1.

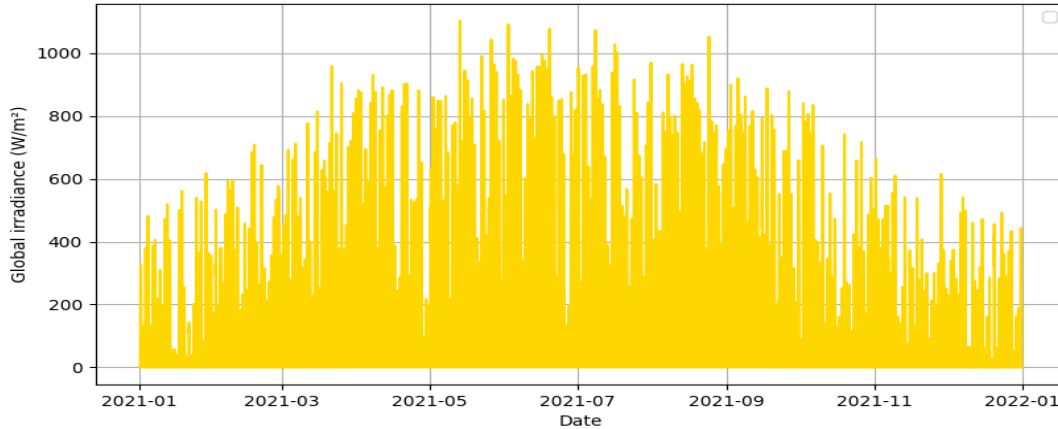


Figure 4–1: Global irradiance for one year 2021

Figure 4–1 reflects the global irradiance received from the sun's rays (direct, diffuse and reflected) that feeds the photovoltaic panels and that strongly depends on the periods of the year therefore, we distinguish 3 different periods for the specified location:

- Important irradiation: from May to September
- Average irradiation: from September to October and from March to May
- Low irradiation: from October to March

The components (inverters, modules, etc.) types are then specified. The output power is calculated in terms of global irradiance, the temperature of the cells, etc. The output power produced for a chosen configuration ($\sim 15\,000\text{ m}^2$ of solar panels) is represented by Figure 4–2. Since the power output is strongly dependent on the global irradiance, the profile shape of the output power is close to the irradiance shape. Therefore, the power levels to be extracted will be categorized into important, average and low power according to the periods distinguished above. This is intended to consider representative durations for the different production levels.

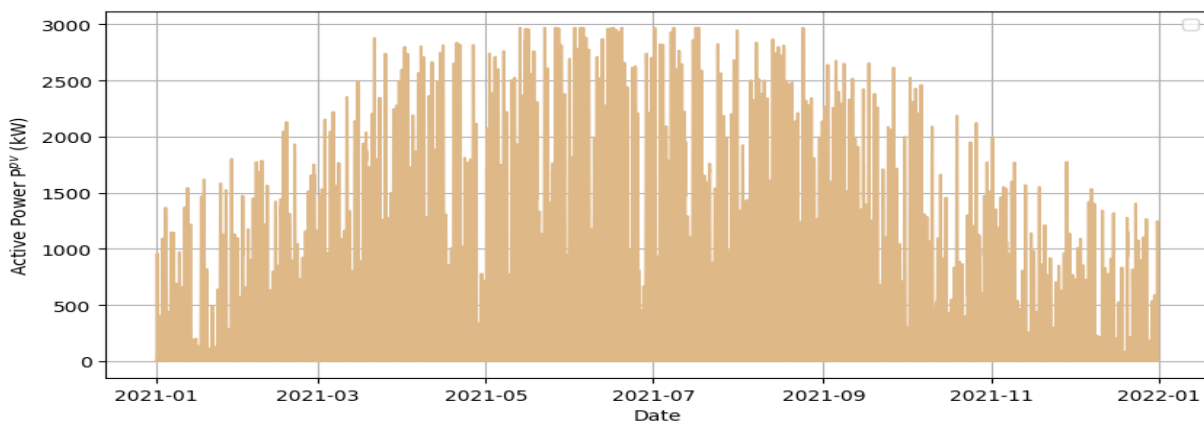


Figure 4–2: Profile of PV generators for one year 2021

4.2.1.2 Wind resources

The wind turbine's power output is calculated in HOMER using a three-step process. In each time step, HOMER calculates first the wind speed at the hub height of the wind turbine. Then, HOMER refers to the wind turbine's power curve to calculate the expected power output at that wind speed under standard temperature and pressure conditions. Finally, the power output value predicted is corrected by applying density correction by multiplying the power value predicted from the power curve by the air density ratio. This returns to the fact that the power curves generally specify the performance of wind turbines under standard temperature and pressure conditions (STP), and this correction is made to adapt them to real conditions.

The location coordinates are also fixed in Nantes-France. As shown in Figure 4–3, wind speed varies almost in intermittent cycles every month, but the detected profile of the period between May and October is lower than the other periods of the year.

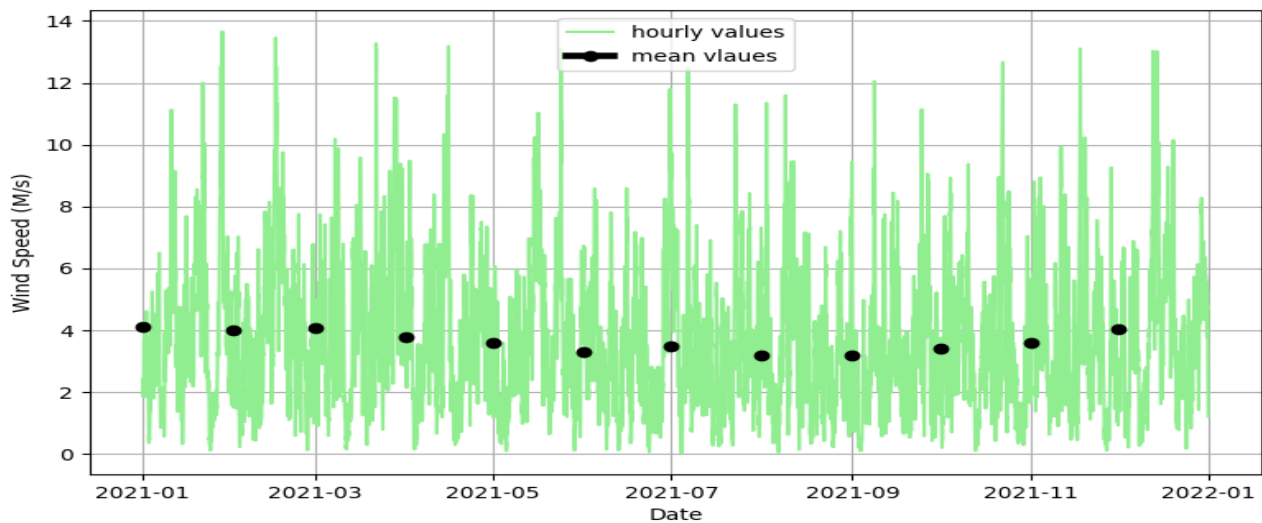


Figure 4–3: Wind speed in Nantes for one year 2021

This wind speed results in a lower power profile between May and October compared to the power produced at other times of the year, as shown in Figure 4–4.

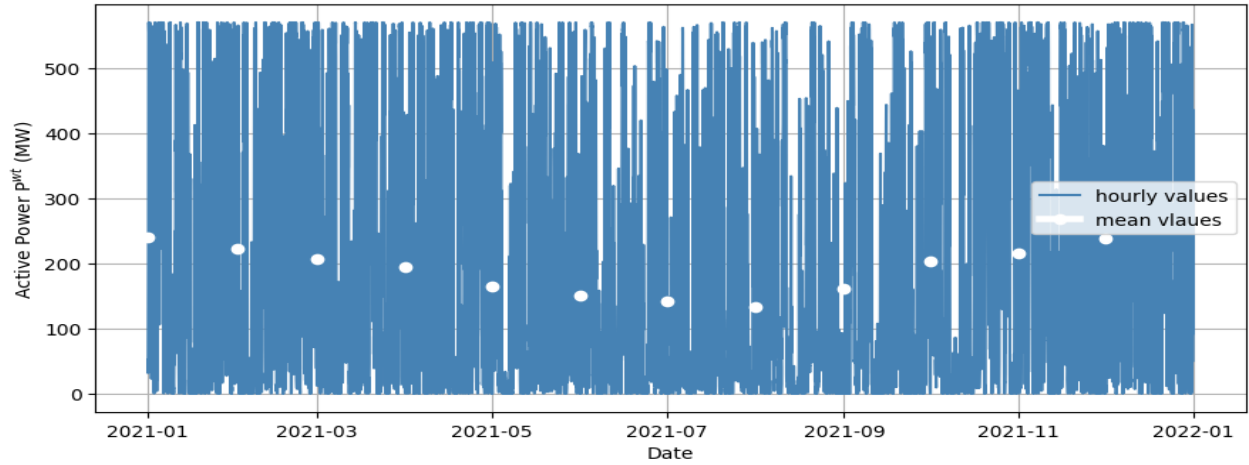


Figure 4-4: Profile for WT generators for one year 2021

4.2.2 Grid characteristics

Reference Grid: IEEE 30-buses

The example grid used for this study is the IEEE 30-bus system [251]. This grid comprises 30 buses with base voltages of 33KV [252]. A schematic of the grid topology can be found in Figure 4-5. The data was downloaded from the IEEE Power Systems Test Case Archive [253].

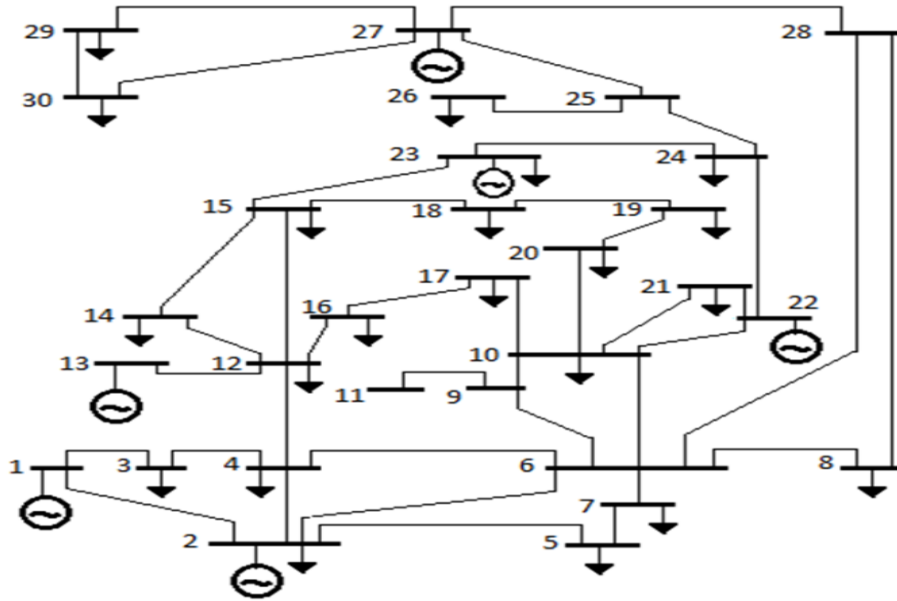


Figure 4-5: IEEE 30-bus system

Grid parameters and constraints

The considered topology contains 30 buses, including 6 generation units that can be either thermal generators or substations and 20 load buses as detailed in Table 4-1. The variable loads combine three different types of archetype load profiles (residential, commercial or a mix of both) with different proportions (detailed in the next section). The voltages, voltage angles and the apparent power flowing in the branches are limited by specified ranges according to the network type. These ranges are also included in Table 4-1. The branch interconnections details with their corresponding characteristics are shown in Table A- 1.

Table 4-1: Summary of IEEE-30 bus system in the base network.

Items	Quantity	Details
Buses	30	[251]
Branches	41	Electrical lines details, resistance and reactance (0) [251] Maximum transmission capacity = 9.2 MVA
Classic generators (CG) (generators or distribution transformers)	6	Buses: 1,2,13,22,23 and 27
Connected load	20	Buses: 2, 3, 4, 7, 8, 10, 12, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 26, 29 and 30 59% of all the consumers are residential, 19.8 % commercial and 21.2% mix
Phase angles	-	Ranges [-0.35; +0.35]
Voltages	-	Ranges [+0.9; +1.1] p.u

4.2.3 Demand

Electric load profiles in this chapter were generated using the load simulator in HOMER [182]. Three different types of archetype load profiles (residential, commercial or a mix of both) are presented in Figure 4–6 for one year.

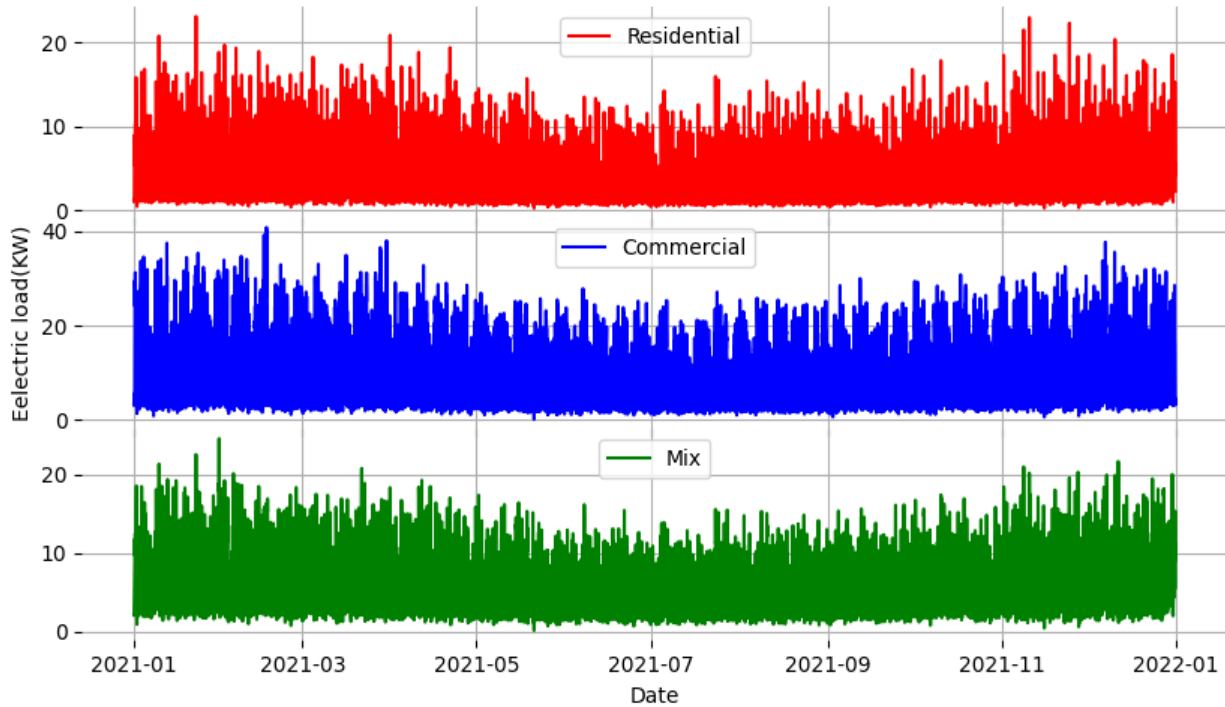


Figure 4–6: Different generated electric load profiles using HOMER

HOMER uses standard time series to obtain load data profiles that don't depend on the location. These hourly time series are simply generated by specifying the load type (Residential, commercial, industrial or community), the peak month (January, July or none of them) and a scaled annual average (kWh/day) defined to generate load curves. Based on the selected location (Nantes-France) in the following parts, January is the peak month in this location, and the different profiles show:

- A high consumption between November and April
- An average consumption between April-June and October-November
- A low consumption between June and September

These time-series (Figure 4–6) are aggregated to generate a realistic load profile for each bus by fixing the peak load and the proportions of each consumer type in the bus (e.g., if bus number 1 is formed by 30% commercial and 70% residential, the generated curves (commercial and residential) are multiplied by 0.3 and 0.7 respectively. The sum of the two curves is made for each time step to obtain the total curve of the bus). Then a week from January (peak week) is used in part **Error! Reference source not found.** to perform DLOPF simulations.

4.2.4 Studied applications to EPSM

The EPSM models' development starts with the OPF equations' linearization. This linearization is validated in the previous chapter. This model is then transformed into a dynamic model (DLOPF) to simulate the network state at each moment. This model constitutes the first application studied in

this thesis (Application 1). This application uses DLOPF to generate and evaluate interesting scenarios of PV, WT and BES deployment based on virtual generator results. The objective function aims to minimize the total cost of all the existing units. The DLOPF is tested on a case study (IEEE 30 bus) of an undersized network in the context of increasing electricity demand in one winter week.

The DLOPF model is then coupled to an optimization stage. The EPSM detailed in the previous chapter is developed following a bi-level approach. This model constitutes the second application studied in this thesis (Application 2). The EPSM optimizes the size and planning of PVs, WTs and BES while considering the minimization of the LCOE and carbon constraints. The virtual generators here are used to guarantee a feasible solution and the installed capacity of RES and BES constitute the technical constraints used as inputs to the model. EPSM is tested on the case study (IEEE 30 bus system) for 9 days covering three different periods levels of the year.

Table 4-2 summarizes the comparison between the two applications that we will expand in the following sections.

Table 4-2: Comparison between applications

	Application 1: DLOPF	Application 2: PSO-DLOPF
Durations of the studied Electric Load and Renewables Generation Case Study	One winter week	Three typical durations of 3 days each one
Technical constraints	IEEE 30 bus system	IEEE 30 bus system
Objective Function	PV/WT/ST availability	- PV/WT available surfaces & possible locations - BES available quantity
Main Output	Total annual cost (TAC) coefficients	Levelized cost of energy and storage
Virtual Generators usage	- Sizing PV/WT/BES for the prefixed locations - Network simulation with time series variables	- Optimal scenario for sizing and placement of WT/PV/BES - Network simulation with time series variables
Simulation time	Used to guarantee a feasible solution To define the possible locations for WT/PV/BES	Used to guarantee a feasible solution
	10 mins	40 hours per scenario (36 mins for each population)

The case study on which the application is built consists of a realistic case where the demand is higher than the distribution capacity of the network. This returns to the evolution of the demand that leads to congestion. The integration of renewable energy sources and storage systems is presented here as a solution to this problem that would avoid the need to reinforce the electrical network. In this application, the DLOPF is applied for an extreme case where the existing sources are insufficient to meet the time-dependent loads (the usual issue of matching between urban densification and existing electricity networks). Therefore, to achieve the supply-demand balance with respect to the network's constraints, different scenarios can be proposed aiming to find the optimal generation dispatch using renewable generations and storage systems.

The DLOPF is used within a methodology for energy planning, aiming to integrate renewables and storage systems. The virtual generators allow the development of feasible energy planning scenarios and guide the decision for renewables and storage integration.

The related objective function minimizes the total annual cost (TAC) coefficients (c) for a given time period. The TAC coefficient (c) of each generator type is estimated in this section by order of TAC per MWh which gives a coefficient for the CGs greater than the RES. The coefficient of VGSs is much higher than the others, so the optimizer uses VGs only in cases where access to other producers is impossible. The objective function is shown in Eq. (4-1).

$$\begin{aligned} \min F_{ob} = & \sum_{t=1}^T \sum_{c=1}^{N^{cg}} [\mathbb{C}^{cg,p} \cdot P_{c,t}^{cg} + \mathbb{C}^{cg,q} \cdot Q_{c,t}^{cg}] \\ & + \sum_{t=1}^T \sum_{i=1}^{N^{vg}} [\mathbb{C}^{vg,p} \cdot P_{i,t}^{vg} + \mathbb{C}^{vg,q} \cdot Q_{i,t}^{vg}] + \sum_{t=1}^T \sum_{w=1}^{N^{wt}} \mathbb{C}^{wt} \cdot P_{w,t}^{wt} + \sum_{t=1}^T \sum_{s=1}^{N^{pv}} \mathbb{C}^{pv} \cdot P_{s,t}^{pv} \end{aligned} \quad (4-1)$$

This function is subjected to equality and inequality constraints detailed previously in Chapter 3.

4.2.5 Input data

- **Energy technologies used, costs and available locations**

The following Table 4-3 summarizes the generators and BES descriptions. For each type, the number of available installable buses is defined. The installable buses are listed in 'Details' in addition to the sizes of the RES and BES. The corresponding TAC coefficient of each type is also specified in the table.

Table 4-3: Installed and installable generation units and BES with their locations and costs

Items	Available installable buses	Details	Cost coefficient (¢)
Classic generators (CG)	6	Buses: 1,2,13,22,23 and 27 / CG=50 MW	$c^{cg} = 1.2$
Virtual generators (VG)	30	All buses	$c^{vg} = 10$
Wind generators (WT)	3	Buses: 3,15 and 21 WT= 30 MW/bus (maximum installable)	$c^{wt} = 0.44$
Solar PV units (PV)	2	Buses: 4 and 16 PV= 50 MWc/bus	$c^{pv} = 0.45$
Storage batteries (BES)	5	Buses: 3,4,15,16 and 21 BES=10 MWh	0
Load	21	Peak demand = 375 MW	-

Different test scenarios will be defined by allocating additional renewable-based systems and batteries. The objective function is structured to maximize the share of RES by assigning lower cost coefficients for renewable producers than for conventional producers. The cost coefficient associated with WTs (0.44) is slightly lower than that of PVs (0.45) since the TAC of WTs is relatively less expensive than for PVs [254].

• Production

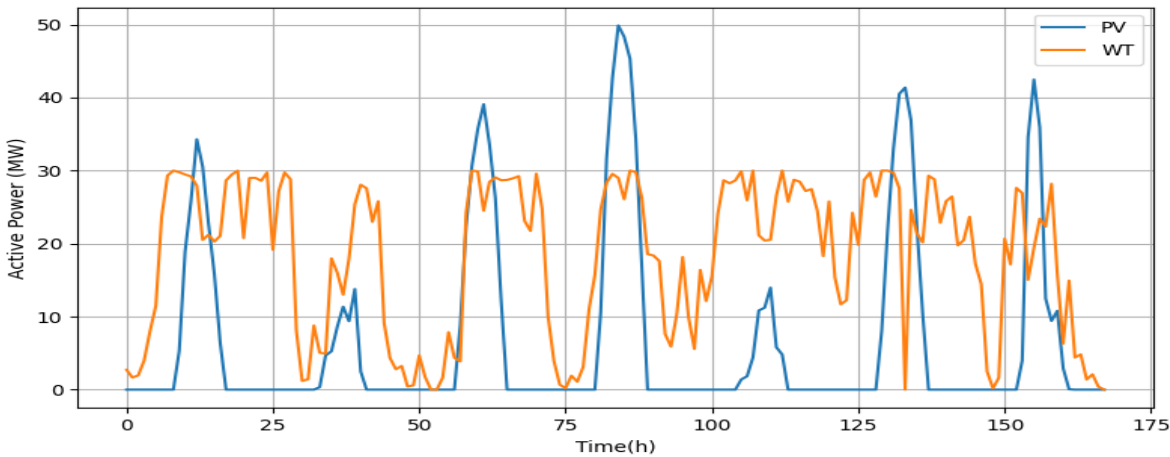


Figure 4-7: Maximum production profiles of WT and PV generators for one winter week

Figure 4-7 shows the simulated available maximum production profiles for the two renewable sources used in the following in one winter week.

- **Demand**

The load profiles are generated with different proportions. An illustration for the first four buses and the cumulated load is presented in Figure 4–8 for the winter week. This figure highlights the diversity of demand from one bus to another, which is important to show that the studied scenario represents real cases.

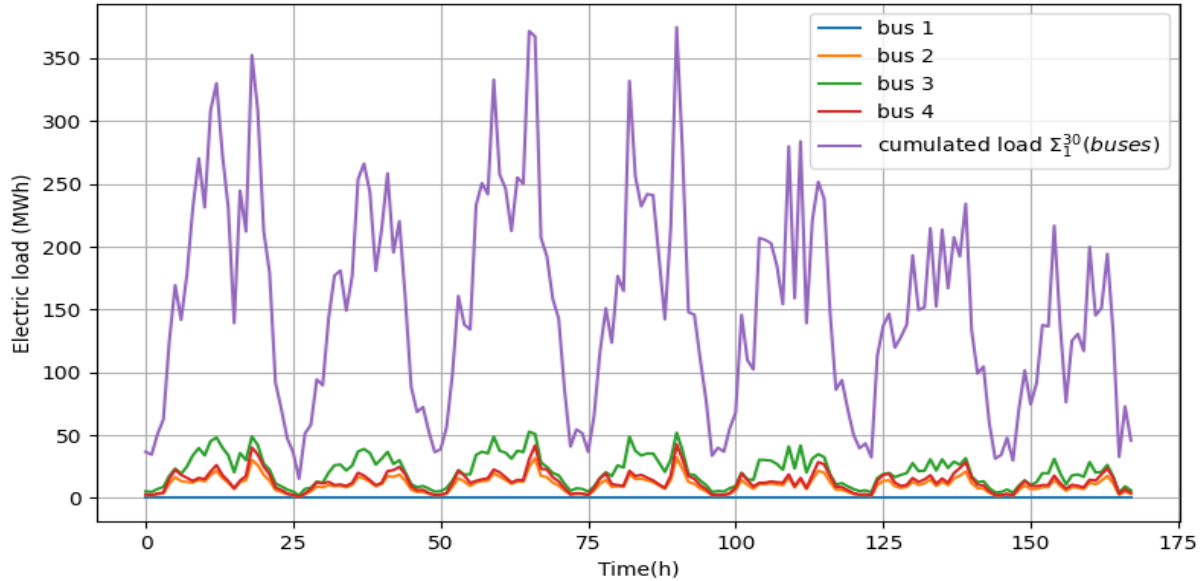


Figure 4–8: Generated load profiles at buses (illustration for buses 1-2-3 and 4) Vs the total cumulated load on all buses.

4.2.6 DLOPF implementation

To illustrate the relevance of the proposed model in handling this type of issue, five different test scenarios are defined. All these scenarios have the same load profile configuration across the different buses, the same CG capacities, and the same cost coefficients. However, some include renewable generation units and storage devices, and others don't.

- **Test scenario A1 (base network)**

In this case, the DLOPF model is applied to the network containing only CGs. Virtual generators are added to all buses to identify lacking sources to meet the demand.

- **Test scenario B1 (A1 without network)**

A simple optimization problem is applied without considering the distribution network, using the same load profiles and CGs as A1. The optimization minimizes the production cost using the same generation cost coefficients and loads.

- **Test scenario A2 (A1 + renewables)**

Referring to the results of A1, renewable energy sources (WT+PV) are added according to the distribution defined in Table 4-3. DOPLF is then applied to optimize the system under the cost coefficients of CGs, VGs, WTs and PVs of Table 4-3.

- **Test scenario B2 (*A2 without network*)**

The same optimization process is applied to the scenario proposed in A2 without considering the grid.

- **Test scenario A3 (*A2 + storage systems*)**

Referring to the results of A2, the same configuration and optimization process is applied by including storage systems (batteries) in this case.

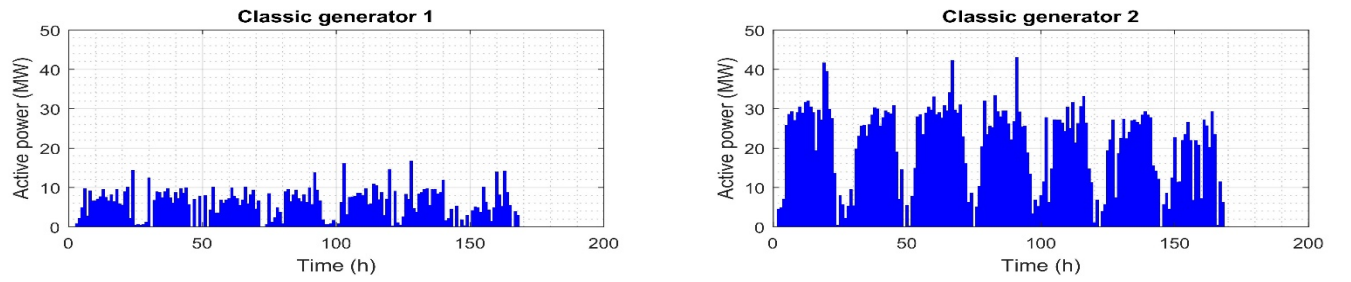


Figure 4-9: Real generated power. Illustration for the buses 1 and 2 (Test scenario A1)

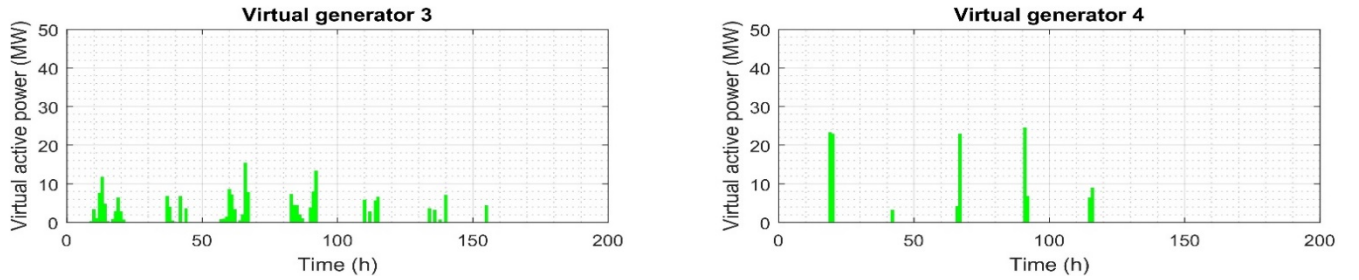


Figure 4-10: Virtual generated power. Illustration for the buses 3 and 4 (Test scenario A1)

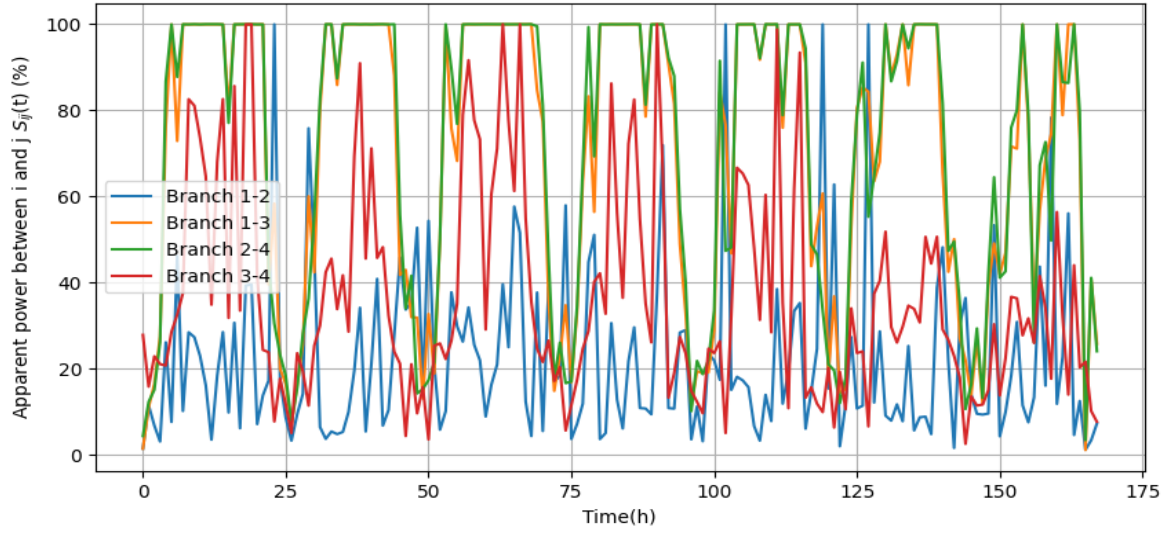


Figure 4-11: Percentage of apparent power in the branches. Illustration for the branches between buses 1-2-3 and 4 (Test scenario A1)

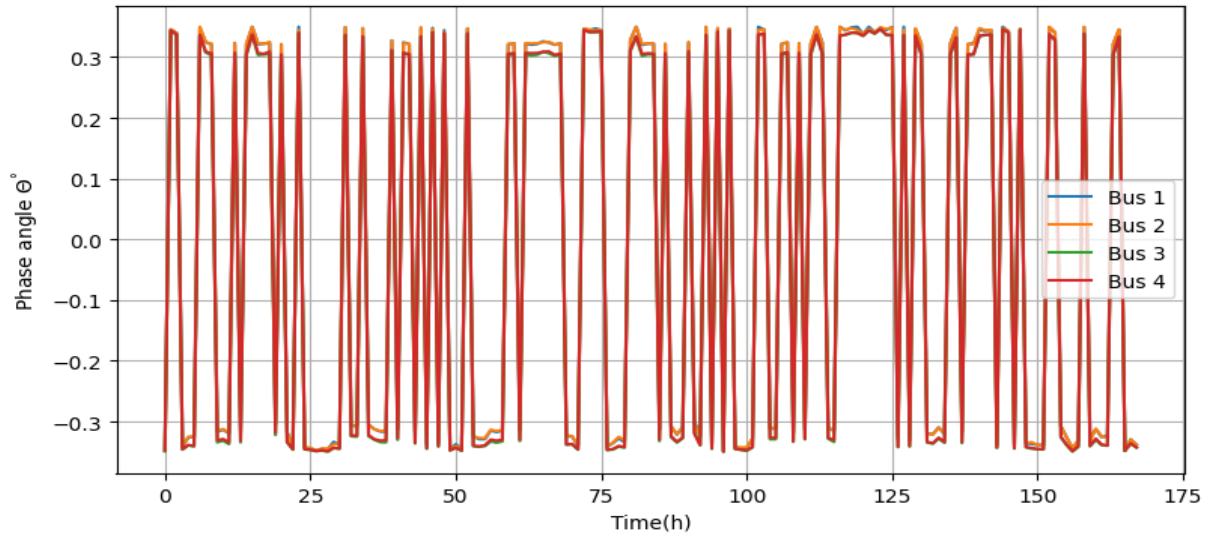


Figure 4-12: Phase angles. Illustration for the buses 1-2-3 and 4 (Test scenario A1)

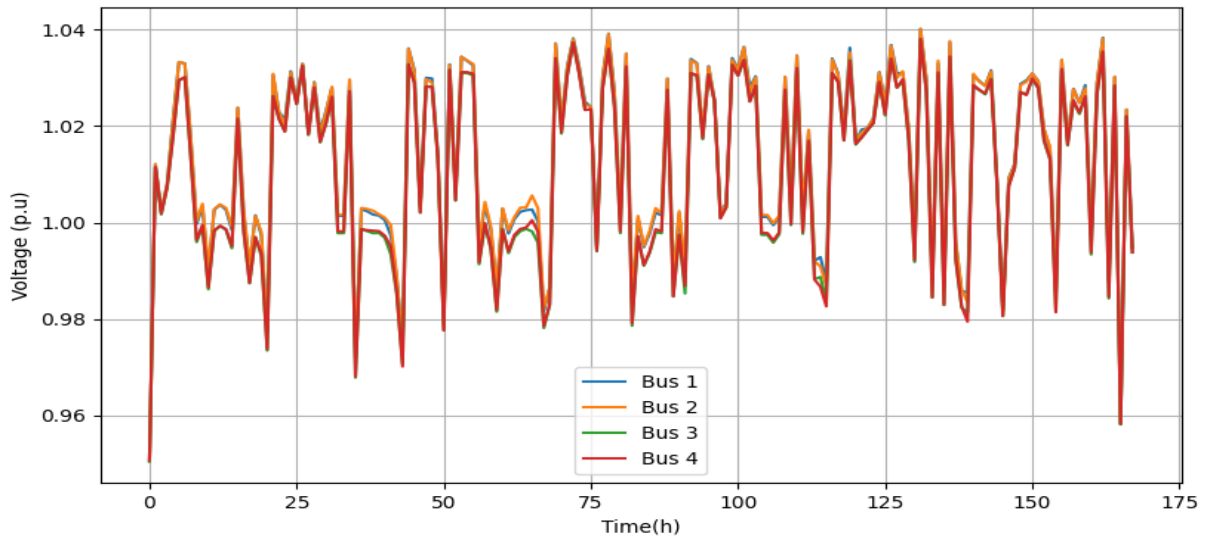


Figure 4-13: Voltages. Illustration for the buses 1-2-3 and 4 (Test scenario A1)

Test scenario A1:

The application of DOPLF to the test scenario A1 provides the power production results of classic and virtual generators in all buses during a winter week, as well as voltages, phase angles and active and reactive power flowing in each branch. As an illustration, the results for buses 1 and 2 are shown in Figure 4-9, where production profiles are presented for the CGs 1 and 2, for the studied period. Active power generated by CGs shows coherent profiles between generated power (Figure 4-9) and loads (Figure 4-8). It can be seen from the results that, in periods of high consumption (e.g., from 4 a.m. to 10 p.m. in Figure 4-8), there is an important solicitation of the generators (same period in Figure 4-9). In some other periods where the consumption is low (e.g., from 22 p.m. to 4 a.m. in Figure 4-8), CGs are less solicited. It is also noticed from Figure 4-9 that the generators are not used equally even though they all have the same production cost. This is the direct effect of the losses in the network in addition to the network's constraints (Table 4-1), handled by the model.

