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Zoning management in marine spatial planning: multi-objective optimization and agent-based conflict resolution

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THÈSE DE DOCTORAT DE

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de l'Information et de la Communication*
Spécialité : *Informatique*

Par

Mohadese BASIRATI

Zoning Management in Marine Spatial Planning: Multi-Objective Optimization and Agent-Based Conflict Resolution

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Contents

Acknowledgments	7
Résumé	15
Abstract	25
1 Introduction	1
1.1 Preamble	2
1.2 Detailed Problem Statement and Objectives	3
1.3 Research Questions	4
1.4 Organization of Manuscript	4
2 Marine Spatial Planning Context	7
2.1 Introduction	8
2.1.1 The Status of the Coastal and Ocean Environment	9
2.1.2 The History of Planning	10
2.2 Land-Use Planning	11
2.3 From Terrestrial Spatial Planning to Marine Spatial Planning	13
2.4 Zoning	18
2.5 Conclusion	20
3 Exact Zoning Model for Marine Spatial Planning	21
3.1 Introduction	22
3.2 Literature Review	23
3.2.1 Spatial-Decision Support System	24
3.2.2 Zoning in a Geographical Information System Framework	25
3.2.3 Data Modeling in Geographical Information System	26
3.2.4 Resolution Approaches	29
3.3 Multi-Objective Single New Marine-Use Zoning Problem in Marine Spatial Planning	31
3.4 Mathematical Formulation	33
3.5 Exact Methods	36
3.5.1 Buffering Technique	36
3.5.2 Weighted Sum and AUGMECON2	37
3.6 The Experimental Validation	39
3.6.1 Data Generation	39
3.6.2 Experimental Protocol	42
3.7 Computational Results	43
3.8 Conclusion	49
4 Extensions to Evolutionary Approaches for Zoning Management in Marine	

Spatial Planning	51
4.1 Introduction	52
4.2 Literature Review	53
4.2.1 Meta-Heuristics	53
4.2.2 Single-Solution Based VS. Population-Based Meta-Heuristics	54
4.2.3 Hybrid Meta-Heuristics	57
4.3 Multi-Objective Evolutionary Algorithms	59
4.3.1 Solution Encoding Schema	59
4.3.2 Synchronous Hypervolume-Based Non-dominated Sorting Genetic Algorithm-II	61
4.3.3 Hybrid Synchronous Hypervolume-based Non-dominated Sorting Genetic Algorithm-II Using Local Search (Memetic Algorithm)	62
4.3.4 Search Components	63
4.3.5 Evaluation and Selection Operators	72
4.3.6 Stop Condition of Multi-Objective Evolutionary Algorithms	73
4.4 Tuning Parameters	74
4.4.1 Multi-Response Surface Methodology Optimization	75
4.4.2 Final Tuned Parameters	82
4.5 Experimental Validation	82
4.6 Computational Results	83
4.7 Conclusion	86
5 Cooperative Multi-Objective Multi-Agent Zoning Management for Marine Spatial Planning	87
5.1 Introduction	88
5.2 Multi-Agent Systems and Their Properties	90
5.2.1 Environment	91
5.2.2 Interactions	92
5.2.3 Cooperation VS. Non-Cooperation	93
5.2.4 Negotiation Heuristics	95
5.3 Multi-Agent Systems Applied to Spatial Zoning Management Planning	96
5.3.1 Selected Literature Review	96
5.3.2 Research Gaps and Objectives	99
5.4 A Cooperative Multi-Objective Multi-Agent System	99
5.4.1 Initialization	101
5.4.2 Compatibility	102
5.4.3 Communication	102
5.4.4 Illustrative Example of Multi-Objective Multi-Agent System	104
5.5 Experimental Validation	105
5.5.1 Scenarios and Parameters Setting	105
5.5.2 Ranking Methods	107
5.6 Computational Results	108
5.7 Discussion	110
6 Conclusions and Perspectives	111
6.1 Summary of the Contributions	112
6.2 Limitations and Perspectives	113
Publications	117
A Tables	119

B Pseudo-code

131

Bibliography

135

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Dad, Mom, all my family and my friends: thank you for everything. Thank you for your support, thank you for your love. I would be nothing without you.

And because these last words mark a new beginning for me, I wish to begin this new chapter of my life by quoting Alain, the great Radical philosopher (from *The Seasons of the Mind* - 1937):

"Il faut croire en soi et espérer ; mais il faut vouloir croire en soi et vouloir espérer. A nous de mieux prendre le tournant, une autre journée commence." One must believe in oneself and hope; but one must want to believe in oneself and to want to hope. It is up to us to take the turn better, another day begins.

"En tout temps obscur et difficile, on ne dit pas que l'année sera bonne ; on n'en sait rien ; ce qui arrive nous surprend toujours. Ce qu'on dit, c'est qu'il faut choisir de la penser bonne." In all obscure and difficult times, one does not say that the year will be good; one does not know; what happens always surprises us. What they do say is that you should choose to think good.

"Je vous souhaite de penser printemps." I wish you to think spring.

Acronyms

ACO	Ant Colonies Optimization	54, 56
AI	Artificial Intelligence	95, 96, 98, 99
ANOVA	Analysis Of Variance	52, 58, 78, 80, 113
BBD	Box-Behnken Design	58, 75, 113
Best Sol	Best Solution	76
CBD	Convention on Biological Diversity	18
COZ	Comprehensive Ocean Zoning	25, 26
CR	Conflict Resolution	5, 20, 88, 97– 99, 104, 110, 113, 115
DAI	Distributed Artificial Intelligence	90, 96, 98
DMs	Decision-Makers	10, 25, 30, 31, 33, 86, 103
DOE	Design Experiment	58, 74, 78, 80, 113
EA	Ecosystem Approach	15, 98
EAs	Evolutionary Algorithms	55, 57, 59
EBC	External Border Cells	31
EBM	Ecosystem Based Management	23, 26
EP	Evolutionary Programming	54, 59
ES	Evolution Strategies	54, 59
GA	Greedy Algorithms	56, 86

GAs	Genetic Algorithms	54, 59, 60
GBR	Great Barrier Reef	18, 19, 26
GIS	Geographical Information System	3, 20, 23–27, 29, 56, 97, 98, 112
GP	Genetic Programming	54, 59
HGT-MPM	Hybrid Game Theory and Mathematical Programming Model	98
HV	Hyper-Volume	62, 63, 73, 74, 76, 82
ICM	Integrated Coastal Management	23
ICZM	Integrated Coastal Zone Management	16, 17
LTH	Low-Level Teamwork Hybrid	57, 59
MA	Memetic Algorithm	5, 52, 59, 62, 63, 65, 67, 78, 82–84, 86, 102, 105– 107, 113
MAS	Multi-Agent Systems	4, 5, 90–93, 95–97, 99, 101, 113
MCDM	Multi-Criteria Decision Making	23–25, 29, 30, 76, 95–99
MCP	Maximal Covering Problem	30
MHs	Meta-Heuristics	3–5, 31, 52–57, 59, 83, 112, 114
MILP	Mixed Integer Linear Programs	30, 58, 97
MIP	Mixed Integer Programming	29, 30

MOEAs	Multi-Objective Evolutionary Algorithms	4, 5, 52, 53, 58, 59, 61–63, 65, 68, 72–78, 82–84, 86, 90, 99, 112– 114
MOILP	Multi-Objective Integer Linear Programming	4, 5, 22, 23, 31, 36, 43, 45, 52, 53, 112– 114
MOMAS	Multi-Objective Multi-Agent System	3–5, 88, 92, 94, 96, 99, 101, 103– 105, 110, 112– 115
MOMP	Multiple Objective Mathematical Program- ming	30
MOO	Multi-Objective Optimization	23, 31, 36, 55, 56, 58, 82
MOOPs	Multi-Objective Optimization Problems	3, 30, 52, 54, 55, 59, 61, 89, 97–99
MPAs	Marine Protected Areas	18, 19, 23, 31, 96
MROPs	Multi-Response Optimization Problems	75, 76
MRSM	Multi-Response Surface Methodology	52, 58, 75, 76, 78, 80, 82, 113

MSP	Marine Spatial Planning	2–5, 8, 9, 11, 13–15, 17, 18, 20, 22– 26, 28, 30, 31, 52, 53, 55, 58, 88, 89, 96, 98, 99, 110, 112, 115
NCS	Non-Cooperative Situation	93, 94
NDC	Normalized Discrete Compactness	39, 40, 72
NPS	Number of Pareto Solutions	76
P-metaheuristics	Population-Based Metaheuristics	53
PSO	Particle Swarm Optimization	54–56
RAS	Rate of Achievement to two objectives Simul- taneously	83
RSM	Response Surface Methodology	74–76
S-metaheuristics	Solution-Based Metaheuristics	53
SA	Simulated Annealing	54, 56, 57
SACs	Special Areas of Conservation	18
SAW	Simple Additive Weighting	86
SAWA	Simple Additive Weighting Algorithm	76, 77
SCP	Set Covering Problem	30
SDSSs	Spatial-Decision Support Systems	25, 29
SEA	Strategic Environmental Assessment	16, 17
SH-NSGA-II	Synchronous Hypervolume-based Non- dominated Sorting Genetic Algorithm-II	5, 52, 58, 59, 61–63, 65, 67, 75–78, 80, 82–84, 86, 112, 113
SPAs	Special Protection Areas	18
SPEA, SPEA-II	Strength Pareto Evolutionary Algorithms	56
SS	Scatter Search	54, 56, 57

TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution	86
TRPP	Traveling Repairman Problem with Profits	57
TS	Tabu Search	54, 56, 57
TSP	Terrestrial Spatial Planning	5, 8, 9, 13, 14
UNCLOS	United Nations Convention on the Law of the Sea	18
VNS	Variable Neighborhood Search	54, 57
WS	Weighted Sum	22, 31, 36–38, 42–45, 49, 107, 112
WSRT	Wilcoxon Signed-Rank Test	59, 83, 84, 86, 113
ZPs	Zoning Plans	18–20, 23, 25, 26, 98

Résumé

La vie sur terre dépend de l'océan car 71% de la planète est couverte par l'océan. Naturellement, les gens s'en préoccupent profondément, avec sa vie abondante et ses vastes ressources. L'océan a une signification différente pour chacun d'entre nous. Nous avons tous nos propres intérêts. Par exemple, des générations de pêcheurs ont tiré leur subsistance de l'océan. Les défenseurs de la nature s'engagent à le protéger, tandis que le capitaine d'un porte-conteneurs a besoin d'eaux profondes et d'un accès direct au port par le chemin le plus court.

Où se situent nos priorités lorsqu'une zone marine abrite à la fois la pêche de la faune et la navigation? Et si la situation est compliquée par les minéraux que l'industrie minière veut extraire, ou si un investisseur prévoit de construire un parc éolien? Le planificateur responsable, généralement un fonctionnaire, doit relever de nombreux défis pour faire face à toutes ces demandes; comment satisfaire exactement toutes ces personnes et leurs intérêts? Comment concilier l'utilisation et la protection d'un même espace océanique?

La planification de l'espace marin (PEM) est un moyen relativement nouveau de gérer les activités humaines qui se déroulent dans l'océan. Il s'agit d'un processus stratégique à long terme qui permet de déterminer où, quand et comment les activités humaines ont lieu. Cela peut être utile lorsqu'il existe des possibilités de nouvelles utilisations ou lorsque les activités ont un impact sur la nature. La planification de l'espace maritime peut contribuer à équilibrer des intérêts contradictoires, en veillant à ce que la société en bénéficie tout en protégeant le milieu marin.

Tout d'abord, la planification de l'espace maritime est mieux réalisée par un groupe de planification mandaté, doté d'une vision commune forte et d'objectifs clairs quant aux objectifs à atteindre. Le planificateur doit écouter le plus grand nombre possible de parties intéressées, non seulement au début, mais tout au long du processus, en collaborant avec toutes les parties prenantes qui ont un intérêt pour l'océan. Les planificateurs veillent à ce que les usagers de la mer établissent une relation de confiance, s'engagent dans le processus et s'approprient le plan produit avec leur aide. Bien sûr, cela soulèvera des questions pour beaucoup d'entre eux. Devons-nous exclure l'exploitation minière des zones de pêche importantes? Devons-nous détourner les voies de navigation pour faire de la place à la faune marine? Peut-on concilier tourisme et conservation au même endroit?

La PEM commence par une analyse de la situation actuelle. Par exemple, quels sont les endroits qui ont la plus grande valeur naturelle? Qui utilise la zone de planification? Quelles sont les priorités du gouvernement concernant l'océan et son utilisation? En rassemblant le plus d'informations possible sur tout, des zones de pêche aux voies de navigation, des habitats naturels importants aux gisements de pétrole et de gaz, nous pouvons cartographier les détails pour comprendre certains des problèmes clés que le plan doit aborder. Ensuite, la PEM identifie les conflits et les synergies possibles, les activités qui peuvent être facilement combinées et celles qui s'excluent mutuellement. Les options pour l'avenir sont également prises en compte dans les différents secteurs. Les exploitations minières en eaux profondes pourraient chercher à se développer, mais que se passe-t-il si les gisements minéraux nouvellement découverts s'étendent jusqu'aux zones de conservation de la nature et de tourisme?

Cela nous met en mesure de développer des alternatives et de décider de l'option spatiale préférée. Cela peut impliquer des compromis entre les intérêts. Pour parvenir à un compromis, il faudra négocier, mais cela ne peut aboutir que si les parties prenantes sont présentes

à la table et peuvent être entendues.

Une fois que l'on s'est mis d'accord sur les solutions spatiales qui répondent le mieux aux besoins de chacun et aux objectifs du plan, il est temps de définir les actions qui garantiront le succès du plan.

Il peut s'agir de zones ou de politiques qui donnent la priorité à certaines utilisations, comme l'exploitation minière ou les parcs éoliens, ou encore de réorienter les voies de navigation pour donner plus d'espace aux baleines. Ces mesures de gestion doivent être élaborées avec la participation de tous les utilisateurs et groupes d'intérêt du milieu marin afin de garantir que le plan soit soutenu par le plus grand nombre possible de parties prenantes. Une fois le plan convenu et adopté, il doit être mis en œuvre. A partir de ce jour, il guidera tous les utilisateurs marins où, quand et comment leurs activités se déroulent dans l'espace océanique.

Enfin, la PEM est un processus continu. Elle implique un suivi, une évaluation et une révision réguliers. Est-ce que atteint-il son objectif? Que devons-nous faire mieux la prochaine fois? De quelles autres De quelles informations supplémentaires avons-nous besoin? Naturellement, les choses changent; le climat, les investisseurs, les intérêts, les politiciens, et leurs priorités. Le plan devra donc être adopté au fil du temps. S'il est bien fait, un plan spatial marin bien fait, un plan spatial marin soutiendra non seulement les moyens de subsistance d'aujourd'hui, mais aussi ceux des générations futures, et ce pour cette excellente raison. Il n'est pas surprenant que la planification de l'espace marin se répande désormais dans toutes les mers et tous les océans du monde.