At the scale of the whole network, the total installed generation capacity of the CGs is 300 MW which is greater than the cumulated maximum power at each bus which is 187.3 MW (Figure 4-8). Despite these conditions, their production is not sufficient to meet the demand. Hence, the production deficits are shown in the form of power generated by virtual generators (e.g., buses 3 and 4 in Figure 4-10). The model, in this case, shows the limitations of the electrical grid in the test scenario A1 which are due to the acceptable ranges of other optimization variables, such as the limits of voltages, phase angles and apparent powers in the branches that constitute the network constraints. At this level of consumption, the maximum apparent power limits are reached at least in the 4 illustrative branches shown in Figure 4-11.

Similarly, Figure 4–12 shows the phase angle differences at buses 1-2-3 and 4, reaching the maximum allowable values. These limits make the CGs unable to inject more power into the grid. This happens in other nodes of the network (not presented here). CGs are not reaching their maximum production capacity returns to the fact that the transmission capacity of the grid limits to power. The model reveals the realistic behavior of a network with constraints and supply-demand equilibrium.

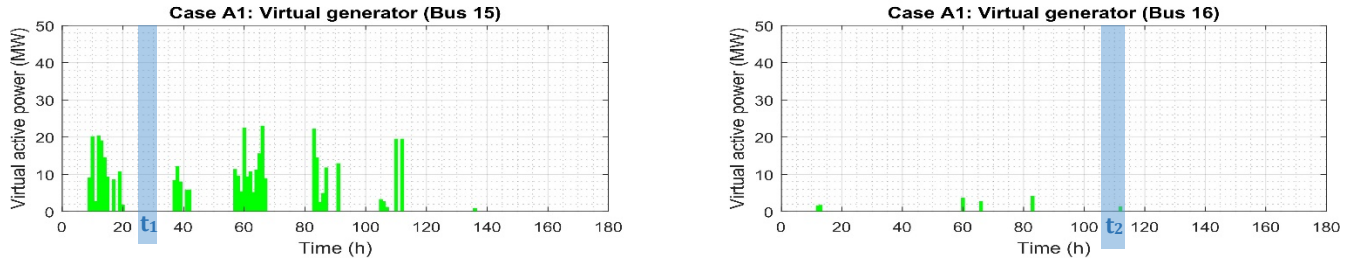


Figure 4–14: Results of virtual generators in A1. Illustration for the buses 15 and 16.

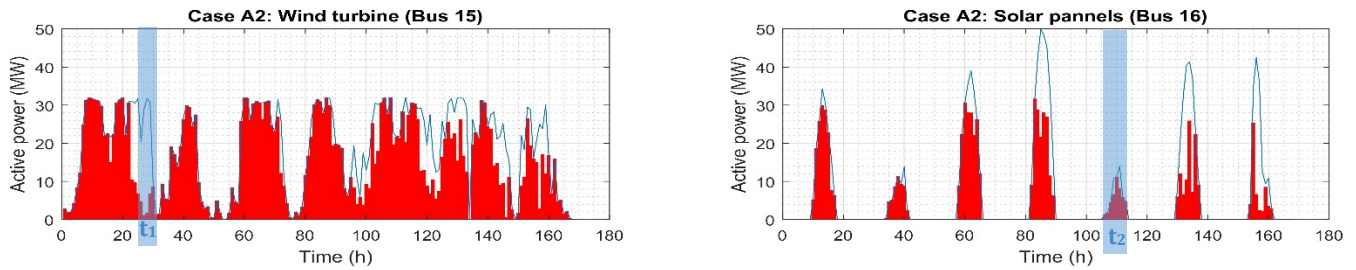


Figure 4–15: Results of WT and PV productions in A2. Illustration for the buses 15 and 16.

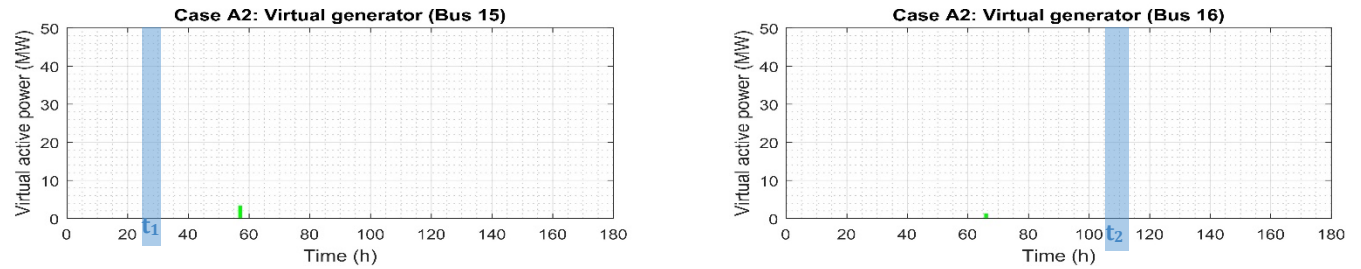


Figure 4–16: Results of virtual generators in A2. Illustration for the buses 15 and 16.

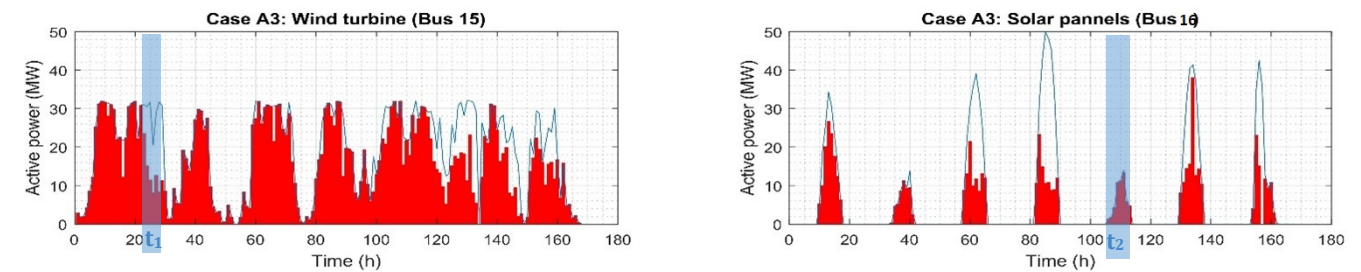


Figure 4–17: Results of WT and PV production in A3. Illustration for the buses 15 and 16.

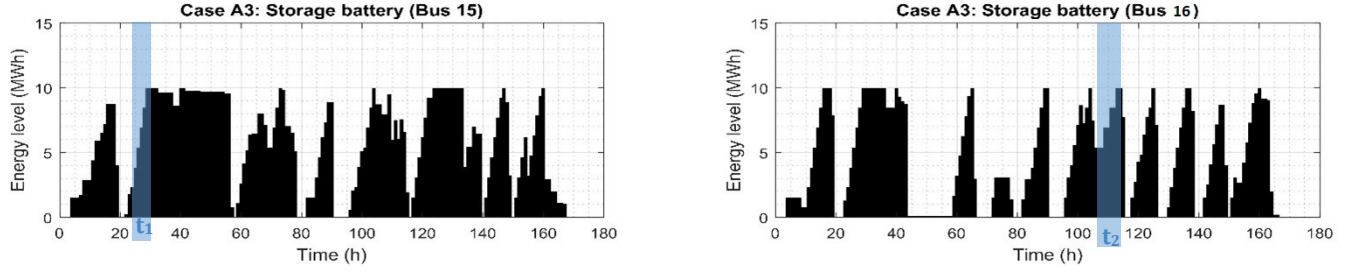


Figure 4-18: Storage batteries in A3. Illustration for the buses 15 and 16.

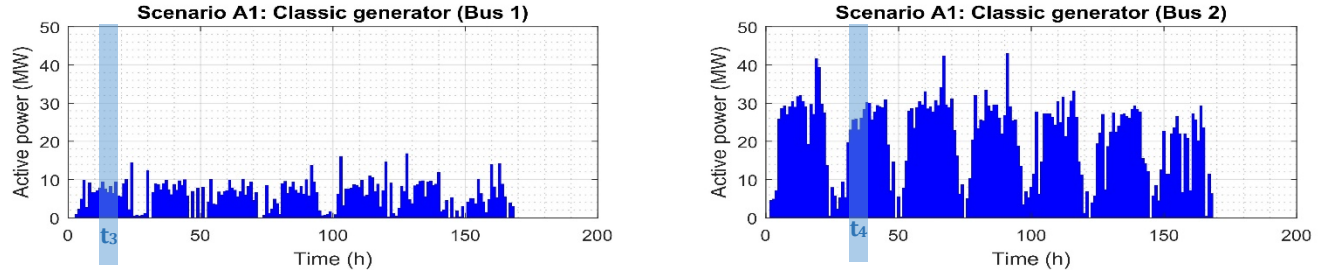


Figure 4-19: Active power production for CGs. Illustration for the buses 1 and 2 (Test scenarios A1)

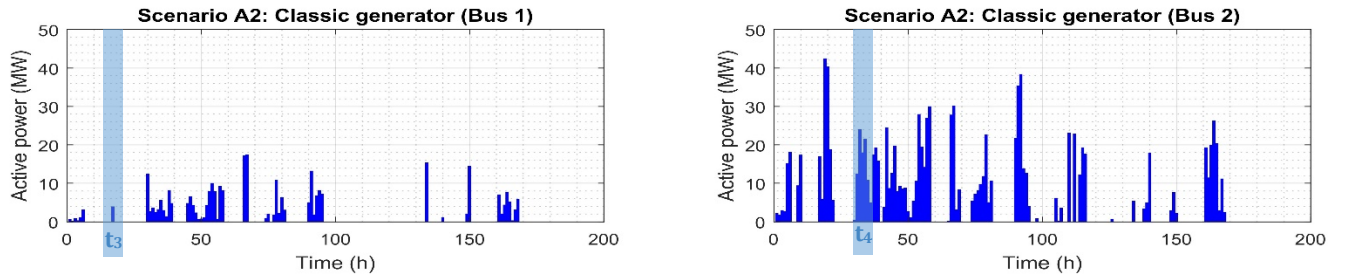


Figure 4-20: Active power production for CGs. Illustration for the buses 1 and 2 (Test scenarios A2)

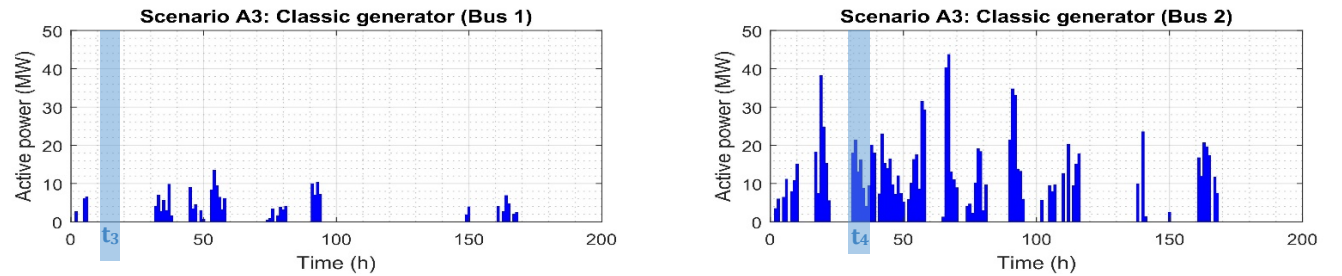


Figure 4-21: Active power production for CGs. Illustration for the buses 1 and 2 (Test scenarios A3)

Buses 15 and 16 presented in Figure 4-14 show the results of the first scenario A1. As can be seen in Figure 4-14, there is a need for generation through virtual generators (VG) at buses 15 and 16 with different levels. This reflects the production deficit in hourly time steps. It shows that the need for power is greater in peak periods (every day between 7 a.m. and 8 p.m.). However, in periods of low

consumption, virtual generators are not used. These VG characteristics are used to define the next scenarios considering renewable sources to compensate for the local deficits. The definition of a scenario for A2 includes the selection of appropriate renewable sources based, at this level, on the amount of energy required on each bus.

Test scenario A2:

In this test scenario, photovoltaic solar panels are added on buses 4 and 16 and wind turbines on buses 3, 15 and 21, as mentioned in Table 4-3.

DLOPF is applied to scenario A2 and hourly power production in classic generators (in buses 1 and 2) is shown in Figure 4–20. This figure shows that the total amount of solicitation of classic generators decreases for scenario A2 (Figure 4–20) compared to scenario A1 (Figure 4–19) during non-peak periods (e.g., period t_3) and during peak periods (e.g., period t_4). This decrease is due to the integration of renewable energy sources, which have a lower cost factor than CGs in the objective function (0.44 for WT and 0.45 for PV (Table 4-3) compared to 1.2 for CG (Table 4-3)), increasing then the integration rate of renewable sources.

Figure 4–15 shows then the amount of use of the installed renewable sources (red area) compared to their hourly maximum production capacity (plotted blue curve). These resources are intermittent and dependent on weather conditions. During high demand periods (every day between 6 a.m. and 19 p.m., Figure 4–8), the power production of the WT and the PV reach the maximum installed capacities most of the time. Despite this integration of renewable sources, it can be seen as a residual need for production illustrated in Figure 4–16 as virtual generated power. For the selected week, this deficit is very brief (only at 9 a.m. on the third day on bus 15 and at 5 p.m. on the same day on bus 16, Figure 4–16). This is due either to the fact that the maximum RES output has been reached or that the maximum transmission capacity has been met in the network since the energy produced by a RES is not necessarily consumed at this bus. These values are minimal compared to the virtual power levels observed in scenario A1. Hence, this scenario highlights the capacity of the proposed model to support the decision-making processes in integrating renewables into the electricity grid.

Test scenario A3:

The same renewables placement is kept as in the previous scenario while installing storage batteries on buses 3,4,15,16, and 21 as mentioned in Table 4-3. Test scenario A3 is proposed as a solution to overcome the shortcomings of scenario A2 by adding storage systems when there is residual virtual production. Batteries are added to store energy for use during periods of high demand and low production. In particular, on bus 15, the batteries eliminate the detected virtual residual production in Figure 4–16 when WTs produce less energy (Figure 4–15) in periods of high demand (Figure 4–8). In this scenario (RES + BES), the producers (CGs, WTs and PVs) generate power either for direct consumption (t_2) or for charging the storage systems (t_1) illustrated by Figure 4–18.

By referring to the total produced energy during the targeted time (one winter week) presented in Figure 4–25, it can be noted that RES in scenario A3 generates more power than in scenario A2 for the same installed capacity. Thus, the PVs generate 1304 MWh in A3 compared to 1 258 MWh in A2, and the WTs produce 7 990 MWh compared to 7 779 MWh in A2. This generation surplus is stored in the batteries to satisfy the lack of production in other periods. Thus, the overproduction of the wind turbine installed in bus 15 in scenario A3 compared to scenario A2 for the same period (e.g., period t_1) is stored progressively in the batteries until they become fully charged. This can be seen by comparing figures 15 and 17 and observing energy levels in some of the batteries in figure 18. Then, they are discharged according to the demand (Figure 4–8) to ensure the supply-demand balance in the periods when the wind turbine does not operate. In some periods, almost all the available PV source in bus 16 is exploited as between 0 and 50 h (Figure 4–15). In other periods, more renewable production is observed in scenario A3 compared to scenario A2. This overproduction is stored in the batteries. For example, in period t_2 (day 5), approximately a full capacity PV production is noticed, and the surplus is stored and then discharged at the end of the PV production period of that day. At other times, a decrease in the local production is observed (e.g., on days 3 and 4 at bus 16) in Figure 4–17. Some nodes take advantage of the presence of storage units to store energy from other sources, which can reduce local production and increase the use of other resources on the grid. This test scenario underlines the complementarity between renewable sources and storage to compensate for the grid constraints. It shows the capacity of the DOPFL to handle this kind of energy integration issue. It is then noticed that there is no longer need for virtual power production in this test scenario.

The integration of storage batteries also reduces the production level of CGs, as shown in Figure 4–21 compared to Figure 4–20. The system favors the use of batteries by charging them using renewables over the use of classic generators due to the difference in production costs. Nevertheless, renewables are not fully exploited due to the limits imposed by the other optimization parameters (V^2 , θ , P_{ij} , Q_{ij} , S_{ij}).

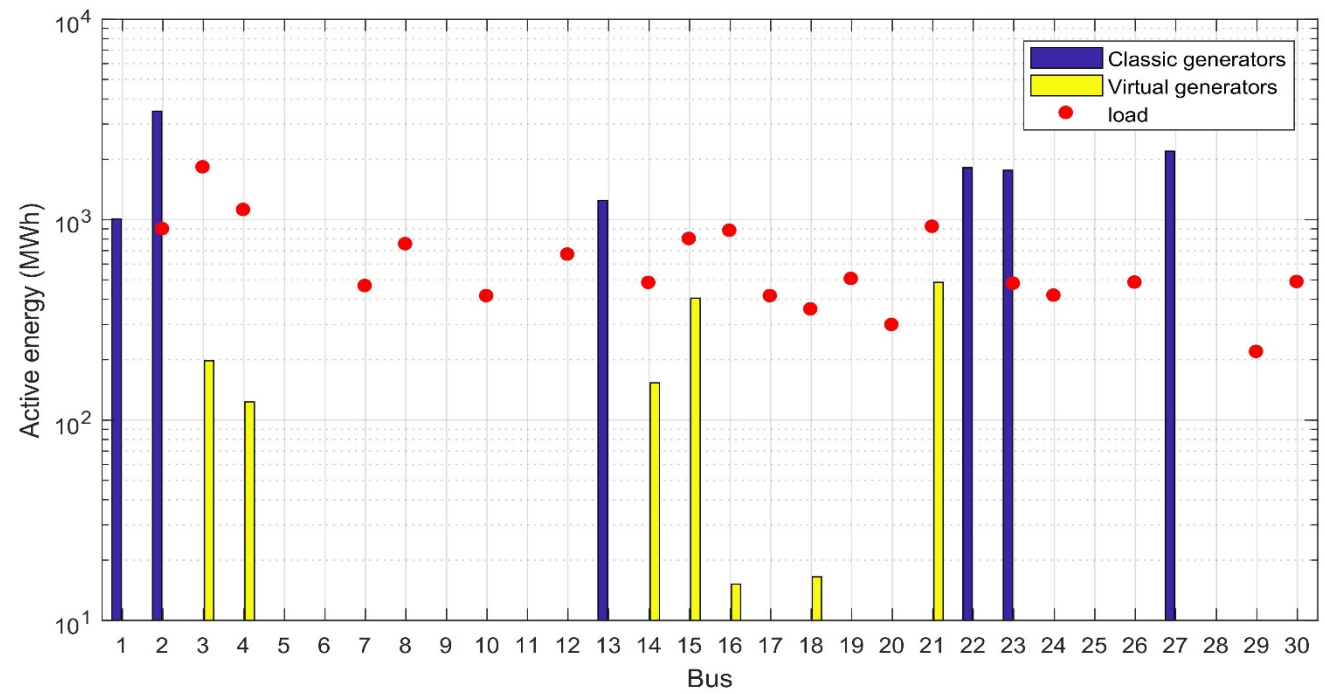


Figure 4-22: Energy analysis. Test scenario A1

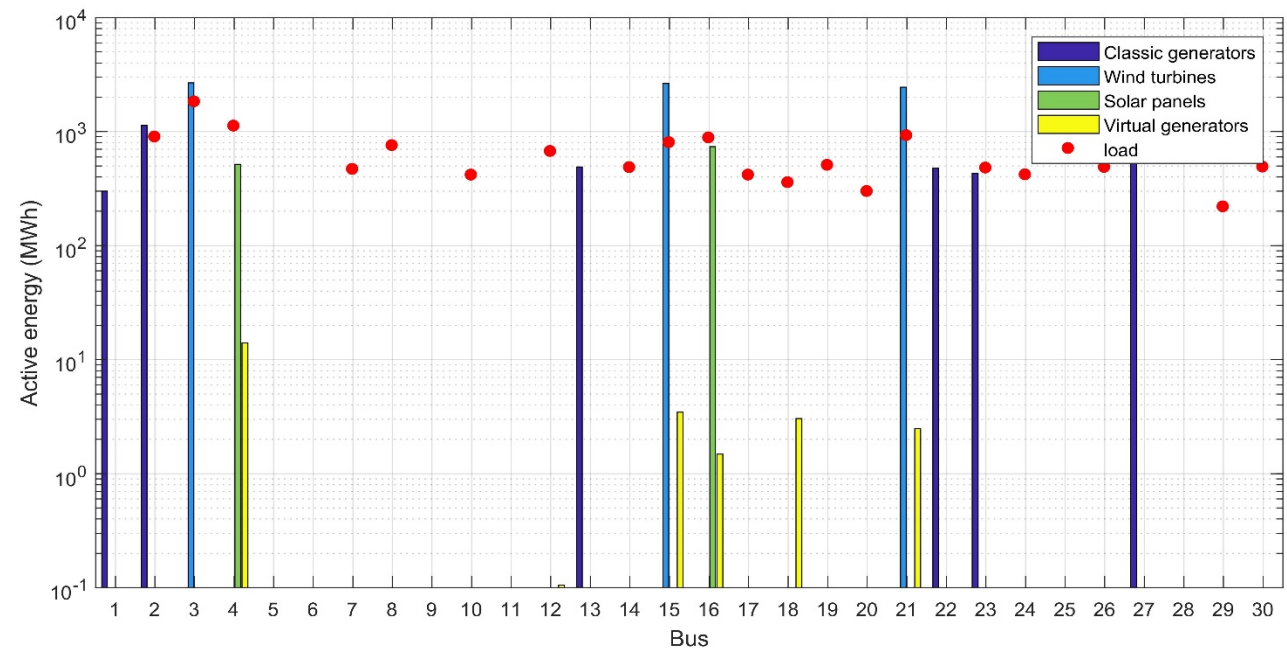


Figure 4-23: Energy analysis. Test scenario A2

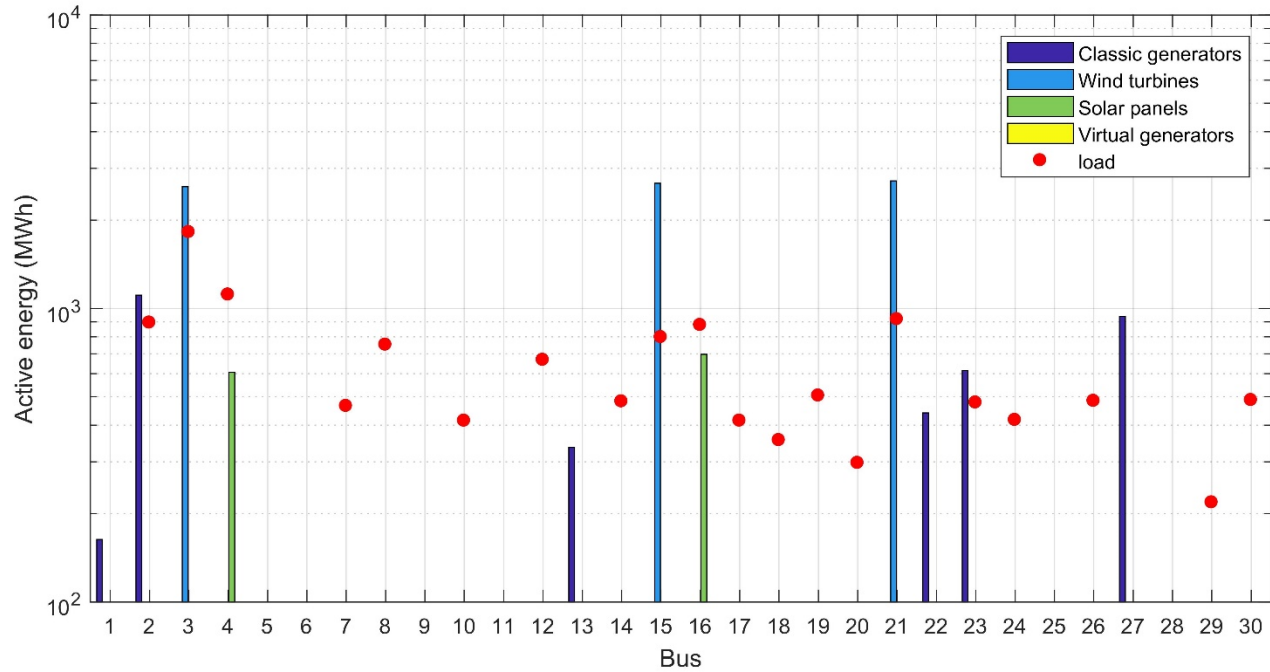


Figure 4-24: Energy analysis. Test scenario A3

Figure 4-22, Figure 4-23 and Figure 4-24 show the energy produced in each bus and by each production type for scenarios A1, A2 and A3, respectively. Figure 4-22 shows that the existing distribution of the classical generators cannot meet the demand of the other buses, which implies the presence of virtual Energy generation in other buses (3, 4, 14, 15, 16, 18, 21). The production rate of the virtual generators of each bus does not necessarily depend on the level of the local loads at the corresponding buses. For example, the maximum demand is found at bus 3, which does not result in a maximum virtual generation compared to bus 15 or bus 21. Moreover, virtual generators exist in some cases near the buses that contain classic generators (e.g., bus 21).

Figure 4-23 shows the total energy produced in the week in each bus for scenario A2, where renewable sources are placed in the buses that showed in scenario A1 the highest virtual energy production level. It can be noticed a decrease in the production of classical generators but still residuals of virtual energy generation with low values on buses 4, 15, 16, 18 and 21. Their presence is due to the intermittent nature of renewable energy sources and grid constraints. In Figure 4-24, the virtual production has disappeared, and an increase in the levels of renewable productions is noticed thanks to the presence of storage units in some buses.

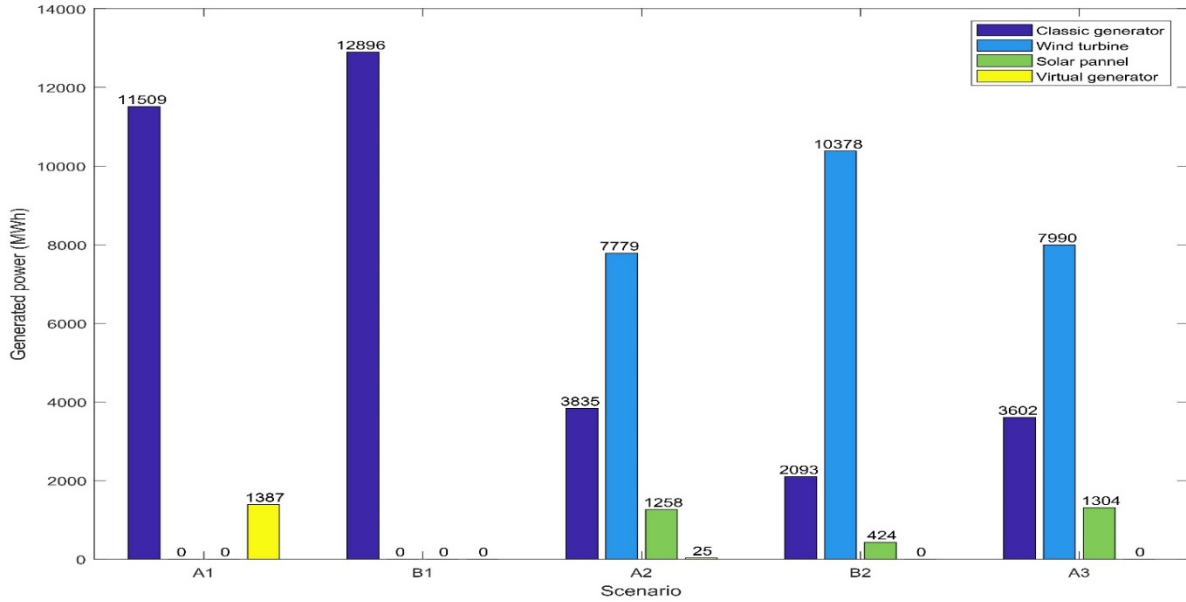


Figure 4–25: Total generated energy. All test scenarios

To highlight the impact of the network constraints on the whole energy integration analysis and the impact of the cost coefficient on the production preference, Figure 4–25 presents the energy configuration of the 3 previously analyzed test scenarios (A1, A2, A3) in addition to the test scenarios B1 and B2 (same as A1 and A2, without considering the network constraints). These results confirm that balancing supply and demand without considering the network's limits is possible using only classical generators (scenario B1), which, compared with test scenario A1, underlines the necessity for more dispatched classic energy production resources. That's yield to the network's effect, considering its connecting branches constraints and resulting losses. Scenario A2 is compared to the simple production dispatch problem (scenario B2) that includes generators, PV and WT at the same buses as in scenario A2 without considering the network and using the same load curves. The results in Figure 4–25 show a decrease in the amount of use of CGs and increased use of renewable. While the grid is not considered (scenario B2), prioritization for using generation sources with the lowest production cost (WTs in this case) is noted, then the PVs and, finally, the classic generators. This is not the case when considering the grid with its constraints because, in A2, there is less WT production compared to B2 and more PV production, even though WT is less expensive. The power deficit when renewables are not produced without the network can be totally compensated using classical generators. While in the real case, with the grid, the lack of production of intermittent sources requires the use of energy storage devices in other periods which is proposed in scenario A3.

The impact of battery inclusion is visible in Figure 4–25. It has a triple effect: first, the extinction of power generation from virtual generators (VG between A2 and A3). Second, a decrease of 6.08% in the level of production of classic generators (from 3 835 MWh in A2 to 3 602 MWh in A3) and third, an increase in the level of production of renewable energy sources (+2.64% in WT production between A2 and A3 and +3.5% in PV production at these storages installed capacity). Thus, the power

requirement is therefore satisfied through the batteries that are charged from renewables. Furthermore, given the small increase in renewable energy production, it can be claimed that batteries play a more significant role in balancing the network face to the intermittency caused by RES than in integrating more renewables and increasing the share of produced energy from these renewables.

4.2.7 Illustration of DLOPF practical implementation

To satisfy the increase in consumption and incorporate renewable sources for existing network configurations with fixed electricity grid characteristics, several solutions can be proposed based on DLOPF model. These solutions may differ by the number of renewables and batteries used, placement, and sizing. An acceptable solution is an application scenario that meets the demand without VGs. In this part, an approach is presented to generate applicable scenarios, and to assess them using different indicators to facilitate the choice of the best one like a decision maker would do. In the table of Figure 4–26, different scenarios of renewable sources placement are detailed for each bus of the same case study described in section 4.2.6. It is supposed that renewable energy sources potentials are known for all nodes. These potentials correspond to a maximum potential surface for PV and a maximum potential capacity for wind turbines. The first scenario is defined by placing renewable production sources in all nodes (Scenario S1, table of Figure 4–26). DLOPF is then applied to this first scenario, and the following indicators are calculated:

- Individual Load Factor (ILF_i)

$$ILF_i = \frac{E_{p,i}}{E_{p,i}^{max}} \times 100 \quad (4-2)$$

Where $E_{p,i}$ is the energy produced by the renewable source located at bus i during the studied period and $E_{p,i}^{max}$ is the maximum energy that could be produced by this source during the same period.

- Global Load Factor (GLF)

$$GLF = \frac{E_p}{E_p^{max}} \times 100 \quad (4-3)$$

Where E_p is the energy produced from all renewable sources connected to the grid during the studied period and E_p^{max} is the maximum energy that could be produced by these renewable sources during the same period.

- Renewable Energy Share (REH)

$$REH = \frac{E_p}{L^T} \times 100 \quad (4-4)$$

Where L^T is the total load for the studied period.

Starting from this initial scenario (S_1), 4 alternatives are proposed. Each scenario S_j is defined based on the DLOPF results of the previous one S_{j-1} as long as this latter (S_{j-1}) has zero VGs production. ILF is calculated for the first scenario. A threshold is defined (yellow circles in Figure 4–26), and the renewable sources with load factors lower than this threshold are eliminated. This selection process defines the next scenario (S_2) and the procedure is repeated until the scenarios S_5 . Then the ILFs are determined for all scenarios (shown in polar histograms of Figure 4–26). Thresholds are chosen in a way that they will be equivalent to the first quartile of the boxplot of individual load factors.

For the present case, renewable sources (PV or WT) with a load factor under 9% are eliminated from the scenario S_1 to generate scenario S_2 for which DLOPF has been applied again (Figure 4–26-b). From S_2 , production sources with ILF less than 12% are eliminated to define S_3 (Figure 4–26-c). Thus, four PVs are eliminated from buses 6, 8, 18 and 20, as shown in Figure 4–26-d. S_4 is then obtained by eliminating renewables with a load factor less than 16%. And to obtain S_5 , PVs and WTs with a load factor less than 36% are eliminated. S_5 is the scenario with the least number of renewable producers (Figure 4–26-e).

Moving from S_1 to S_5 , the load factors of the remaining renewables increase (e.g., in WT for bus 3, PV on bus 6, etc.) because of the need for more power to be withdrawn from the remaining generators/renewables in the grid.