Cependant, lorsqu'un ensemble de ressources, de droits, de charges, d'avantages ou de coûts est temporairement détenu en commun par un groupe de secteurs, les débats se poursuivent sur les meilleures stratégies de gestion de l'aménagement du territoire pour les répartir entre eux.

En outre, la question de l'allocation de l'espace est devenue plus importante à la lumière des récents points chauds politiques, alimentés par les luttes de pouvoir politique et la demande sans cesse croissante d'espace marin/terrestre pour les utilisations traditionnelles et émergentes de l'espace marin/terrestre.

L'objectif ambitieux de cette thèse serait de développer une approche appropriée d'allocation de l'emplacement dans le cadre d'un processus plus large de prise de décision spatiale, où les utilisateurs marins interagissent les uns avec les autres afin de parvenir à un accord d'allocation spatiale à travers leurs objectifs conflictuels.

Cet objectif difficile peut être considéré comme un problème complexe, la gestion du zonage pour le système multi-objectifs multi-agents (SMOMA) avec l'application au PEM. La complexité ne doit pas être confondue avec la complication. Là où un problème compliqué comporte de nombreuses parties différentes et bien définies avec des comportements bien connus et peut être réduit à des problèmes plus simples (un puzzle, par exemple, peut être divisé en plus petits puzzles avant d'être résolu), un problème complexe est défini par un nombre important de petites parties en interaction, et ce sont leurs interactions qui produisent le comportement global. Un problème complexe est comme un système complexe. Une partie d'un système complexe est guidée par des règles simples et individuelles. Le comportement du système ne peut être prédit à partir des règles individuelles : " le tout est plus grand que la somme des parties " [Fun10].

Les problèmes complexes du monde réel mentionnés ci-dessus peuvent être trouvés dans une pluralité de domaines et de sciences. Ces problèmes comportent trois aspects qui les rendent impossibles à résoudre par les processus décisionnels centralisés classiques et les logiciels d'optimisation commerciaux existants dans le monde entier. La résolution de tels problèmes est un sujet important en informatique. Premièrement, il s'agit de problèmes d'optimisation multi-objectifs, où la résolution du problème pour chaque objectif conduit à une solution différente.

Par conséquent, une approche est nécessaire pour trouver un ensemble de solutions mathématiquement "égales" appelées solutions optimales de Pareto. Différentes méthodes de résolution ont été développées. Elles sont communément classées en deux catégories : les méthodes exactes et inexactes. La première garantit de trouver (si elle existe) la solution optimale. Cependant, comme elles explorent tout l'espace de recherche, elles sont trop lentes et ne peuvent pas être appliquées pour résoudre des problèmes complexes.

Les méthodes approximatives trouvent une solution en utilisant une heuristique ou des méta-heuristiques (MHs) pour traverser l'espace de recherche. Un inconvénient important de toutes ces méthodes est qu'elles ne peuvent pas gérer la dynamique, qui est l'une des caractéristiques des problèmes complexes. Deuxièmement, il s'agit de problèmes multi-agents, où les préférences de tous les agents possibles doivent être incorporées dans le processus de décision.

Par conséquent, une approche d'optimisation interactive est nécessaire pour prendre en compte les préférences des agents et trouver un compromis optimal en conséquence. Cette interaction agent-optimisateur aide les agents à apprendre le problème et leur permet de modifier et de changer leurs préférences progressivement. Le troisième aspect est l'interdépendance entre les agents qui affecte leurs décisions. Ce problème nécessite un mécanisme de collaboration entre les agents pour partager l'information ou même gérer les préférences et les contraintes conflictuelles. Grâce à ce mécanisme de collaboration d'agent à agent, les agents peuvent modifier leurs préférences et leurs contraintes et finalement mettre à jour leurs décisions. Cette méthodologie peut résoudre un tel problème d'optimisation multi-objectif et multi-agent en fournissant un optimiseur d'agent à agent et un mécanisme de collaboration d'agent à agent avec une application d'optimisation, qui n'existe ni théoriquement ni en tant que méthodologie décisionnelle.

Exposé détaillé du problème et objectifs

L'objectif principal de cette thèse est la coordination des activités marines et la résolution des problèmes d'allocation d'emplacement qui pourraient potentiellement conduire à des conflits spatiaux. Le défi consiste à choisir une stratégie de zonage appropriée dans le cadre d'un processus décisionnel spatial plus large, où les utilisateurs marins interagissent les uns avec les autres pour parvenir à un accord d'allocation spatiale. Il n'est pas simple de parvenir à un tel accord lorsque les utilisateurs poursuivent leurs objectifs internes et particuliers, qui sont le plus souvent en conflit avec d'autres. Pour faire face à ce problème, un processus de prise de décision efficace doit être développé dans lequel trois exigences différentes, comme le montre la Figure 1, doivent être satisfaites comme suit :

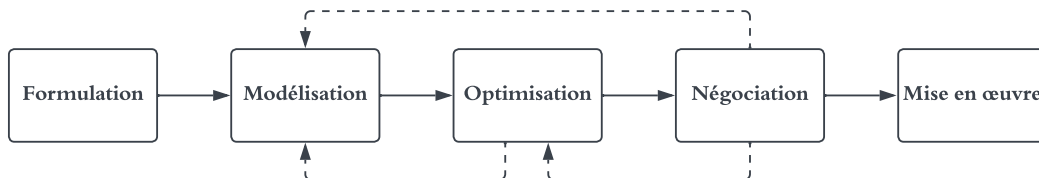


FIGURE 1 : Proposition d'approche décisionnelle

- **Formulation et modélisation** : formuler et modéliser le problème dans le cadre d'un système d'information géographique (SIG) réaliste, et développer un modèle mathématique pour le résoudre,
- **Optimisation** : mise à l'échelle du problème afin de fournir des solutions optimales pour les cas à grande échelle,
- **Négociation et mise en œuvre** : développement d'un processus de prise de décision qui aide plusieurs acteurs à résoudre d'éventuels conflits en parvenant à un compromis.

Conformément aux objectifs susmentionnés, cette thèse présente un système multi-agent multi-objectif (SMAMO) pour modéliser les processus de prise de décision à plusieurs niveaux de la gestion du zonage spatial des utilisations marines, avec trois contributions principales :

1. Programmation linéaire en nombres entiers multi-objectifs (LEMO) : Solutions d'allocation optimales pour des problèmes de taille acceptable, garantissant l'efficacité de Pareto et l'allocation de tout l'espace revendiqué.
2. Algorithmes évolutionnaires multi-objectifs (AEMO) : MHs approxime des solutions quasi-optimales pour des problèmes à grande échelle.

3. Processus de décision coopératif avec les systèmes multi-agents (SMA) et les méthodes heuristiques : Dans le contexte d'une collaboration à long terme, soutenir les parties prenantes multi-objectifs dans la négociation et l'obtention de l'allocation la plus appropriée et équitable en termes de zonage de la zone marine.

Questions de recherche

Cette thèse apporte des contributions pour répondre aux trois questions de recherche suivantes, qui sont au cœur de cette méthodologie complexe d'aide à la décision.

1. Comment formuler un modèle linéaire exact en tant que LEMO pour le problème de gestion du zonage spatial dans la PEM?
2. Comment résoudre le modèle proposé et déterminer la solution optimale pour le modèle exact? Quelles méthodes exactes doivent être utilisées?
3. Comment résoudre la complexité informatique de ce modèle LEMO en le mettant à l'échelle? Quelles méthodes approximatives doivent être choisies pour résoudre les cas à grande échelle?
4. Comment développer un mécanisme où les multi-utilisateurs collaborent efficacement pour partager les informations et apprendre les préférences en termes de solutions des autres utilisateurs, ainsi que pour modifier leurs propres solutions, en particulier en cas de conflit? Comment développer un mécanisme basé sur la négociation pour atteindre un accord d'allocation spatiale à travers leurs objectifs conflictuels?

Proposition de cadre général pour chaque chapitre

Le présent manuscrit est organisé en quatre chapitres principaux, à savoir : *Contexte de l'aménagement de l'espace marin*, *Modèle de zonage exact pour l'aménagement de l'espace marin*, *Extensions des approches évolutionnaires pour la gestion du zonage dans l'aménagement de l'espace marin*, et *Gestion coopérative du zonage multi-objectif multi-agent pour l'aménagement de l'espace marin*.

Chaque chapitre comprend différentes phases pour nous rapprocher des objectifs de cette thèse. Le reste du manuscrit est structuré comme suit :

- Dans le chapitre [2], un état des lieux du développement de la planification spatiale est dressé en passant en revue l'état de l'environnement côtier et océanique et l'histoire de la planification. Nous orientons cet état des lieux vers les études d'aménagement du territoire pour répondre à la principale raison de la transition de l'aménagement de l'espace terrestre (AET) au PEM. Pour caractériser ces méthodes, nous proposons leur problématique principale, le zonage.

Ce chapitre fait le point sur les enjeux disponibles de l'environnement côtier et océanique en expliquant les principaux éléments qui en découlent. Au cours des 5 à 10 dernières années, la PEM est apparu comme un nouvel outil de gestion des eaux nationales et internationales et a déjà attiré un nombre important de recherches multidisciplinaires sur ses objectifs et ses processus politiques.

À l'échelle mondiale, la planification des zones marines, des régions côtières aux régions de haute mer, est créée pour promouvoir la gestion et la gouvernance durables des océans. Ce processus de planification est le plus souvent appelé PEM, mais il porte également de nombreux autres noms, notamment planification spatiale maritime, planification des océans, planification marine, zonage des océans, gestion spatiale marine, gestion de l'utilisation des mers, etc.

Ce chapitre présente l'histoire de la planification avec différentes définitions. Alors que la planification spatiale a évolué au fil des décennies en tant qu'outil de gestion du développement et de l'utilisation de l'environnement terrestre, le développement de systèmes de planification spatiale pour l'environnement marin n'en est qu'à ses débuts. Pour tenter d'initier une telle approche de gestion, ce chapitre passe en revue l'aménagement du territoire et explore la relation entre la PEM et son cousin terrestre, l'AET en clarifiant leur transition. Une condition préalable importante pour l'application efficace de la PEM

est l'utilisation d'approches intégrées appropriées. En particulier, le développement de schémas de zonage pourrait s'avérer précieux pour la répartition des zones où des activités spécifiques devraient avoir lieu avec des intérêts concurrents. Par conséquent, ce chapitre se termine par une description des avantages du zonage, en se concentrant sur son application intégrée dans le cadre de la PEM et en mentionnant la première question de recherche potentielle qui devrait être abordée dans cette thèse.

- Dans le chapitre [3], étant donné que l'un des principaux problèmes de la PEM est de localiser et d'allouer une zone optimale pour une nouvelle activité humaine tout en tenant compte des autres activités existantes, un nouveau problème dans le cadre du zonage en la PEM est défini et décrit. Ensuite, nous nous concentrons sur la formulation d'un modèle linéaire exact comme un LEMO pour ce problème en travaillant sur des données matricielles. Nous présentons les méthodes exactes de résolution qui ont permis de résoudre et de déterminer les solutions optimales. Ensuite, après avoir souligné leurs principaux inconvénients, nous présentons des méthodes qui peuvent gérer et améliorer la résolution du modèle en utilisant des techniques de mise en mémoire tampon. Enfin, nous validons et étudions les approches en générant un ensemble de jeux de données artificielles.

Comme mentionné dans le chapitre [2], la PEM a récemment gagné en popularité en tant qu'outil efficace de prise de décision. La PEM est un processus stratégique à long terme qui réunit de nombreux utilisateurs concurrents de l'océan dans le but de trouver un équilibre entre la simplification des choix sur le lieu, le moment et la manière dont chaque utilisation durable des ressources marines pourrait avoir lieu et la protection de l'environnement côtier et marin. Pour résoudre ce problème, l'un des enjeux de la PEM est de déterminer la meilleure zone pour localiser chaque activité disponible tout en gardant à l'esprit les contraintes et les relations de compatibilité des autres activités existantes. La majorité des techniques de zonage spatial, en particulier pour les usages multiples, sont écrites comme des modèles d'optimisation non linéaires avec des objectifs multiples, qui sont souvent résolus à l'aide d'algorithmes de recherche stochastique, ce qui donne des résultats sous-optimaux. Dans ce chapitre, nous proposons de modéliser le problème comme un LEMO pour une seule nouvelle activité afin de déterminer une zone optimale pour l'implanter tout en tenant compte des emplacements fixes des autres activités existantes dans cette étude. Le modèle est développé pour des données matricielles et cherche à maximiser l'intérêt de la zone dédiée à la nouvelle activité tout en optimisant sa compacité spatiale. Nous étudions deux méthodes de résolution : premièrement, une méthode de la somme pondérée (SP) des deux objectifs, et deuxièmement, une approche interactive basée sur une version augmentée améliorée de la technique des ϵ -contraintes, AUGMECON2. Nous faisons des expériences sur des données créées artificiellement pour valider et étudier le modèle. Nos résultats expérimentaux révèlent que AUGMECON2 est la stratégie la plus prometteuse en termes de pertinence et de diversité des solutions, de compacité et de temps de calcul.

- Dans le chapitre [4], à partir d'une analyse des manques du chapitre [3], de nouvelles méthodes pour gérer le problème de complexité de calcul des modèles LEMO en utilisant l'AEMO sont décrites. Après une introduction à MHs, l'accent est mis sur l'AEMO pour définir une algorithmique génétique de tri non-dominé basé sur un hypervolume synchrone-II (SH-NSGA-II) et algorithmique mémétique (MA). Nous montrons les différentes expériences et tests que nous avons effectués pour régler les paramètres des deux algorithmes, les valider et les comparer sur des jeux de données artificiels. Enfin, une preuve de la cohérence des solutions avec la méthode exacte pour des cas à petite échelle est proposée.

Dans le chapitre [3], un modèle LEMO exact pour la gestion du zonage spatial en la PEM est développé comme modèle d'optimisation et validé par des études expérimentales. Cependant, en raison de la complexité de calcul des modèles LEMO, les résultats du chapitre [3] sont limités à une petite échelle et ne prennent pas en charge le problème donné avec une application réelle à grande échelle. Par conséquent, ce chapitre présente et compare les résultats de deux AEMO, SH-NSGA-II, qui est une extension de NSGA-II, et un MA dans lequel SH-NSGA-II est amélioré par une recherche locale. Ces algorithmes proposés sont utilisés pour résoudre le problème multi-objectif d'optimisation du zonage spatial, qui cherche à maximiser la valeur d'intérêt de la zone attribuée à la nouvelle activité tout

en maximisant simultanément sa compacité spatiale. Nous introduisons plusieurs innovations dans ces algorithmes proposés afin de tenir compte des contraintes du problème et d'améliorer la robustesse des approches traditionnelles NSGA-II et MA. Contrairement aux approches traditionnelles, une condition d'arrêt différente, des opérateurs multiples de croisement, de mutation et de réparation, ainsi qu'un opérateur de recherche locale, sont développés. Nous présentons une étude comparative des résultats obtenus à l'aide des deux algorithmes. Pour garantir des résultats robustes pour les deux algorithmes, leurs paramètres sont calibrés et réglés à l'aide de la méthodologie de la surface multi-réponse (MSMR). Les composantes effectives et non effectives, ainsi que la validité des modèles de régression, sont déterminées à l'aide de la méthode d'analyse de la variance. Bien que SH-NSGA-II ait révélé une bonne efficacité, ses performances peuvent encore être améliorées en utilisant un schéma de recherche locale au sein de SH-NSGA-II, qui est spécialement adapté aux caractéristiques du problème.