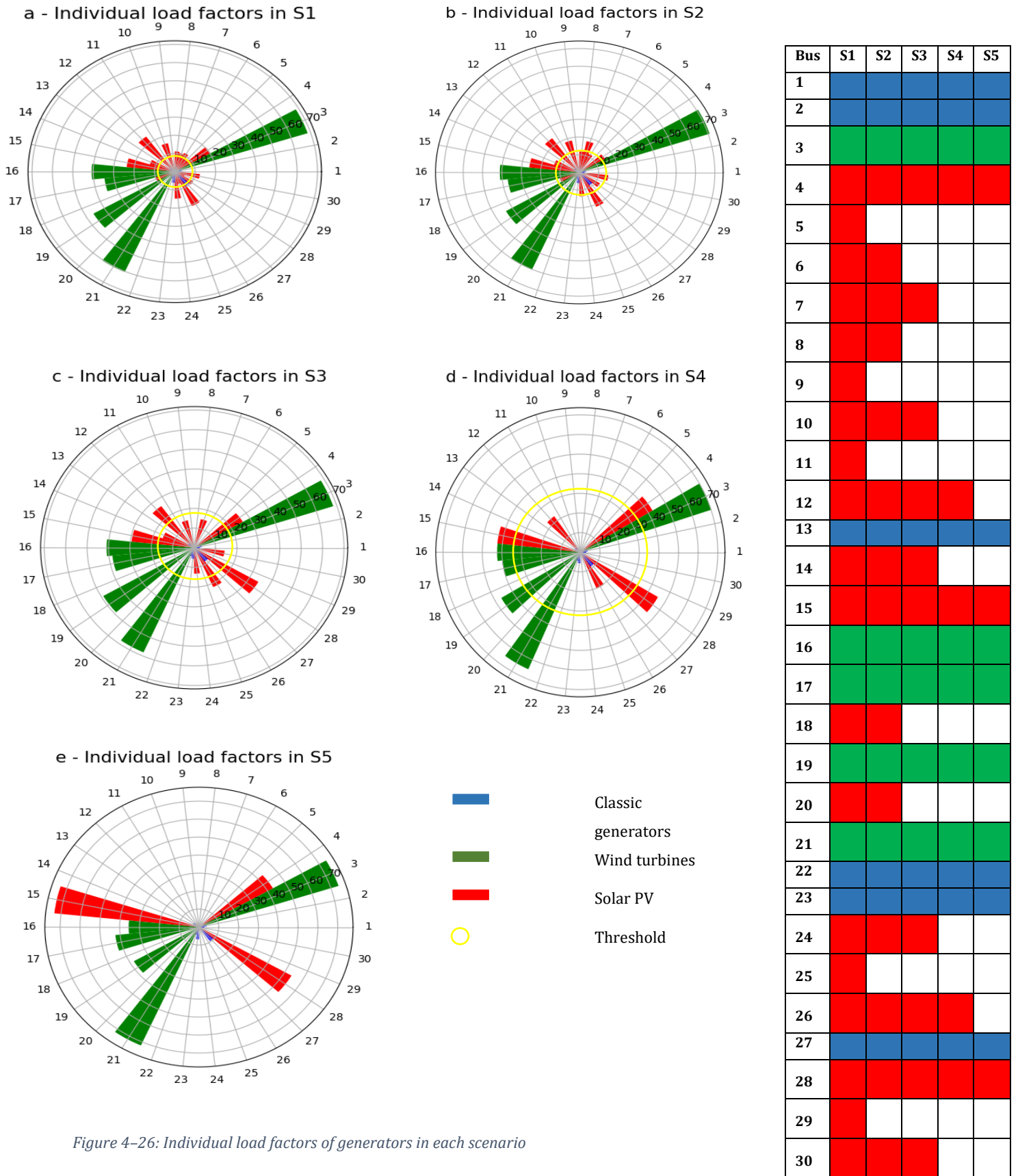


Figure 4-26: Individual load factors of generators in each scenario

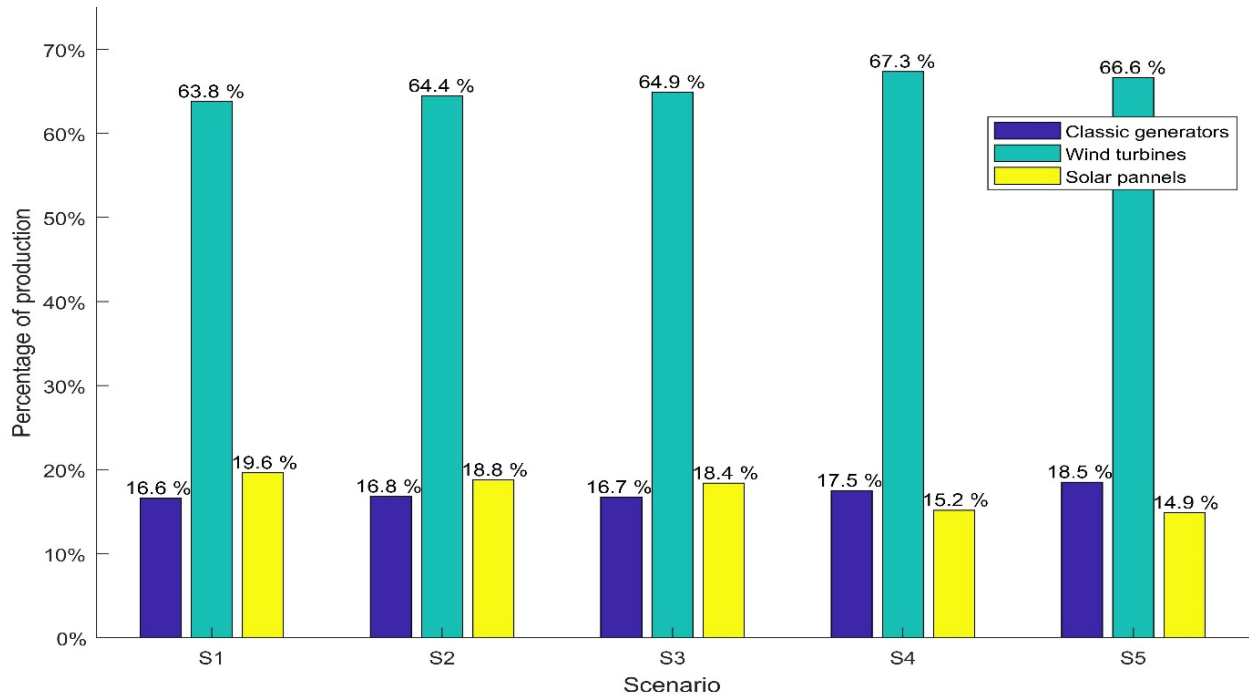


Figure 4-27: Production by each source type

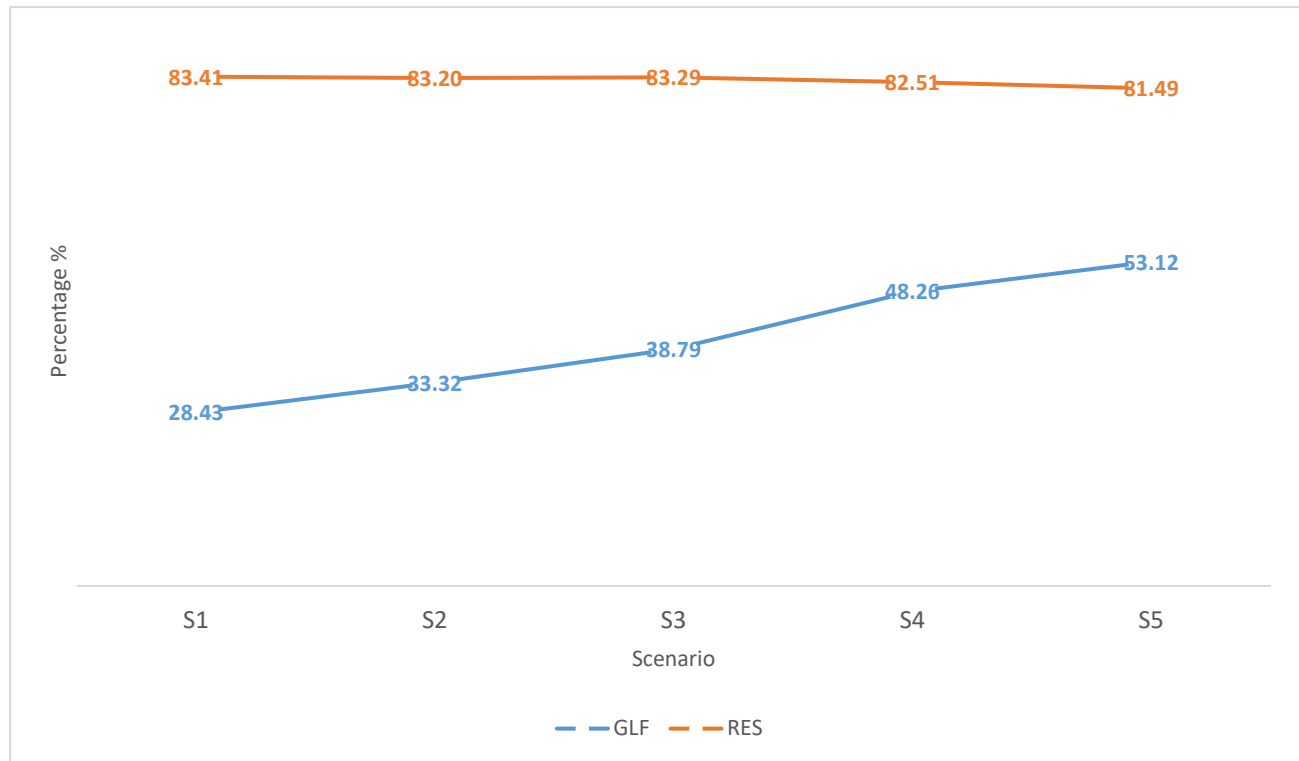


Figure 4-28: Global load factor (GLF) and renewable energy share (RES)

Figure 4–27 illustrates the percentage of production for each source type and for each scenario. With the decrease in the number of renewable systems (PVs and WTs), CGs will be more used (from 16.6% in S1 to 17.5% in S4 and up to 18.5% in S5). PVs are removed in S5 compared to S1, which explains the decrease in renewable production via PVs (from 19.6% to 14.9%). WTs but also CGs will then be used more. The solicitation of the WTs is more important because of the lower cost, but the percentage of renewable production shows a slight decrease due to the limited number of wind turbines, while some PVs are removed at each step between S1 and S5.

The global load factor increases progressively, as shown in Figure 4–28 (from 28.43% in S1 to 53.12% in S5), with the decrease in the total number of sources from S1 to S5, reflecting a better global efficiency of the system. In comparison, the renewable energy share remains almost constant (a minor decrease is observed from 83.41% in S1 to 81.49% in S5). The amount of renewable produced power remains constant with a decrease in the renewables number. Thus, the extracted power from each remaining source increased progressively from one step to another, and therefore they became more efficient. Note that zero production from VGs is provided in all scenarios.

This example shows a practical and efficient implementation of DLOPF for the definition of scenario of renewables placement and sizing. Based on DLOPF, additional indicators could be defined (production cost, carbon emission, installable surfaces, etc.) regarding different expectations that may depend on project stakeholders. Complementary scenarios could also be defined (e.g., taking advantage of the capacity DLOPF offers to highlight the importance of storage at some levels). Finally, DLOPF could be coupled with decision-makers' advanced methods (multi-criteria decision analysis, decision trees, etc.).

4.3 Application 2: Integrated optimization of sizing and operation of RES and BES using PSO-DLOPF

In this section, the PSO-DLOPF presented in Chapter 3 is applied to find the optimal integration of RES and BES to minimize the total energy cost, considering various constraints such as installable PV surfaces and WT available in each zone, the maximum number of BES systems, the existing network constraints and carbon emissions constraints.

4.3.1 Input data

- **Energy technologies used, costs and available locations**

The operational and investment costs of the different production sources are given in Table 4-4.

Table 4-4: Investment and operation costs [255]

Production type	Operational cost (\$/MWh)	Investment cost	O & M cost (\$/MW/yr)
PV	$C^{pv} = 0$	$J^{pv} = 178 \text{ (\$/m}^2\text{)}$	$O^{pv} = 8,000$
WT	$C^{wt} = 0$	$J^{wt} = 997\,000 \text{ \$/MW}$	$O^{wt} = 33,000$
CG	$C^{cg,p}, C^{cg,q} = 36$	0 (already installed)	$O^{cg} = 10,500$
VG	$C^{vg,p}, C^{vg,q} = 10^9^*$	0	0

*This cost ensures that virtual generators are excluded as much as possible

In the upper-level of the optimization, the PSO aims to size and locate the BES using three optimization variables for each installed battery (i^b , D_{i^b} and $P_{i^b}^b$).

1. The bus index (i^b) for the batteries belongs to a continuous interval with boundaries limited by the number of available buses. Thus $i^b \in [1, \mathcal{N}]$ with $\mathcal{N} = 30$ buses. i^b is the closest rounded value of a continuous variable that is optimized by the PSO. There are as many i^b of batteries to install. $\{i_j^b\}$ with $j = [1, Nb]$ where $Nb = 4$ batteries.
2. Battery duration (D_{i^b}) limited to 8 hours. $D_{i^b} \in [0, 8]$.
3. The power capacity ($P_{i^b}^b$) is limited by the maximum battery power $P^{bmax} = 8 \text{ MW}$.

All existing buses are considered as candidates for installation of 4 BES. Storage cost constants are presented in Eq.(3-4), values: $\alpha = 100\,000$, $\beta = 200\,000$ (calculation based on lithium-ion capital cost interpolation for 2, 4 and 6 hours in [241], as explained in Chapter 3).

In the lower-level optimization, two design optimization variables are considered to size and locate the RES.

1. The installation area of PV (A^{pv}) is limited by the maximum installable surface for PV (A^{pvmax}) $300,000 \text{ m}^2$ each, in buses 4, 9, 10, 12, 20, 26 and 30. The solar resource per unit of surface area at the location (Nantes, France) is given in Figure 4–29. This profile is the same for all buses in this work.

2. The continuous design variable (R^{wt}) defines the ratio of installed local wind energy. R^{wt} is bounded by $R^{wt^{max}}$ which corresponds to the maximum installable wind power that is estimated based on unitary WT production and is indirectly defined by the maximum number of wind turbines allowed per wind farm; in this case, this number is limited to 25 at buses 3,16, 19,21, 25, and 30. The wind power production for 1 MW of rated power based on local wind resources in Nantes is shown in Figure 4–30 for nine typical days (as explained below). This profile should be the same for all candidate buses for WT installation in this work.

• Production

Figure 4–29 shows the PV profile simulated for the corresponding typical days selected for demand.

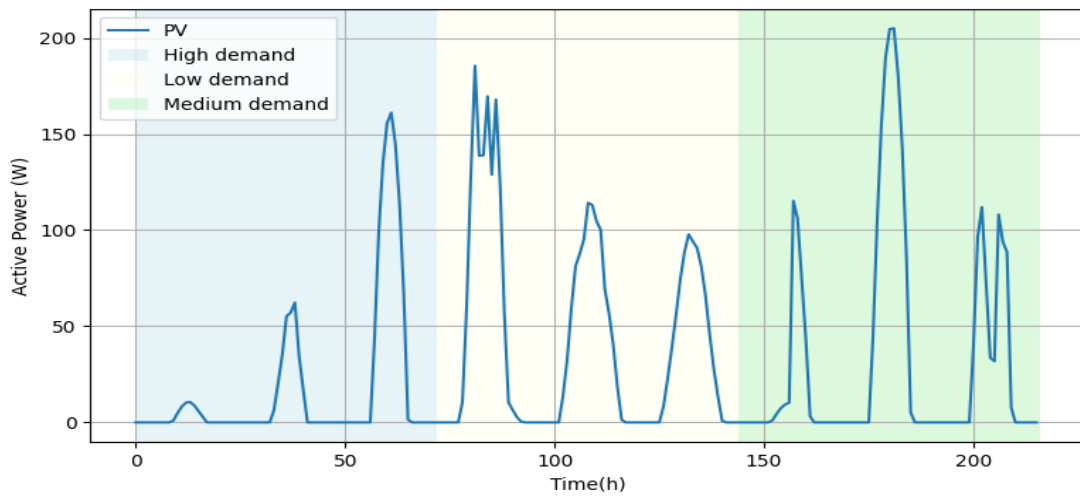


Figure 4–29: Profile of one m^2 of PVs for nine typical days from three seasons (high = winter, low = summer, medium = spring) (HelioScope)

Figure 4–30 shows the simulated production profile for a wind turbine (WT) for the selected typical days corresponding to the demand. The profile is normalized.

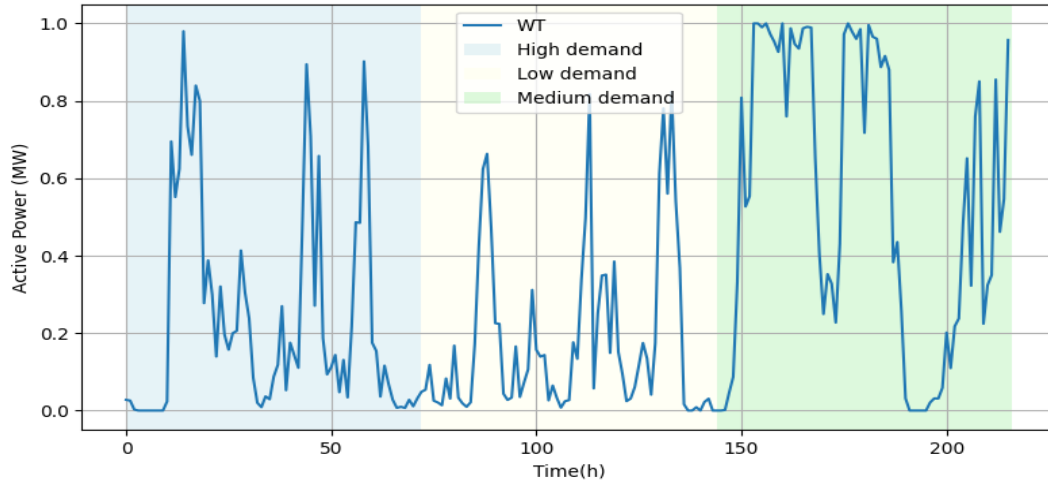


Figure 4–30: Profile of one WT for nine typical days from three seasons (high = winter, low = summer, medium = spring)

• Demand

Considering one year of data for electricity demand, wind power, and solar power in hour scale would result in a very big optimization problem and, therefore, a long calculation time. The usual procedure in this case is to refer to days rather than the full year. To select the most significant typical days, the total load profile is calculated for one year first. Then, this total profile is sliced into subgroups of 3 consecutive days each (72 continuous hours). This continuation allows visualizing the continuous behavior of the storage systems. One hundred twenty-two different subgroups are obtained. Thus, these subgroups are separated into 3 clusters using k-means clustering that classifies similar time series in the same cluster (here 3: winter, summer and spring). This clustering was based on three different features: the total energy demand of the three days, the maximum power reached and the variance of the power demand in each period. The means (centroids) are calculated for the 3 clusters to select one representative period from each cluster. The calculation of the Euclidean distance between each subgroup and the centroids follows this step. Then the nearest element to the 3 different centroids is selected. The ‘selected days’ are defined as the days that correspond to the chosen periods. Then, the demand profiles for each individual bus are formed by selecting the ‘selected days’ through the demand curve of the whole year. These periods are placed for each bus alongside each other (9 days classified 3 by 3 continuously). The sum of all demand profiles is shown in Figure 4–31 for the selected typical periods; these periods represent the dynamics occasioned by seasonal variations (summer, winter and mid-season), allowing nine days to consider storage dynamics.

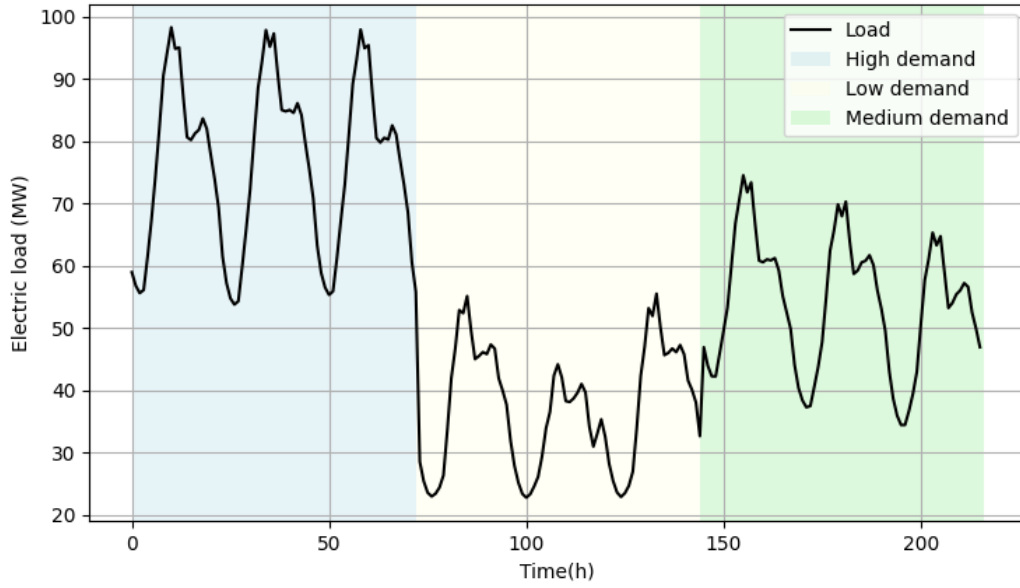


Figure 4–31: Total demand for nine typical days from three seasons (high = winter, low = summer, medium = spring)

4.3.2 PSO-DLOPF: mono-objective application results

The PSO-DLOPF is applicable in cases where the existing CGs are insufficient to meet the loads. The results of the PSO-DLOPF approach are presented in this section.

The focus in this part is targeting the minimization of the LCOE function; carbon emissions are not considered. Two cases are compared to confirm the proposed PSO-DLOPF model's effectiveness. For case 1, the DLOPF is operated with CGs only, with no RES or BES. For case 2, the optimization configuration outlined in section III.4.3.1 is used.

In case 1, the results for buses 1 and 2 are shown in Figure 4–32, which shows production profiles for CGs 1 and 2 for the period. The active power generated by the CGs shows coherent profiles between load (Figure 4–31) and generated power (Figure 4–32). The results show that in periods of high demand (e.g., between 4 am and 10 pm in Figure 4–31), there is high usage of the generators (Figure 4–32). In periods of low consumption (e.g., between 100 h and 110 h in Figure 4–31), there is less usage of the CGs. For medium demand, an intermediate generation is noted. Note also in Figure 4–32 that the generators were not used equally even though the production cost was equivalent for all generators. This is the direct effect of network constraints handled by the model in addition to the network losses.

In terms of the overall network, the total installed generation capacity of the CGs is 180 MW, i.e., greater than the cumulated maximum power demand in the network, which is approximately 100 MW (Figure 4–31). Despite these conditions, production is not sufficient to meet demand. The deficits are shown in the form of power generated by virtual generators (23.26 MWh) as detailed in Table 4-5 where the obtained results of produced energy in cases 1 and 2 are compared.

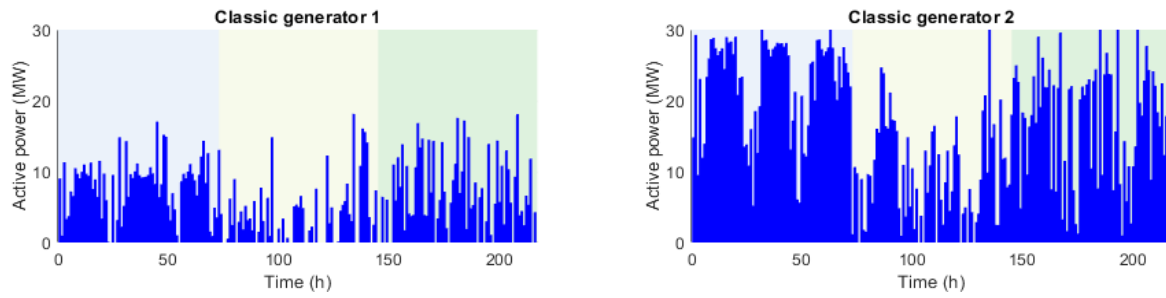


Figure 4-32: Actual generated power. Illustration for buses 1 and 2 (Case 1)

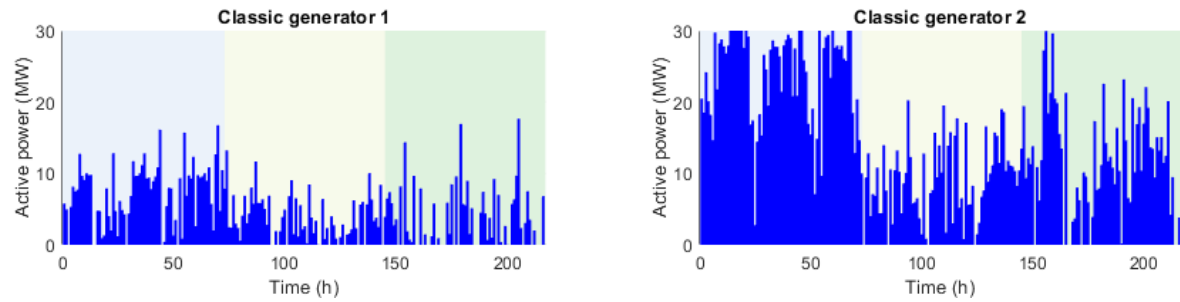


Figure 4-33: Active power production for CGs, buses 1 and 2 (Case 2)

Table 4-5: Optimization results

Energy supply over 9 days (MWh)	Case 1	Case 2
CG	12131	11359
VG	23.26	0
WT	-	738.05
PV	-	258.58
Total	12154.6	12355.6
Loss (%)	0.05	1.6

Table 4-6: Final optimal plan

Bus number (case 2)	12	16	18	19	20	26	30
WT (MW)	-	7	-	4	-	-	2
PV (A_p)* 10^4 (m ²)	-	-	-	-	2.7	-	1.5
BES (P^b) (MW)	5.33	-	7.16	4.26	-	7.64	-
BES (D^T) (h)	4.9	-	7.02	5.84	-	3.14	-

For case 2, Table 4-6 shows that the optimum corresponds to an installation of 13 MW of installed WT power in three of the candidate buses (16, 19 and 30) and the investment in solar energy PV

is limited to buses 20 and 30. With these additional production sources (WTs and PVs), the reduction of classic production extraction proven in Table 4-5 (from 12131 MWh to 11359 MWh for 9 days) and shown in Figure 4-33 (compared with Figure 4-32) is justified, especially for medium demand.

Figure 4-34 and Figure 4-35 give a summary of the energy produced in case 1 and case 2, respectively. The bars represent the energy extracted from the available energy in each bus and for each energy source (existing CGs, available WTs and available surfaces for PVs). The percentage of energy extracted from CGs is reduced by 6.5% (Table 4-5), and the remaining energy is extracted from WTs (5.97%) and PVs (2.09%). The penetration rate of renewables is therefore significant ($\sim 8\%$), reducing dependence on CGs and, consequently, the need for VGs. The total power produced in both cases is greater than the demand. The differences correspond to the losses along the network lines. These losses are greater in the second case (1.6% more than in case 1). This is due to the interconnection between the different buses in the network. Although the positioning selected is considered optimal in terms of price, there are still losses along the lines due power being transmitted from some buses and stored in others (batteries are not necessarily located on the buses containing the generators). Moreover, the optimization tends to install RES even if it leads to more production (for cost reasons).

Regarding BES, the proposed optimization method places them in buses 12, 18, 19 and 26 whether they contain producers, e.g., bus 19 or not, e.g., buses 12, 18 and 26. The production and storage behaviors are illustrated in Figure 4-36 and Figure 4-37.

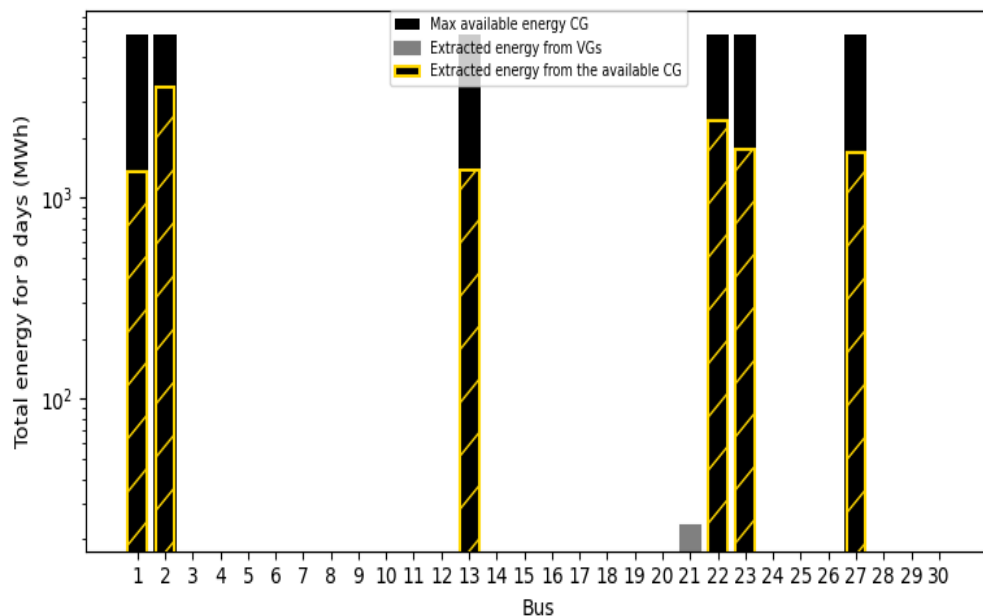


Figure 4-34: Use of energy resources on different buses (case 1: without RES-BES)

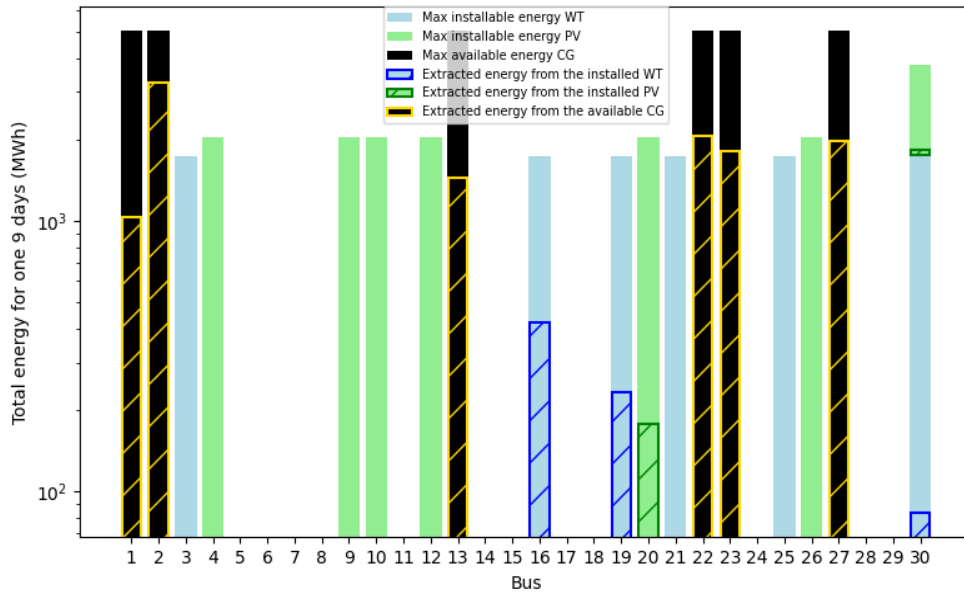


Figure 4-35: Use of energy resources on different buses (case 2: with RES-BES)

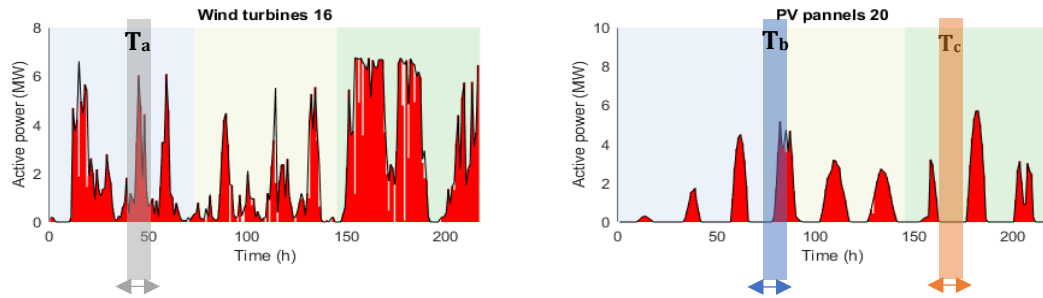


Figure 4-36: Results of WT production, buses 16 and 20

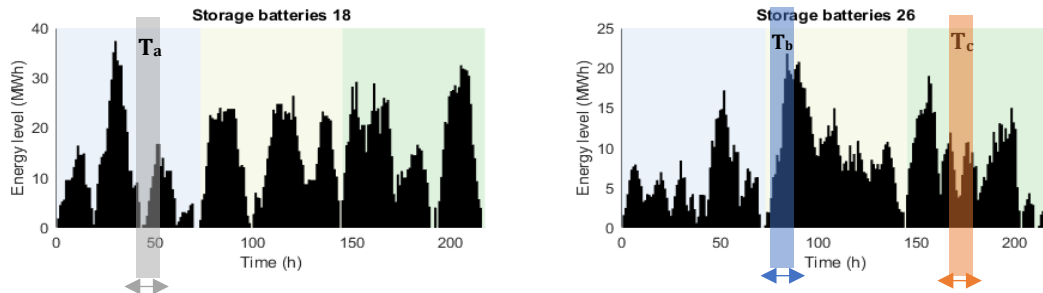


Figure 4-37: Storage batteries, buses 18 and 20 (case 2: with RES-BES).

Figure 4-36 shows the use of the installed renewable sources (red area) compared to their maximum production capacity (plotted black curve). These resources are intermittent and dependent on weather conditions. All the installed power is extracted from the PVs at bus 20 (presented here as an illustrative example), and 95% of the installed power is extracted from the

WTs of bus 16 (also used as an example). WTs and PVs operate almost all the time at their full capacity (the load⁴ factor of the WTs at bus 16 is 95% and 99% for the PVs at bus 26).

A comparison of Figure 4–36 and Figure 4–37 shows a synchronous or coherent behavior between RES and BES. A WT production – BES charging is noted in T_a : bus 16 between 45 h and 50 h depending on the local WT production, and a PV production – BES discharging is shown in T_b : bus 20 between 75 h and 80 h. The storage batteries are charged directly from the RES on the nearest buses in these cases. Since some charging and discharging phases are not coherent with RES production (e.g., T_c : bus 20 between 160 h and 170 h for PV production and the corresponding storage period in bus 26), it can be concluded that optimal storage also serves the network as a whole. This stored energy is imported from the power injected by different producers into the network. The total stored energy is injected into the grid, demonstrating their optimal operation.

Table 4-7: Final optimal costs

Associated costs over 30 years	Case 1	Case 2
PV inv. Cost (\$m)	-	4.47
WT inv. cost (\$m)	-	15.5
BES inv. cost (\$m)	-	17.4
CG inv. cost (\$m)	55 (\$1.1m/MW [256])	-
PV O&M cost (\$m)	-	2.66
WT O&M cost (\$m)	-	12.87
CG O&M cost (\$m)	72.45	56.7
CGs op. cost (\$m)	532.3	497.46
Total (\$ m)	659.7	644.9
Total reduction amount (%)	2.25%	

Integrating RES and BES into the grid is not inexpensive considering the estimated real investment and O&M costs (\$109.6m), as detailed in Table 4-7. Still, it reduces the production cost by 4.8% due to the decrease in CG production. This contributes to a 2.25% reduction in cost, compared to case 1, over the project lifetime of both RES and BES. In this case, the production deficit (energy

⁴ The load factor is calculating by dividing the sum of extracted power (red plots) by the installed power (black curve profile)

produced by virtual generators) is supposed to be extracted from an installed 50 MW combined cycle power plant (CCGT).

4.3.3 PSO-DLOPF: Bi-objective application results

4.3.3.1 Renewables, costs and emissions analysis

To illustrate the potential of the PSO-DLOPF in a bi-objective model, CO₂ emission constraints (Ta) (see Eq. (3-47)) are included in the problem, with different values in four different scenarios. This bi-objective approach leads to a Pareto distribution. Following the ε – constraint method [246], the equation Eq. (3-47) is used.

The CO₂ emitted by 1 MWh of CG power is $En^{cg} = 48000 \text{ g CO}_2/\text{MWh}$ [257]. In each scenario, the ε – constraint (Ta) is chosen relative to the amount of CO₂ emitted in the first case (Table 4-8) so Ta is the percentage of admissible amount of CO₂ emissions compared to the first scenarios (reference case without CO₂ constraint). In the results obtained (Table 8), the RES portion follows exactly the same trend as the CO₂ reduction rate. In the last 4 scenarios, the optimization is heavily influenced by the emission constraint. In contrast, for the first scenario where there are no CO₂ emissions to limit the CG, power extraction is only influenced by cost minimization which, explains the 8% portion of RES. Figure 4–38 shows the extraction rate of renewable energy invested in the corresponding nodes following a high CO₂ emission requirement (limited to $Ta = 30\%$ of the maximal possible emissions when only CGs are used). The figure shows that almost 75% of the available energy is used to produce zero-emission renewable energy.