- Chapitre [5] s'appuie sur résolution des conflits (RC) dans systèmes multi-agents et les contributions applicatives pour proposer SMOMA coopératif pour le problème donné. SMOMA est un système multi-agent pour résoudre une approche décisionnelle multi-objectifs basée sur l'évolution afin de laisser les multi-utilisateurs négocier pour une PEM coopérative à long terme. Ce chapitre présente les différents scénarios et expériences que nous avons réalisés pour classer et valider différents modèles de négociation sur des ensembles de données artificielles.

Même si cette thèse a jusqu'à présent partiellement justifié la gestion du zonage spatial pour une seule nouvelle activité en ayant une relation semi-coopérative avec d'autres activités dans les chapitres [3] et [4], elle ne répond toujours pas au deuxième objectif posé dans le chapitre [1] sur la négociation. Ce chapitre présente une approche formelle et exécutable pour résoudre un conflit dans SMOMA de gestion du zonage spatial par la négociation. La modélisation SMOMA fournit un cadre puissant pour simuler les processus décisionnels à plusieurs niveaux de l'allocation optimale de l'utilisation marine dans un processus collaboratif et décentralisé d'aide à la décision. Les niveaux de décision comprennent le mécanisme de collaboration agent-optimisateur et agent-agent. Nous développons un système heuristique basé sur la négociation qui classe les paramètres SMOMA sur la base d'une structure de négociation en chaîne. Cette stratégie est mise en œuvre après avoir exécuté l'algorithme MA pour chaque agent et rassemblé leurs solutions Pareto optimales. Différentes stratégies de négociation pour RC sont également présentées, testées et classées à l'aide de la méthode d'agrégation de Condorcet. Les résultats montrent comment les agents peuvent arriver à de bonnes solutions en utilisant les stratégies ci-dessus.

- Enfin, dans le chapitre [6], les contributions, les limites et les perspectives sont présentées, d'un point de vue scientifique et applicatif.

L'objectif notable de cette thèse est de créer un système d'aide à la décision spatiale permettant de localiser et d'allouer des zones d'espace marin à diverses parties prenantes, malgré des objectifs et des contraintes éventuellement contradictoires.

Pour surmonter ce problème, nous nous concentrons sur trois besoins distincts dans cette thèse :

1. Définir et modéliser le problème dans un environnement SIG réaliste, ainsi que développer un modèle mathématique pour le traiter,
2. Être capable de fournir des solutions à des problèmes à grande échelle,
3. Développer un cadre de prise de décision coopérative pour aider de nombreuses parties prenantes à régler des conflits potentiels par la négociation.

Résumé des contributions

En somme, pour répondre aux objectifs mentionnés, cette thèse propose une SMOMA. Cette approche a permis de représenter dans une certaine mesure les processus décisionnels à plusieurs niveaux de la gestion du zonage spatial pour les utilisations marines, avec les contributions suivantes :

- **Formulation et modélisation du problème de zonage :**

Étant donné que la localisation et l'attribution d'une zone optimale pour une nouvelle activité humaine tout en gardant à l'esprit les autres activités présentes est l'une des questions clés de la PEM, un nouveau problème dans le cadre de la gestion du zonage dans la PEM est identifié et discuté. Le chapitre [2] a rendu compte de la raison de l'utilisation généralisée de la planification spatiale en passant en revue la littérature pertinente. Pour modéliser ce problème, la technique la plus répandue est basée sur des modèles multi-objectifs non linéaires, qui sont souvent résolus à l'aide d'algorithmes de recherche stochastique, ce qui aboutit à des solutions sous-optimales. Ainsi, la première contribution ici conduit à formuler un modèle linéaire exact comme un LEMO qui vise à maximiser l'intérêt de la surface de la zone dédiée à une activité marine, tout en maximisant sa compacité spatiale. Ensuite, pour rendre le modèle proche de la réalité plutôt que des données vectorielles, on choisit de travailler sur des données matricielles, qui couvrent entièrement les données géospatiales des zones. Dans le chapitre [3], un nouveau modèle mathématique multi-objectifs est proposé pour résoudre le problème.

- **Résolution exacte :**

Deux approches de résolution sont utilisées pour résoudre le modèle LEMO et établir la meilleure solution : SP et AUGMECON2. En raison du grand nombre de variables et de contraintes entières dans ce modèle LEMO, la résolution est améliorée dans une étape de prétraitement en appliquant la technique de mise en mémoire tampon. Cette étude, présentée au chapitre [3], confirme les résultats selon lesquels AUGMECON2 est la technique la plus prometteuse en termes de pertinence et de variété des solutions, de compacité et de temps de calcul. En effet, AUGMECON2 peut être utilisé pratiquement à chaque exécution pour fournir une réponse unique. Elle nous permet également de réguler simplement le nombre de solutions créées. SP fournit des solutions moins équilibrées entre les deux objectifs d'intérêt et de compacité tout en étant moins sensible à l'approche de mise en mémoire tampon. Dans l'ensemble, ces approches spécifiques sont limitées à une petite échelle et ne prennent pas en charge la question concernée à grande échelle. Afin d'évaluer toutes les méthodologies et d'analyser la sensibilité des méthodes de résolution et des temps de calcul concernant divers paramètres, un ensemble de jeux de données artificielles est établi pour toutes les évaluations expérimentales.

- **MHs :**

Des obstacles peuvent apparaître, entre-temps, lorsqu'on tente d'élargir le problème. Ces obstacles sont le coût de calcul élevé et la difficulté de calcul des solveurs exacts pour les cas à grande échelle du problème. Dans le chapitre [4], à partir d'une analyse des limitations du chapitre [3], de nouvelles méthodes pour gérer ces obstacles du modèle LEMO en utilisant AEMO sont décrites. Après une introduction aux MHs, nous mettons l'accent sur deux nouvelles P-métaheuristiques basées sur GA développées pour résoudre le problème d'optimisation du zonage spatial (SH-NSGA-II et MA). Plusieurs innovations et contributions sont suggérées et appliquées dans l'initialisation, la condition d'arrêt, le codage des chromosomes, les opérateurs de croisement, de mutation, de vérification et de réparation, les méthodologies de gestion des contraintes et la structure de l'algorithme basée sur les données matricielles. Ces AEMO visent à optimiser non seulement l'intérêt mais aussi la compacité de la nouvelle zone d'activité. Pour régler les paramètres des AEMO, nous utilisons des MSMR. Nous mettons en place un Design d'expérience comme Box-Behnken Design (BBD), qui implémente un modèle de régression multi-réponse pour trois tailles de cartes différentes du problème afin de déterminer la valeur optimale des paramètres de AEMO. De plus, l'efficacité de tous les modèles est validée par l'analyse de la variance. Différentes mesures de performance sont proposées et calculées pour mieux caractériser les solutions de Pareto afin de comparer les deux AEMO. Il en résulte une analyse plus efficace des deux algorithmes pour des problèmes à petite ou grande échelle. La valeur significative des tests de Wilcoxon Signed-Rank (WSRT) de toutes les mesures de performance pour la méthode exacte, SH-NSGA-II, et MA dans les trois niveaux de taille de problème est évaluée et comparée pour valider toutes les conclusions. 24 cas de test avec 30 répétitions sont utilisés pour illustrer la surperformance de la méthode AEMO suggérée. Les résultats montrent qu'en moyenne, le MA proposé fournit de meilleures solutions en moins de temps de calcul et présente une meilleure cohérence que le SH-NSGA-II.

Enfin, une série de (24×30) WSRT indique que la MA proposée surpasse largement la SH-NSGA-II.

- **RC :**

Pour répondre au troisième besoin de l'objectif de la thèse, il faut ajouter l'hypothèse d'une coopération entre de multiples intérêts concurrents. Cette exigence nous guide vers le développement un cadre RC dans le processus de décision coopératif en utilisant des méthodes de la système multi-agent et heuristiques dans le chapitre [5]. Cette méthode vise à aider les demandeurs à trouver un compromis dans lequel on leur propose des alternatives qui maximisent le bénéfice qui leur est alloué et qui garantissent l'équité et un niveau hautement satisfaisant pour la coopération à long terme. Les mécanismes de collaboration d'agent à optimiseur et d'agent à agent constituent les niveaux de décision dans SMOMA. Nous proposons une méthode heuristique basée sur la négociation pour classer les propriétés de SMOMA en utilisant une structure de négociation en chaîne. Tout d'abord, au niveau de décision agent-optimiser, les agents complètent leur module de perception. Une fois l'algorithme SMOMA exécuté sur chaque agent et leurs solutions Pareto optimales collectées, le niveau de décision agent-à-agent est mis en œuvre. Dans cette technique, les agents dans une négociation prennent toujours une ou plusieurs décisions et entreprennent une ou plusieurs actions afin d'atteindre le compromis raisonnable optimal tout en évitant les goulots d'étranglement. Les coûts de communication de la négociation sont minimales car le nombre de messages transmis est limité et les agents ne sont pas tenus de divulguer toutes les informations les concernant. Divers scénarios de négociation sont également décrits, évalués et notés à l'aide de l'approche d'agrégation de Condorcet. Les résultats montrent comment les agents peuvent arriver à de bonnes solutions en utilisant les techniques susmentionnées.

Limitations et perspectives

Les limites et les perspectives de cette thèse pourraient être énumérées comme suit :

1. Dans notre modèle LEMO, nous couvrons les contraintes globales et ne creusons pas plus profondément les contraintes de chaque activité. Par exemple, dans le monde réel, l'une des contraintes difficiles pour certaines activités maritimes, comme le transport maritime, est la planification du temps. Ce problème consiste à déterminer les temps d'arrivée, de départ et d'attente de chaque navire dans chaque port pour servir la cargaison. Par conséquent, des fenêtres de temps (dures ou souples) peuvent être ajoutées aux contraintes des problèmes de routage et d'ordonnancement des navires. Bien que la prise en compte d'un plus grand nombre de contraintes rende le modèle LEMO plus complexe, elle est plus susceptible de faciliter le mécanisme de négociation au final. Étant donné que la plupart des conflits proviennent de ces restrictions, leur assouplissement par les décisions des agents au cours de la négociation pourrait les aider à trouver un compromis.
2. Dans notre modèle LEMO, nous définissons les fonctions objectives globales, qui ne sont que deux. Ce sont les fonctions objectives globales pour toutes les utilisations marines considérées. L'ajout de quelques fonctions objectives supplémentaires pourrait aider à couvrir plus de critères et de préférences des acteurs. Par conséquent, d'autres fonctions objectives pourraient être ajoutées, comme la minimisation du coût de l'allocation des zones localisées à chaque utilisation marine tout en maximisant le profit total pour chacune d'entre elles.

L'amélioration du modèle exact en considérant plus de deux fonctions objectives pourrait être évaluée par deux idées dans le cadre de recherches futures. Par exemple, une idée pourrait considérer les objectifs globaux comme des objectifs généraux et utiliser les méthodes d'optimisation à deux niveaux pour chaque acteur. En procédant ainsi, les objectifs de chaque acteur imbriqués dans les objectifs globaux seraient d'abord atteints et aideraient ensuite à optimiser les objectifs généraux.

Un autre choix consiste à avoir deux fonctions objectives différentes ou plus pour chaque agent. Par conséquent, trouver les méthodes de résolution applicables comme MHs pourrait être un défi pour ces idées.

Dans notre modèle LEMO, qui est un problème de zonage spatial semi-coopératif, une nouvelle activité humaine doit être localisée et allouée en fixant d'autres activités humaines. Par conséquent, une question qui n'est pas abordée est la modélisation de la programmation mathématique exacte par localisation-allocation de plusieurs nouvelles utilisations marines en même temps. Le développement de la programmation mathématique pour ce type de problème (SMOMA) pourrait faire passer le modèle de linéaire à non linéaire et beaucoup plus compliqué. Disposer du modèle mathématique de SMOMA pourrait aider à trouver les solutions optimales, et non des solutions approximatives pour tous les acteurs. Cette idée nécessite davantage de recherches et d'investigations.

3. Dans les méthodes de résolution, bien que les conclusions de SMOMA aient permis de résoudre en partie le problème spécifique donné à grande échelle, d'autres améliorations seraient possibles pour réduire le temps de calcul tout en augmentant la vitesse de convergence. Par exemple, certaines améliorations des opérateurs de génération de population pourraient aider à cet égard en diminuant le besoin d'opérateurs de réparation, puisqu'un temps remarquable dans notre AEMO est consacré à ces opérateurs.

De plus, l'évaluation et le développement d'autres AEMO à comparer avec ceux proposés actuellement pourraient aider à trouver le AEMO le plus rapide pour ce problème. Cette perspective pourrait être atteinte avec un morceau d'extension dans l'algorithme actuel.

Une autre méthode de recherche future que nous pourrions étudier est celle des algorithmes *Matheuristiques*. Il s'agit d'algorithmes heuristiques créés par l'interopérabilité des MH et des techniques de programmation mathématique, ce qui serait intéressant. Cette méthode pourrait mélanger le modèle actuel LEMO avec AEMO d'une certaine manière.

4. Les modèles AEMO et LEMO, dans notre recherche, sont basés sur des données matricielles. Cependant, la recherche actuelle n'est pas conçue pour évaluer ces modèles sur la base de données vectorielles. Bien que la prise en compte des données matricielles augmente la précision de nos solutions et soit plus préférable pour les compagnies maritimes, les données vectorielles réduisent le coût de calcul et la difficulté de nos algorithmes.

Par conséquent, le développement d'un modèle non linéaire basé sur le polygone pour faciliter la transformation tout en utilisant les données vectorielles plutôt que les données matricielles pourrait être évalué dans des travaux futurs.

La présente thèse n'a examiné que la certitude des paramètres sans tenir compte de leur incertitude. L'incertitude des données d'entrée, en particulier lorsque les données d'entrée incorporent statistiquement de nombreuses distributions, et la dynamique des données d'entrée sont deux défis essentiels à relever dans les problèmes d'optimisation du monde réel. Pour rendre les méthodes plus compatibles avec le monde réel, la prise en compte de l'hypothèse d'incertitude pourrait être utile. Par exemple, une approche de recherche intéressante pour l'incertitude des données pourrait consister à utiliser des techniques ML telles que les algorithmes de regroupement (par exemple, k-means, SOM) pour regrouper les données d'entrée dans le but de différencier les données avec diverses distributions. Ces classes de données peuvent ensuite être utilisées/intégrées pour relever le défi de l'optimisation.

On peut penser à l'optimisation robuste ou à la programmation stochastique. Deux facteurs principaux permettent de les distinguer :

- Dans l'optimisation stochastique, on suppose presque toujours que l'on connaît la distribution de probabilité (éventuellement sous la forme de probabilités discrètes de chaque scénario) des paramètres aléatoires. En optimisation robuste, on suppose généralement (mais pas toujours) que l'on ne connaît pas la distribution.

Dans l'optimisation stochastique, le but est généralement d'optimiser la valeur attendue de la fonction objectif (coût attendu minimum, bénéfice attendu maximum, etc.). Dans l'optimisation robuste, comme nous ne connaissons pas les probabilités, nous optimisons plutôt une autre mesure. Les mesures courantes consistent à optimiser le résultat le plus défavorable (par exemple, minimiser le coût maximum, maximiser le profit minimum, etc. – parfois sur un sous-ensemble seulement des scénarios possibles. Il existe également de nombreux autres objectifs communs.

En ce qui concerne la dynamique des données, des approches d'apprentissage automatique (ML) peuvent être utilisées pour surveiller/prédire l'évolution des données d'entrée et,

lorsqu'une nouvelle évolution est identifiée, les variables d'optimisation sont modifiées en conséquence.

5. L'SMOMA est considéré comme un système fermé, et non comme un système ouvert. Le système ouvert permet aux nouveaux agents de s'intégrer de manière transparente tout au long du processus. Ce faisant, il pourrait être possible que les agents apparaissent et disparaissent au cours du processus. Par conséquent, cette hypothèse pourrait rendre le mécanisme de négociation plus flexible pour les agents tout en réduisant les communications inutiles entre eux. Elle pourrait donc conduire à une réduction de la complexité et des coûts de la négociation.

Cette idée devrait être mise en œuvre par la nouvelle heuristique de négociation.

6. L'interaction entre l'environnement et le système par rétroaction n'est pas considérée. L'ajout de l'hypothèse de rétroaction à SMOMA pourrait aider les agents à atteindre la meilleure solution de compromis. Par exemple, les agents pourraient retourner à leur environnement optimiseur pendant la négociation en fournissant un retour d'information tout au long ou à la fin de la négociation. Ce faisant, la communication interactive entre l'optimiseur et les agents pourrait permettre à l'optimiseur de rester informé des changements de solution.

Cette idée devrait être mise en œuvre par la nouvelle heuristique de négociation.

7. Certaines autres techniques pour aborder l'analyse RC pour les usages multiples, qui devraient aider à aborder la gestion du zonage dans la PEM, pourraient être les suivantes. Cette perspective pourrait se définir comme une nouvelle recherche. Ces orientations ouvrent également d'autres questions de recherche qui méritent d'être approfondies.

- évaluant le mélange de l'apprentissage par renforcement ou de l'apprentissage profond avec des techniques d'optimisation. Cependant, ces techniques nécessiteraient une quantité considérable de données synthétiques ou réelles précises pour démontrer leur efficacité. L'accès à des ensembles de données réelles est une préoccupation future pour la recherche la PEM.
- étudie l'optimisation polyédrique et hiérarchique multi-objectifs basée sur l'apprentissage hybride pour SMOMA. Cette méthode pourrait aider à satisfaire non seulement les contraintes et les objectifs globaux, mais aussi les objectifs spécifiques à chacun d'entre eux.
- mélangeant les modèles de simulation basés sur les agents et les techniques d'optimisation (en utilisant l'optimisation AnyLogic qui est construite au-dessus du moteur d'optimisation OptQuest, l'un des outils d'optimisation les plus flexibles et les plus conviviaux du marché). Bien qu'Anylogic soit un logiciel propriétaire, qui n'est pas utilisable pour une étude de recherche, il pourrait être appliqué à des cas réels dans l'industrie.

Abstract

In recent decades, the increasing demand for the use of marine space has led to conflicts due to the overlap of various human activities (e.g., renewable energy facilities, aquaculture, fisheries, etc.) with economic development, social objectives, and environmental protection (European Maritime Affairs Commission, 2017). To effectively address these potential conflicts, a planning approach is needed to analyze and spatially and temporally allocate human activities in marine areas. This planning process is commonly referred to as Marine Spatial Planning (MSP), an ecosystem constraint-based spatial organization process that aims to allocate marine spatial areas to multiple actors to ensure that human activities at sea occur in an efficient, safe, and sustainable manner.

The challenging issue of this thesis is to develop a spatial decision support system for locating and allocating areas of marine space to multiple actors, despite potentially conflicting initial objectives and constraints.

To address this issue, in this thesis, we focus on three different requirements as follows:

- Modeling the problem in a realistic Geographical Information System (GIS) framework and formulating a mathematical model to solve it,
- Being able to propose solutions for large-scale problems,
- Developing a decision-making process that helps multiple actors to resolve possible conflicts by reaching a trade-off.

According to these objectives, this thesis proposes a Multi-Objective Multi-Agent System (MOMAS) that simulates the multi-level decision-making processes of marine use spatial zoning management with three main contributions:

1. Multi-Objective Integer Linear Programming (MOILP): Optimal allocation solutions for problems of reasonable size that guarantee Pareto efficiency, where all claimed space is allocated.
2. Multi-Objective Evolutionary Algorithms (MOEAs): Near-optimal solutions for large-scale problems, approximated by Meta-Heuristics (MHs).
3. Cooperative decision-making process with Multi-Agent Systems (MAS) and heuristics methods: Helping multi-objective actors to negotiate and select the most appropriate and fair set of allocation solutions in terms of zoning of the maritime space, in view of long-term cooperation.

This thesis proposes a formal and executable approach to address the spatial zoning management problem with both multiple objectives and actors. In the case of conflict, different cooperation scenarios are compared and ranked. The experimental results on synthetic datasets highlight the fact that good tradeoffs can be reached when the actors agree to cooperate. The proposed work paves the way for future online decision support tools applied to real-world cases.

List of Figures

1	Proposition d’approche décisionnelle	17
2	Proposed decision-making approach	4
3	Illustration of the organization of the manuscript, allowing to visualize the contributions related to the different deployment phases, reaching to Cooperative Systems.	5
4	Schematic of coastal system [OK20]	10
5	Changing planning paradigms	13
6	Spatial planning incorporates planning process traditions	15
7	Zoning matrix for the Great Barrier Reef Marine Park’s Far Northern Section [Day02]	19
8	Different phases of MSP	24
9	Real MSP map [Bas+21]	27
10	Vector and Raster Data GIS [Mcc37]	28
11	Raster concept [LT92]	29
12	Problem Definition	33
13	Modification of the feasible region by the buffering technique	37
14	A sample fictive map generated by artificial datasets	40
15	Different types of interest maps	40
16	The sample validity map with one compact area	44
17	The sample validity map with one very compact area	45
18	The sample validity map with multiple non-compact areas	46
19	The Average Compactness Comparison between WS and AUGMECON2: (a) 3 Pareto-optimal solutions of AUGMECON2 with increasing the objective function (4); (b) that of WS w.r.t λ	47
20	The Pareto Front of AUGMECON2	47
21	The Average Candidate Cells of all Configurations for each Buffer Size between WS and AUGMECON2	48
22	The Average Time Comparison of all Configurations for each Buffer Size between WS and AUGMECON2	48
23	MHs ancestry. As per the original date, the application to optimization and/or machine learning is considered. [Tal09].	55
24	Two conflicting criteria in designing MHs: exploration (diversification) versus exploitation (intensification) [Tal09].	55
25	The trend of MOEAs in spatial optimization during recent 13 years	56
26	A combination of LTH. P-metaheuristics contain S-metaheuristics [Tal09].	57
27	A generation in EAs	59
28	Mapping between the space of solution and the space of encoding.	60
29	Graphical representation of NSGA-II [Deb11]	61
30	The flowchart of SH-NSGA-II for spatial zoning optimization problem	62
31	The flowchart of MA for the spatial zoning optimization problem	63
32	Random population using circle filling on a grid by bounding box	66
33	Single-point vertical cutting crossover (Crossover-1)	66
34	Single-point horizontal cutting crossover (Crossover-2)	67

35	Semi-proportional vertical single-point cutting crossover Crossover-3	69
36	Capacity improver operator	71
37	Crowding-distance calculation. Points marked in filled circles are solutions of the same non-dominated front [BAJH20]	74
38	HV indicator for a non-dominated approximation set of solutions [FPLI06]	74
39	The response surface 3D plots of interaction of important factors on S/N : (a) interaction of population size and mutation rate; (b) interaction of population size and mutation probability; (c) interaction of mutation rate and crossover rate; (d) interaction of mutation probability and crossover rate	80
40	The response surface 3D plots of interaction of important factors on S/N : (a) interaction of population size and mutation rate; (b) interaction of population size and mutation probability; (c) interaction of mutation rate and crossover rate; (d) interaction of mutation probability and crossover rate	81
41	The comparison among MOEAs algorithms and exact optimal solutions for small size: (a) Comparison based on HV performance metric; (b) Comparison based on <i>Best Sol</i> performance metric; (c) Comparison based on MID performance metric; (d) Comparison based on SNS performance metric; (e) Comparison based on RAS performance metric	85
42	Centralized decision-making process with no collaboration between subsystems	89
43	Decentralized decision-making process with collaboration between subsystems .	89
44	Multi-objective multi-agent collaborative-interactive decentralized decision-making process	90
45	The feedback loop	92
46	The different modules of a cooperative agent [GPB04]	93
47	NCS in the agent life-cycle	94
48	The diagram of the negotiation-based MOMAS for spatial zoning management in MSP	100
49	The graphical CR between three agents: (a) the conflict between $Agent_1$ and $Agent_2$; (b) the conflict between $Agent_1$ and $Agent_3$; (c) the conflict between $Agent_2$ and $Agent_3$	104

List of Tables

2	Definitions of “Planning” in terrestrial and maritime environments	11
1	Data generation parameters for exact methods	42
2	WS parameter	42
3	Data generation parameters for MOEAs	75
4	Search range of algorithm parameters	75
5	Results of metrics for SH-NSGA-II	77
6	Computational results obtained for the tuning parameters of SH-NSGA-II for small map size.	78
7	Summary table SH-NSGA-II for small map size	79
8	Tuned parameters for SH-NSGA-II and MA	82
9	Stopping Condition for SH-NSGA-II and MA	82
10	The comparison between MOEAs and the optimal solution	84
11	The result of MOEAs	86
12	Requirements for a negotiation protocol	95
13	Assumptions of MOMAS	101
14	Experimental protocol	105
15	The coded negotiation models	106
17	Data generation parameters for MOMAS	106
18	Aggregated normalized value of the first objective functions	109
19	Finalized Condorcet rank	109
20	Computational results obtained for the tuning parameters of SH-NSGA-II for medium map size in Subsection [4.4.1]	119
21	Computational results obtained for the tuning parameters of SH-NSGA-II for large map size in Subsection [4.4.1]	120
22	Computational results obtained for the tuning parameters of MA for small map size in Subsection [4.4.1]	120
23	Computational results obtained for the tuning parameters of MA for medium map size in Subsection [4.4.1]	121
24	Computational results obtained for the tuning parameters of MA for large map size in Subsection [4.4.1]	123
25	Summary table SH-NSGA-II for medium map size in Subsection [4.4.1]	125
26	Summary table SH-NSGA-II for large map size in Subsection [4.4.1]	126
27	Summary table MA for small map size in Subsection [4.4.1]	127
28	Summary table MA for medium map size in Subsection [4.4.1]	128
29	Summary Table MA for large map size in Subsection [4.4.1]	129

Chapter 1

Introduction

Contents

1.1 Preamble	2
1.2 Detailed Problem Statement and Objectives	3
1.3 Research Questions	4
1.4 Organization of Manuscript	4

1.1 Preamble

Life on earth depends on the ocean because 71% of the planet is covered by the ocean. Naturally, people care deeply about it, with its abundant life and vast resources. The ocean means something different to all of us. We all have our own interests. For example, generations of fishermen have gained a livelihood from the ocean. Conservationists are committed to protecting it, while a container ship's captain needs deep water and direct access to the port via the shortest route. Where do our priorities lie when a marine area is home to wildlife fishing and shipping at the same time? What if the situation is complicated by minerals the mining industry wants to extract, or if an investor plans to build a wind farm? The responsible planner, typically a government official, faces many challenges in dealing with all these demands; exactly how do you satisfy all these people and their interests? How do you balance using and protecting the same ocean space?

Marine Spatial Planning (MSP) is a relatively new way to manage human activities that occur in the ocean. It is a long-term and strategic process that guides where, when, and how human uses take place. This can be useful where there are opportunities for new uses or where activities impact nature. **MSP** can help to balance competing interests, making sure society benefits while protecting the marine environment.

Firstly, **MSP** is best carried out by a mandated planning group with a strong shared vision and clear goals regarding what needs to be achieved. The planner must listen to as many interested parties as possible, not just at the start, but right through the process by working together with all those stakeholders that have an interest in the ocean. Planners ensure that marine users build trust, commit to the process, and feel ownership of the plan produced with their help. Of course, this will raise questions for lots of them. Shall we exclude mining from important fishing grounds? Shall we reroute the shipping lanes to make space for marine wildlife? Can we have tourism and conservation at the same time in the same location?

MSP begins with an analysis of the current situation. For example, which locations have the highest natural value? Who is using the planning area? What are the government's priorities for the ocean and its use? By drawing together as much information as we can on everything from fishing grounds to shipping lanes, from important natural habitats to oil and gas fields, we can map the details to understand some of the key issues that the plan must address. Next, **MSP** identifies where conflicts and synergies may lie, which activities can be easily combined, and which are mutually exclusive. Options for the future are also considered; what trends do we expect in different industries? Deep-sea mining operations might look to expand, but what if newly discovered mineral deposits extend into nature conservation and tourism areas? This puts us in a position to develop alternatives and decide on the preferred spatial option. This might involve trade-offs between interests. Reaching a compromise will require negotiation, but this can only be successful if the stakeholders are at the table and can be heard.

Once spatial solutions that best accommodate everyone's needs and meet the plan's objectives have been agreed upon, it is time to set out actions that will ensure the success of the plan. These may include areas or policies that prioritize certain uses, such as mining or wind farms, or rerouting shipping lanes to give more space to whales. Such management actions should be developed with the input of all marine users and interest groups to help ensure that the plan is supported by as many stakeholders as possible. Once the plan is agreed upon and adopted, it must be implemented. From this day on, it will guide all marine users where, when, and how their activities occur in ocean space.

Finally, **MSP** is an ongoing process. It involves regular monitoring, evaluation, and revision. Is it achieving what it was supposed to? What do we need to do better next time? What further information do we need? Naturally, things change; the climate, investors, interests, politicians, and their priorities. So the plan will need to be adopted over time. If done well, a marine spatial plan will support not just today's livelihoods but those of future generations for that very good reason. It is no surprise that **MSP** is now spreading across the world's seas and oceans.

Taken together, however, whenever a bundle of resources, rights, burdens, benefits, or costs are held temporarily in common by a group of sectors, debates continue about the best strategies for spatial zoning management to distribute them among them. Moreover, this issue has grown

in importance in light of recent political hotspots, fueled by political power struggles and the continuously increasing demand for marine/land space for both traditional and emerging marine/land uses.