Table 4-8: RES portion by scenario

Ta (%)	RES production share (%)
Ø (No limit)	8
70	30
55	46
40	62
30	70.10

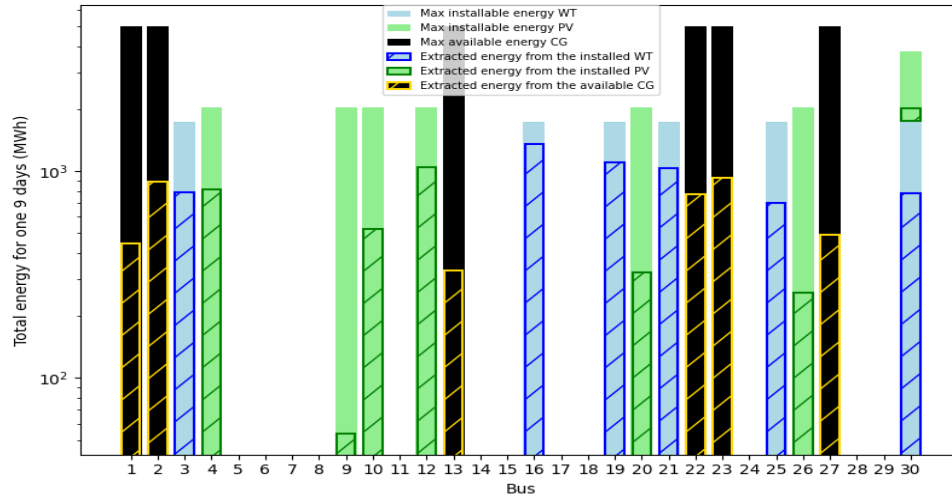


Figure 4-38: Use of energy resources at different buses ($T_a = 30\%$)

Reducing CO₂ emissions means increasing the total investment cost (Figure 4-39). Using less power from classic generators therefore requires the installation of more RES and BES. This justifies the cost increase (from \$75.2m to \$353m, +371% between the 5 limits). In Figure 4-40, the total cost (investment + O&M + operation) variation in terms of emissions is presented. The total cost increases (from \$645m to \$660m, +2,3%) with the reduction in CO₂ emissions resulting from the decreased use of CGs. Consequently, as stricter emission constraints are imposed, the total cost increases. A 62% reduction in CO₂ emissions compared to the first scenario entails a 2.3% cost increase. The detailed results of all the buses are shown in Appendix B.

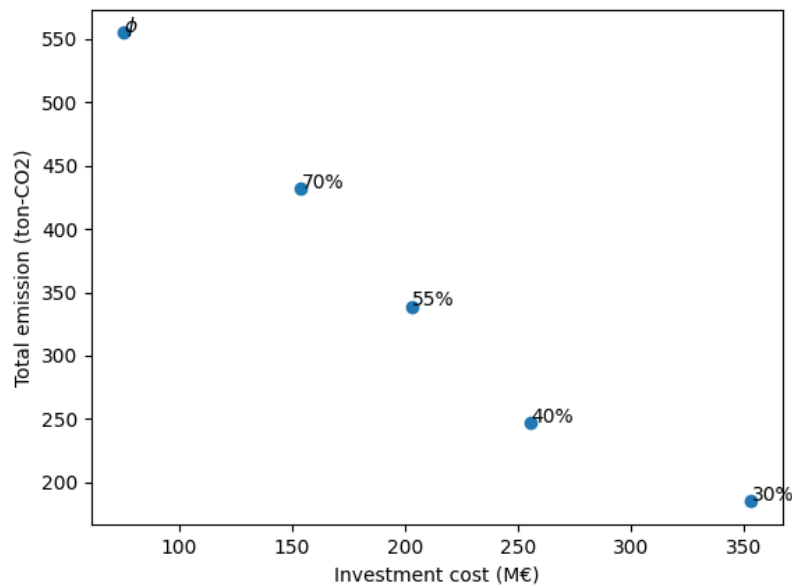


Figure 4-39: CO₂ emissions in terms of total investment cost

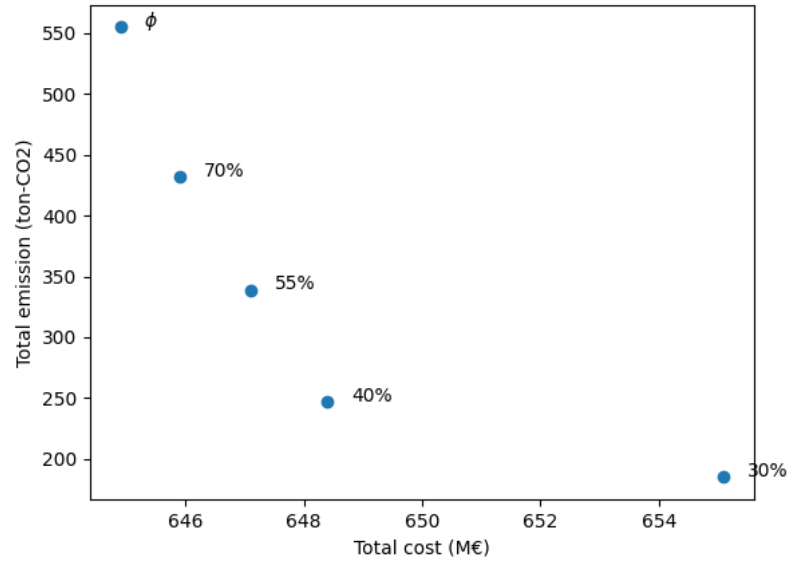


Figure 4-40: Evolution of bi-objective functions

4.3.3.2 BES analysis

The distribution of BES is summarized in Table 4-9. In some cases, the BES is located where the WTs are installed (bus 19 in $\emptyset$ and 70%, bus 30 in 40% and 16 in 30%). In other cases, the BES are located where there are PVs (bus 12 in 70%, bus 26 in the first 4 scenarios and bus 4 in the last scenario). Note that in all cases, the batteries are never placed where there are the classic generators. This comes down to the existence of continuous production (CGs), which reduces the need for BES in the same buses.

Table 4-9: BES allocation in the network for the different CO2 constraint scenarios

Bus number	4	12	15	16	17	18	19	20	26	30
$\emptyset$ (no limit)	-	BES	-	-		BES	BES	-	BES	-
70%	-	BES	-	-	BES	-	BES	-	BES	-
55%	BES	-	-	-	BES	-	BES	-	BES	-
40%	-	-	BES	-	-	-	-	BES	BES	BES
30%	BES	-	-	BES	-	-	-	BES	-	BES

As seen in Chapter 3, the design characteristics of BES are the maximum power (P_{ib}^b) and the duration (D_{ib}). These characteristics are shown as bar plots in Figure 4-41 for the different CO2 emission scenarios. These factors increase on average until they reach the upper bounds for $Ta = 30\%$, where the BES are most needed to recover production. When classic production decreases, the batteries in the discharge phase (without RES production) will need to provide more power

to meet the instantaneous demand. And this power, to be sufficiently from the batteries, requires bigger charge durations to cover longer periods.

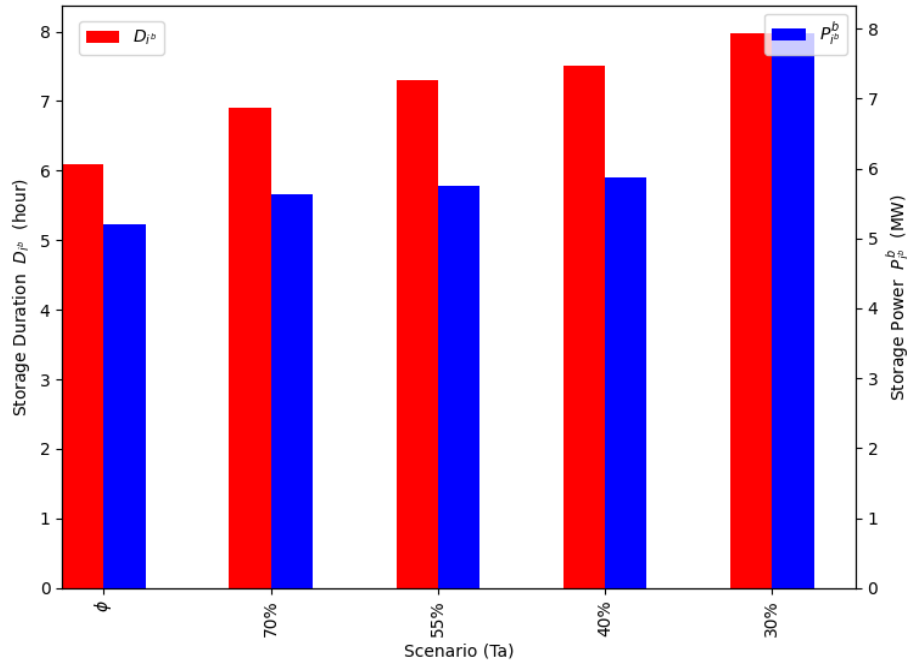


Figure 4–41: Bar plots for BES maximum storage power and storage duration for each scenario (MW)

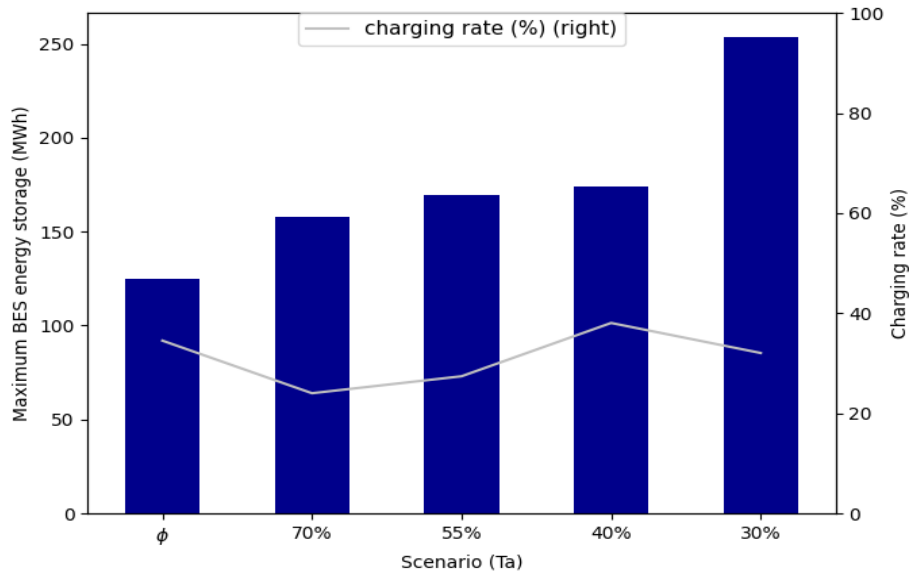


Figure 4–42: Maximum energy storage for each scenario (MWh)

The product of these two factors (D_{p^b} and $P_{p^b}^b$) gives the size of the BES in terms of maximum energy (E^b), as in Figure 4–42. The maximum energy storage increases, and the BES increases in size with the reduction in CO₂ emissions. With the constraint $Ta = 30\%$, the upper limits are approximately achieved (64 MWh), which means that the BES investment limit is already reached.

By designing different sizes of batteries, the charging rate is not following a clear trend. With this charge rate (mean = 32%) in the largest possible batteries ($Ta = 30\%$), the emissions limit would be improved ($\leq -70\%$).

4.4 Summary

The results obtained through the DLOPF application (Application 1) show the ability to map the spatial-temporal behavior of the generators, renewables, grid and BES in the network. Knowing how the energy is distributed in the network and the branches in which it is in transit allows for better control and operation of the system. The results obtained throughout the five scenarios in the progressive procedure show the variation of different performance indicators that it is possible to support the decision-making process (energy planning) by considering additional characteristics to remove or to maintain local producers.

The obtained results from the EPSM (Application 2) show the model's ability in network planning and operation while reducing the LCOE. Moreover, the RES and BES are optimally placed and sized while respecting the carbon emissions constraints. This bi-level model highlights the importance of storage and its design in terms of battery specifications. However, obtaining these results is time demanding as metaheuristic methods are used (40 hours per scenario).

For this reason, the next chapter proposes a framework for sensitivity analysis using an adapted EPSM (2min:30s) from the presented bi-level model without considering the details of battery specifications.

Chapter 5: Uncertainty and Sensitivity Analysis for the EPSM of Distributed Energy System

5.1 Introduction

As discussed in the previous chapters, EPSM is a powerful tool for effectively designing RES and BES to perform energy planning and operation. However, it is prone to uncertainty. It returns to the existence of time-dependent aspects that introduce uncertainty to the planning process. These aspects are the followings:

- Human behavior that makes forecasts of future energy demand sensitive to uncertainties
- Renewable energy intermittency and the future climate
- Errors in forecasts of fuel prices, investment costs, etc.
- The quality of input data which can result in uncertainties

The existence of uncertainties in the planning process can affect the quality of the model's outcome and potentially lead to sub-optimal solutions. Thus, it is recognized that the success of energy system planning depends critically on considering uncertainties and their impacts. Therefore, this chapter presents a methodological framework for the investigation of uncertainties in the EPSM. This framework is summarized in Figure 5–1 and developed in this chapter. The model inputs considered in this part of the work are the demand curves extracted from the load forecasting model (out of the scope of the thesis); the uncertainties are first characterized according to probability models at each time step which is used to generate additional curves. A set of macro-parameters describing these patterns are then defined and represented. The generated cases based on the input demand curves are used to run the EPSM on a predefined distribution network to create different planning scenarios. In addition to the input macro-parameter, a number of indicators are then defined to study the uncertainty analysis, to perform a sensitivity analysis to correlate input parameters and output indicators and find the most effective ones.

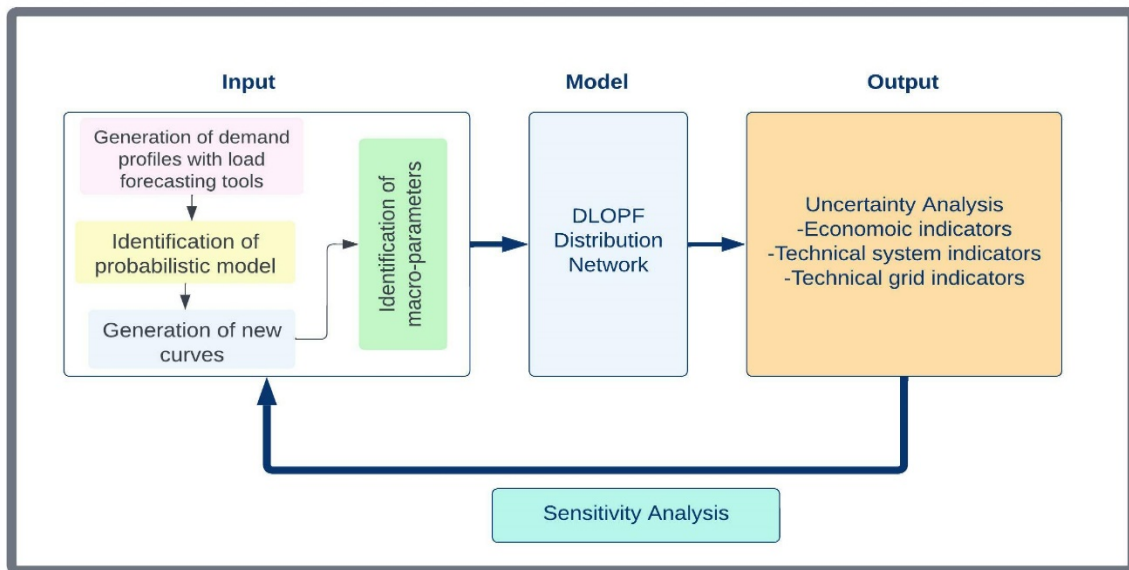


Figure 5–1: General workflow for uncertainty/sensitivity investigation in EPSM

5.2 Input Data

The demand curves are the input data on which we focus our interest in this uncertainty investigation. The generation procedure of these curves is explained in the following subsection. The characterization of these curves' uncertainties and the demand curves analysis based on different parameters are detailed afterward.

5.2.1 Generation of demand profiles with load forecasting tools (MOSAIC)

Since this chapter is dedicated to the specific case of the electrical distribution system, a bottom-up load forecasting model is adopted to simulate electric load curves. The load forecasting model used in this work is MOSAIC [196]. The simulator takes the characteristics of French loads extracted from the database as input values. This database results from the crossing of various national databases, particularly those of the INSEE's residences (Institut Nationale de la Statistique et des Etudes Economiques) and Enedis customers.

The modeling approach starts with a targeted geographical area determination by defining the longitude and latitude. Then MOSAIC takes as input data from the database, for this area, the buildings parameters (surface, height, number of occupants, etc.) and the data of the nearest weather station. The data defining the perimeter of the simulation (loads, i.e., the electricity consumption locations to be simulated) is considered as well as the power and usage assumptions over time (launches) of the electrical equipment in these loads. These assumptions contain values and associated probability laws (the parameters and their distributions are detailed in [258]). MOSAIC uses these values and makes random draws, according to the assumptions, to calculate a possible scenario. The scenario constitutes the power demands by the loads of the perimeter as a function of time between the start date and the end date of the simulation. This result is translated into electricity consumption per time step (load curves).

There are two different types of loads considered in MOSAIC, residential loads (houses or apartments) and tertiary loads (offices, hotels, restaurants, parking lots, etc.). The electrical appliances considered are divided into three groups according to their modeling in the simulator: static uses (e.g., television, oven, etc.), periodic uses (e.g., freezer) and thermo-sensitive uses are those that take into account the temperature-dependent parameters for their modeling (e.g., electric heating, air conditioning). This distribution into three groups of equipment is made for the characterization of the data of each type.

Two types of simulations are also considered at two different scales: at the HTA/BT transformer level or blocks (set of loads). Each of the blocks constitutes a set of loads (clients). These clients form the micro-simulations and constitute the finest mesh at which the results of the macro-simulation can be deconstructed. To move from one scale to another (from loads to a block), MOSAIC performs the sum of the load curves, i.e., the load curve of a block is the sum of the load curves of the loads corresponding to their blocks.

In this approach, the input parameters are data coming from large databases (e.g., national databases, Distribution System Operators (DSO)'s client information, temperature and solar

irradiation data, etc.). The input parameters of the database are heterogeneous since they are extracted from different sources. This results in the existence of missing values in the matched database. In this case, missing data is replaced by random values that follow the probabilistic distribution of the input data. Therefore, repeating the same calculation several times without fixing this randomness will result in different curves. The random draws lead to a lot of randomness in the modeling, requiring an uncertainty analysis study.

In this chapter, the geographic area is fixed in Nantes-France, especially in “île de Nantes.” An HTA electrical feeder is chosen in this fixed area; this feeder is shown by a black circle in Figure 5–2. This feeder feeds all the HTA/BT attached to the yellow line. On this feeder, most of the loads are residential (1142 BT (BT=low voltage) customers and 215 commercial customers, see Figure 5–2).

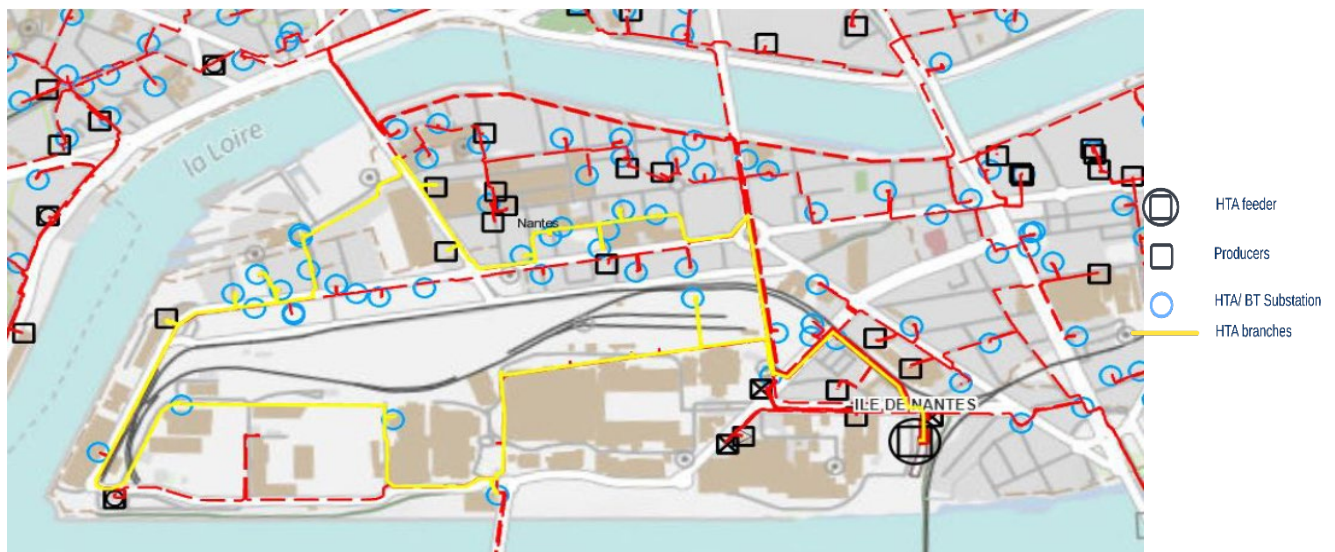


Figure 5–2: The chosen HTA feeder to launch the load curve calculations on the Ile de Nantes.

The load curve calculated by the simulation tool MOSAIC is the sum of the powers consumed by all equipment (static, periodic and thermos-sensitive devices). These consumption profiles result from a random draw associated with probability laws. Thus, different results are obtained if the same calculation is run twice (with the same input parameters). In our case, the HTA feeder supplies 14 HTA/BT substations (blue circles in Figure 5–2). For each HTA/BT, 25 calculations are made. An example of the obtained demand curves is shown in Figure 5–3. Figure 5–3 describes the total load curve (taking into account residential and tertiary customers); the average value of the 25 calculations is shown in red color. If we focus on the maximum curve, we can see that the highest power value is almost 280 kW (recorded in the cold period). As for the minimum value is about 60 kW (recorded in July, in a hot period). The profile of the load curve corresponds to the Nantes weather conditions, which results in a higher consumption during the winter months because of the existing of electric heating and a lower consumption during the summer months since, in Nantes, the use of air conditioning is minimal. The load curve shows that the randomness induces a high uncertainty on the consumptions.

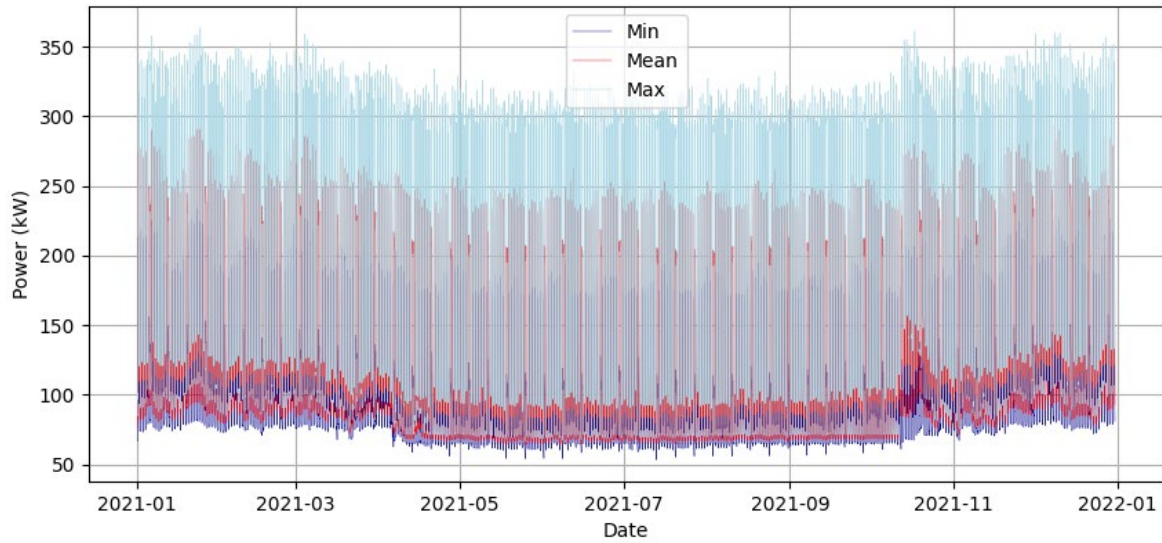


Figure 5–3: Representation of the average load curve (red), the maximum load curve (dark blue) and the minimum load curve obtained (clear blue) in the 25 simulations of an HTA/BT substation.

5.2.2 Uncertainty characterization: Identification of probabilistic model

The Uncertainty Characterization (UC) aims to identify the model's uncertain parameters and assign a probability distribution of these uncertainties. The most common methods used to describe parameter uncertainties are the probabilistic methods that treat parameters as random variables following probability density functions [259]. The input data for the electricity demand model are randomly selected from the database used by MOSAIC (e.g., INSEE, MAJIC (The database of land tax files [260]), Enedis Database, etc.), in ranges corresponding to the buildings' characteristics of studied Nantes district. Thus demand curves at the level of each HTA/BT substation are generated for one year. This selection is repeated 25 times for each substation. To illustrate the curves, a week from the samples of the 25 simulations generated for one HTA/BT substation is shown in Figure 5–4.

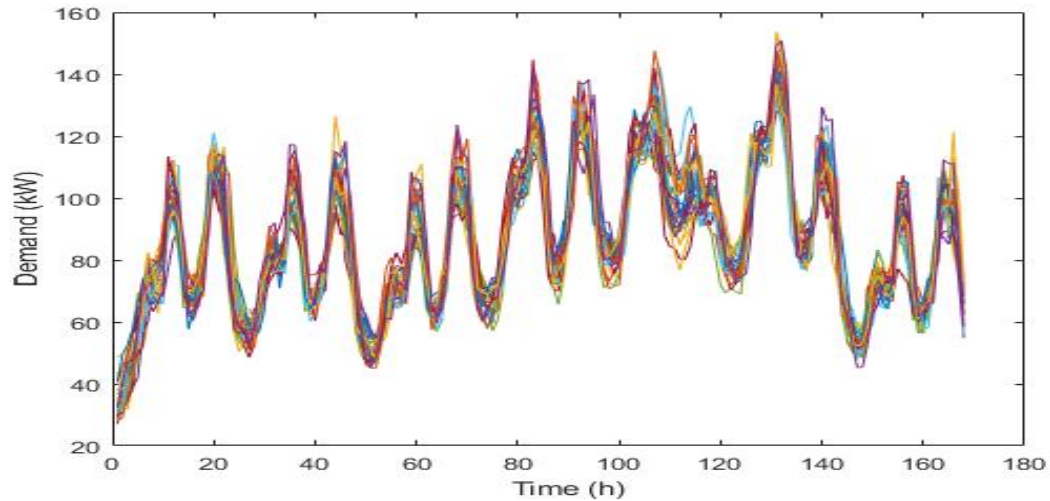


Figure 5-4: Simulation results example for one substation

To attribute a probability distribution law that describes the patterns of uncertainties, different hypothesis tests of distribution to represent these data are performed. A sample of points is formed by 25 points extracted for a one-time step (t). Firstly, different samples at different time steps were tested with 12 tests existing on Minitab [261]. To perform the tests, α (the threshold for statistical significance) is selected (5%), then a p -value (p) less than α indicates that the data do not follow the law. p -value (p) is the probability, for a given statistical model, that, when the null hypothesis is true, the statistical summary would be equal to or more extreme than the actual observed results. Minitab performs the fit tests on the data for many distributions and estimates their p -values. The distribution that best fits the data and is most suitable for analysis is the one with the highest p -value [262]. The results of the adequacy of fit testing are presented in Table 5-1.

Table 5-1: Extraction from Minitab Fit tests

Distribution Law	p-value (p)
Normal	0.925
Log-Normal	0.917
Exponential	0.250
Weibull	0.250

Based on these results, 4 tests were selected according to their highest 'p' values (Normal, gamma, Weibull and Log-Normal).

To select the best distribution law representing the demand values over the duration, the selected tests were applied to the 25 points at each time t during the simulation period (one year) using RStudio [263]. For each law test, a 'p' value is calculated at each time step ($p_t / t \in [1: 8760]$) for the 25 points.

A probability law is given to a set of values if its p -value is less than 0.05 (statistical tests adapted to the 5% risk (to reject the correct hypothesis wrongly) [264] i.e., we accept the test hypothesis if p is greater than α). The test is applied here on all sets (25 points at time t) of values that belong to all time steps in order to choose the test for which the largest number of sets match it.

The proportion (Pr) of the number of sets (25 points at time t) that validate a probability test ($p_t < 0.05$) is calculated according to the following formula Eq. (5-1).

$$Pr(\%) = \frac{Nb(p_t < 0.05)}{8760} \times 100 \quad (5-1)$$

The obtained results of the 4 probability laws are summarized in the following Table 5-2.

Table 5-2: Results of probability law tests on demand curves

Probability law	$Pe(\%)$: Percentage of values with ($P < 0.05$)
Normal	8.4 %
Weibull	41 %
Log normal	5.35 %
Gamma	1.38 %

5.2.3 Generation of new curves

Based on the results, the Gamma distribution is identified as the best distribution law to represent the uncertainty of the simulated demand curves. Then, the alpha and beta of Gamma law are identified for each time step of the demand time series, and N curves are generated

An example of $N=100$ generated curves is shown in Figure 5–5.

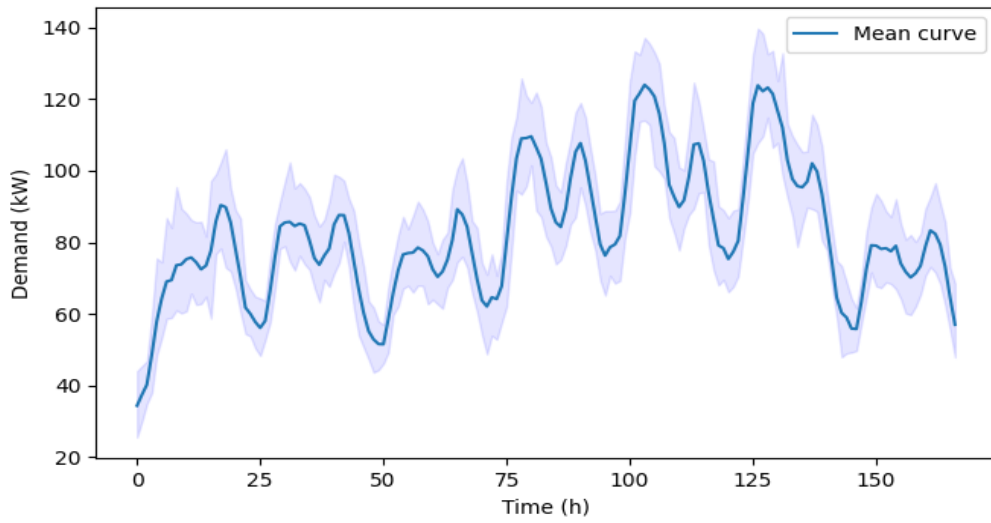


Figure 5-5: Generated load patterns for a defined substation

5.2.4 Identification of macro-parameters

The demand curves are generated for one year, then the same clustering procedure explained in the previous Chapter 4: is applied to choose 9 typical days. Thus, the total demand is calculated for the $N=300$ cases, then a mean total demand profile is calculated for one year. This total profile is sliced into subgroups of 3 days (72 continuous hours). One hundred twenty-two different subgroups are obtained. Thus, these subgroups are separated into 3 clusters using k-means clustering that classifies similar time series in the same cluster (here 3: winter, summer and spring). This clustering is based on three different features attributed to each period: the total energy, the maximum power and the variance of the power values. The means (centroids) are calculated for the 3 clusters to select one representative period from each cluster. The calculation of the Euclidean distance between each subgroup and the centroids follows this step. Then the nearest element to the 3 different centroids is selected. The selected days are defined. The demand values attributed to these days in each bus are used for the bus loads (9 days classified 3 by 3 continuously).

The variation of the total power demand at each time-step is shown in Figure 5-6. The total power demand at each time step is calculated for the $N=300$ cases, and the repartition of these 300 points is represented using the boxplots. The range of variation of the values at each time is around 300 kW in high-demand periods and lower in low-demand periods (~ 50 kW) where the boxplots are shorter.

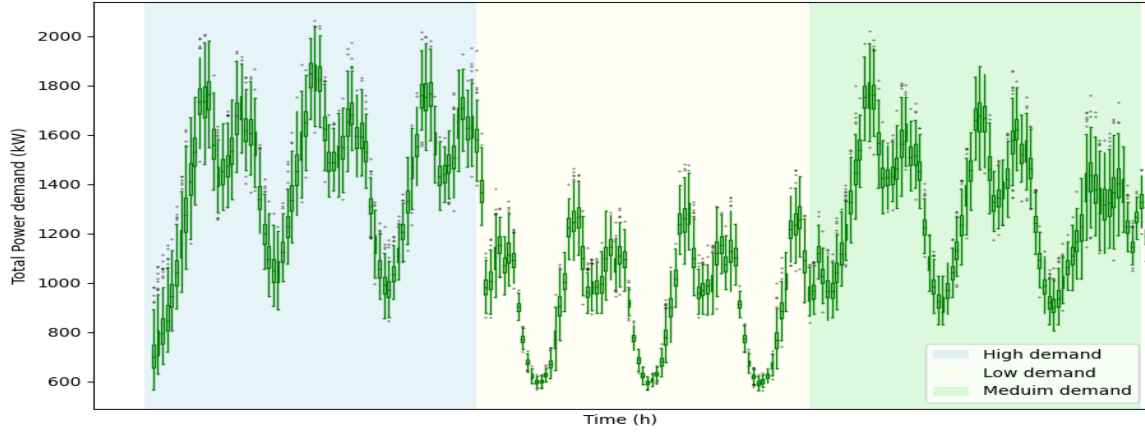


Figure 5-6: Ranges of variation of the generated energy demand curves

The available demand data summarize 300 load curves at each bus covering the 216 hours of the 9 typical days. At each bus from the 14 buses (HTA/BT transformers) located, as shown in Figure 5-2, 300 different demand values are available.

Several characteristics can be derived when analyzing load on the demand side to describe load demand conditions and perform the sensitivity analysis study regarding these uncertain factors. The chosen characteristics in this work are:

- Peak demand values
- Variances of demand values
- Duration of maximum loads
- Total energy demands at each period level
- Simultaneity factor

These characteristics are described and represented in the followings.

5.2.4.1 Peak demand values

The peak demand represents the higher demand value recorded in a time frame. The peak demands in each bus (i) are collected for the N cases (e) using the following equation (5-2).

$$P_{i,e}^{max} = \max_t (P_{i,t,e}) \quad i \in [1:14] \quad t \in [1:216] \quad e \in [1:300] \quad (5-2)$$

The distribution of peak demand values is presented in Figure 5-9 using boxplots to better visualize the power demand level at each bus. These peak demands are related to the location of each bus which is the same as the location of the corresponding HTA/BT substation. Peak powers vary according to the number of connected consumers, their types and their consumption behaviors. It can be noted that the range of variation is greater (larger boxplots) in the buses where the assigned peak demand values are higher (buses 3,4,10, and 14) than for the other buses where the peak values are close and form very short boxplots (buses 1, 5, 6, 7, 8, 9 and 12).