The challenging objective of this thesis would be to develop an appropriate location-allocation approach within a wider spatial decision-making process, where marine users interact with each other in order to reach a spatial allocation agreement through their conflicting objectives.

This challenging objective can be considered a complex problem, the zoning management for [Multi-Objective Multi-Agent System \(MOMAS\)](#) with the application to [MSP](#). Complexity should not be mistaken for complicated. Where a complicated problem has many different and well-defined parts with well-known behaviors and can be reduced to simpler problems (a puzzle, for example, can be divided into smaller puzzles before being solved), a complex problem is defined by an important number of interacting little parts, and it is their interactions that produce the global behavior. A complex problem is like a complex system. Part of a complex system is guided by simple and individual rules. The behavior of the system cannot be predicted from individual rules: “the whole is greater than the sum of the parts” [Fun10].

The above-mentioned complex real-world problems can be found in a plurality of domains and science. These problems contain three aspects that make them impossible to be solved by classical centralized decision-making processes and existing commercial optimization software all around the world. Solving such problems is an important subject in computer science.

Firstly, they are [Multi-Objective Optimization Problems \(MOOPs\)](#), where solving the problem for each objective leads to a different solution. Accordingly, an approach is required to find a set of mathematically “equal” solutions called Pareto optimal solutions. Different solving methods have been developed. They are commonly classified into two categories: exact and inexact methods. The first one guarantees to find (if it exists) the optimal solution. Still, as they explore the whole search space, they are too slow and cannot be applied to solve complex problems. Approximate methods find a solution using a heuristic or [Meta-Heuristics \(MHs\)](#) to cross the space search. An important drawback of all of those methods is that they cannot manage dynamics, which is one of the characteristics of complex problems.

Secondly, they are multi-agent problems, where the preferences of all possible agents should be incorporated into the decision process. Therefore, an interactive optimization approach is required that effectively takes the agents’ preferences and finds a compromise optimal decision accordingly. This agent-to-optimizer interaction helps agents learn about the problem and allows them to modify and change their preferences progressively. The third aspect is the interdependency between the agents that affects their decisions. This issue necessitates a collaborative mechanism between agents to share information or even handle conflicting preferences and constraints. Through this agent-to-agent collaboration mechanism, agents can modify their preferences and constraints and finally update their decisions. This methodology can solve such a multi-objective and multi-agent optimization problem by providing an agent-to-optimizer and an agent-to-agent collaborative mechanism with an application to [MSP](#), which exists neither theoretically nor as a decisional methodology.

1.2 Detailed Problem Statement and Objectives

The main objective of this thesis is the coordination of marine activities and the solution of location-allocation problems that could potentially lead to spatial conflicts. The challenge is to choose an appropriate zoning strategy within a wider spatial decision-making process, where marine users interact with each other to reach a spatial allocation agreement. Reaching such an agreement is not straightforward when users follow their internal and particular objectives, which are mostly in conflict with others. To cope with this issue, an efficient decision-making process needs to be developed in which three different requirements, as shown in [Figure 2](#) should be met as follows:

- **Formulation and Modelization:** formulating and modeling the problem in a realistic [Geographical Information System \(GIS\)](#) framework, as well as developing a mathematical model to address it,

- **Optimization:** scaling up the problem to provide optimal solutions for large-scale cases,
- **Negotiation and Implementation:** developing a decision-making process that helps multiple actors to resolve possible conflicts by reaching a trade-off.

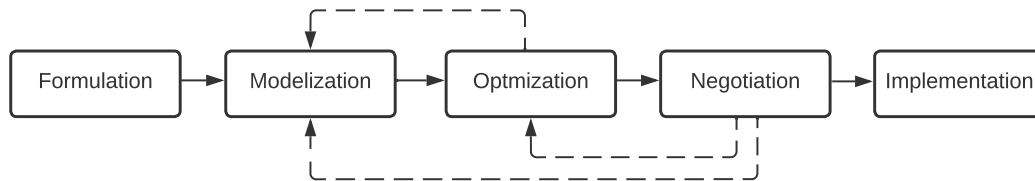


Figure 2: Proposed decision-making approach

According to above-mentioned objectives, this thesis presents a **MOMAS** to model the multi-level decision-making processes of marine use spatial zoning management, with three primary contributions:

1. **Multi-Objective Integer Linear Programming (MOILP):** Optimal allocation solutions for problems of acceptable size, ensuring Pareto efficiency and allocating all claimed space.
2. **Multi-Objective Evolutionary Algorithms (MOEAs):** MOEAs approximates near-optimal solutions for large-scale problems.
3. Cooperative decision-making process with **Multi-Agent Systems (MAS)** and heuristics methods: In the context of long-term collaboration, supporting multi-objective stakeholders in negotiating and reaching the most appropriate and equitable allocation set in terms of zoning of marine area.

1.3 Research Questions

This thesis contributes by bringing contributions to answer the three following research questions, which are at the core of this complex decision-aiding methodology.

1. How to formulate an exact linear model as a **MOILP** for the spatial zoning management problem in **MSP**?
2. How to solve the proposed model and determine the optimal solution for the exact model? Which exact methods should be used?
3. How to solve the computing complexity of this **MOILP** model through scaling it up? Which approximate methods should be selected to solve the large-scale cases?
4. How to develop a mechanism where the multi-uses effectively collaborate to share the information and learn the preferences in terms of the solutions of the other uses as well as modify their own ones, especially when facing a conflict. How to develop a negotiation-based mechanism to reach a spatial allocation agreement through their conflicting objectives?

1.4 Organization of Manuscript

The present manuscript is organized into four main chapters, including *Marine Spatial Planning Context*, *Exact Zoning Model for Marine Spatial Planning*, *Extensions to Evolutionary Approaches for Zoning Management in Marine Spatial Planning*, and *Cooperative Multi-Objective Multi-Agent Zoning Management for Marine Spatial Planning* (Figure 3).

Each chapter includes different phases to bring us close to the objectives of this thesis. The horizontal axis shows the direction of the complexity level from the start point of non-cooperative

to cooperative methods applied to the problem. The execution of all stick notes is in order from left to right for each phase of each chapter.

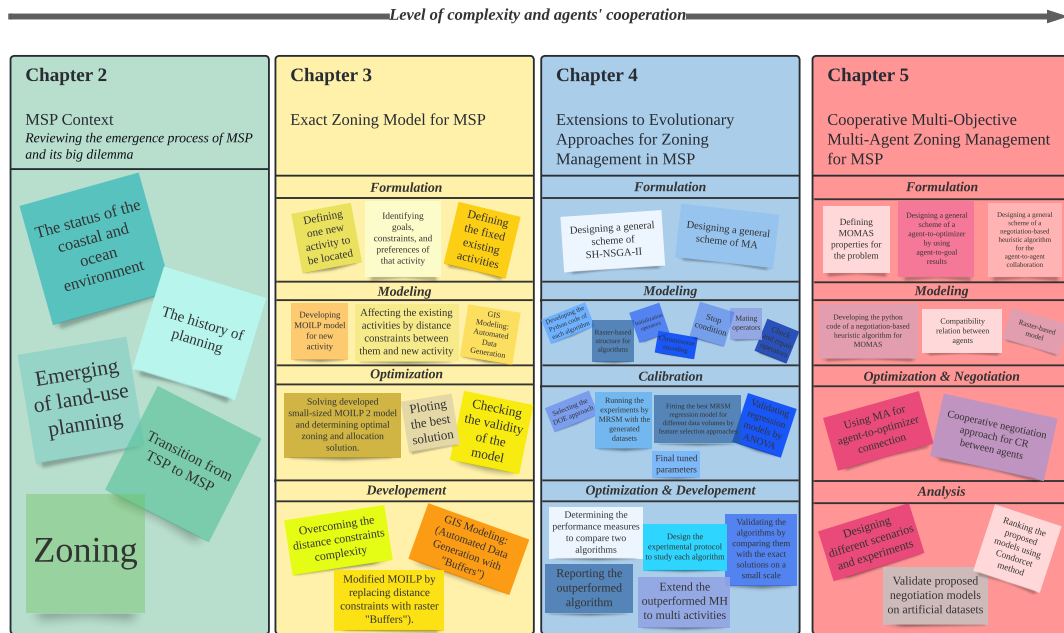


Figure 3: Illustration of the organization of the manuscript, allowing to visualize the contributions related to the different deployment phases, reaching to Cooperative Systems.

The rest of the manuscript is structured as follows:

- In Chapter [2], a state-of-the-art in the development of spatial planning is made by reviewing the status of the coastal and ocean environment and the history of planning. We direct this state-of-the-art toward land-use planning studies to answer the main reason for the transition from **Terrestrial Spatial Planning (TSP)** to **MSP**. To characterize those methods, their main issue, zoning, is proposed.
- In Chapter [3], since one of the main issues in **MSP**, is to locate and allocate an optimal zone for a new human activity while considering the other existing activities, a new problem in the scope of zoning in **MSP** is defined and described. Then, we focus on formulating an exact linear model as a **MOILP** for this problem by working on raster data. We present the resolution exact methods which solved and determined the optimal solutions. Then, after pointing out their major drawbacks, we present methods that can manage and improve the model resolution by using buffering techniques. Finally, we validate and study the approaches by generating a set of artificial datasets.
- In Chapter [4], from an analysis of the lacks in Chapter [3], new methods to manage the computing complexity issue of **MOILP** models using **MOEAs** are described. After an introduction to **MHs**, a focus is made on **MOEAs** to define **Synchronous Hypervolume-based Non-dominated Sorting Genetic Algorithm-II (SH-NSGA-II)** and **Memetic Algorithm (MA)**. We show the different experiments and tests we have performed to tune the parameters of both algorithms, validate them, and compare them on artificial datasets. Finally, proof of the coherence of solutions with the exact method for small-scale cases is proposed.
- Chapter [5] relies on **Conflict Resolution (CR)** in **MAS** and applicative contributions to propose the cooperative **MOMAS** for the given problem. **MOMAS** is a **MAS** to solve a multi-objective evolutionary-based decision-making approach to let multi-uses negotiate for long-term cooperative **MSP**. This chapter shows the different scenarios and experiments we have performed to rank and validate different negotiation models on artificial datasets.
- Finally, in Chapter [6], contributions, limitations, and perspectives are made, from a scientific and an applicative point-of-view.

Chapter 2

Marine Spatial Planning Context

Contents

2.1 Introduction	8
2.1.1 The Status of the Coastal and Ocean Environment	9
2.1.2 The History of Planning	10
2.2 Land-Use Planning	11
2.3 From Terrestrial Spatial Planning to Marine Spatial Planning	13
2.4 Zoning	18
2.5 Conclusion	20

ABSTRACT

This chapter reports the available issues of the coastal and ocean environment by explaining the main affecting elements. Over the last 5–10 years, MSP has emerged as a new management tool for national and international waters and has already attracted a substantial body of multi-disciplinary research on its goals and policy processes. Globally, marine area planning, from coastal to open-ocean regions, is being created to promote sustainable ocean management and governance. This planning process is most commonly referred to as MSP, but it also goes by many other names, including maritime spatial planning, ocean planning, marine planning, ocean zoning, marine spatial management, sea use management, and so on. This chapter presents the history of planning with different definitions. Whilst spatial planning has evolved as a tool to manage the development and use of the terrestrial environment over decades, the development of spatial planning systems for the marine environment is in its infancy. In an attempt to initiate such a management approach, this chapter reviews land-use planning and explores the relationship between MSP and its land-based cousin, TSP by clarifying their transition. An important prerequisite for the effective application of MSP is the use of appropriate integrated approaches. In particular, the development of zoning schemes could be valuable for the location-allocation of areas where specific activities should occur with competing interests. As a result, last but not least, this chapter ends up with a description of the advantages of zoning, focusing on its integrated application in the framework of MSP and mentioning the first potential research question that should be addressed in this thesis.

2.1 Introduction

The creation of a European Marine Strategy Framework Directive and special UK MSP law reflects an international increase in effort aimed at better protecting the marine environment and planning and managing human interaction with the sea in a more thoughtful and coordinated manner. UNESCO defines MSP as “a public process of analyzing and distributing the geographical and temporal distribution of human activities in marine areas to fulfill ecological, economic, and social objectives that are normally established via a political process” [ED+09].

The development of MSP as a unique and distinct sector of environmental governance has resulted in an increasing amount of policy and intellectual discussion on the nature of MSP, its potential advantages, and normative norms for its implementation. The discourse has been diverse, attracting an interdisciplinary community of researchers who have covered topics such as the identification of key policy drivers [VMC09], reviews of initial MSP experiences [ED+09], and territory-specific analysis of institutional arrangements [Ard+08].

Furthermore, there have been a few attempts to describe the social side of MSP, such as the influence on coastal communities [FC08] and the participation of other stakeholders [RE10; Cal+12]. Some scholars have conducted evaluations of the growing legislative frameworks for MSP (e.g., [Mae08]) and the function of MSP in promoting certain economic activity [Jay10]. Given the precedence of its land-based relative, TSP¹, it is unavoidable that the focus has shifted to this to guide and explain the evolution of MSP.

A variety of organizations, including the Intergovernmental Oceanographic Commission and the Man and the Biosphere Programme of UNESCO, have acknowledged the potential advantages of this specific field of inquiry [ED07].

There, however, has been remarkably little interaction between practitioners or academics within the larger terrestrial planning community to date [Cla06]. While this growing body of work has been extremely useful in informing the emerging institutional structures and policy

¹The term “TSP” is used here to differentiate it from the previous practice of land use planning from which it emerged.

regimes for *MSP*, as a generalization, it has tended to lack the deeper reflexivity². Reflexivity has been a more common feature of the social scientific evaluation of *TSP*, which has resulted in the production of a substantial body of theoretical literature related to both the purpose and process of planning.

However, when we look at the burgeoning literature on *MSP*, we see relatively few attempts to connect larger theoretical arguments to practice and pose questions about the virtues of the developing institutions, practices, and governance regimes of *MSP*. While some work has begun to explore and direct issues about economic development and environmental protection to address potential marine spatial conflicts [PL04; Pla08], we believe that the necessity for practical engagement with *MSP* has not been underlined sufficiently, nor has it yet contributed substantively to spatial zoning management.

We are interested in triggering such a conversation by drawing on *TSP*'s long legacy of critical thought on the planning process and demonstrating how this may enrich the new area of *MSP* theory. The main goals of this chapter are to investigate the background of *MSP*, as well as to discuss the potential value of using zoning in *MSP* and to encourage further theoretical and practical discussion on reaching a negotiation-based decision-making platform for competing interests across the land/sea.

As a result, the chapter first investigates the contextual differences and similarities that must be recognized when exchanging *TSP* and *MSP* experience before moving on to investigate a variety of issues related to the planning activity process where theoretical exchange between the two regulatory systems could be instructive. Particular emphasis is placed on the UK's experience, which has been a worldwide leader in the establishment of formal *MSP* provisions and where the new system has been heavily influenced by terrestrial planning regulations. The chapter finishes by outlining a number of topics where theoretical interchange between *MSP* and *TSP* may be beneficial, as well as calling for a second generation of *MSP* research that would provide a critical turn to this thesis contribution in this burgeoning field.