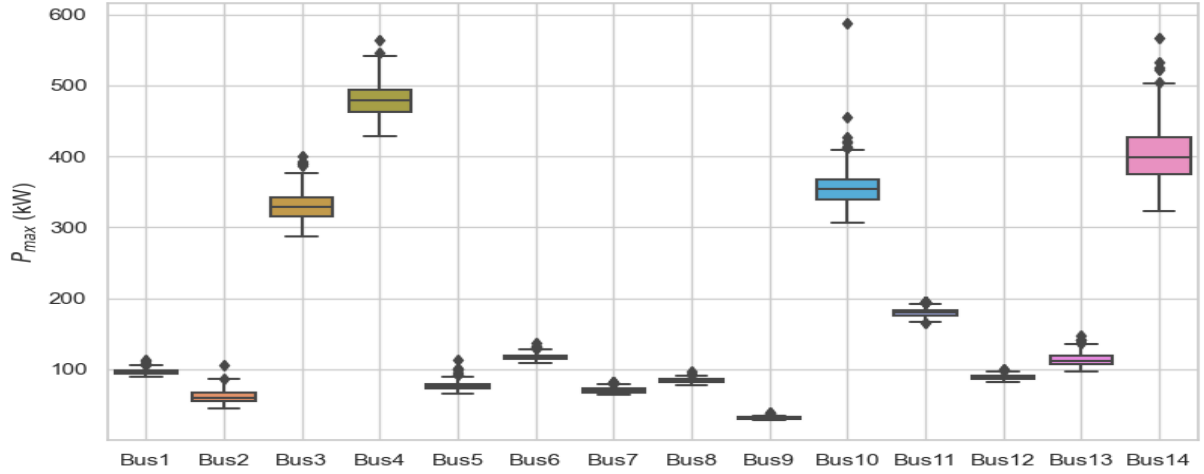


Figure 5-7: Boxplots for the peak demands repartition

5.2.4.2 Standardized Variances

The variances ($Var_{i,e}$) in load demand curves designates the spread between demand values in each curve. More specifically, variance measures how far each value number in the curve is from the mean (average). The variances are calculated using Eq. (5-3).

$$Var_{i,e} = \frac{1}{216} \sum_{t=1}^{216} (P_{i,t,e} - \frac{\sum_{t=1}^{216} P_{i,t,e}}{216})^2 \quad (5-3)$$

In this work, variance values are standardized to facilitate comparing buses. The set of 300 variance values in each bus is divided by the identified maximum variance of each bus. The obtained values of standardized variances are represented by the violin plots of Figure 5-8.

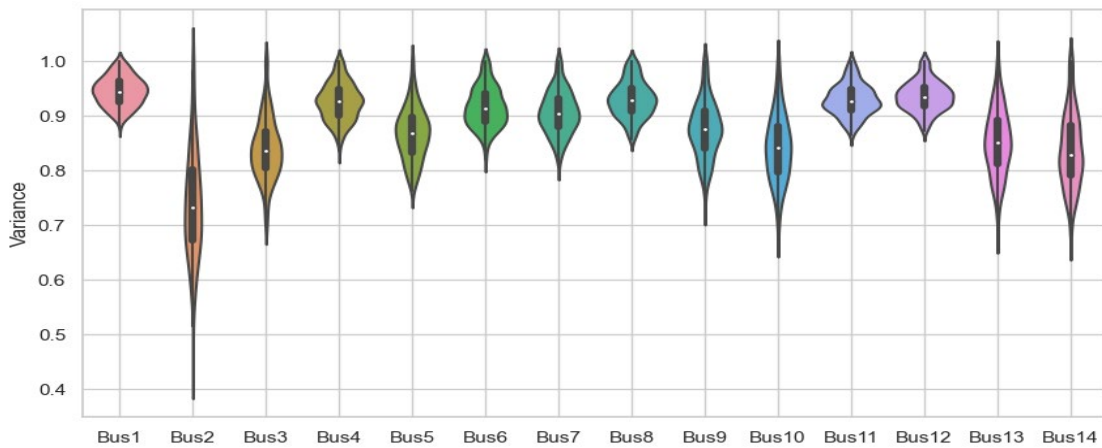


Figure 5-8: Violin plots for standardized variances in all buses

The distribution of standardized variances varies from one bus to another. Thus, in some cases, this variation is about 15% between the maximum and the minimum value (buses 1, 8, 11 and 12) where the violin plots are small compared to others. That means that the variances are quasi-similar. In other cases, the difference is more than 30% (buses 2, 3, 10, 13 and 14), so the presence

of uncertainties in these buses makes the variances differ as well, especially in bus 2, where the variation is about 60% (longest violin plot) this identifies a non-similarity between the different curves generated in this bus.

5.2.4.3 Duration of maximum loads

The maximum demands are defined here as demands higher than 95% of the total peak demand. The periods during which these demands are encountered are defined as maximum durations Du_e , the frequency of occurrences of the determined periods is displayed in Figure 5–9.

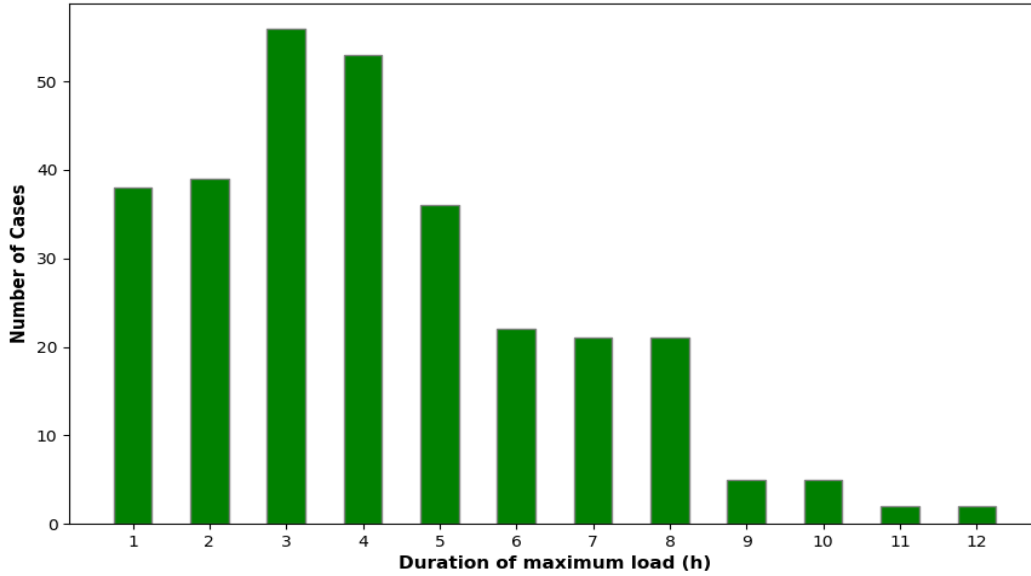


Figure 5–9: Duration of total maximum load of the total demand curve in the different cases

In a quarter of the cases (25.6%), the durations of maximum demand values are reached for one or two hours. In half of the cases (48.3%), the maximum demand values are reached for 3, 4 and 5 hours. The maximum duration can reach up to 12 hours of length. Starting from 6 to 12 hours, the number of cases that reach the maximum duration decreases (22 cases that reach 6 hours of maximum duration against 2 cases that reach 12 hours). This variation in duration (Du_k) is resulted from the existence of uncertainties and could affect the design of the EPSM with respect to the simulated case.

5.2.4.4 Total energy demand variation

The differences between the total power demands, the variances, the peak demands and their durations among the different cases certainly lead to variations between the total energies demanded among different periods. For that, we define 3 different parameters summarizing the total energy demanded in each demand level period (low, medium and high) according to the selected periods' 3 types of days resulting from clustering in Chapter 4:. These parameters are calculated using the following formulas Eq.(5-4), Eq.(5-5) and Eq.(5-6).

$$E_e^{High} = \sum_{i=1}^{14} \sum_{t=1}^{72} P_{i,t,e} \quad (5-4)$$

$$E_e^{Low} = \sum_{i=1}^{14} \sum_{t=73}^{144} P_{i,t,e} \quad (5-5)$$

$$E_e^{Medium} = \sum_{i=1}^{14} \sum_{t=145}^{216} P_{i,t,e} \quad (5-6)$$

The total energies vary by 4 MWh in each of the different demand levels as shown in Figure 5–10.

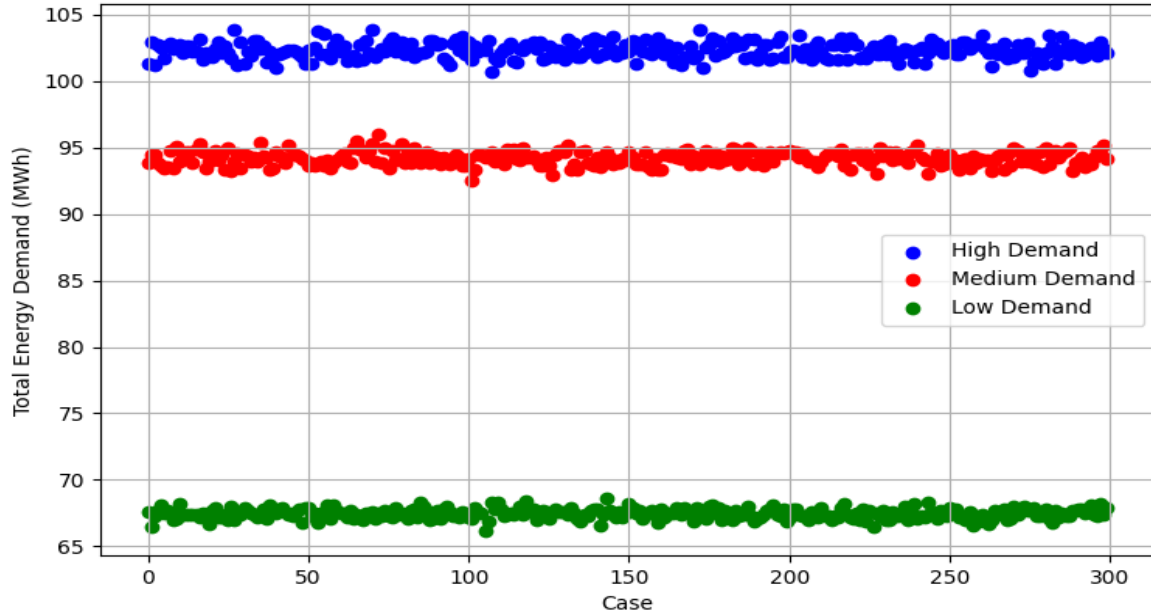


Figure 5–10: Total energy demands for 300 cases in low, medium and high periods

5.2.4.5 Simultaneity factor (Load coincidence)

The simultaneity factor represents how many electric consumers are operated with full power on all buses simultaneously. This factor can be used to make decisions regarding the total connected load that needs to be planned in some studies. Customers have different load curve patterns. The maximum demand for each bus may not occur at the same time. The ratio of the simultaneous maximum demand of the whole bus during a particular time to the sum of the maximum demand of individual consumers is called simultaneity factor eq. (5-7)

$$SF_e = \frac{P_e^{MAX}}{\sum_{i=1}^{14} P_{i,e}^{max}} \quad (5-7)$$

Where P^{MAX} = total load maximum value

P_i^{max} = maximum value of the partial node at bus i

This ranges between 0 and 1 as coincident demand, so it is always less than or equal to the maximum demand.

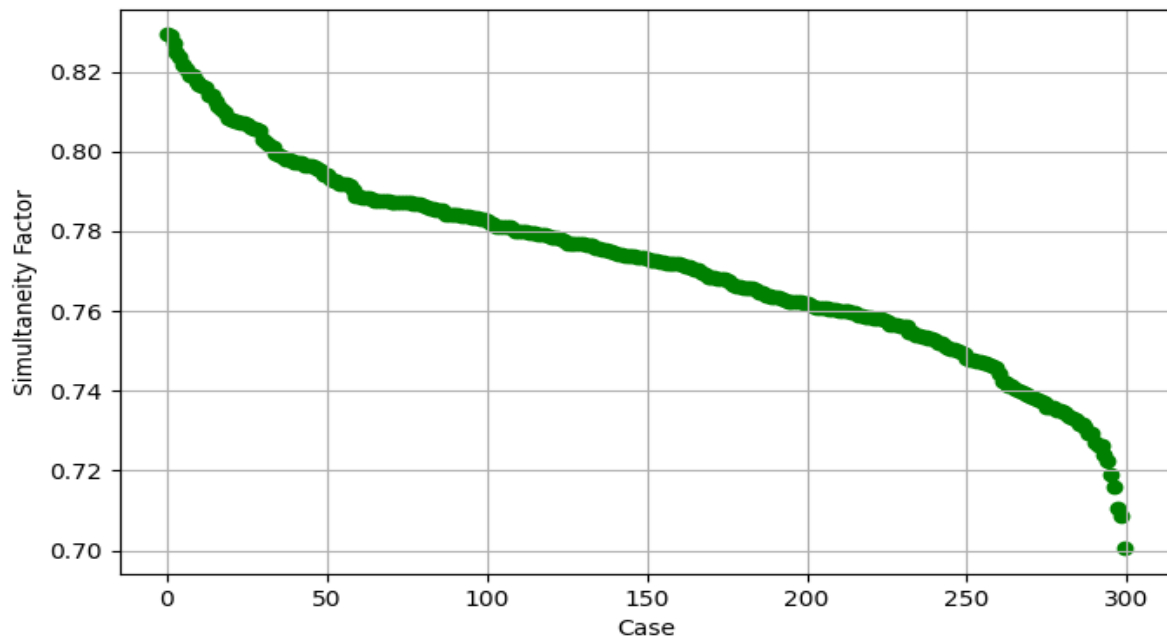


Figure 5–11: Simultaneity factors of the 300 cases

The resulted simultaneity factors of the different cases are shown in Figure 5–11. As can be seen, this factor varies between 70% and 84%. A lower simultaneity factor indicates a larger distribution at the time of maximum bus demand than higher simultaneity factors.

The 5 different uncertainty indicators identified above will be used for the sensitivity analysis to identify the most influential factors in the defined scenarios. To do this, we first define a deterministic model that will be applied to the case studied. The results obtained are then analyzed, and the sensitivity analysis is performed.

5.3 EPSM configuration and case study

Performing uncertainty and sensitivity analysis requires a large number of simulations (300 in our case). As seen in the previous chapter, the use of PSO-DLOPF has shown performance in the results, especially those of storage in terms of optimal sizing of batteries, considering the storage power and duration. It also offers the possibility to limit the number of installed batteries. However, this approach is computationally intensive, which is not practical for multi-simulations and for uncertainty studies. This comes back to the nonlinearity of the battery cost equation, which required using the PSO. In order to reduce the computation time, a new application of EPSM is defined for this part in which the cost of the batteries is defined as a linear correlation of the batteries' capacity without requirements in terms of duration and a maximum power of the batteries. This leads to important results regarding the effect of uncertainties on the established scenarios.

5.3.1 EPSM model used

To facilitate the comparison of the EPSM used in this part with those presented in the previous chapters, the model's specifications are shown in the following Table 5-3.

Table 5-3: Application specifications of the EPSM

	DLOPF
Durations of Studied Electric Load and Renewables Generation Case Study	Three typical durations of 3 days each
	Medium voltage rural distribution network
Initial Conditions	PV/WT/ST available surfaces & possible locations
Objective Function	Levelized cost of energy
Main Output	- Optimal scenario for sizing and placement of WT/PV/ST - Network simulation with time series variables
Virtual Generators Utility	Used to guarantee a feasible solution

Only the lower-level optimization model explained in chapter 3 is used in the following. With one modification in the objective function in the objective function (eq.(3-14)) where the investment cost of the batteries is added to the investment cost term (Γ'_{inv}) (eq.(3-15)). In the updated investment cost of the whole system and the batteries are given in equations (3-15) and (6).

$$\min F_{obj} = \frac{(\Gamma_{op} + \Gamma_{o\&m}) + \Gamma'_{inv}}{\sum_{i=1}^N \sum_{t=1}^T \frac{P_{i,t}^l}{(1+r)^t}} \quad (5-8)$$

Such that

$$\Gamma'_{inv} = j^{wt} + j^{pv} + j^{st} \quad (5-9)$$

$$j^{st} = \sum_{s=1}^{N^{st}} j^{st} \cdot E_{max}^{st} \quad (5-10)$$

The same equations used in the DLOPF model of chapter 3 are used in this part:

Eqs. (3-16)to (3-25), (3-31)to (3-39), (3-42) to (3-49), (3-52) to (3-57), (3-59)to (3-60)

Model illustration on the real case (île de Nantes)

This EPSM DLOPF presented in this section is tested by applying it to the real case study shown in Figure 5–2. The demand curves are those extracted from MOSAIC, and the branch details are extracted from the database specific to the study area. The total demand for a winter week is depicted in Figure 5–12. and the resulting production is shown in Figure 5–13. The results show consistency between demand and production. This production comes entirely from the HTA substation. So, the results reflect the reality of the network behavior without virtual generators.

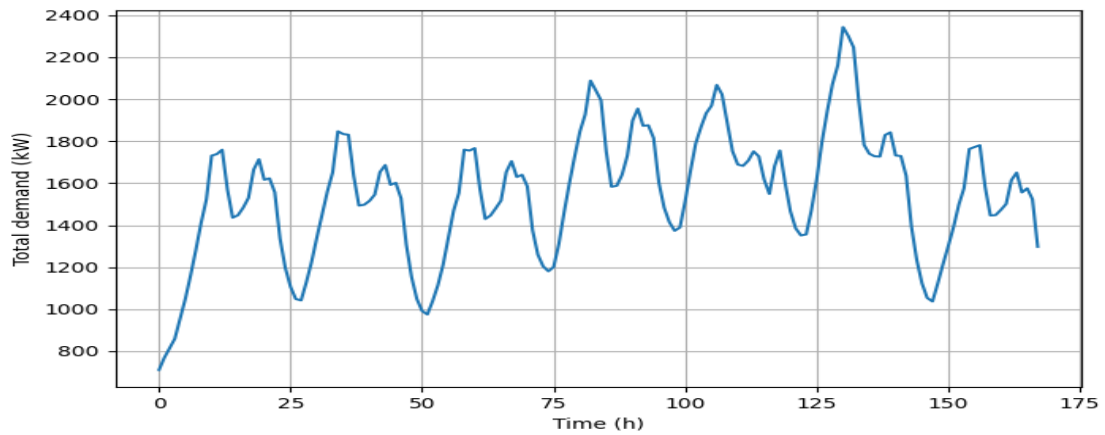


Figure 5–12: Total demand profile for the 14 HTA/BT substation in île de Nantes

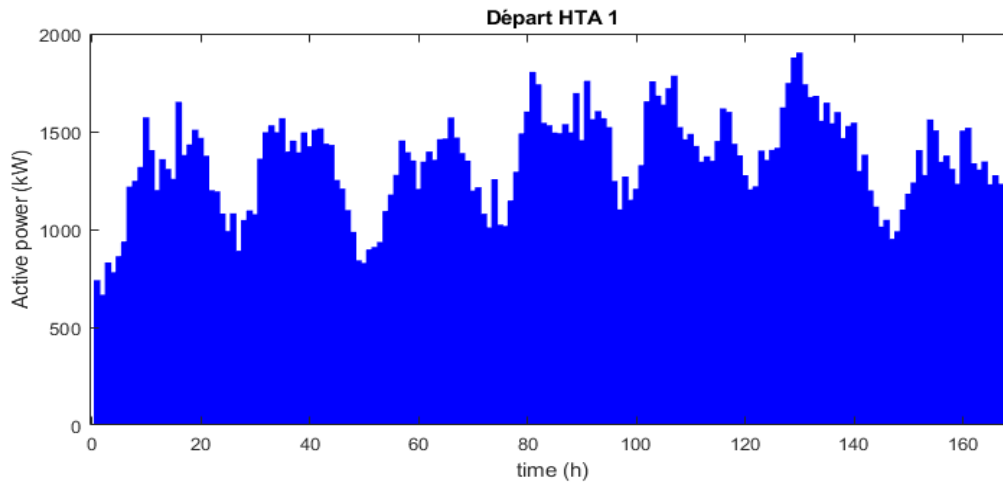


Figure 5-13: The resulted production profile from DLOPF

5.3.2 Case study

In this work, and for the following parts, a theoretical case study is selected instead of the case of île de Nantes because the following case has a more complex topology and a distributed generation. The chosen topology is a Medium-voltage rural distribution benchmark network shown in Figure 5-14 [265]. The branches' details are presented in Appendix A.

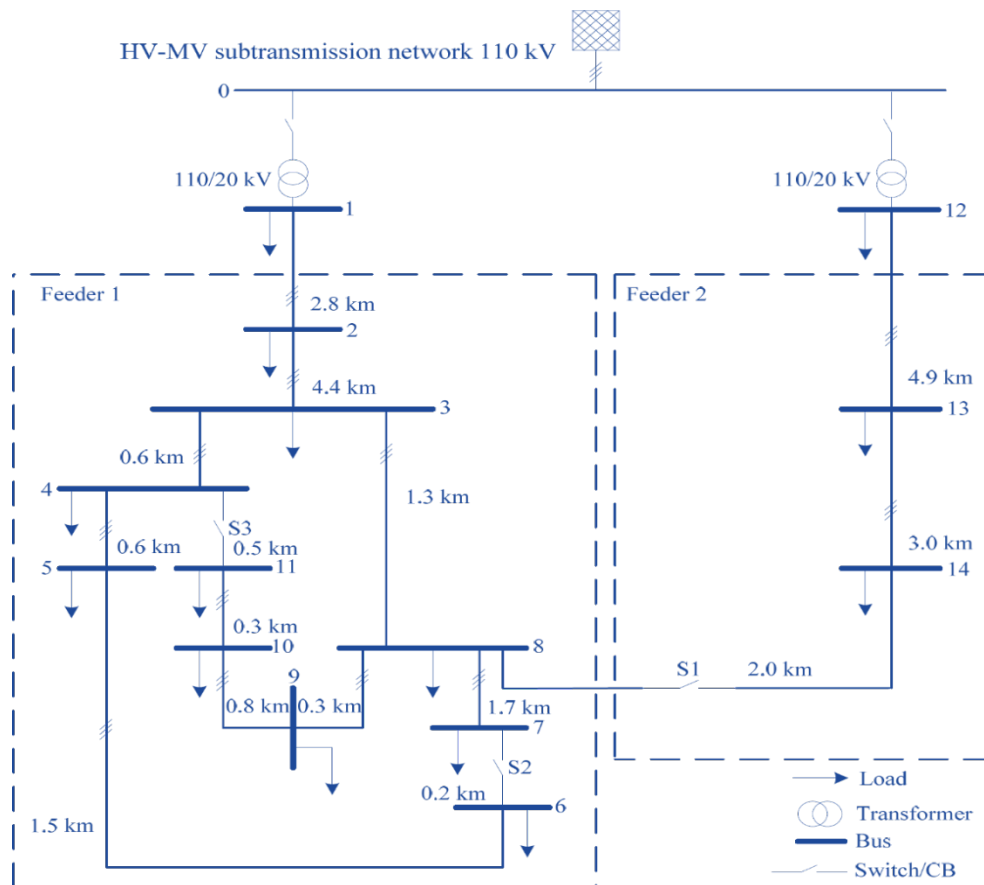


Figure 5-14: Medium voltage rural distribution benchmark network [265]

The benchmarking network comprises two separate subnetworks supplied by classic generators located in buses 1 and 12. These subnetworks are connected by buses 8 and 14. In this case, WTs, PVs and BESs could be added to specified buses concerning available surfaces for PVs and the existing potential of WTs. BES systems could also be added within the limit of maximum allowed capacities. This information is detailed in Table 3 with the corresponding costs.

The production profiles of PVs (Figure 4–29) and wind turbines (Figure 4–30) are the same generated and used in the previous Chapter 4:. The demand profiles generation procedure for the 14 HTA/BT substations is also the same as in the last chapter. These profiles are presented in Figure 5–3, and the total demand is shown in Figure **5–12**.

Table 5-4: Summary of buses specifications

Production type	Buses	Maximum capacity	Costs		
			Production (\$/MWh fuel)	Investment	O & M (\$/MW/yr)
PV	3,4,7,11,13	$A^{pv^{max}} = 800 \text{ m}^2$ $PV_t \text{ (peak load)} = 205 \text{ W/m}^2$	$C^{pv} = 0$	$J^{pv} = 178 \text{ (\$/m}^2\text{)}$	$O^{pv} = 8000$
WT	2,3,4,5,10,14	$R^{wt^{max}} = 10$ $WT_t \text{ (peak load)} = 1000 \text{ KW}$	$C^{wt} = 0$	$J^{wt} = 997\,000 \text{ \$/MW}$	$O^{wt} = 33000$
CG	1, 12	20 MW	$C^{cg,p}, C^{cg,q} = 36$	0 (already installed)	$O^{cg} = 10500$
VG	all buses	10000 KW	$C^{vg,p}, C^{vg,q} = 10^9$	0	0
BES	2,3,4,5,7,9,10,11,13,14	100 kWh	0	$I^{ST} = 350 \text{ \$/kWh}$	0

5.4 Sensitivity Analysis

5.4.1 Sensitivity of model outputs to input uncertainties

For the uncertainty analysis step, 300 simulations of the deterministic model of section 5.3 are performed. The results are presented in this section. Four different types of output indicators are studied:

- The economic indicator: LCOE (Levelized Cost Of Energy)
- Technical indicators of energy production and storage technologies: extracted energy from CG – Installed PVs, WTs – Total produced energy – Batteries investments
- Technical grid indicators: Percentage of branch saturation (Δ_{ij}) – Duration in which this percentage is less than 10% (D_{ij})
- Losses

5.4.1.1 Impact on the economic indicator

The impact of load data uncertainty on the economic indicator is important since the objective function here is initially based on minimizing the LCOE. The violin plot of Figure 5–15 represents the shape of the Levelized cost of energy results from the 300 cases generated above.

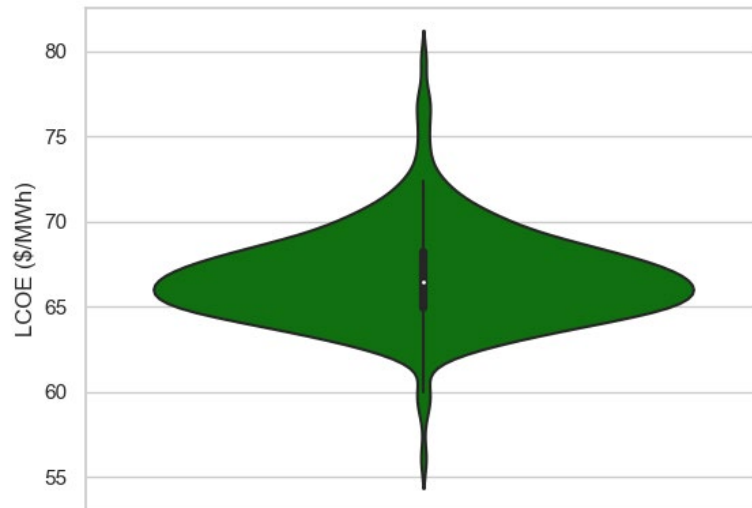


Figure 5–15: Violin plot for the variation of the levelized cost of energy in the different cases

The results are centered around the median value (white point) and are almost symmetrically distributed in a range of $\pm 50\%$ of the variation around the median value. The LCOE analysis revealed that the randomness in the input variables significantly impacts the LCOE and results in a variation of 28 \$/MWh and then millions of dollars over the project lifespan.

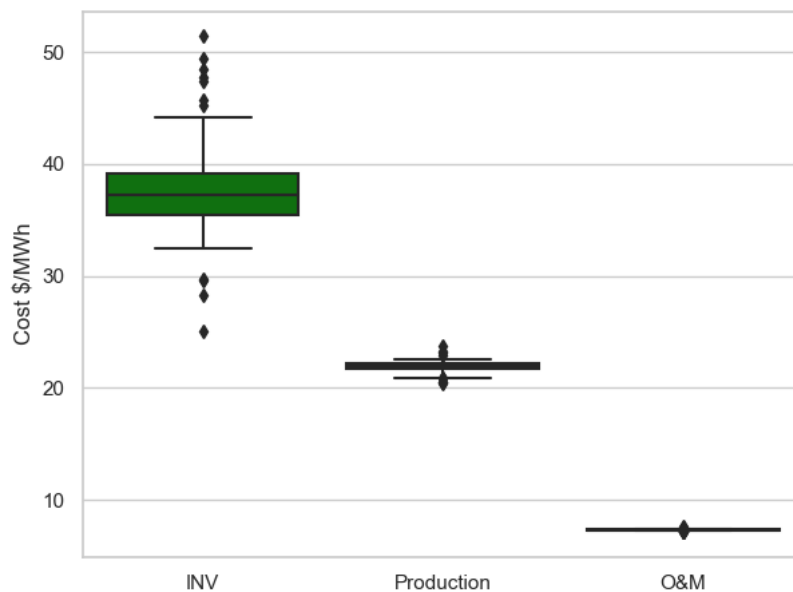


Figure 5–16: Cost details over the lifetime

The variation in the LCOE is a combination of variations between the investment, production and O&M costs. These variations are presented in Figure 5–16. We find that the variation of the LCOE is mainly due to the investment cost (between 25\$/MWh and 51\$/MWh) since this includes the investment in PVs, WTs and batteries. This LCOE is affected to a minor extent by the production

cost which is based on the CG production. The O & M cost variation is negligible compared to others and has a negligible effect on the LCOE.

5.4.1.2 Technical system indicators

The impact of uncertainties affects the technical indicators of energy production and storage technologies differently. These indicators include the extracted energy from the existing CGs, the installation surface of PVs, the fraction of installed WTs, and the total energy produced in addition to the installed batteries. The results are summarized in the parallel coordinate plots of Figure 5–17.

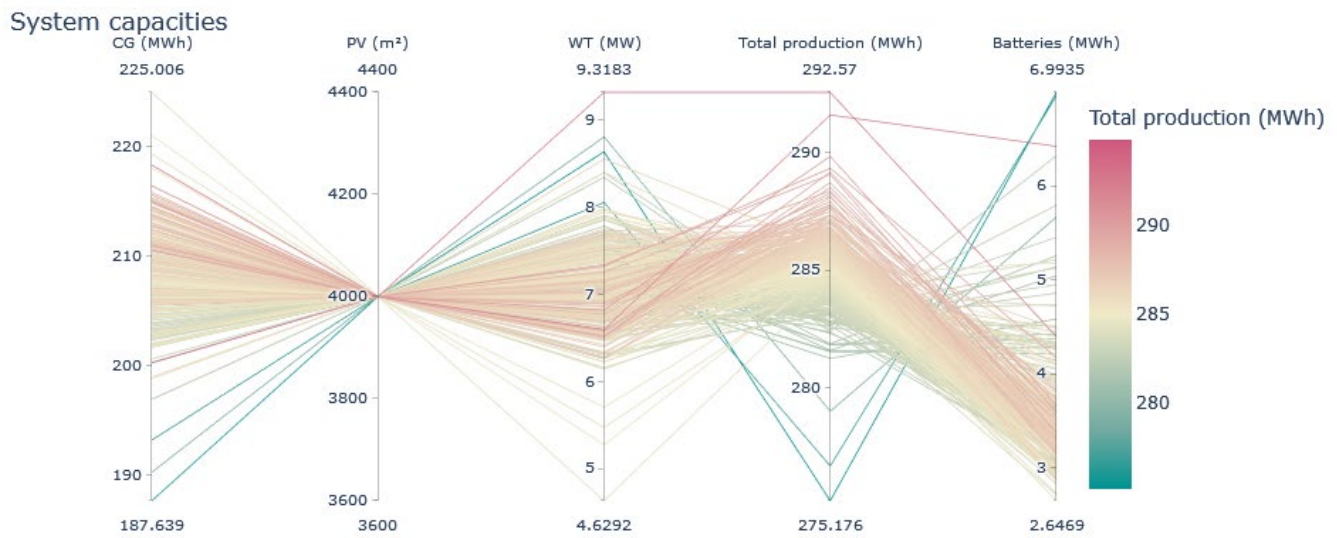


Figure 5–17: Parallel coordinate plots for the different cases results

It can be seen that the quality of the input data has no effect on the investment cost of the PVs. The installed area is constant at the maximum level for all cases (4000 m^2), which means that the model always prioritizes the investment in the cheapest production technology compared to the other sources (CGs and WTs) so that the variations in investment and production amounts will be concentrated in the CGs and WTs. Furthermore, substantial variations (16.6%) are shown in the energy extracted from the classic generators (up to 40 MWh) as well as in the installation of WTs (50.2%), where the maximum installed power (9.3 MW) is almost double of the minimum (4.6 MW) which necessarily varies the total production. The variation in the total production (5.94%) is less important than in the WT and CG since the sum contains both, and this balances the total variation because tracking the extreme points, we notice a maximum energy extracted from CG (225 MWh) that corresponds to a minimum installed WT power (4.6 MW) and a minimum CG (187.6 MWh) corresponds to a significant WT (8.6 MW) and so on. The variation in the WTs and PVs that produce intermittent energy induces the variation in the dimensioning of the batteries that aim to compensate for this intermittence. As long as the installed power of PV does not vary, the installed power of WT causes this important variation in the battery installation (62.13%). The dependencies and correlations between the different indicators will be better shown in the sensitivity analysis part 5.4.2.

5.4.1.3 Technical grid indicators

To focus on the network itself, we use technical indicators related to the grids, especially the amount of power flowing in the branches. The first indicator is the percentage of saturation of the branches (Δ_{ij}) and the second is the time (D_{ij}) during which the saturation is low and does not exceed 10%.

- The percentage of saturation (Δ_{ij}) in apparent power is calculated using eq.(5-11)

$$\Delta_{ij} (\%) = \frac{S_{ij}}{S_{ij}^{max}} \times 100 \quad (5-11)$$

The power flow behavior is depicted in Figure 5–18 for four different branches of one of the 300 simulated cases during the three typical days. In the high demand period, some branches are almost fully saturated, like branch 3-4; this branch also reaches a complete saturation in specific hours in medium (72h to 75h) and low (190h-195h) demand periods. Since this branch transmits power to several other branches, it affects the power delivery to the succeeding buses during these saturation periods, and therefore, it may influence the installation of generation sources to compensate for the lack of power delivery.

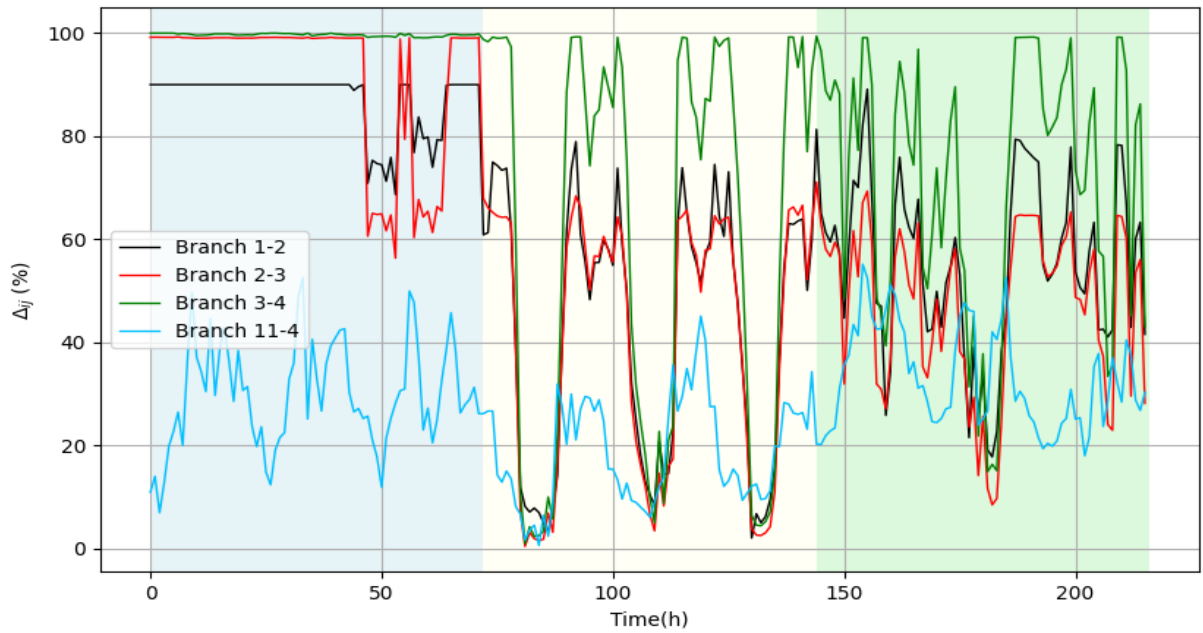


Figure 5–18: Percentages of apparent power saturation in 4 different branches

Other branches do not reach a saturation point that exceeds 60% of their capacity (e.g., branches 11-4). The maximum Δ_{ij} reached are identified for each branch in the 300 cases. The boxplots of Figure 5-21 show the repartition of the 300 values attributed to each branch. The uncertainties in input demand do not affect the maximum saturations of the first four branches. The first 3 branches are saturated most of the time because they are responsible for the delivery of energy to other branches. Full saturation is noticed in branches 6-7 also, and it comes back to the non-possibility of installation of RES and BES on bus 6. However, the maximum saturation rates achieved in the other branches vary by ranges of about 5% (12-13, 13-14, etc.).