2.1.1 The Status of the Coastal and Ocean Environment

News of increased degradation, ongoing over-exploitation, escalating conflict, the effects of climate change, and even unexpected environmental problems affecting our ocean and coastlines are reported every day. While there are some small-scale success stories, the race is on for a new paradigm and new method of doing business, the *ocean management business*. The continued deterioration of the global ocean and its shores endangers human well-being worldwide. Although coastal and marine ecosystems are dynamic, they are changing faster than ever [ass05].

Human pressures on coastal and marine resources jeopardize the supply of several ecological services critical to the well-being of coastal peoples and national economies. Coastal fishing stocks, like those of most offshore fisheries, have been severely reduced. According to the most recent UN Food and Agriculture Organization assessment, over 80% of commercially fished stocks worldwide are at capacity or over-exploited [FAO09]. According to a recent analysis of global fisheries' management, it is impossible to identify a single coastal nation that is not influenced by the overcapacity of fishing fleets or the perverse incentives for fisheries growth. While there is considerable disagreement about whether fisheries management can keep up with the increasing pressures to supply fisheries products for consumption, support agriculture, and even provide fertilizers for landscaping, even conservative fisheries managers generally agree that better management is required [Wor+09]. Depletion of fisheries stocks not only causes resource scarcity (and significant wealth inequality in many parts of the world), but also impacts the productivity of coastal and marine food webs, affecting the provision of other services important to humanity [Day+95; TD02].

Among these services are coastal development protection from erosion and storm damage, as well as boosting the value of recreational and tourism experiences. Biological modifications are linked to physical changes in the coastal zone and marine area. Habitat change persists

²By 'reflexivity' we refer here to both the overt reflection on previous experience to inform current practice, and a deeper exploration of the intuitive predispositions of those engaged in planning that predetermine conscious practice [HL02].

in the coastal zone, and degradation of habitats within and outside these systems contributes to reduced ecological functioning. Similarly, human activities far inland, such as agriculture and forestry, have an influence on coastal and marine ecosystems by diverting freshwater from estuaries and introducing land-based contaminants into coastal waterways (nearly 80 percent of the pollutant load reaching the oceans comes from terrestrial sources). These chemical changes have an influence on the viability and capability of coastal systems to offer services. Thus, changes in ecosystems and services occur as a result of land use, freshwater usage, and sea-based activities, despite the fact that these land-freshwater-marine links are frequently ignored (Figure 4).



Figure 4: Schematic of coastal system [OK20]

In general, management of coastal resources and human influences in these places is insufficient or poor, resulting in conflict, reductions in services, and diminished resilience of natural systems to changing environmental conditions. Inadequate fisheries' management occurs, frequently because **Decision-Makers (DMs)** are uninformed when marine resource management is inadequate, while coastal zone management seldom tackles problems caused by land-based sources of pollution and degradation [KA17]. Funds are seldom available to support long-term management solutions, resources become over-used and subsequently unavailable, and disputes escalate. A new paradigm, or, at the absolute least, a significant increase in really effective management, is urgently required. It seems doubtful that traditional management techniques and practices will be enough to tackle these ever-increasing, and sometimes freshly developing, issues.

But what is the primary priority for a brighter future for the ocean? Like many other studies and publications before and subsequently, the 2006 National Academy of Sciences book *Increasing Capacity Building for Stewardship of Oceans and Coasts: A Priority for the 21st Century* [Cou+07] highlighted fragmentation of management as one of the most persistent and significant challenges to sustainable marine management.

2.1.2 The History of Planning

However, to find the best answer for the above-mentioned question, it is necessary to emphasize on the crucial element in management. The critical and fundamental role in management is planning. Planning specifies how the objectives will be met and predicts the actions in advance, implying that planning should come before doing. According to George R. Terry, "planning is crucial to the three core management responsibilities of organizing, actuating, and controlling." Without the actions established by planning, there would be nothing to organize, no one to

actuate, and no need to control. The significance of planning in the management process is remarkable. To begin with, let go through the history of the planning.

The history of “planning” began in the late nineteenth century in Britain with the creation of land use planning under the influence of intellectuals such as Patrick Geddes. After WWII, the core characteristics of town and country planning were embraced and widely applied, particularly in the United Kingdom. While the system’s initial focus was on urban planning [Che96], it has now grown to provide a more complete system of land use control throughout both urban and rural regions, as well as to support to sustainable development goals and the implementation of good environmental management [ABS02]. The concept of sea use planning emerged much later, in the 1970s, [YF75]. The practical development of such a system, together with the reform of national land use planning systems and the rise of larger spatial planning in the context of an enlarged Europe with complicated social and economic integration to the need, has led to a resurgence of interest in public sector planning [Ald16]. Meanwhile, academic circles have largely ignored the concurrent growth of spatial planning for the economic sector and governmental agencies. The scope of planning, particularly “spatial” planning, has been hotly contested in recent years, but some agreement has arisen over the linked terms mentioned in Table 2.

Table 2: Definitions of “Planning” in terrestrial and maritime environments

Land-Use Planning: A field of public policy that deals with facilitating and regulating the use and development of land and property opportunities to balance economic development and environmental quality [Tau07]. Strategic plans with goals are frequently at the heart of such systems, which guide instruments like zoning, permits, and development control legislation. Other words for land-use planning that are often used in the English-speaking world include town and country planning and development planning. Urban and regional planning are both concerned with urban and regional land use planning.

Spatial Planning: A broader concept and activity than land-use planning that connects the former with economic, social, and environmental development policies, operating at all spatial scales but focusing on the regional level to provide a roadmap and framework for future regional development and resource allocation and investment. Commonly emphasizes the notion of balance and long-term polycentric growth [BCS10].

Strategic Planning: Organizational or sectoral planning aimed at increasing the long-term efficacy of operations. Based on some type of macro-environmental study of social, technical, and political trends, or scenarios that describe internal and external causes of future growth [Min94]. Depending on the function of the organization, there may or may not be a spatial component.

Sea Use Planning: The creation of integrated management plans for a marine area with the goal of harmonizing ocean-related regulations, such as protected area management and sectoral activities [SV91].

MSP: A strategic, forward-thinking planning tool for regulating, managing, and protecting the marine environment, including through space allocation, that addresses multiple, cumulative and potentially conflicting uses of the sea, ideally through a series of nested 20-year plans at different spatial scales, focused on marine regions and based on an ecosystem-approach [GL08].

2.2 Land-Use Planning

The concept of spatial planning has long been useful in controlling land uses [Tau07; DT+16]. In the 1950s, the concepts of “sustainable development goal” and a “system approach” began to be incorporated into land-based spatial planning in response to the dangerous environmental

consequences left by the industrial revolution, as well as the need to satisfy ongoing economic growth [Dou08; Smi+11; DT+16].

As previously stated, a substantially integrated land use planning system has emerged since its inception in the mid-twentieth century. It is beyond the scope of this thesis to go into depth on land use planning. Rather, the goal is to call attention to specific temporal and spatial aspects of land use planning that are particularly important in the current context. It is worth mentioning that most of the early development of thought and actual application occurred in Britain, beginning in the late nineteenth century [Che96]. The creation of a development planning system to guide the development control process was a prominent subject in the early phases of land use planning.

In contrast to many areas of environmental policy, where EC policy has pushed development, land planning systems have been affected by national agendas and needs rather than supra-national ones. As a result, land use planning has evolved autonomously at the national level, affected by each country's distinct legal, administrative, and socioeconomic settings [Ald16; FO09]. Despite the resulting diversity of planning systems, some characteristics are similar. These include the allocation of development types in metropolitan regions, such as industrial, commercial, and residential land.

Many systems also included provisions for restricting urban expansion through the use of green belt policies applicable to the rural-urban fringe, such as the restricted zones in the *Ley de Costas* (Spain, 1988-); the littoral band in the *Loi Littoral* (France, 1986-); and the *Galasso Law* (Italy, 1986-). To control development, national parks and other designations such as Areas of Outstanding Natural Beauty (England and Wales 1949-); the Conservatoire littoral (France, 1975-); landscape reserves and National Parks under the Federal Nature Conservation Act (Germany, 1998-); and protected dune areas (Belgium, 1995-) have been established.

However, such designations have been founded on a static conception, with a tendency toward rigidity of application. As economic development has advanced, such classifications have become less suited for dealing with dynamic economic, social and environmental change. Beginning in the United Kingdom in the 1960s and now widespread throughout Europe, a multilayered and flexible strategic planning strategy has evolved to better account for the dynamics of land use change. These new procedures have permitted comprehensive local or municipal plans to be developed within the framework of larger strategic plans generated at the county and regional levels, albeit there has been some difference in whether these plans apply to all land areas (both urban and rural).

Throughout much of Europe, the rise of these systems is related to the rebirth of regional governance, as well as with the increasing concept of regional competence in the context of economic growth [KMT04] and associated European policy including the ESDP, referred to above. The offshore oil sector had significant development in the 1960s, particularly in Scotland and Norway. This had a significant impact on terrestrial planning systems, with coastal planning regulations focused on huge sites like platform yards, oil and gas terminals, and gas processing plants.

In Scotland, the answer was the limited implementation of both national planning and extra local planning measures in Shetland and Orkney. Notably, in both instances, the law stretched over the land-sea interface (Zetland County Council Act 1974). In Sweden, in response to possible offshore growth, municipal terrestrial planning systems were extended to 12 nautical miles offshore in 1985 [Tau98]. Since 1996, Norway has had a regional coastal planning scheme [HS07].

German federal *Länder* have lately had their spatial planning rights extended to the territorial waters and, more recently, the EEZ. Significant development demands from tourism, renewable energy, ports, and shipping have resulted in particular planning policy guidelines from national governments to assist the formulation of land use plans for coastal regions. The ongoing pressure for large-scale infrastructure and industrial projects in the United Kingdom has now been recognized in the national planning system with the establishment of the Infrastructural Planning Commission, whose writ will run at sea and on land, constituting a second direct integration of land and sea use planning. It also highlights the link between spatial planning and

actual regional economic strategy.

Finally, land use planning evolved as a set of national systems that affected urban growth and, to a lesser degree, the rural-urban fringe. Rural regions are increasingly being incorporated into planning schemes. Transportation provision—railways, highways, airports, and huge ports—and coastal planning for the offshore oil sector are two famous instances of this process. There are strategic plans for really rural regions, as well as those developed long ago for large estates and accompanying rural farms, as well as those for places of landscape and recreational significance, such as national parks, on a more local scale.

As large-scale spatial plans for regions and devolved administrations are developed, the spatial framework for both urban and rural development should become explicit, longer-term, and more strategic [Ald16]. However, managing the implementation of real spatial planning systems and determining the essential linkages with economic regional, following the guidelines is a challenging task that requires a high level of institutional integration.

2.3 From Terrestrial Spatial Planning to Marine Spatial Planning

Figure 5 shows the long-term development of MSP measures. Figure 5 offers an overview of major shifts in thinking in TSP that drive the development of the present spatial planning methodology, and by then how this understanding might feed critical reflection on the growing MSP process. To begin, unlike MSP, which has tended to have natural scientific foundations both in the UK and overseas, the early years of TSP as a field were strongly founded on an art-based physical design approach intimately related to architecture and engineering.

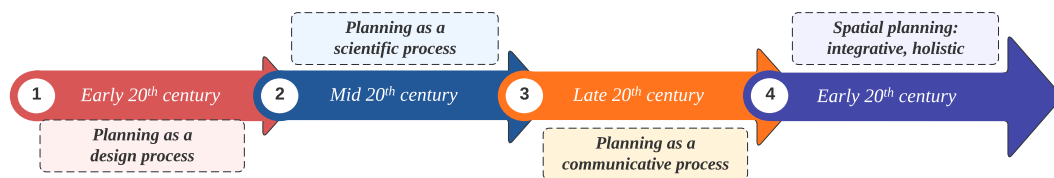


Figure 5: Changing planning paradigms

However, with the rise of notions like as [McL+69]’s system thinking, which depended on breakthroughs in the natural sciences and cybernetics of the time, this approach came under increased scrutiny in the 1960s. [McL+69] envisioned planning as a rational and scientific process, rather than a creative one, involving the meticulous collection and analysis of data pertaining to urban systems. Unsurprisingly, given its inspiration, this perspective on planning resonates with several areas of current MSP action and discussion.

Thus, it is beneficial to explore the broad critique of the systems approach to planning that has developed from a variety of points of view. For example, planning theorists have argued for many years (e.g., [FFS98; Lin18]) that the practicalities of most planning situations mean that time and resources are limited, and that the ambitions for rationality and comprehensiveness implicit in systems thinking are frequently replaced by a piecemeal, incremental, opportunistic, pragmatic, and politicized process. An alternative and even more fundamental line of criticism, based on complexity theory and associated notions of “wicked problems” relates to a growing acceptance of the impossibility of constraining the intense complexity of terrestrial planning situations and their intricate and ever-changing web of interactions [Hea06]. These lines of argument suggest that the search for rationality and comprehensiveness in both TSP and MSP is unrealistic or, at the very least, heavily bounded, implying that planning styles geared more towards trial-and-error experimentation, controlled risk-taking, long-term adaptation, and the *realpolitik* of governance may be more appropriate in such a “age of uncertainty” [Chr85; Plø04]. An underlying movement in philosophical thought from modernism inspires such ideas to

post-modernism in the late twentieth century, which brought with it the basic questions about the very concept of impartial rationality in planning procedures.

This underlying change is crucial because the “planning paradigm”, in both its art and science forms, shares the concept of the planner as an expert who, through the application of specialist knowledge and skill using powers granted by the state, makes decisions on behalf of the broad public about what types of environments are desirable to build. This notion of an unbiased or value-free planning process, however, has been increasingly challenged, with some arguing that planning is not only a *descriptive* process concerned with explaining the world, but also a *prescriptive* activity that intervenes in economic, social, and environmental processes for predetermined purposes. Planning is thus essentially political [Tay98].

As a result, a new vision of the planning process arose in the late twentieth century, which regarded the planner as a communicator and mediator between various interests, and planning as a transactive process aimed at facilitating communicative or collaborative action. This method, developed by authors such as [Hea20], recognizes the existence of various points of view and emphasizes the significance of consensus building in producing equitable, resilient, and implementable planning solutions. Such approaches are based on a growing understanding of the complexities of current planning issues such as urban regeneration, climate change, river basin management, and sustainable development, which have highlighted the need for coordinated or integrated action across traditional sectoral and territorial divides [CM03]. Facilitation, communication, multi-party cooperation, and listening skills are crucial traits for planners in this perspective of the planning process.

Although incorporated in many terrestrial planning systems across the world, this communicative vision of planning has been challenged as idealist, possibly deceptive, and even naive in its lack of acknowledgement of power in the planning process [HY00; TJGM10]. Thus, as terrestrial planning progressed, such discussions continuously changed and altered the planning process, and the contemporary paradigm that holds sway in many areas of the world, *spatial planning*, may be understood to reflect a synthesis and refinement of all that has gone before.