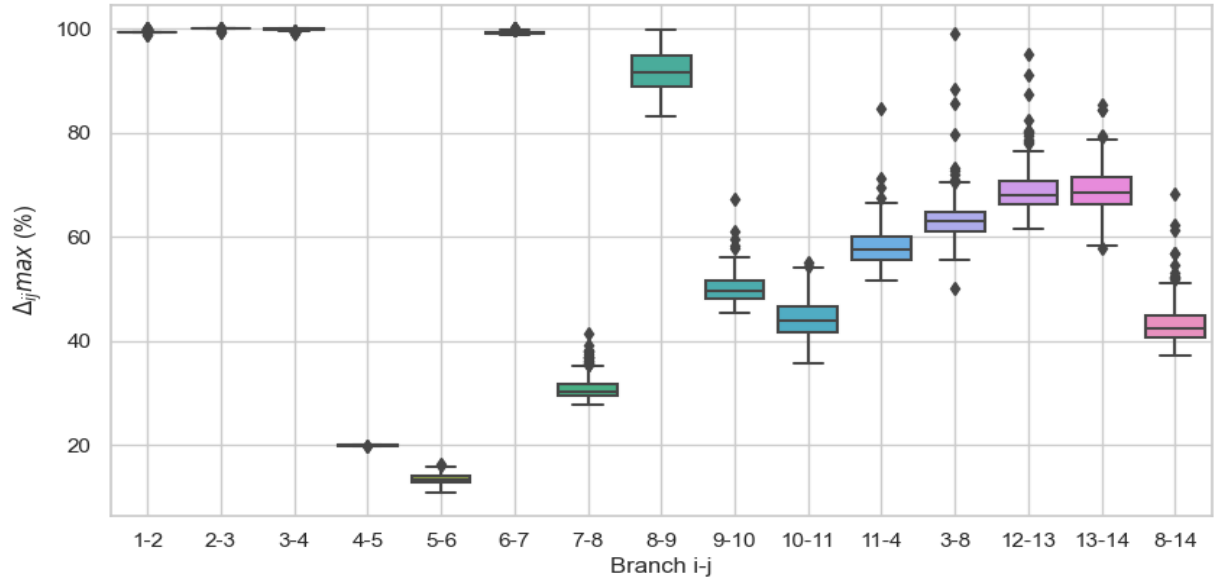


Figure 5-19: Boxplots of the apparent power saturations in each branch

- The duration with very low branch saturation is expressed in (5-12).

$$D_{ij} = \text{duration of } \Delta_{ij} < 10\%$$

(5-12)

The time during which the branches are within 10% of their saturations over the defined duration is considered as a technical indicator for the grid since it concerns the grid's branches dimensioning and their maximum apparent power. The results of the 300 cases are presented in the boxplots of Figure 5-20 for each branch.

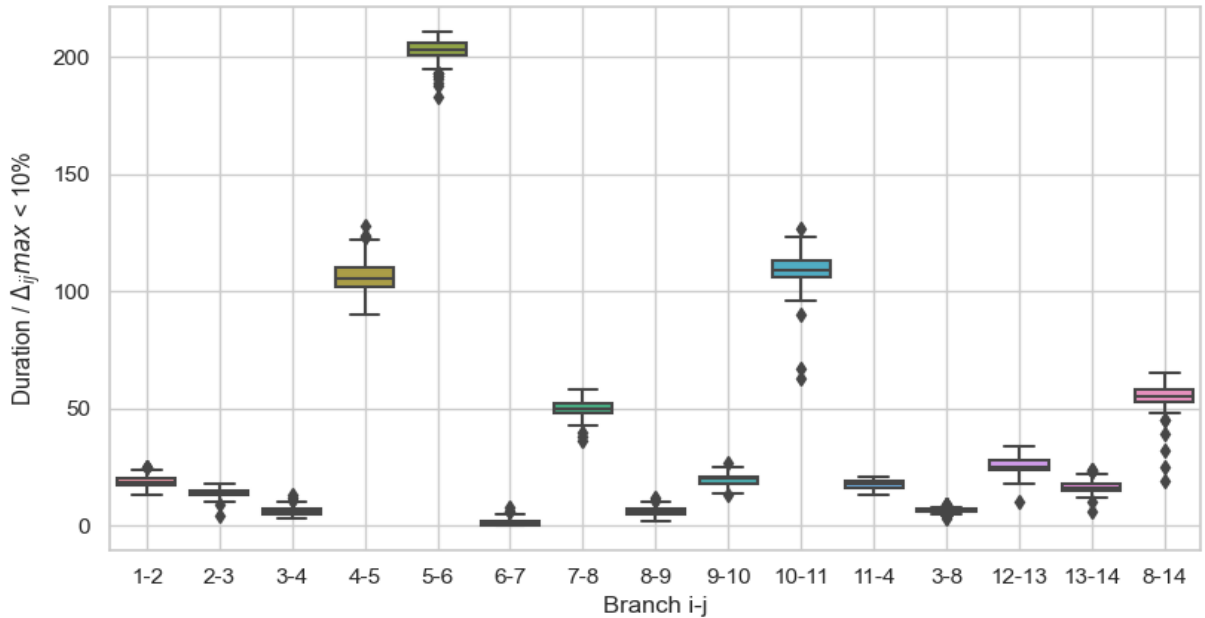


Figure 5-20: Boxplots of the duration of less than 10 % of saturation in each branch

D_{ij} is varying more in the branches where its values are more significant than in those where D_{ij} is about few hours that corresponds to the branches with higher maximum Δ_{ij} . The more the branches are saturated, the less they reach saturation less than 10%. For better understanding,

we select the most critical branches (with $\Delta_{ij} > 80\%$ and $D_{ij} < 25$ hours). The selected branches are, therefore (1-2, 2-3, 3-4, 6-7 and 8-9). The first branch (1-2) is critical since it is one of the main branches importing power from the classic generators to an important part of the network. The other two branches (2-3 and 3-4) are part of the branch (1-12) that will feed an important part of the network; in addition, they contain RES and BES that satisfy their demands first and transmit as much as possible for the rest of the network. Branches 6-7 and 8-9 are critical because they are connected to buses 6 and 8, where no installation is possible (neither RES nor BES) as shown in

Table 5-4. Therefore, these branches deliver power with their maximum capacity to be able to saturate the demand for these buses.

- The grid losses

The grid losses are estimated by calculating the difference between production and demand. The results are presented in the following Figure 5-21. In most cases, losses have less than 1% of differences since they vary between 7.1 % and 7.8%. In some cases, losses are at the level of 9.8 %, while in other cases are at 4% of losses.

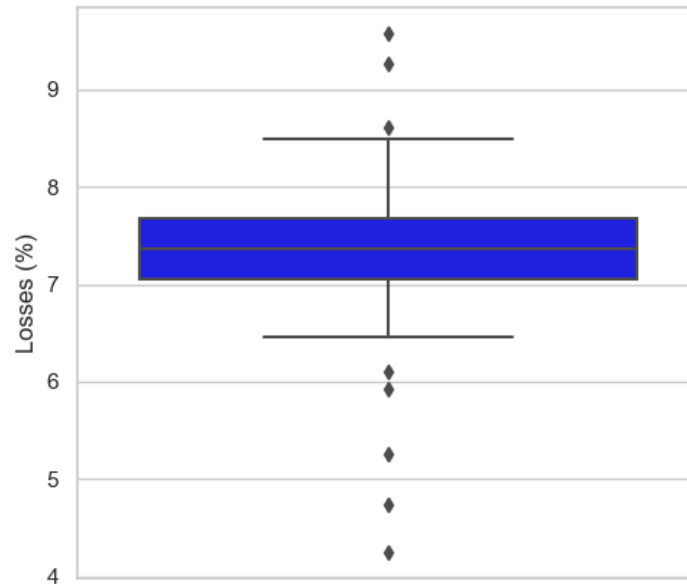


Figure 5-21: Boxplot representing the variation of the losses in different cases

5.4.2 Sensitivity between parameters

The objective of sensitivity analysis is to determine which model parameters are important and their relative importance. For example, in what order can we rank the parameters in terms of their importance because of their impact on the outputs? Can we draw conclusions about where to put effort or resources if we need to reduce the total uncertainty in system predictions? In this work, among the different SA technics presented in chapter 2, we make quantitative tests for sensitivity analysis using correlation analysis.

5.4.2.1 Tests based on correlation analysis

The Pearson correlation coefficient is widely used. It measures the association between each input considered separately and the output. A number between -1 and 1 measures the strength and direction of the relationship between two variables. The correlation is given by the equation (5-13).

$$r = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2} \sqrt{\sum_i (y_i - \bar{y})^2}} \quad i = 1, \dots, N \quad (5-13)$$

Where N is the number of samples.

The values of r are interpreted as follows [266]:

- Between 0 and 1: a positive correlation exists between variables (strong $r > 0.5$, moderate $0.3 < r < 0.5$ and weak $0 < r < 0.3$) – when one variable changes, the other variable changes in the same direction.
- 0: No correlation (there is no relationship between the variables)
- Between 0 and -1: a negative correlation exists between variables (strong $r < -0.5$, moderate $-0.3 > r > -0.5$ and weak $0 > r > -0.3$) – when one variable changes, the other variable changes in the opposite direction.

To perform the Pearson correlation test, both variables should be quantitative. They should be normal or a little non-normally distributed. In our case, this distribution is visualized by the diagonal of Figure 0–24. In Pearson correlation tests, choosing a sample size of up to 258 variables means a correlation test with a power 90%, an error 5% and an alternative correlation 0.2 as detailed in the sample size guideline for correlation analysis [267].

Table 5-5: Lists of input parameters and output indicators (bus index - k : case index - ij : branch index)

Input Parameters	Output Indicators
$P_{i,e}^{max}$	$LCOE_e$
$Var_{i,e}$	WT_e
Du_e	PV_e
E_e^{Low}	BES_e
E_e^{Meduim}	$losses_e$
E_e^{High}	$\Delta_{ij,e}$
SF_e	$D_e = \sum D_{ij,e}$

The input parameters and output indicators are summarized in Table 5-5. The results of the test of linear relationships between the parameters ($Var_{i,e}, P_{i,e}^{max}$) and indicators are presented respectively in the following Figure 5–22 and Figure 5–23. The Pearson correlation index r is calculated for the remaining parameters and represented in Figure 0–24. The indicator of PVs is excluded since it is demonstrated in part 5.4.1.2 that the uncertainties do not affect this investment.

From Figure 5–22, we notice that 4 buses (1,3,10 and 14) have marked an effect of variances on the output indicators. The increased standardized variances of buses 1, 10 and 14 cause an increase in the installed WT power and a decrease in the extracted CG energy. The batteries are affected by the variances in buses 3 and 14. The LCOE increases with the increase of standardized variances of buses 3, 10 and 14. Even if the correlation exists, it is considered weak ($r < 0.3$). The most influencing bus based on variances is the last one (bus 14) since the increase of variances of bus 14 also causes an increase in the duration of minor saturations, and a decrease in losses.

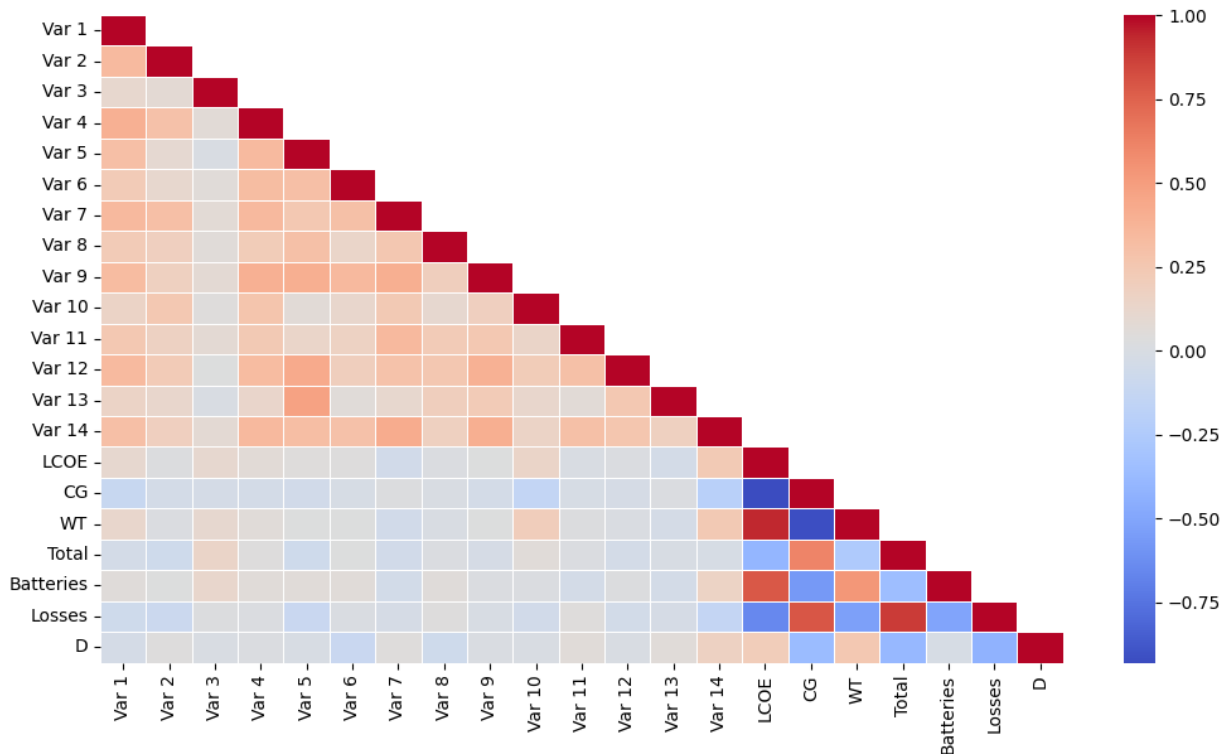


Figure 5–22: r values resulted from Pearson correlations tests of standardized variances ($Var_{i,k}$) on each bus with the output indicators

In Figure 5–23, the results show that 4 buses (1,4,8 and 14) could affect the indicators but also with weak correlations ($r < 0.15$). An increase in the peak power of bus 1 leads to an increase in WT investment and a decrease in CG extraction because this bus conveys power to other buses; when the demand increases, the saturation effect of the branch decreases the quantity conveyed, and consequently the system invests more in WTs. Increasing the peak power of bus 8 leads to an increase in battery investment since this bus does not contain a RES or BES and receives power from the grid. If enough power is injected into the grid, this increase in the peak power will be compensated with more storage.

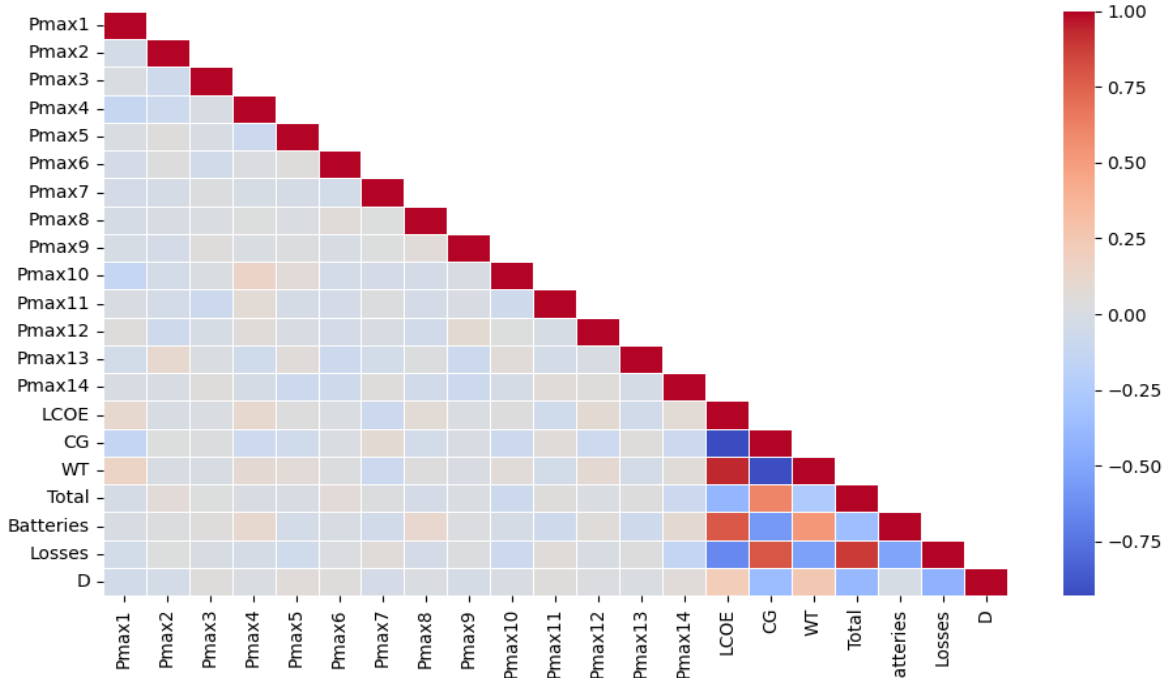


Figure 5–23: r values resulted from Pearson correlations tests of P^{max} on each bus with the output indicators

The five other parameter correlations are displayed in Figure 0–24. The increase of the first parameter (the maximum duration parameter (Du)) leads to a decrease in the duration with very low branch saturation D_k ($r = -0.15$). By the fact that as long as the maximum demand values are reached, the low saturations of the branches appear less.

The total energy demand calculated by Eq. (5-4), Eq.(5-5) and Eq.(5-6) are expressed in Figure 0–24 respectively by E1 for E_k^{High} , E2 for E_k^{low} and E3 for E_k^{Medium} . The values of LCOE increase with the high demand total energies E_k^{High} increasing. Thus, E1 has a strong effect ($r = 0.56$) on the LCOE, while others (E1 and E2) have moderate effects ($r = -0.04$) for E2 and ($r = 0.03$) for E3. When the total low demand energy E2 increases, the extracted energy from CGs increases also ($r = 0.13$) which means that this low-level energy is mainly extracted from CGs. This returns to the grid behavior in the low-demand period when the branch limits are not reached, and the energy from the classic generators can be continuously transmitted. The increasing in E2 also results in a

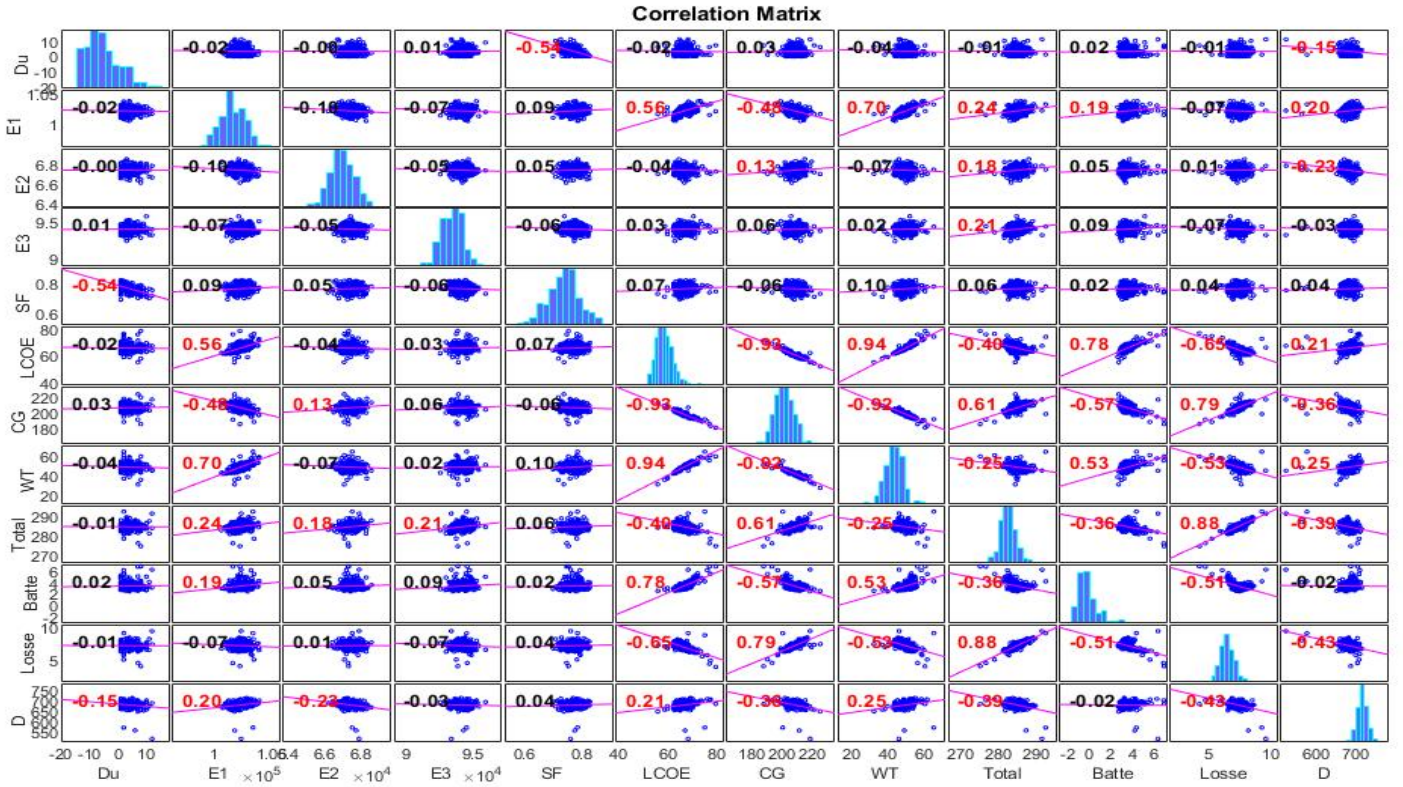


Figure 0-24: Tests on the different input parameters correlations with the output

decrease in the D_k ($r = -0.23$) because this demand period is the one with the longest duration of less than 10% of Δ_{ij} . So, a decrease in the demand increases these durations.

High total energy demand ($E1$) is the most impactful parameter. An increase in $E1$ leads to a strong increase in investment in WTs ($r = 0.7$) and, therefore, an increase in battery dimensioning ($r = 0.19$). This leads to a decrease in CGs energy extraction ($r = -0.48$) and a strongly decrease of the LCOE ($r = -0.5$). An increase in duration D_k is observed ($r = 0.2$). This is due to the effect of decentralization of producers (WTs and BES) and the limitation of the transition of the power from CGs, which reduces the saturation of the nearest branches to CGs after recourse to renewables and batteries.

The simultaneity factor (SF) has very weak influences on the indicators ($r < 0.1$).

The distribution of the parameters is shown in the diagonal of Figure 0-24. The Gamma test is applied to the output indicators distribution, and the results give p-values lower than 0.05, so the hypothesis of this law is rejected. The difference in distributions between the input parameters and the output indicators means that the model does not propagate uncertainties in a linear way between inputs and outputs. The distribution of most parameters is close to a normal distribution as shown in the distributions of $E1$, $E2$, $E3$, SF , CG , $Losses$, etc. Therefore, the use of Pearson correlations is validated.

5.5 Conclusion

This chapter uses an EPSM model to perform uncertainty and sensitivity analysis. An uncertainty characterization of real demand data is first accomplished, then an uncertainty representation is used to define uncertainty analysis parameters. After that, a sensitivity analysis study is done using correlations between input parameters and output indicators to identify the most influential parameters. The results show that the uncertainties have dramatic effects on the results. In economic terms, uncertainties lead to a 35% variation range of the LCOE. In terms of system design, it calls for more installed power from WT, more extracted energy from CGs and more BES installation. The uncertainties are also affecting the grid's saturation in the branches. The most impactful parameter is the total energy demand in the high-demand period (winter) since this parameter strongly affects the defined indicators. This makes from this parameter an essential parameter in the dimensioning of the RES, BES and thus in the planning of the network.

Chapter 6: Conclusions and Future Works

6.1 Introduction

This chapter summarizes the main results and observations that are discussed in the previous chapters. It also highlights the limitations and possible ways to complement and improve the model and the methodology developed in this thesis. In addition, technical research paths that can be followed using the tool as a platform are identified.

6.2 Conclusions

The problem of increasing electricity demand occurs with an energy transition shift from traditional fossil fuels to more sustainable energy production. This transition involves the integration of Renewable Energy Sources (RES) and Battery Energy Storage (BES). The integration of these technologies presents the design and operational challenges. Traditional planning and operational strategies have solved these problems in the past by strengthening the distribution or transmission grid infrastructures. In the case of high RES and BES penetration, these infrastructure upgrades can become costly and thus be an economic barrier to renewable energy development. Therefore, a new problem emerges, requiring the optimization of new decentralized components in existing grids.

The research question motivating this thesis are the followings:

- 1- *“Which solutions for network modeling in a perspective of analysis of RES integration and storage take into account the characteristics of the network?”*

This question concerns the presentation and application of the Electrical Power System Model (EPSM) to an energy planning and operation problem. This EPSM optimizes the planning and operation of the network while considering all the network characteristics. To do this, the presentation of the methods is systematically associated with their verification on the case study of an electrical system.

- 2- *“What optimization strategies to implement?”*

The challenge given by this question is to select and combine the most suitable optimization tools to benefit from their advantages in terms of the global solution, consideration of all parameters, modeling of the studied network and the ability for them to be dynamically projected in time to cover estimated simulation periods. To respond to this problem, the EPSM developed is based on a bi-level combining a metaheuristic model with an Optimal Power Flow (OPF) model.

- 3- *“How does uncertainty in demand impact energy planning?”*

This question concerns a framework representation ranging from energy modeling to uncertainty characterization and sensitivity analysis. The uncertainties studied here result from the demand's variability and unpredictability, which make demand profiles extracted from load forecasting models uncertain.

Overall, the thesis offers a complete framework covering all energy planning phases, from the electrical system's modeling to its optimal planning and operation, to study the effect of

demand uncertainties. This framework, together with full documentation of models, methods and data, can support decision-makers in the energy planning process.

Main contributions summary

In Chapter 2:, a literature review has been detailed, presenting the existing EPSM in the literature. The difference between planning and operational models reveals the importance of models combining planning and operational optimization. Existing power analysis tools were presented, including the OPF analysis. The OPF was described in detail to justify the choice of the developed Dynamic Linearized Optimal Power Flow (DLOPF). Then, in the context of the EPSM, the methods for sizing the RES and BES and the different evaluation objectives are discussed. The problem of uncertainties in the EPSM is also addressed. This study starts with the existing load prediction models and the methods of characterization of the uncertainties up to the analysis of the uncertainties and the methods of sensitivity analysis with their application in the energy models. This chapter provides a detailed guide to the literature on the various parts of the energy planning models.

Main outcomes: The different parts of the literature show that in the existing EPSMs, there is a lack of an optimization model for the planning and operation of the power system that takes into consideration all the constraints of the system. A model is applicable to both the transmission and distribution network that performs a multi-objective economic and environmental optimization and relies on a hybrid bi-level optimization between metaheuristics and linear modeling of the different RES and BES design. And finally, the possibility to provide through sensitivity analysis studies. This is what motivated the development of our EPSM, which combines all the details mentioned above.

In Chapter 3:, a bi-level EPSM model is detailed. This model leads to an economic dispatch of generation units (RES, CGs) and BES, with full consideration of the network's parameters. A bi-level approach is developed based on a meta-heuristic optimization algorithm (PSO) combined with the DLOPF. It is applied to find the optimal locations and sizes of RES and BES. An environmental indicator was considered using the ε -constraint method namely CO_2 emissions using ε – constraint method. The PSO is used in this case to optimally place a limited number of batteries by sizing them according to their characteristics, such as duration and storage power. The algorithm is developed on Julia. Whenever it is required to simulate different network configurations, the user needs only to change buses and branch characteristics and specify the installable capacities of RES and BES. The system of equations required for the PSO-DLOPF problem is automatically configured.

Main outcomes: The linear model (LOPF) was validated with Matpower reference, and the results justified our approach in linearization. Both a global and detailed explanation of the EPSM model was presented. This model can be adapted to any type of network by varying the parameter limits and the configuration of the buses and branches in addition to the initial conditions.

In Chapter 4:, two different applications for planning methodologies are presented. The first application was capable to simulate the existing network facing an increasing demand using the DLOPF only. The addition of Virtual Generators (VG) was present on all the buses guaranteed

feasible solutions in the cases of insufficiency in generation units and grid constraints limitations. These VGs constituted the main indicators for RES selection and placement. A step-by-step approach is used in this application to progressively eliminate the RES based on the individual load factors. Such approach helped to define a planning scenario that integrates the RES while maximizing the global Load factor of the system. The bi-level EPSM presented in chapter 3 was applied in the second application. The PSO successfully integrated an optimization strategy for the storage system into the sizing and placement exercise with respect to both economic and environmental objectives. The DLOPF could size and locate the RES in the existing network under known batteries constraint. It decides the hourly behavior of the generation and the storage units without violating the grid's constraints.

Main outcomes: The main findings in the application are:

Decreasing progressively the total number of RES in DLOPF results in an increase in the global load factor by 24.69%, reflecting a better global efficiency of the system, while the renewable energy share remains almost constant (a minor decrease is observed from 83.41% in S1 to 81.49% in S5). So the use of this elimination technique will help to locate the minimum number of RES in the best places to increase their efficiency.

The non-linearity of the BES costs was handled using bi-level optimization, while keeping acceptable computing performances.

The obtained results from the EPSM show the model's ability in network planning and operation while reducing the LCOE. Moreover, the RES and BES are optimally placed and sized while respecting the carbon emissions constraints. This bi-level model highlights the importance of storage and its design in terms of battery specifications (Battery power and duration).

The increase in environmental requirements (minimizing the CO_2 emissions) is costly in terms of LCOE.

Uncertainties in distribution grids EPSM are relatively high due to different uncertain input parameters, especially in the load profiles generated using load forecasting models. To prove that, Chapter 5: presented a general framework for uncertainty characterization and sensitivity analysis through an adapted EPSM model and proposed a solution that models the uncertainties based on the results of a Bottom-Up model. The main finding of this chapter is that uncertainty strongly impacts energy planning scenarios. In fact, uncertainty characterization or the quantification of input uncertainties reveals that uncertainty levels vary significantly for different parameters that describe the demand patterns (peak demands, total energies for each period, variances, duration of maximum loads and simultaneity factors). The sensitivity analysis shows the effect of these parameters on the different economic and technical indicators chosen to describe scenarios and highlights the importance of the winter power demand compared to others in the system design, LCOE and losses.

Main outcomes: The results show that the uncertainties have a strong effect on the results. In economic terms, it means millions of dollars of difference. In terms of system design, it is an increase in installed WT capacity, an increase in energy extracted from the EGTs, and an increase in BES installation. Uncertainties also affect the results of grid saturation in the branches. The

parameter that has the most impact is the total energy demand during the high-demand period (winter), as this parameter strongly affects the defined indicators. This makes this parameter a key parameter in the sizing of RES, BES and thus in the planning of the network. The other parameters could be classified in terms of importance by this order: Total energy in low demand, the total energy in medium demand, duration of maximum branches saturation, variances and peak demand.

The work in this thesis contributes to the need to develop energy planning and operation methodologies for the future. The success of the energy transition is highly dependent on the smart evolution of the current electrical network. This evolution is essential to ensure a future with easy access to high-quality electricity. The need to improve the accuracy of the load forecasting models is highly important to prevent scenarios with more or less production and storage capacities. And the used of decision aid tools (Multicriteria decision analysis, decision tree, etc.) is also quite important to optimize the model under uncertainties.

6.3 Limitations and recommendations for future works

The presented EPSM, which considers PV, WT, and BES sizing and placement, could be expanded to include other generation sources and to select between battery technologies (e.g., Lithium-ion, Lithium polymer (Li-Po), Nickel-Cadmium, etc.). The PSO had the ability to incorporate non-linear cost functions concerning battery storage power and duration. These non-linear costs add mathematical complexity to the problem. Another interesting improvement to the cost function could include integrating these variables (storage power and duration) into the DLOPF. This would allow the algorithm to size and place battery systems and suggest the best battery technology to install based on the case study. Future work can be done to incorporate these features into the DLOPF algorithm.

Scenario generation in the bi-level model constitutes a step towards developing more efficient and faster heuristics that consider business indicators or the development of MCDA approaches.

In the case studies, the boundary conditions and physical parameters are, as much as possible, very close to the real systems. Validations are performed analytically, ensuring that the results are logical and in accordance with reality. This model is applied to a real network configuration. Moreover, this model could be compared to other EPSM commercial models by applying the same conditions.

The presented DLOPF model in application 1 could be further coupled with decision-makers' advanced methods (multi-criteria decision analysis, decision trees, etc.).

The sensitivity analysis study was mainly based on energy demands, while intermittent renewable energy sources (PV, WT) included in different case studies are assumed to be very accurate forecasts. The HOMER and HelioScope simulation tools are used to estimate the generation outputs for WTs and PVs, respectively. The forecasting procedure includes assumptions that include uncertainties coming from missing data and the data association to probability laws and making random draws for each simulation. The forecasted prices are also assumed to be accurate. The upcoming work can consider all uncertain parameters (weather, costs, efficiency, emissions, etc.) and perform a study from the uncertainty's characterization to a global sensitivity analysis.

The developed EPSM is useful in multiway. For example, a diffuse demand reduction can be considered as a distributed source. This opens the door to the use of the model for Demand Side Management scenarios. Otherwise, this model could be extended to include self-consumption situations (individual or collective). The influence of economic scenarios (incentives, variable electricity prices, etc.) could also be tested. All this opens the field to study flexibilities solutions (supply as well as demand, or both coupled).

The uncertainties could be integrated into the EPSM to perform a robust optimization under uncertainty. Global sensitivity analysis methods could be performed (Morris, Sobol, etc.) to study the interactions between the input parameters with regard to their effect on the model output variability. And therefore, the study of the propagation of these uncertainties on all parts of the model.

Appendix A

A-1: The per-unit (p.u) system

The per-unit method of calculation is used as an aid in electrical system analysis operating at different voltage levels. The analysis of electrical system requires different values: voltage, current, power, impedance and admittance. Per-unit system is used to make the calculation easier as all the values are taken in the same unit. The p.u system is mainly used in the circuit where variation in voltage occurs.

The per-unit value of any quantity is calculated as the ratio of actual value to the reference or base value. Both values should have the same unit.