For example, Figure 6 depicts two of the key major axes of debate in TSP, highlighting on the one hand the extent to which planners should lead or facilitate the planning process, reflecting dominant issues of governance, power, and democracy, and on the other the epistemological basis of planning, which has shifted from the “softer” arts to an attempt to incorporate “harder” quantitative analysis. These dimensions may be considered as symbolizing some of the most powerful dialectic effects on modern spatial planning, which can be philosophically understood as aiming to find a balance between these numerous factors, which is why it is placed in the center of this figure. On the other side, we may conceptualize MSP as part of a more modernist, technologically driven industry, and its endeavor to moderate both scientific evidence and stakeholder interests [Gle+10].

The first large-scale development of integrated MSP, however, occurred in the 1970s, concurrently with the introduction of structural planning in the UK, but on the opposite side of the world, on the Australian Great Barrier Reef. This was a deliberate strategy that prioritized spatially constrained conservation and research zones while subjecting the vast majority of the Reef to two levels of general use zones. Except for the concurrent United States Federal Coastal Zone Management Act of 1972; offshore planning in the US State of Oregon; and regional planning in New Zealand’s Territorial Waters, there has been minimal full-scale development since then.

In Europe, the development of MSP systems, principally at national level, is most advanced in the core region of North West Europe, notably the Netherlands, Belgium, Germany and the UK [DE08; Dou+07], including separate powers for Scotland where two tiers of offshore planning have been established under a Marine Act (2010). Two distinct characteristics stand out when MSP systems are being developed. The first is the three-dimensional aspect of sea use planning, as opposed to the two-dimensional nature of land use planning. The design of the land under the sea—the seabed—might be simpler to grasp because all main use groups have defined unchanging qualities in respect to the seabed. Planning the water column, including the sea surface, includes overlays of the fundamental sea use groups, which are typically extremely distinct. Some of them, most notably pelagic fisheries and some sea routes, are not even static

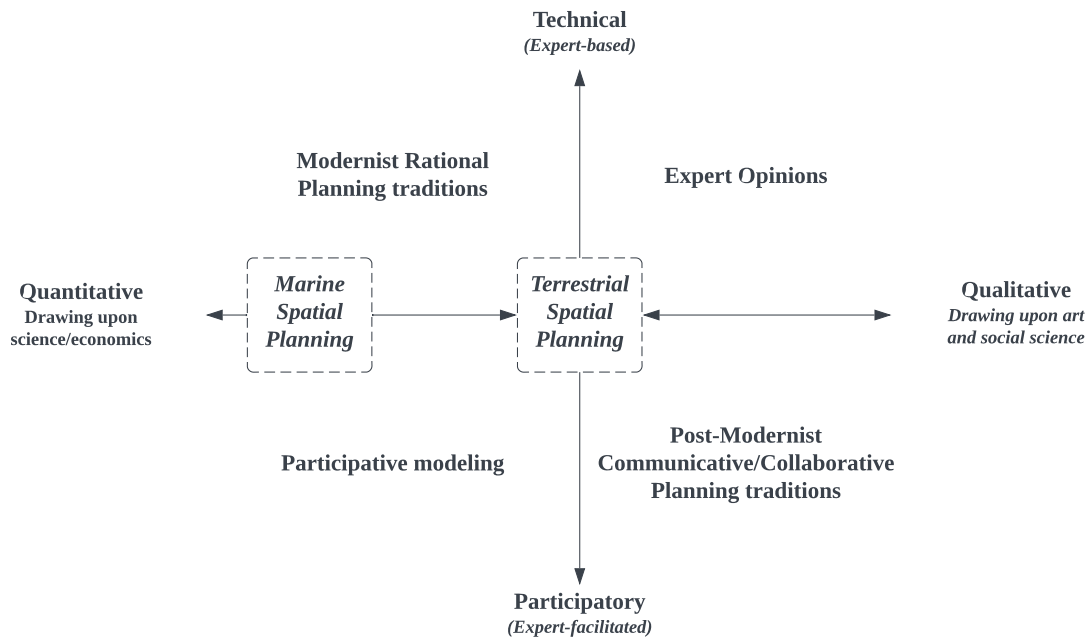


Figure 6: Spatial planning incorporates planning process traditions

with respect to the bottom underneath and may have no visible links to it.

The second distinguishing feature of **MSP** is its early relationship with an **Ecosystem Approach (EA)**. This is not only because the Great Barrier Reef, the first big example, prioritized marine conservation. Rather, it is linked to the post-1990s recognition of the critical relevance of marine ecosystem management for the world's dwindling fisheries as well as other sea uses. This insight did not exist at a comparable previous level of land use planning. This complicates the introduction of **MSP** since understanding of marine ecosystems is, with few exceptions, rather restricted.

It also emphasizes the significance of the relationships between spatial planning, on the one hand, and the parallel development of other tools in the environmental management toolbox, such as science and information management, as well as the various manifestations of assessment and professional practice. An important requirement for spatial planning is to provide accessible knowledge that represents the state-of-the-art of physical and ecological features of the zones at issue, existing and prospective users, and their potential consequences on ecosystems and on each other.

Marine planning strives for an optimal allocation for all relevant activities (historical, present, and future) based on balanced management decisions that take into account not only economic and social benefits, but also the characteristics of the various zones and the environmental effects produced by the activities currently taking place or planned [Mae+07].

As previously discussed, a set of spatial planning systems involving both land and sea are currently developing. Although land use planning systems are typically well established, marine use planning systems are still in their beginnings. These offshore planning systems, which are being developed in a number of nations, are concerned not just with the "urban" seas mentioned before, but also with the larger "rural" seas.

Clearly, integration across diverse planning regimes is required to maintain the coherence of objectives in both a temporal and spatial sense. There are two approaches to integration. The first is concerned with spatial planning frameworks in general and involves the integration of land and sea use planning systems. The second entails the operation of these systems within the framework of environmental management. As new offshore plans emerge or are considered across Europe, attention is focused on the coastal zone, where these contrasting planning systems intersect, often alongside a variety of other plans such as flood and coastal

erosion risk management plans, river basin management plans, and conservation plans.

Although the line between land and sea use planning differs from nation to country, as discussed below, there is still a need to promote consistency across this artificial barrier [FO09].

The interconnection of land and offshore systems promotes the need for integration of terrestrial and marine planning systems, despite administrative and institutional inertia making this integration challenging. Both systems must deal with situations that develop “out of their area”. However, in practice, there has traditionally been limited opportunity for local terrestrial interests to contribute to the use of maritime space, since national sectoral agencies have planned it with little local engagement [SS07].

The large-scale spatial development and regional seas methods being advanced in Europe also require that coastal zones be seen as integrated to larger socioeconomic and ecosystem-based systems and linked areas, rather than as boundary zones.

There are a variety of processes and tactics that can help integrate in the setting of the land-sea divide. Before considering the integration of spatial planning systems, particularly the function of **Integrated Coastal Zone Management (ICZM)** in bringing together land and marine systems, a review of traditional land and sea use planning systems is performed. Finally, an assessment of spatial planning integration within overall environmental management is given. This is done initially at the general concept level, which includes organizational and associated geographical scales, technical management inter-relationships with spatial planning, policy, and the function of strategic planning by organizations. **ICZM** and **Strategic Environmental Assessment (SEA)** are two examples. Other European environmental requirements will require cross-coast planning, as well as increased guidance and capacity training to promote greater awareness and knowledge of the needs of both marine and terrestrial components. This will cause solid connections among those engaged in establishing the various strategies.

It may also necessitate the employment of strong and suitable planning “advice” and accompanying assistance in order for marine and terrestrial planning groups to adjust their professional practice to each other’s demands. Among the mechanisms mentioned above, **ICZM** has been proposed by a diverse group of academics, policymakers, and policy documents to improve the integration of the planning system while drawing attention to the broader field of environmental management and the role of spatial planning within it. This is proposed not just at the European level, such as in the European Integrated Maritime Policy (COM 2007/575), but also at the national and regional levels.

In the United Kingdom, for example, while the Marine and Coastal Access Act 2009 is being created, great attention is being paid to this element. Despite the development of a European Recommendation and Strategy in the early 2000s, there is significant diversity in the understanding and application of **ICZM** at all levels (2000 and 2002, respectively). EU Member States have been urged to establish national **ICZM** policies to help achieve fundamental concepts of good practice and effective coastal resource governance, and nations bordering the Mediterranean must now comply with the recently adopted **ICZM** protocol under the Barcelona Convention.

To yet, however, much of the **ICZM** effort has come from grassroots, local initiatives. In practice, this local development and nurturing of **ICZM** has meant that **ICZM** initiatives and their *modus operandi* have been shaped and driven by local issues and needs, even if some of these initiatives and *modus operandi* have been partially funded from Europe in the context of a somewhat “loose” European **ICZM** concept. There is no “quick fix”, straightforward answer to employing **ICZM** as a vehicle for improving land-sea integration of planning systems because of the variety of **ICZM** across Europe and even within individual Member States. There is, without a doubt, no comprehensive system of coastal zone planning throughout the whole European area capable of “zipping” together land and sea-based planning systems.

There are a few common features of **ICZM** projects and initiatives that may assist to recognize the potential of **ICZM** as an integrative tool. On the plus side, **ICZM** places a clear emphasis on participatory planning and stakeholder participation, both of which could improve integration [SB09a]. Although the extent to which **ICZM** programs address land and sea components of coastal regions varies, most projects pay some attention to land-sea inter-linkages [Bal+08]. Furthermore, many **ICZM** efforts go beyond the planning process itself and involve capacity

building, collaborative projects between partners, and measures targeted at influencing human behavior and attitudes. However, many ICZM activities are limited to tiny segments of the coast and have minimal institutional support [SB09b; SS07].

Furthermore, with a few exceptions,³ they have a weak legal foundation and have little or no acknowledgment in either land or sea use planning possibilities [Tau07]. Current ICZM practice has also failed to adequately address the allocation of the coastal zone to fulfill its objectives.

With ICZM practice at a stalemate, several policy documents and policymakers argue that the ICZM principles, rather than the *ad hoc* ICZM projects themselves, are the distinguishing feature of ICZM and should be the focus of land-sea planning integration.

Given that the ICZM principles were designed as principles of good environmental governance [Com02]), these do indeed have considerable credence in the land-sea planning integration context, particularly as the ICZM principles include participatory planning and wide stakeholder engagement. Given that both ICZM and MSP have been identified to share similar aims of reducing jurisdictional fragmentation among governmental levels and sectors, a variety of international and national programs and contexts have recognized ICZM principles to facilitate MSP. This includes, for example, the PLANCOAST handbook on Integrated Maritime Spatial Planning for the Adriatic, Baltic and Black Sea areas [SZ+08]. On the contrary, others suggest that MSP can make the ICZM principles more operational by better defining what they imply in space and time [DM09].

While ICZM may not be the cure for land-sea integration as academic research suggests, integration between sectors and plans may be encouraged in the near term by needs to comply with other, tougher EU regulations. This includes the need for all statutory plans (including terrestrial and marine ones) to undergo SEA under the SEA Directive (2001/42).

Compliance with the demands of the Habitats Regulations for the marine site appears to have provided a legally binding driver for the partnership work and the associated coordination of “relevant” and “competent authorities” plans in the Severn Estuary, a major coastal plain estuary in the UK [BS10]. In relation to the Water Framework Directive, [HW02] and [PK03] have suggested that the Directive will provide for new networks and governance arrangements as the river basin management process involves a diverse range of water environment users in both the formulation and implementation of river basin plans. Given the river basin plans’ catchment-to-coast view and tight links to land-based planning systems, these plans are an important piece of the “integrating” coastal zone puzzle.

In a broader context, there are five areas of concern in the promotion of integration.

1. The organizations and decision-making involved, as well as related geographical scales;
2. The relationships between technical management tools and associated professional practice, on the one hand, and spatial planning, on the other;
3. The role of policy;
4. The role of strategic planning by organizations in the public, private, and voluntary sectors;
5. The role of strategic planning by organizations in the public, private, and voluntary sectors.

It is critical in this portion of the chapter to situate MSP within the larger framework of environmental management when discussing the integration of land and MSP. The organizations involved, as well as the relevant geographical scales on which they operate, serve as the beginning point. The historical reality is that the emergence of MSP over the last four decades, first as an idea and now as an emerging reality, has been primarily associated in Europe and elsewhere with the extension of state jurisdiction to 200 nautical miles seaward of the coast, as agreed in

³On 22 January 2008, the parties to the Barcelona Convention in the Mediterranean Sea chose a clear legal framework for ICZM by adopting a Protocol on Integrated Coastal Zone Management. ICZM motivated the Protocol not just by threats to coastal zones caused by climate change and the recognition that the coastal zone is a shared natural and cultural legacy that should be protected for the benefit of present and future generations.

the 1982 [United Nations Convention on the Law of the Sea \(UNCLOS\)](#). In Europe, the national scale, or collection of scales, is the most important. However, as actual application advances, the new scales will be mostly sub-national and local, such as those connected to ports, fisheries, and marine conservation, as well as the national and local organizations principally responsible for these applications.

The need to protect biological diversity and establish networks of [Marine Protected Areas \(MPAs\)](#) by 2012 is one of the driving forces behind the introduction of [MSP](#), as reflected in decisions taken by the Conference of the Parties in the 1992 [Convention on Biological Diversity \(CBD\)](#), in the Plan of Implementation accepted at the 2002 World Summit on Sustainable Development, and at the EU level.⁴ Parties decided to employ Integrated Marine and Coastal Area Management as the best framework for addressing human impact on marine and coastal biological variety and promoting conservation and sustainable use of marine and coastal biological diversity at the [CBD COP2](#) in Jakarta (1995). Institutional, administrative, and legal procedures should be developed, as well as plans and strategies for marine and coastal regions, for this integrated management. In addition, the EU Marine Policy asks for [MSP](#) to regulate competing maritime economic activity and to protect biodiversity. It will be critical for any policy to be based on practical realities and influenced by in-depth stakeholder interaction.

Organizational strategic planning—not to be confused with land and [MSP](#)—is a vital role that includes policy creation and implementation. In a world where quick appears to play a prominent role in both the public and private sectors, it is critical to emphasize that significant organizations in all sectors employ long-term planning techniques that include their operations. Oil and shipping businesses, government departments and organizations, and the International Council for the Exploration of the Sea are all notable examples. Finally, understanding the time scales involved in the evolution of spatial planning systems is critical. As previously stated, notions in a maritime setting are founded in the establishment of the [UNCLOS](#) process in the 1960s and 1970s, along with the theory and implementation of coastal zone management and more strategically oriented land use planning. However, with the notable exception of the Great Barrier Reef, it has taken four decades for definite and functional national [MSP](#) systems to evolve.