- Per unit value = $\frac{\text{Actual value}}{\text{Base or reference value}}$

In general, the per-unit values are determined as

- Base current, $I_{p.u} = \frac{I}{I_{base}}$ where $I_{base}(A) = \frac{S_{base}}{U_{base}}$
- Per unit Impedance, $Z_{p.u} = \frac{Z}{Z_{base}} = Z \times \frac{S_{base}}{U_{base}^2}$
- Per unit Resistance, $r_{p.u} = \frac{r_{base}}{Z_{base}}$
- Per unit reactance, $x_{p.u} = \frac{x_{base}}{Z_{base}}$

Where,

$Z(\Omega)$ = Actual Impedance

$Z_{base}(\Omega)$ = Base Impedance

$S_{base}(VA)$ = Base power

$(V)_{base}(V)$ = base voltage

A-2: Branches characteristic for IEEE-30 bus system

Line No.	From Bus	To Bus	Series Impedance (p.u)	
			r: resistance	X: reactance
1	1	2	0.02	0.06
2	1	3	0.05	0.19
3	2	4	0.06	0.17
4	3	4	0.01	0.04
5	2	5	0.05	0.2
6	2	6	0.06	0.18
7	4	6	0.01	0.04
8	5	7	0.05	0.12
9	6	7	0.03	0.08
10	6	8	0.01	0.04
11	6	9	0.00	0.21
12	6	10	0	0.56
13	9	11	0	0.21
14	9	10	0	0.11
15	4	12	0	0.26
16	12	13	0	0.14
17	12	1	0.12	0.26
18	12	15	0.07	0.13
19	12	16	0.09	0.2
20	14	15	0.22	0.2
21	16	17	0.08	0.19
22	15	18	0.11	0.22
23	18	19	0.06	0.13
24	19	20	0.03	0.07
25	10	20	0.09	0.21
26	10	17	0.03	0.08
27	10	21	0.03	0.07
28	10	22	0.07	0.15
29	21	22	0.01	0.02
30	15	23	0.1	0.2
31	22	24	0.12	0.18
32	23	24	0.13	0.27
33	24	25	0.19	0.33
34	25	26	0.25	0.38
35	25	27	0.11	0.21
36	28	27	0	0.4
37	27	29	0.22	0.42
38	27	20	0.32	0.6
39	29	20	0.24	0.45
40	8	28	0.06	0.2
41	6	28	0.02	0.06

Table A- 1: Transmission Line Data

A-3: Branches characteristic for Medium-voltage rural distribution benchmark network

Line No.	From Bus	To Bus	Series Impedance	
			r: resistance (Ω/km)	X: reactance (Ω/km)
0	0	1	--	--
1	1	2	0.579	0.367
2	2	3	0.164	0.113
3	3	4	0.262	0.121
4	4	5	0.354	0.129
5	5	6	0.336	0.126
6	6	7	0.256	0.13
7	7	8	0.294	0.123
8	8	9	0.339	0.13
9	9	10	0.399	0.133
10	10	11	0.367	0.133
11	11	4	0.423	0.134
12	3	8	0.172	0.115
13	0	12	--	--
14	12	13	0.337	0.358
15	13	14	0.202	0.122

Table A- 2: Parameters of network elements used for case studies [254]

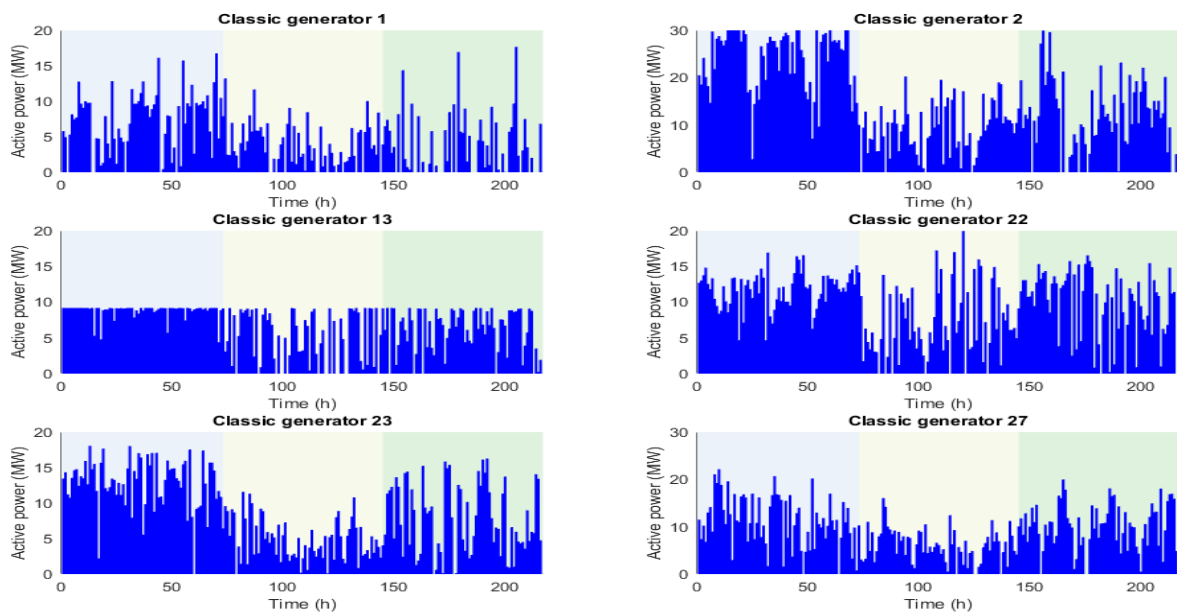
Appendix B

B-: Application 2

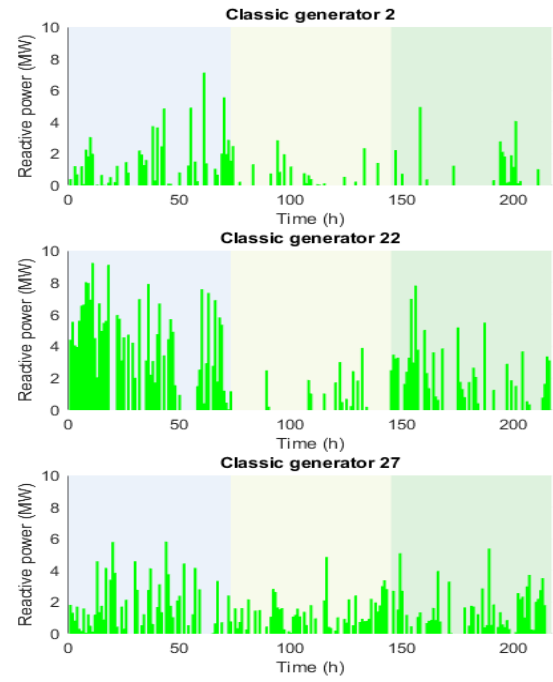
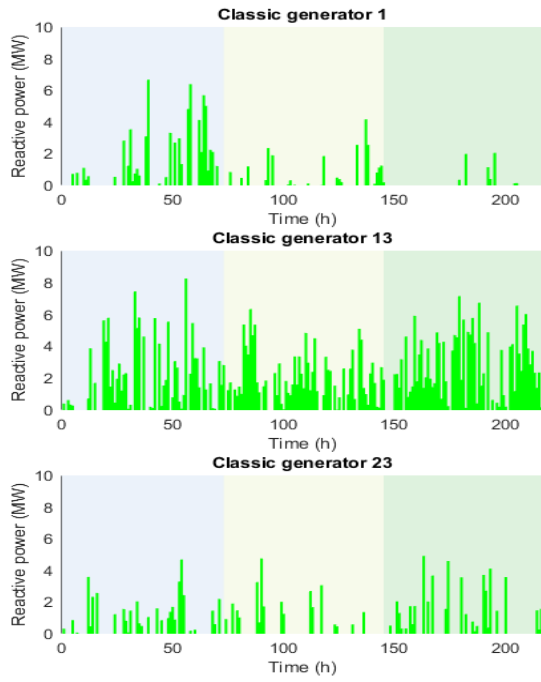
The production results from the 5 different scenarios of the bi-level approach are presented in this part.

Scenario 1: Without CO_2 limits

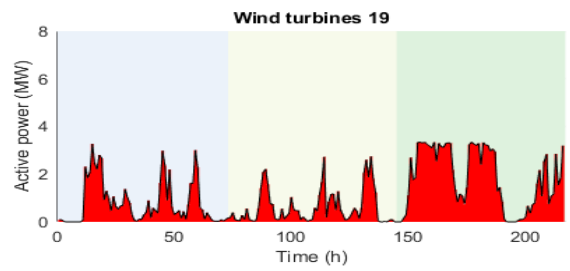
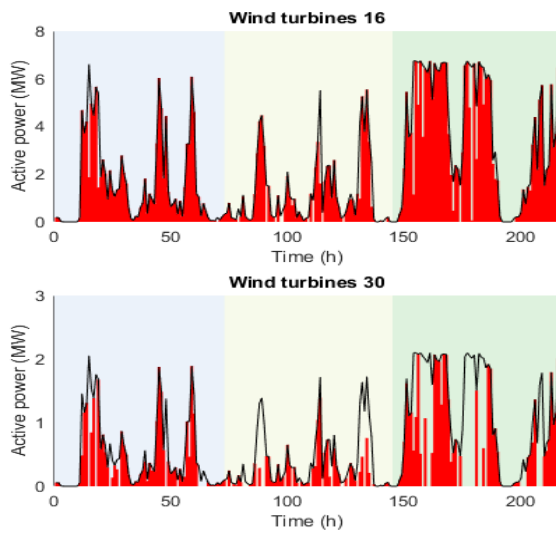
- Scenario 1: Classic generators active power results



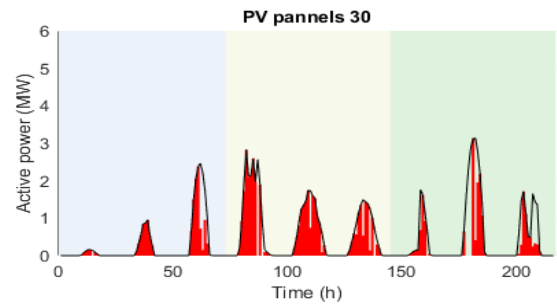
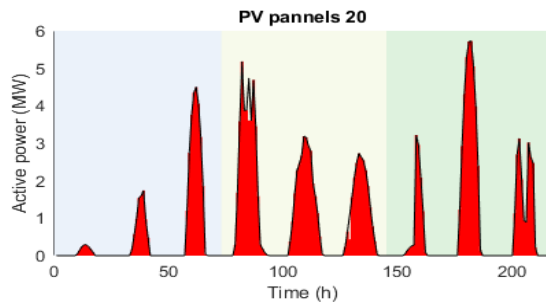
- Scenario 1: Classic generators reactive power results



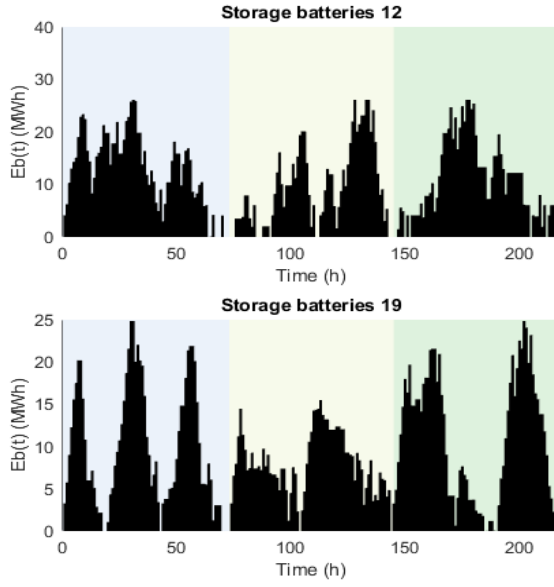
- Scenario 1: Wind turbines results



- Scenario 1: Photovoltaic solar panels results

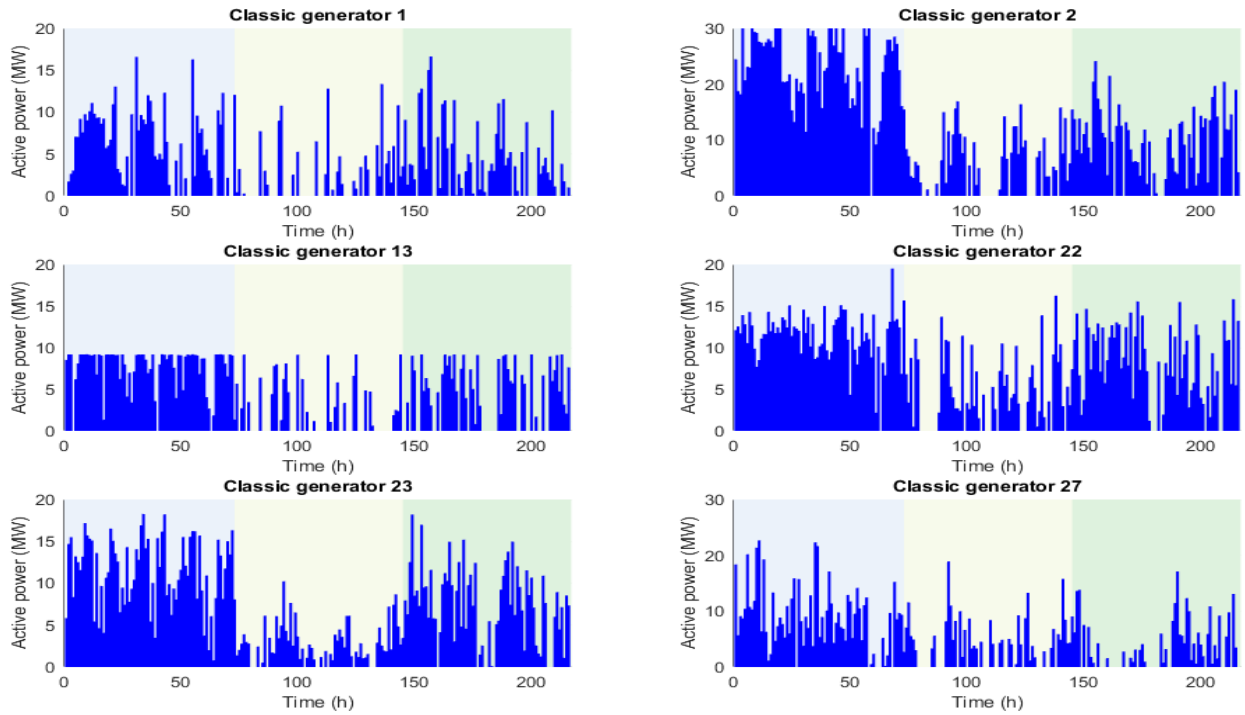


- Scenario 1: Batteries energy storage results

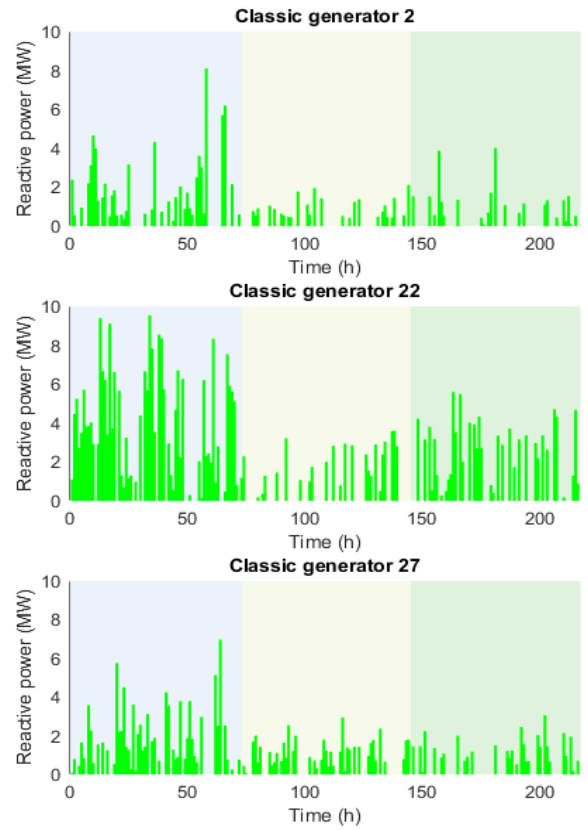
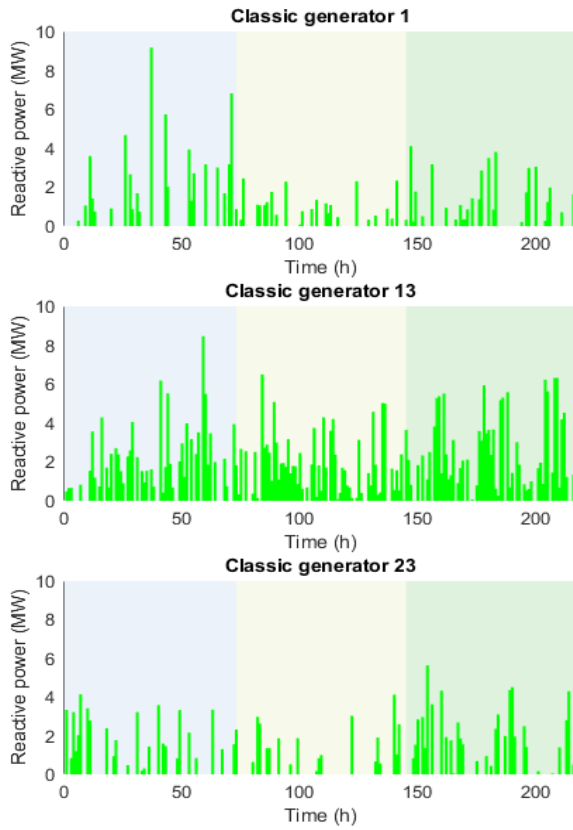


Scenario 2: $Ta = 70\%$

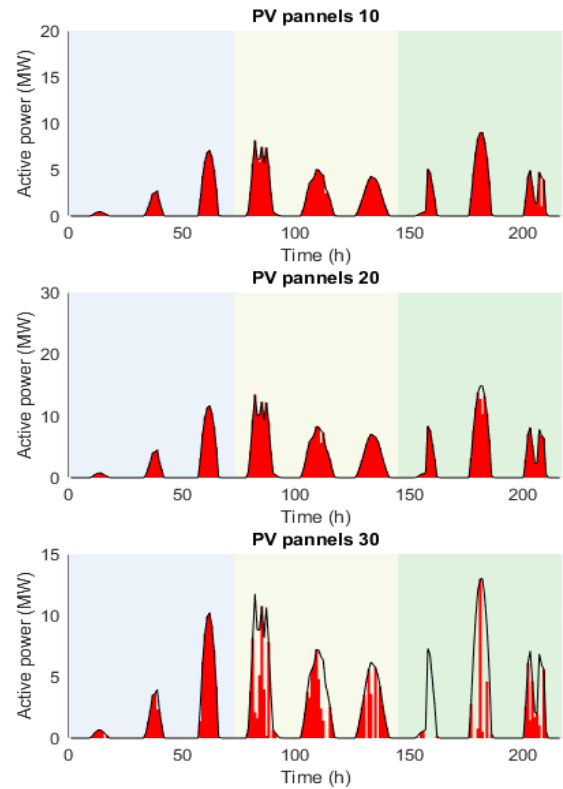
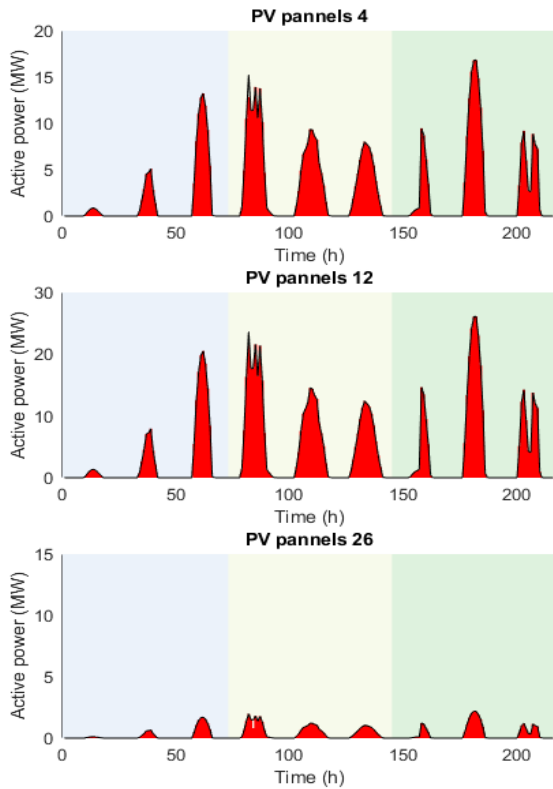
- Scenario 2: Classic generators active power results



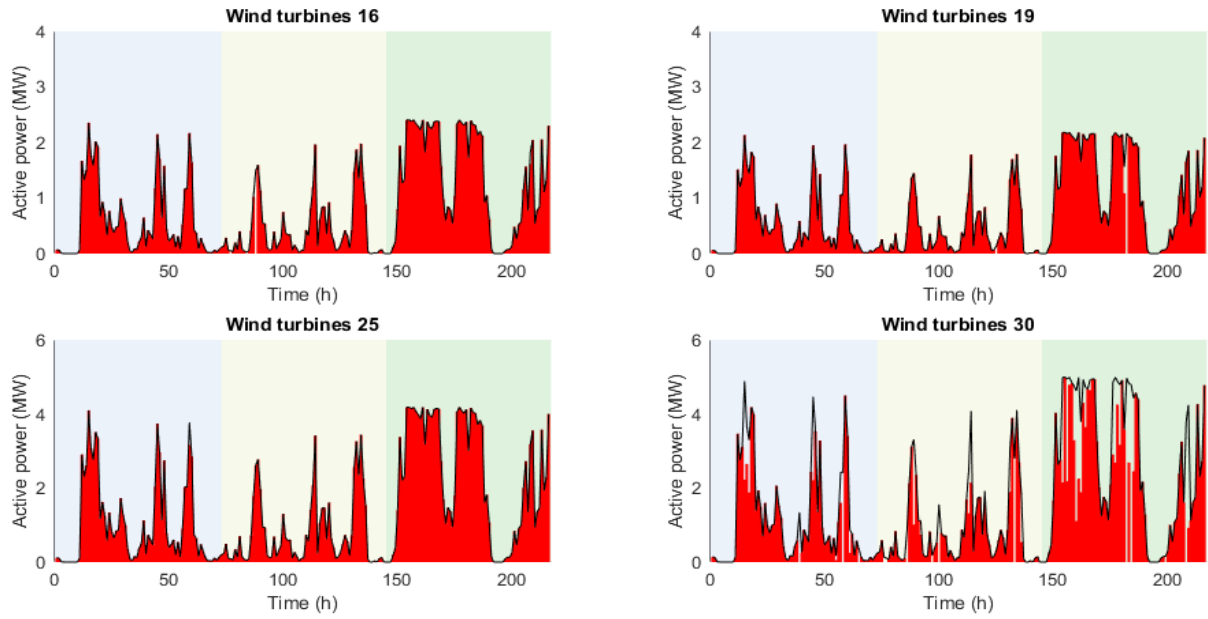
- Scenario 2: Classic generators reactive power results



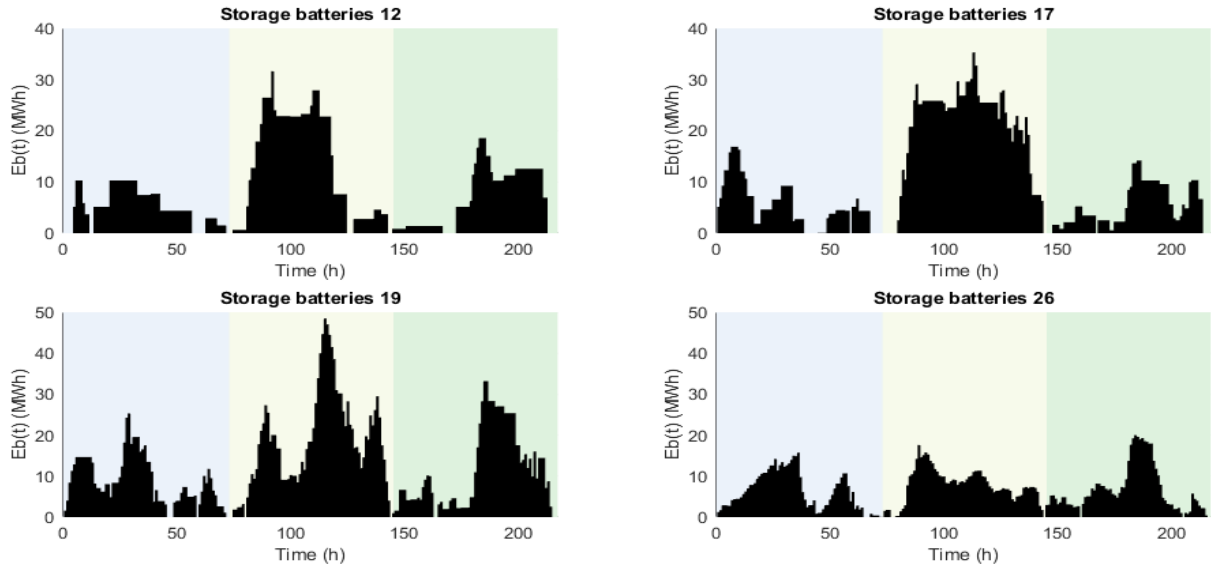
- Scenario 2: Photovoltaic solar panels results



- Scenario 2: Wind turbines results

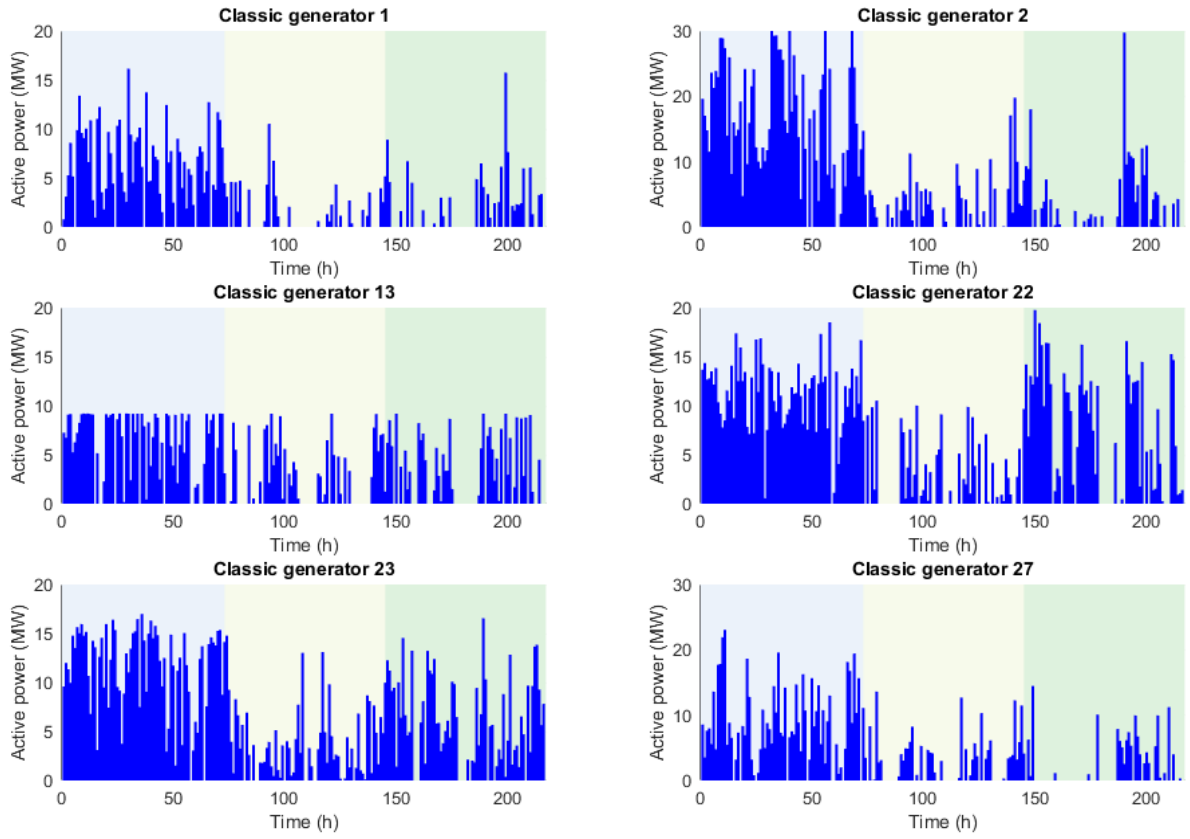


- Scenario 2: Batteries energy storage results

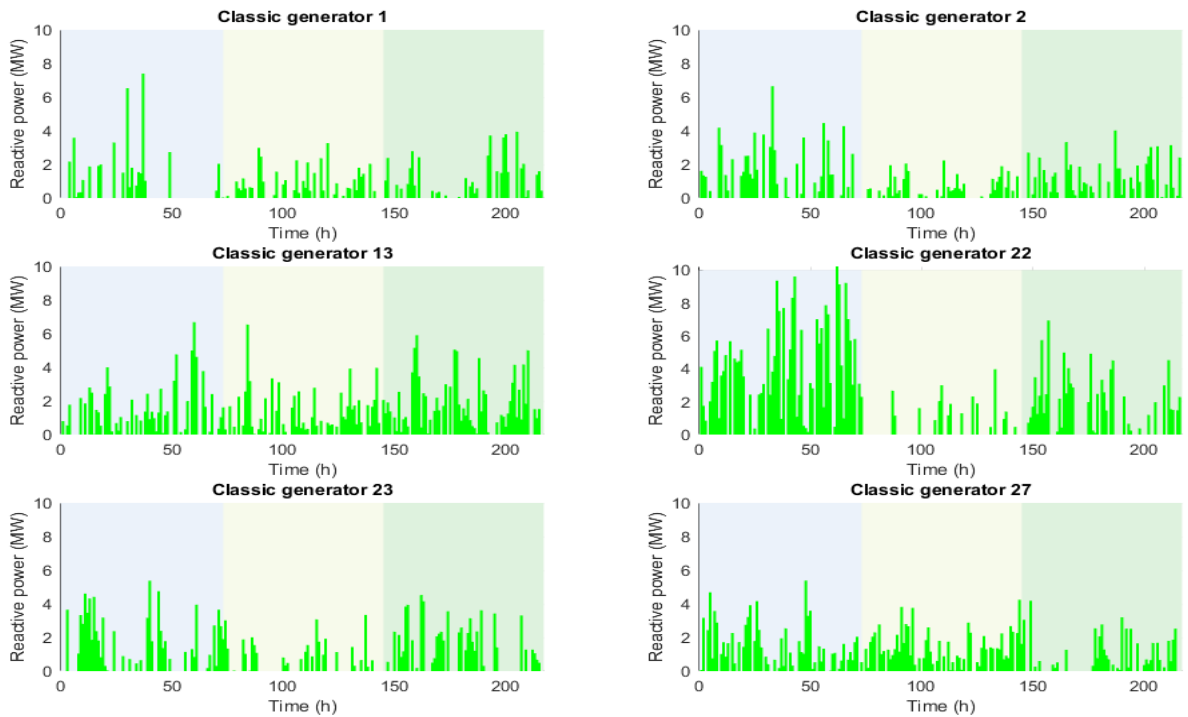


Scenario 3: $Ta = 55\%$

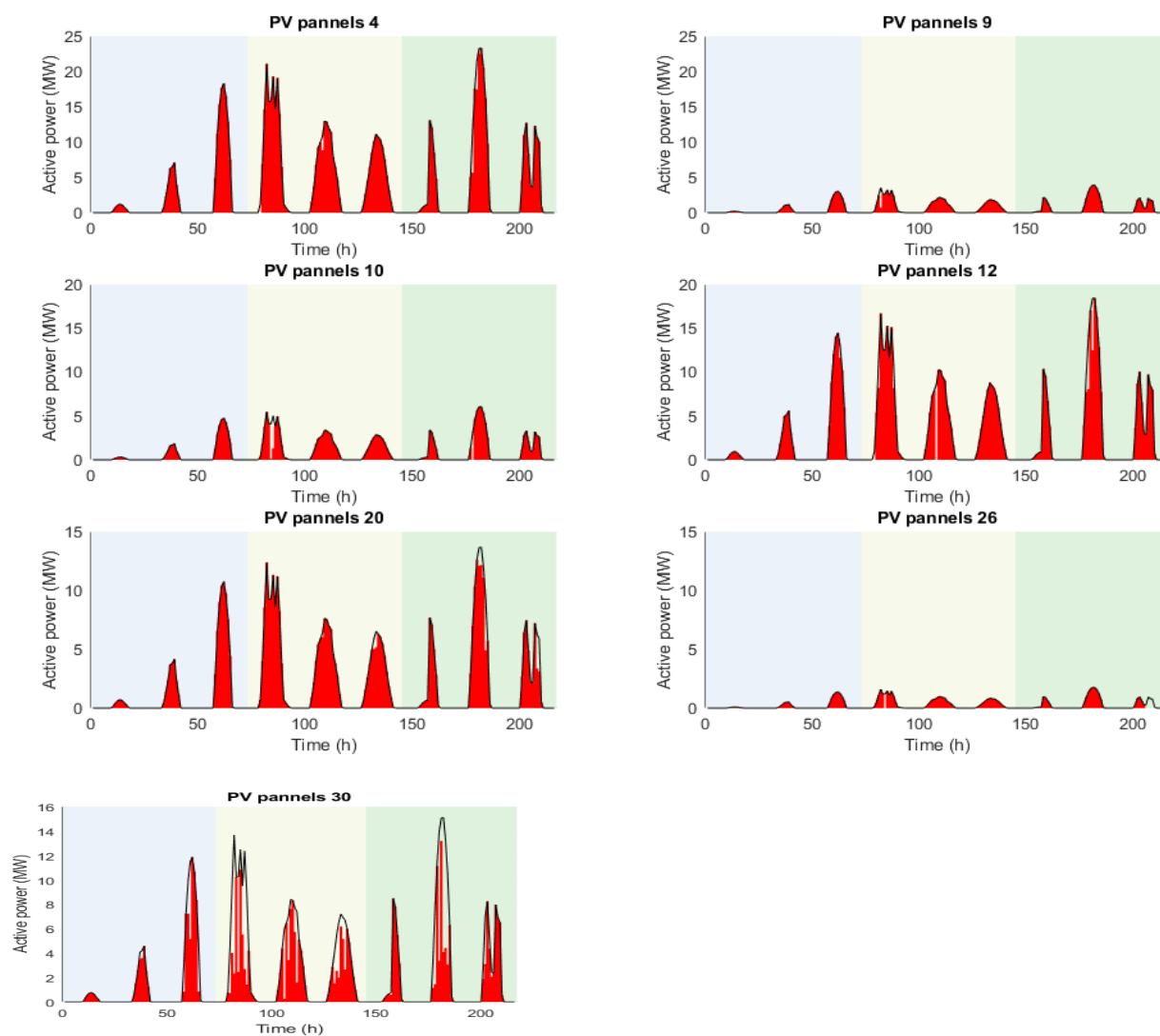
- Scenario 3: Classic generators active power results



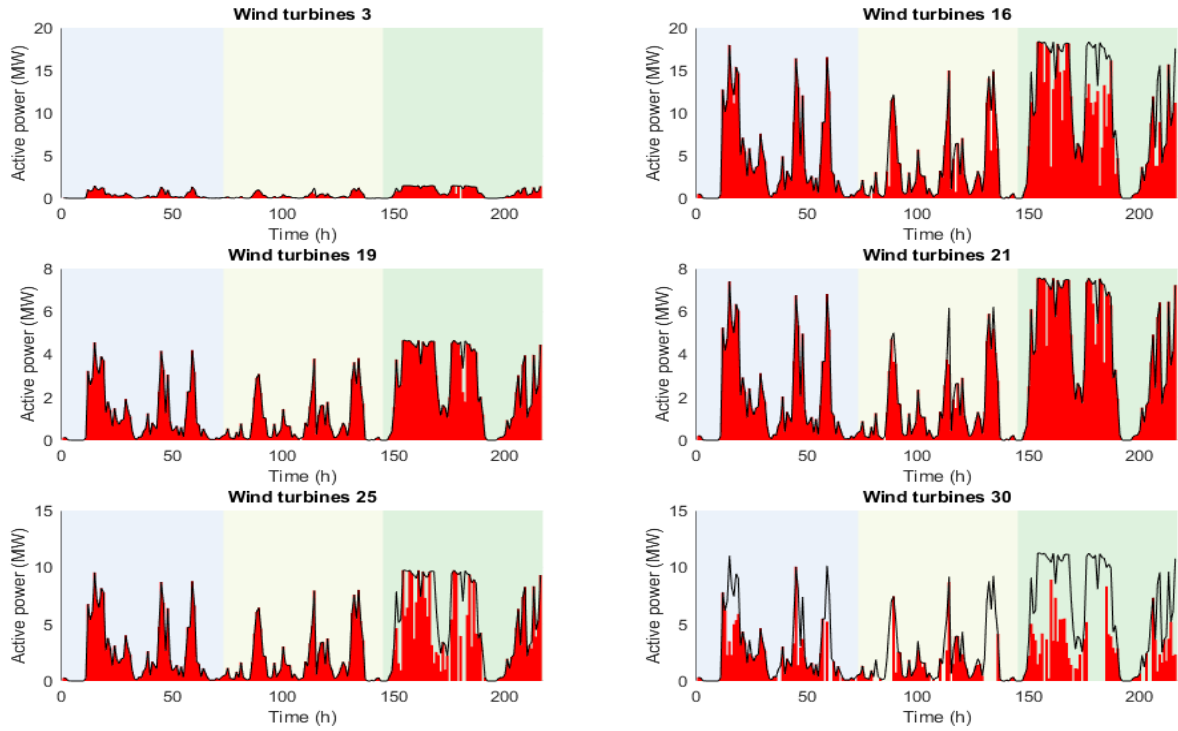
- Scenario 1: Classic generators reactive power results



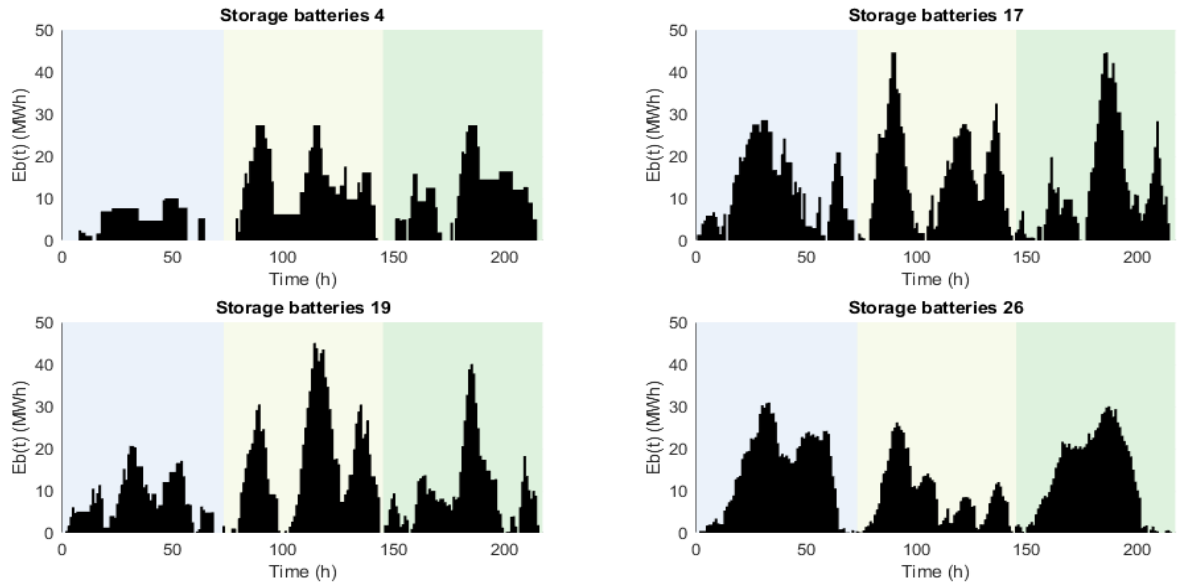
- Scenario 3: Photovoltaic solar panels results



- Scenario 3: Wind turbines results

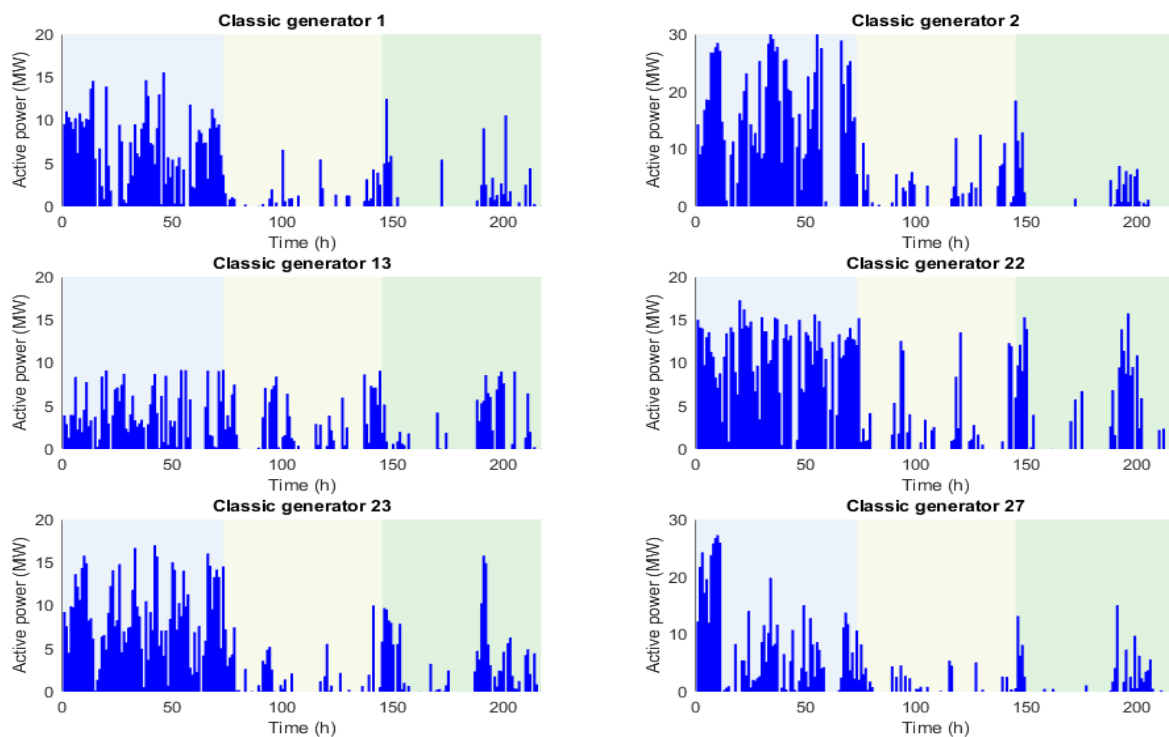


- Scenario 3: Batteries energy storage results

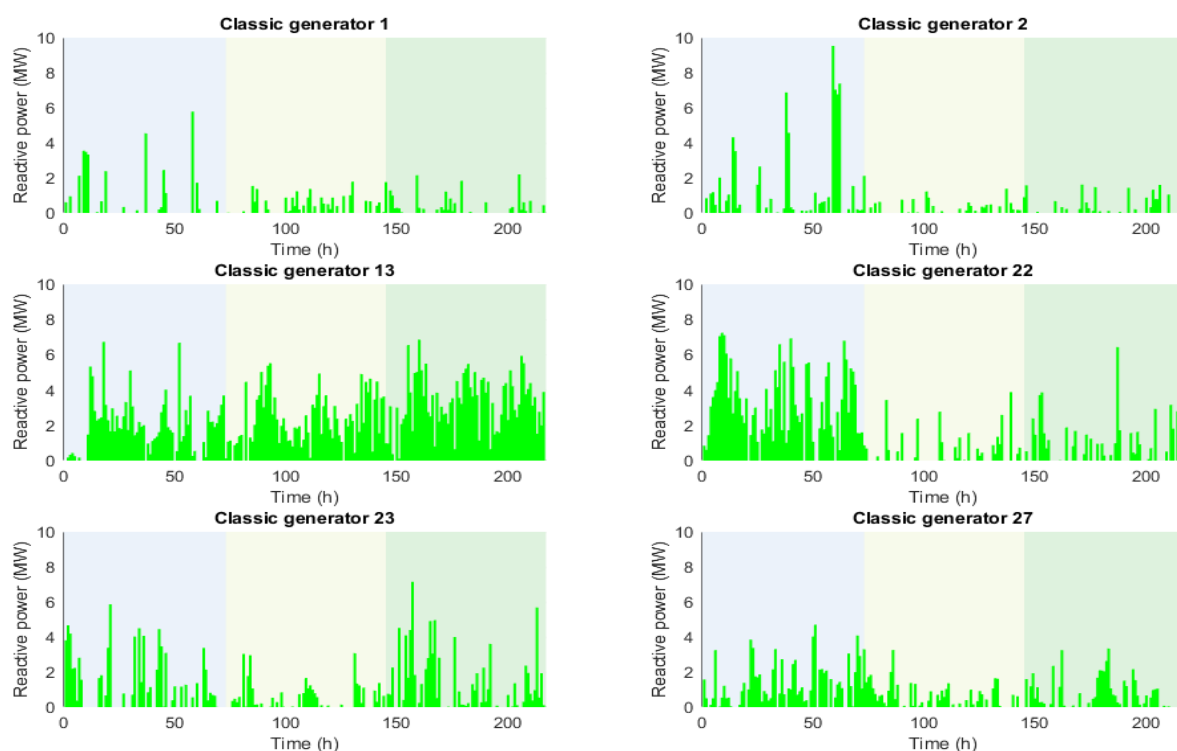


Scenario 4: $Ta = 40\%$

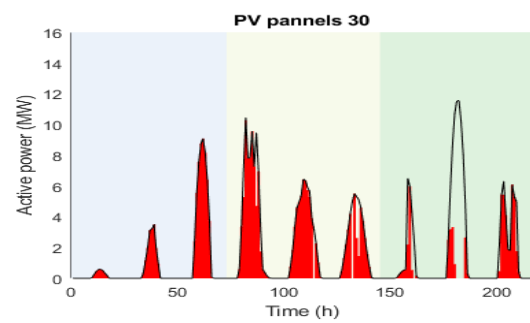
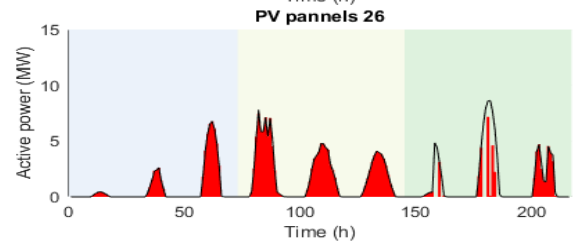
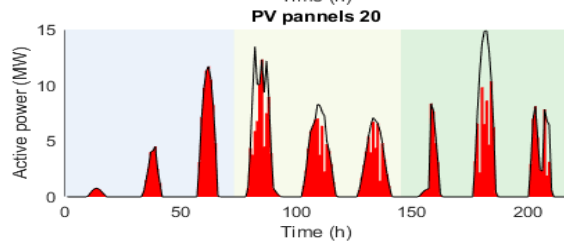
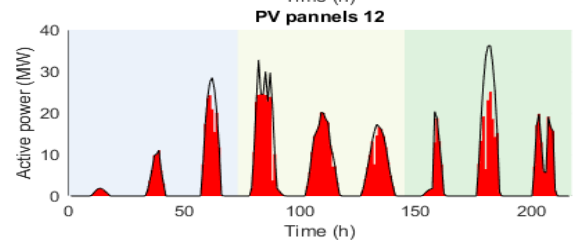
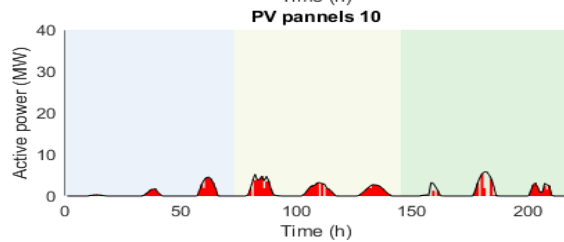
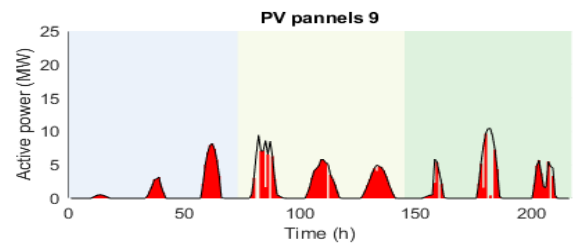
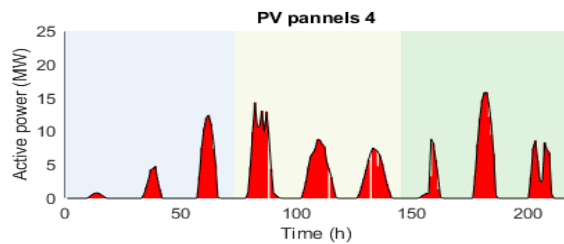
- Scenario 4: Classic generators active power results



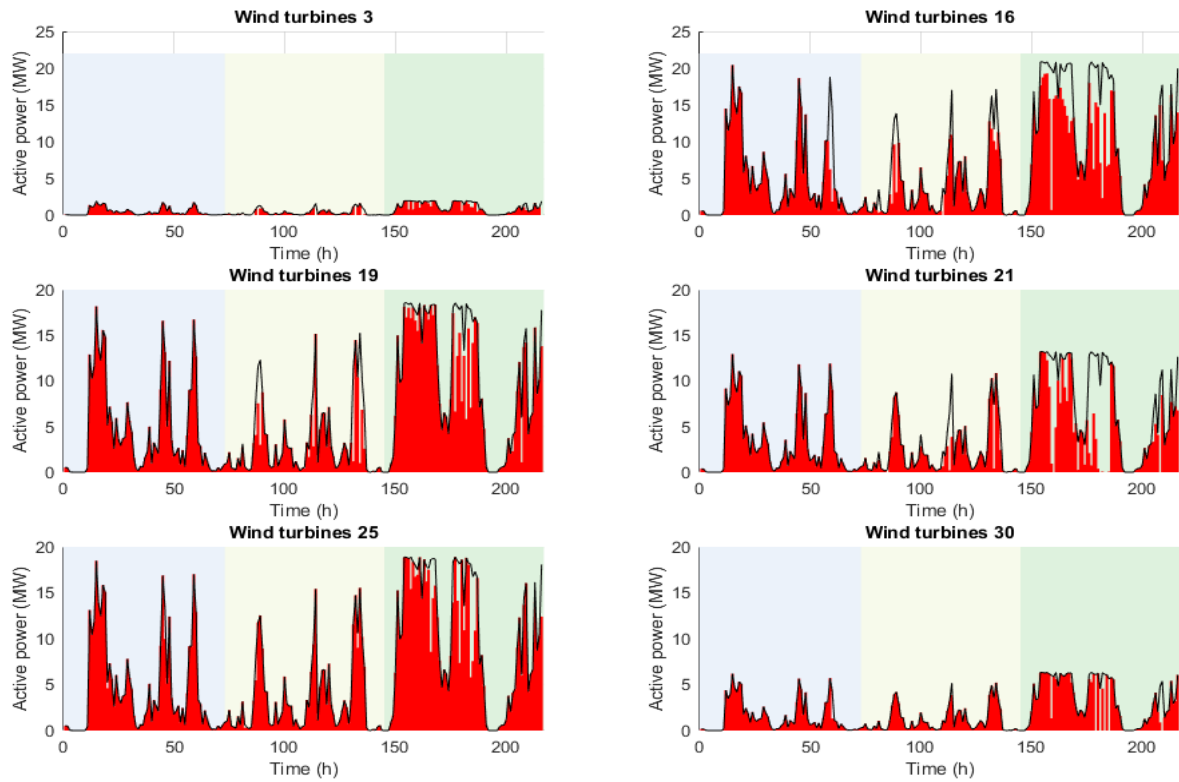
- Scenario 4: Classic generators reactive power results



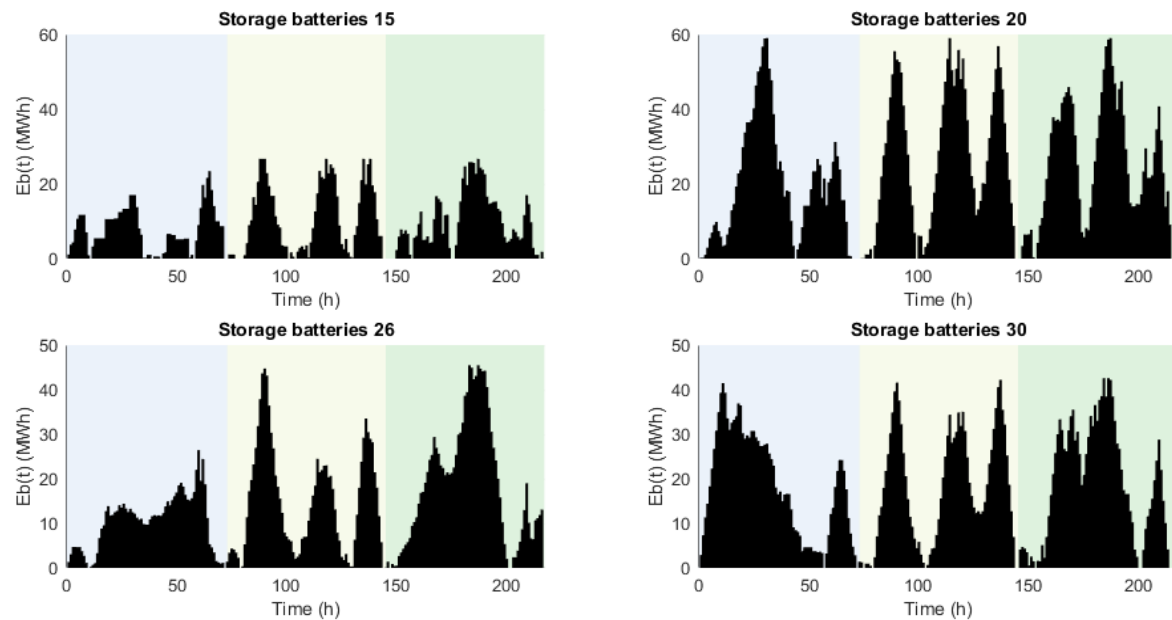
- Scenario 4: Photovoltaic solar panels results



- Scenario 4: Wind turbines results

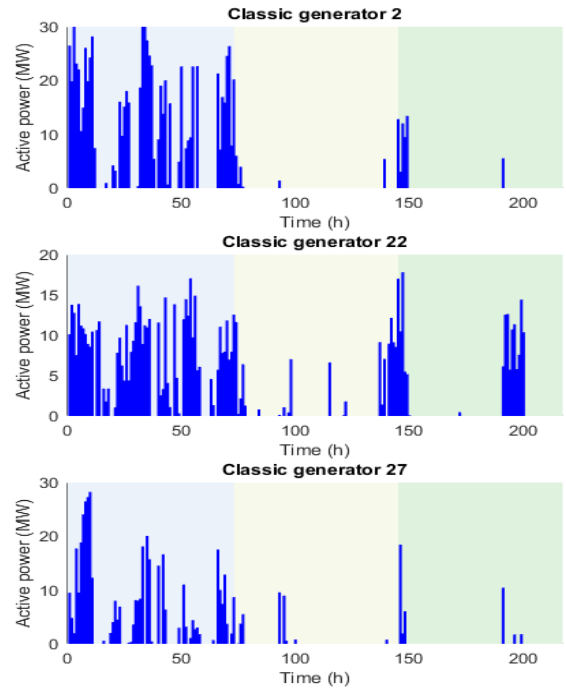
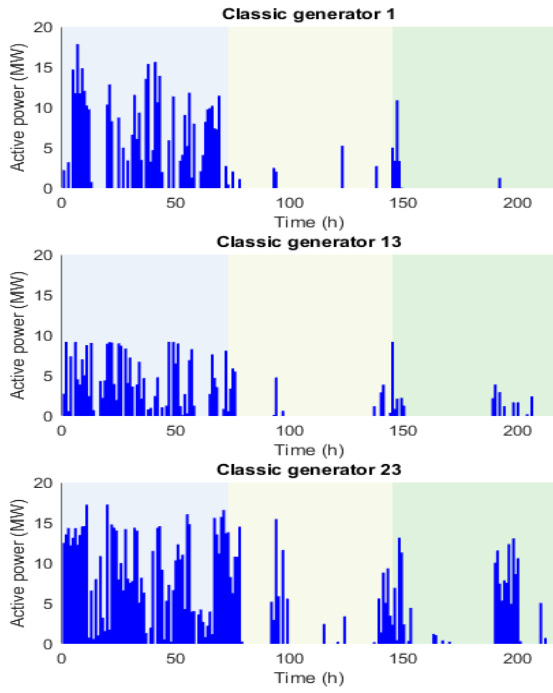


- Scenario 4: Batteries energy storage results

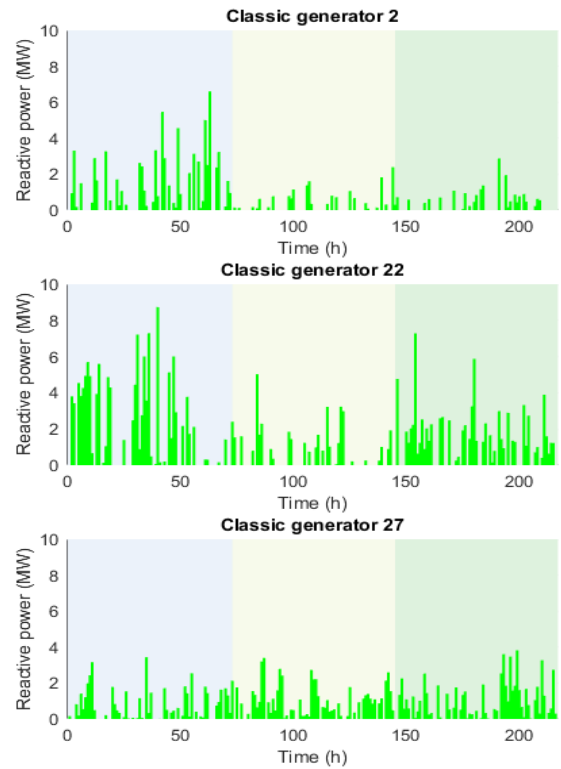
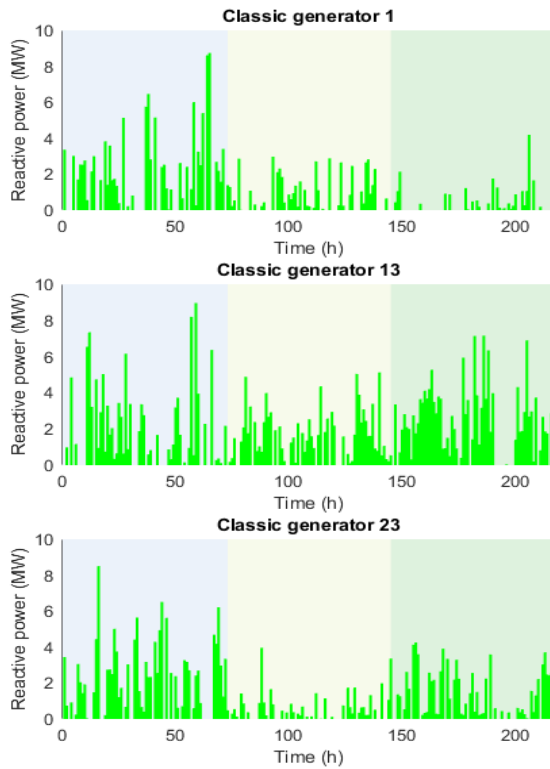


Scenario 5: $Ta = 30\%$

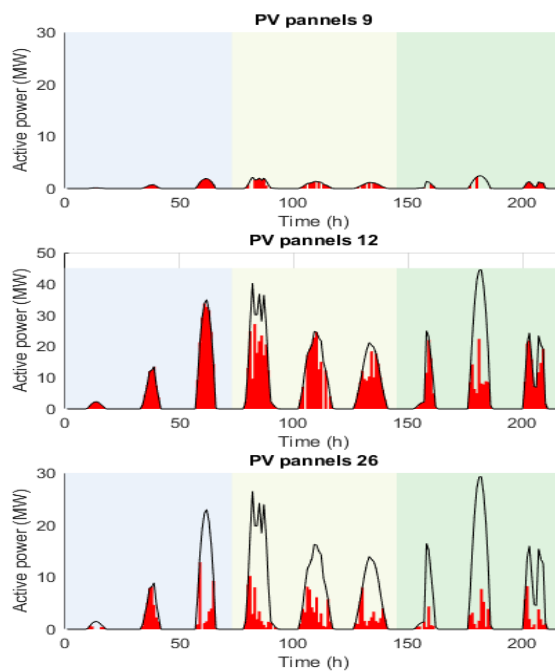
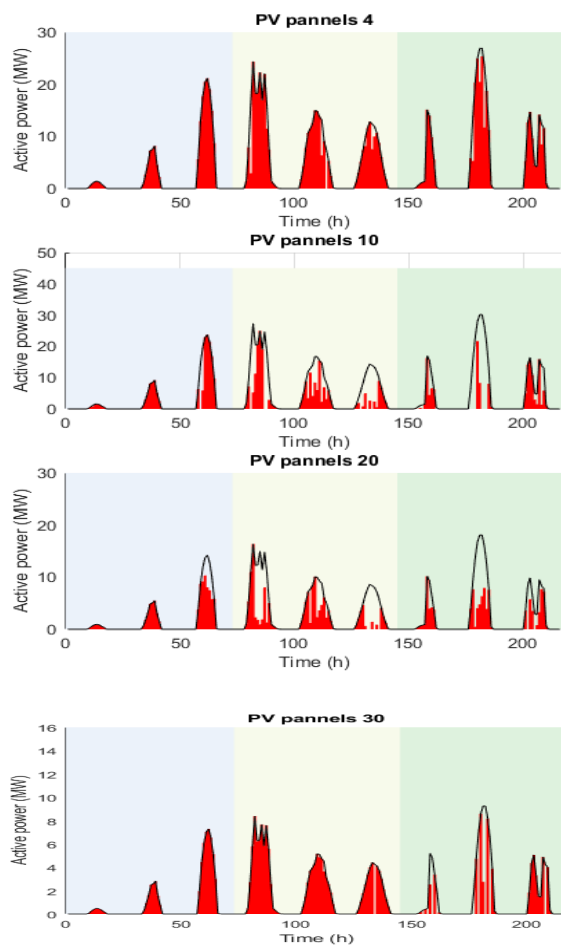
- Scenario 5: Classic generators active power results



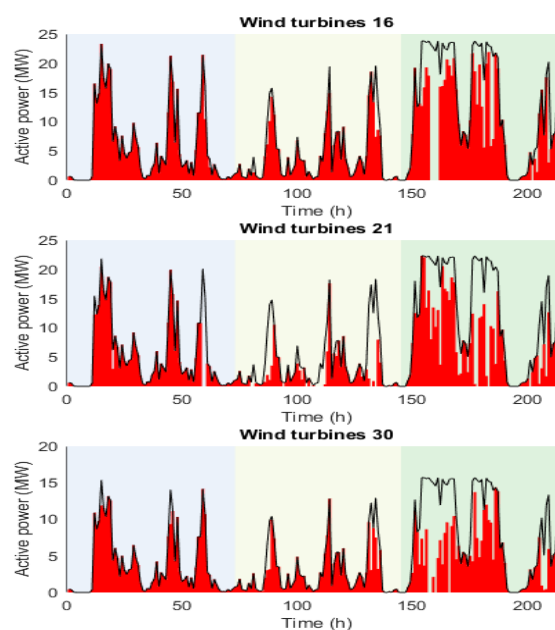
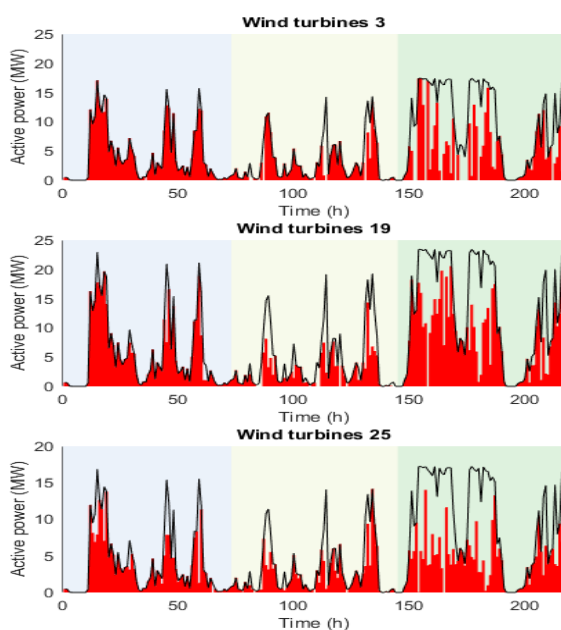
- Scenario 5: Classic generators reactive power results



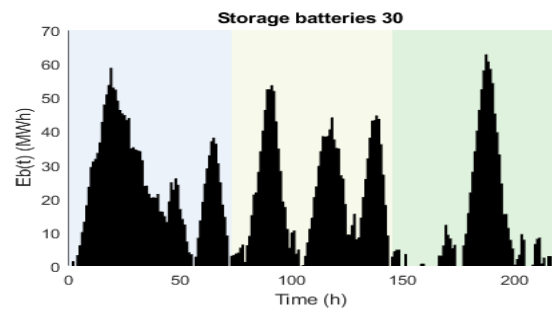
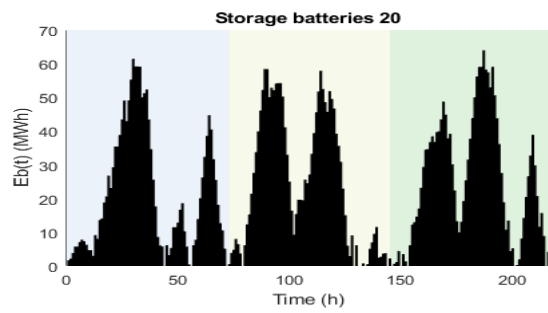
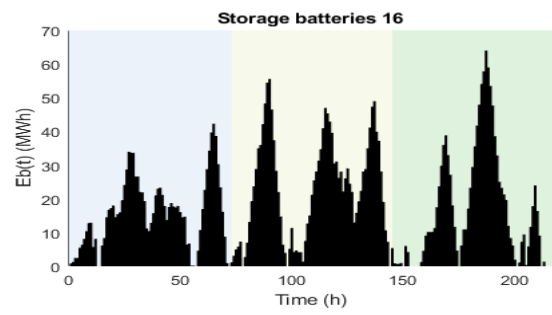
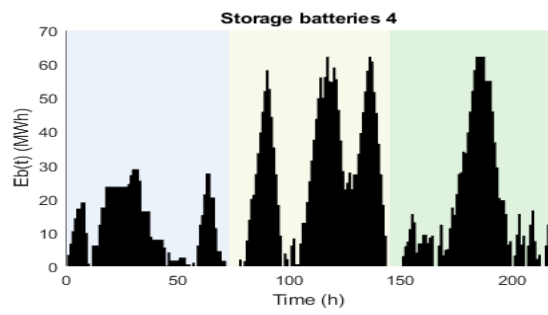
- Scenario 5: Photovoltaic solar panels results



- Scenario 5: Wind turbines results



- Scenario 5: Batteries energy storage results



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Titre : Optimisation de l'intégration d'EnR et de batteries en soutien aux réseaux électriques existants intégrant une demande variable et incertaine

Mots clés : Planification énergétique, Optimisation à deux niveaux, OPF linéarisé dynamique, Réseau électrique, Sources d'énergie renouvelables, Stockage d'énergie par batterie, analyse d'incertitude et de sensibilité

Résumé : En raison de la transition énergétique mondiale, les systèmes d'énergie électrique sont soumis à un ensemble de transformations profondes des systèmes de production et de distribution d'énergie illustrées par l'utilisation accrue d'unités de production décentralisées renouvelables ou à faible émission de carbone. En particulier, la production d'électricité à partir de sources renouvelables (hydraulique, éolienne et solaire photovoltaïque) est en passe de croître fortement dans le monde pour répondre à l'augmentation prévue de la demande mondiale d'électricité et aux engagements des collectivités dans leurs politiques de transition énergétique. Cependant, la prédiction et le contrôle rigoureux de ces énergies renouvelables augmentent la complexité du processus de planification du système électrique. Pour faire face à ces complexités, des modèles de systèmes d'alimentation électrique (EPSM) pour la planification et l'optimisation de l'exploitation sont développés. Dans cette thèse, un modèle dynamique linéarisé AC-Optimal Power Flow (DLOPF) est développé sur la base d'une approche de résolution de programmation linéaire successive du modèle AC OPF. Dans la première étape du travail, le modèle DLOPF permet d'identifier le besoin de production d'électricité pour chaque bus du réseau sur une base horaire, en utilisant le concept de générateurs virtuels.

Ces informations permettent de générer et d'évaluer des scénarios de déploiement d'énergies renouvelables et d'unités de stockage. Cette méthodologie est testée dans le cas d'un réseau sous-dimensionné dans un contexte d'augmentation de la demande d'électricité.

Dans un second temps, le modèle DLOPF est couplé à une étape d'optimisation pour proposer un EPSM suivant une approche bi-niveau. Ce modèle optimise la taille et la planification des sources d'énergie renouvelables (RES) et du stockage d'énergie par batterie (BES) tout en tenant compte de la minimisation des coûts et des contraintes d'émissions carbone. Le niveau supérieur utilise un modèle d'optimisation par essaims de particules (PSO) et est responsable du dimensionnement et du placement des BES. Le niveau inférieur (DLOPF) place et dimensionne les RES dans un cadre spatio-temporel en considérant les résultats du niveau supérieur. Cette combinaison permet de répartir la production et le stockage d'électricité dans un réseau dans un contexte d'augmentation de la demande, en évitant le renforcement le réseau. Enfin, une analyse d'incertitude couplée à une analyse de sensibilité est utilisée pour évaluer l'impact de l'incertitude de la demande (due à sa variabilité imprévisible), à chaque bus, sur les résultats de l'EPSM et les indicateurs de performance du réseau proposés.

Titre : Optimization of Renewable Energy Sources and storage integration to support existing electricity grids considering variable and uncertain demand

Mots clés : Energy planning, Bi-level optimization, Dynamic linearized OPF, Electrical network, Renewable energy sources, Battery energy storage, uncertainty and sensitivity analysis

Abstract: Due to the energy transition worldwide electrical energy systems are subject to a set of deep transformations in the energy production and distribution systems illustrated by increased usage of decentralized renewable or zero-carbon emissions production units. In particular, electricity generation from renewable sources (hydro, wind, and solar PV) is on track to grow strongly around the world to meet the forecasted increase in global electricity demand and to fulfill the local authorities' commitments to energy transition policies. The hard prediction and control of these renewables increase the complexity of the electrical system planning process. To tackle these complexities, Electrical Power System Models (EPSM) for planning and operation optimization are developed.

In this thesis, a dynamic linearized AC-optimal power flow (DLOPF) model is developed based on a successive linear programming resolution approach of the AC OPF model. In the first step of the work, the DLOPF model enables the identification of the need for power production for each bus of the grid on an hourly basis by using the concept of virtual generators.

This information helps generate and assess interesting scenarios of renewable energy and storage unit deployment. This methodology is tested on a case study of an undersized network in the context of increasing electricity demand.

In a second step, based on the DLOPF model coupled with an optimization stage, an EPSM is developed following a bi-level approach. This model optimizes the size and planning of Renewable Energy Sources (RES) and Battery Energy Storage (BES) while taking into account cost minimization and carbon constraints. The upper level implements a Particle Swarm Optimization (PSO) model and the lower level the DLOPF. The PSO sizes and identifies the placement of the BES systems and DLOPF places and sizes RES in a spatial-temporal framework. This combination helps to dispatch power generation and storage in a network in the context of increasing demand, avoiding the need to reinforce the grid.

Finally, an Uncertainty Analysis (UA) coupled with a Sensitivity Analysis (SA) is used to assess the impact of demand uncertainty (due to its unpredictable variability) at each bus on the EPSM and the proposed grid performance indicators.