2.4 Zoning

By definition, ocean zoning decreases fragmentation by pushing managers from all sectors that use marine resources and ocean space to think strategically and plan for long-term use. Proper management is crucial in the face of a climate-changed and difficult future with over 8 billion people to house and feed. Only healthy and well-functioning ecosystems can adapt to changing environmental conditions while continuing to provide the commodities and services that keep life on Earth running. Only laws and standards designed with the active involvement of those who will be affected will be acceptable, resulting in the least amount of conflict and harm to national security. However, “zoning” is a collection of regulatory mechanisms used to execute [MSP](#), which are similar to land-use planning in that they outline authorized uses throughout the target environment(s). Different zones accommodate various purposes or degrees of use. Regulations, like municipal zoning, address restrictions, authorized uses, or both. Because zoning restrictions are always area-based, all [Zoning Plans \(ZPs\)](#) are depicted on maps. Most recent publications on maritime area management, for example [[Gub96](#); [Sal+00](#); [Cou01](#)], allude to the notion of zoning to separate conflicting uses or to protect sensitive, biologically significant, or recovering regions free of usage. [[Ken03](#)] explains why and how zoning was first implemented in the [Great Barrier Reef \(GBR\)](#). Zoning has been widely considered as the cornerstone of [GBR](#) administration since the first [GBR ZPs](#) were developed in 1981. The following are the broad aims of zoning in the [GBR Marine Park](#):

1. conservation of the Great Barrier Reef;

⁴The EU Birds Directive (1979) establishes a framework for identifying and classifying [Special Protection Areas \(SPAs\)](#) for migratory birds that are uncommon, vulnerable, or occur on a regular basis. The Habitats Directive (1992) mandates member states to choose, designate, and safeguard [Special Areas of Conservation \(SACs\)](#) that sustain certain natural habitats or species of plants or animals. Natura 2000’s goal is to establish networks of [SACs](#) and [SPAs](#) throughout the EU.

2. management of Marine Park usage in order to safeguard the GBR while enabling appropriate human use of the GBR Region;
3. the regulation of activities that exploit the resources of the GBR Region in order to minimize their impact on the GBR;
4. the reservation of some areas of the GBR for public appreciation and enjoyment;
5. the preservation of some areas of the GBR in their natural state, untouched by man except for scientific research purposes.

The Act requires GBR ZPs outlining the reasons for which sections of the Marine Park may be used or entered. They permit legitimate activities like as tourism, fishing, boating, diving, and research to take place in certain places while also separating conflicting uses by zones and determining the appropriateness of particular extractive activities (refer to the zoning matrix in Figure 7). A multiple-use zoning system protects specific regions while allowing a variety of reasonable uses, including certain extractive industries, to continue in other zones. Zoning in the Marine Park has developed and altered since the initial ZPs, as have other management measures. Significant experience with zoning has now been obtained in terms of what has worked effectively and what has not, both inside the GBR and in other Australian MPAs. Many characteristics, such as enabling but segregating conflicting usage, have shown to be quite effective. However, experience has revealed that some zoning elements required to be refined; also, what works in the GBR may not necessarily function elsewhere and may need to be modified in other maritime circumstances.

ACTIVITIES (see Zoning Plan for full details)	General Use Zone	Habitat Protection Zone	Conservation Park Zone	Buffer Zone	National Park Zone	Preservation Zone
Boating, diving	Yes	Yes	Yes	Yes	Yes	No
Collecting (e.g. béche-de-mer, shells, coral, aquarium fish)	Permit	Permit	No	No	No	No
Line fishing	Yes	Yes	Yes	No	No	No
Mesh netting	Yes	Yes	No	No	No	No
Bait netting	Yes	Yes	Yes	Yes	No	No
Trolling (for pelagic species)	Yes	Yes	Yes	Yes	No	No
Spearfishing	Yes	Yes	No	No	No	No
Pole and line tuna fishing	Permit	Permit	No	No	No	No
Trawling	Yes	No	No	No	No	No
Traditional fishing and collecting	Yes	Yes	Yes	Yes	Yes	No
Traditional hunting	Permit	Permit	Permit	Permit	Permit	No
Cruise ships	Yes	Permit	Permit	Permit	Permit	No
General shipping (other than shipping area)	Yes	No	No	No	No	No
Crayfishing	Yes	Yes	No	No	No	No
Mariculture	Permit	Permit	No	No	No	No

Islands: All Commonwealth owned islands in the Far Northern Section are zoned "Commonwealth Island Zone". See Zoning Plan for full details.
Zoning: This map does not purport to show zoning for areas outside the Great Barrier Reef Marine Park Far Northern Section.
Emergencies: Access to all zones is allowed in emergencies.

Figure 7: Zoning matrix for the Great Barrier Reef Marine Park's Far Northern Section [Day02]

However, to generally speaking, the main purposes of ZPs in marine spatial zoning management are aimed to:

1. protect biologically and ecologically important habitats, ecosystems, and ecological processes;
2. clarifying the human activities' relation by compatibility matrix to separate conflicting human activities or combine compatible human activities;
3. protect the natural values of the marine management area while also allowing reasonable human uses of the area;
4. location and allocation areas for reasonable human uses while minimizing the effects of these human uses on each other and nature;

5. preserve some areas of the marine managed area in their natural state, undisturbed by humans except for scientific or educational purposes;
6. identify areas where financial investments in certain sectors (activities) should be beneficial [ED+09].

The difficulty of present analytical techniques to **MSP** to incorporate several types of zones at the same time to reflect the variety of management measures or conservation activities being considered as part of a spatial plan is a fundamental restriction. Indeed, several conflicting stakeholders carry out a wide range of management measures. Furthermore, human activities take place within a matrix of different land and sea uses, many of which are in conflict with marine spatial goals. Zoning is a typical management method used to define regions for certain functions, both geographically and temporally [Rah+78a; Wat+09b]. When considering these opposing objectives, **ZPs** give an explicit strategy to resolving conflicts between activities and calculating trade-offs [Hal+08].

2.5 Conclusion

To sum up, **MSP** is an ecosystem-based spatial organization technique that tries to allocate marine spatial to various sectors in order to guarantee human activities at sea are efficient, safe, and sustainable. When a collection of resources, rights, burdens, advantages, or expenses held temporarily in common by a number of sectors must be dispersed among them, marine spatial allocation difficulties occur. This problem has turned into a political flashpoint, spurred by governmental power struggles as well as the ever-increasing demand for maritime space from both conventional and developing marine users. In this case, we should make a decision about where and how the resources should be allocated. The difficult goal of this thesis would be to establish an effective allocation technique inside a larger geographical decision-making process, where maritime users engage with one another in order to reach a spatial allocation agreement despite their competing aims. Therefore, to begin with, the problem formulation, like identifying stakeholders to participate in the **CR** process, classifying the stakeholders, identifying the constraints, and **GIS** data collection, should be defined. Mathematical modeling is the conversion of problems from an application zone into manageable mathematical formulations using a hypothetical and arithmetic analysis to give perception, solutions, and advice for the application developer. Mathematical modeling is useful in a variety of applications because it provides accuracy and strategy for problem-solving, while also allowing for a systematic knowledge of the system being modelled. It also enables improved system design, control, and the optimal use of contemporary computer capabilities. Hence, It should model this formulation using the mathematical modeling to determine desirable spaces for each marine use. However, the main research question here is developing the exact linear mathematical model for resource allocation in the **MSP**. To take all this into account, in the first step, we start the next chapter by defining the problem formulation and presenting some exact methods to develop and solve the spatial zoning model.

Chapter 3

Exact Zoning Model for Marine Spatial Planning

Contents

3.1	Introduction	22
3.2	Literature Review	23
3.2.1	Spatial-Decision Support System	24
3.2.2	Zoning in a Geographical Information System Framework	25
3.2.3	Data Modeling in Geographical Information System	26
3.2.4	Resolution Approaches	29
3.3	Multi-Objective Single New Marine-Use Zoning Problem in Marine Spatial Planning	31
3.4	Mathematical Formulation	33
3.5	Exact Methods	36
3.5.1	Buffering Technique	36
3.5.2	Weighted Sum and AUGMECON2	37
3.6	The Experimental Validation	39
3.6.1	Data Generation	39
3.6.2	Experimental Protocol	42
3.7	Computational Results	43
3.8	Conclusion	49

ABSTRACT

As mentioned in Chapter [2], *MSP* has lately gained popularity as an effective decision-making tool. *MSP* is a long-term strategic process that brings together many competing ocean users with the goal of balancing between simplifying choices on where, when, and how each sustainable use of marine resources could take place and protecting the coastal and marine environment. To tackle this problem, one of the issues in *MSP* is determining the best zone to locate each available activity while keeping other existing activities' constraints and compatibility relations in mind. The majority of spatial zoning techniques especially for multi-uses are written as non-linear optimization models with multiple objectives, which are often solved using stochastic search algorithms, resulting in sub-optimal results. In this chapter, we suggest modeling the problem as a *MOILP* for a single new activity to determine an optimal zone to locate it while taking into account the fixed locations of the other existing activities in this study. The model is developed for raster data and seeks to maximize the interest of the zone dedicated to the new activity while also optimizing its spatial compactness. We investigate two resolution methods: first, a *Weighted Sum (WS)* of the two objectives, and second, an interactive approach based on an enhanced augmented version of the ϵ -constraint technique, *AUGMECON2*. We do experiments on artificially created data to validate and investigate the model. Our experimental results reveal that *AUGMECON2* is the most promising strategy in terms of relevance and diversity of solutions, compactness, and computing time.

3.1 Introduction

MSP is to the ocean what land-use planning is to the land: a method of organizing activities that aims to prevent conflicts between actors and activities, develop synergies, and reduce environmental consequences. For many years, maritime activities were not supervised because the sea was thought to be unlimited and its resources infinite [DC+09]. However, it is now obvious that human activities have an influence on the maritime environment (pollution, biodiversity loss, etc.) and its resources (overfishing and pollution). As a result, sectorial administration of these activities has gradually arisen (quotas for fishing, traffic management, ...). However, each sector created its own planning, with little regard for continuity with the others. This is where *MSP* attempts to rise above these constraints as a systemic approach whose purpose is to organize human activities in the ocean sustainably while accounting for interactions between diverse activities and stakeholders [Aga15].

One activity of *MSP* is related to marine zoning. Its goal is to determine areas in the sea for locating different types of uses (e.g., fishing areas, restricted areas, ...). The interest in locating such a use in a specific area of the ocean depends on various elements, like the distance to other activities, the distance to the coast, and possibly other environmental factors that influence the optimal location of the activity (interest for an activity, risk of polluting, fauna density, wind probability, ...) [Aga10].

Marine zoning is therefore a set of legislative actions that go in the way of *MSP* [Aga10], which is a more comprehensive idea that includes an ecological, social, and economic objective cyclical process for the study and allocation of space and time, as needed [Ade+19]. *MSP* and marine zoning are used to achieve various objectives in various environments. As the spatial zoning in *MSP* is a multi-objective and multi-use location-allocation problem, developing a linear mathematical model could be impossible. To address this issue, this chapter addresses the ocean zoning issue for a new human activity in order to improve *MSP* implementation. This activity considers the impact of existing activities occurring in the same maritime region and at the same time. A crucial element in this problem is to introduce spatial compactness and interest objectives. These objectives are used to address the problem of locating and allocating the new activity not only at the highest possible interesting zone map but also at maximum compactness.

Therefore, a challenge lies in developing and implementing linear mathematical programming

for this problem by considering suitable combined **Multi-Criteria Decision Making (MCDM)**, **Multi-Objective Optimization (MOO)**, and **GIS** techniques. Generally speaking, optimization techniques (another subset of **MCDM** techniques) can be combined with **GIS** to support the spatial design of marine **ZPs**. The purpose of this chapter is to express the zoning issue in **MSP**, model it using a raster-based **MOILP**, and then suggest and compare different exact resolution techniques.

This chapter is based on the published article [Bas+21] and structured as follows. Section [3.2] provides a review of the literature on the topic and a summary of the contributions. In Section [3.3], the problem is defined at hand. Section [3.4] proposes its **MOILP** formulation, while we suggest different resolution methods in Section [3.5], which may lead to different results. In Section [3.6] an experimental setting is described to solve the proposed formulation with computational results on artificially generated synthetic instances shown in Section [3.7]. We draw conclusions in Section [3.8].

3.2 Literature Review

The world's seas are vital to both economic and food security, as well as a worldwide conservation priority. Over the last several decades, the demand for ocean space for many uses has skyrocketed due to the rise of both conventional uses (such as fisheries and maritime transportation) and new applications (such as energy development and aquaculture). Overfishing and ecosystem degradation are causing a fast ecological change in the world's ocean resources, with far-reaching consequences. The resources, the people who use and consume them, the production processes, the management institutions, the environment that sustains them, and the local, national, and international legal instruments that control their ownership and usage will all be affected. Low-income people in different countries will be hurt the hardest when their frail buying power and frequently precarious access to the resources on which they rely for food and livelihoods is further diminished [All]. Competition and conflict for space and resources characterizes the waters [Sal+07]. Because of some of the highest rates of population growth, as well as increasing food and development needs, marine areas are now experiencing increased levels of conflict and social unrest as a result of differing and uneven levels of economic development, resource use, and technological change within a country. Economic and technological advancements over the previous 15 years have resulted in significant disparities in access to maritime resources [PBM+14; Pom+07].

Marine space uses and abuses such as fisheries, tourism, aquaculture, energy, and land-based pollutants interact in complicated ways, as do natural catastrophes, climate change, and climatic variability [FMM11]. Increased activity in the ocean environment has resulted in two types of conflict in the region: (1) conflicts between human uses (user-user conflicts), and (2) conflicts between human uses and the marine environment (user-environment conflicts, such as aquaculture development and mangrove clearing). These disputes erode the ocean's ability to supply the essential ecological services on which people and all other species rely.

To address this growing competition and conflict, a variety of ocean and coastal management paradigms have been proposed and implemented in many regions over the years, including conventional fisheries' management, Ecosystem Approach to Fisheries, Ecosystem Approach to Fisheries Management, **Integrated Coastal Management (ICM)**, **MPAs**, regional ocean governance, **ICM**, and **Ecosystem Based Management (EBM)** [Ves+11]. Despite the language of integrated management, these paradigms have had inconsistent success, most times because of real separate sector management practices. Recently, spatial planning as a new paradigm for influencing the placement of human activities in space and time has been introduced.

Spatial planning has traditionally been used to manage land usage [Tau07; DT+16]. By recognizing the dangerous environmental consequences left by the industrial revolution, and while needing to satisfy the ongoing economic growth, the concepts of "sustainable development goals" and an "system approach" began to be incorporated into land-based spatial planning in the 1950s [Dou08; Smi+11; DT+16].

Similarly, in the marine environment, even though spatial management of fisheries has long

been standard practice, the increasing number of additional economic uses has prompted the need for a more precautionary, comprehensive, and long-term approach to planning [SPS00; Nor10].

3.2.1 Spatial-Decision Support System

As explained before, the area of “resource allocation” deals with the spatial distribution of (natural-) resources such as water or land. On the one hand, to ensure the effective development of spatial distribution in MSP, several key phases should be fulfilled, as shown in Figure 8.

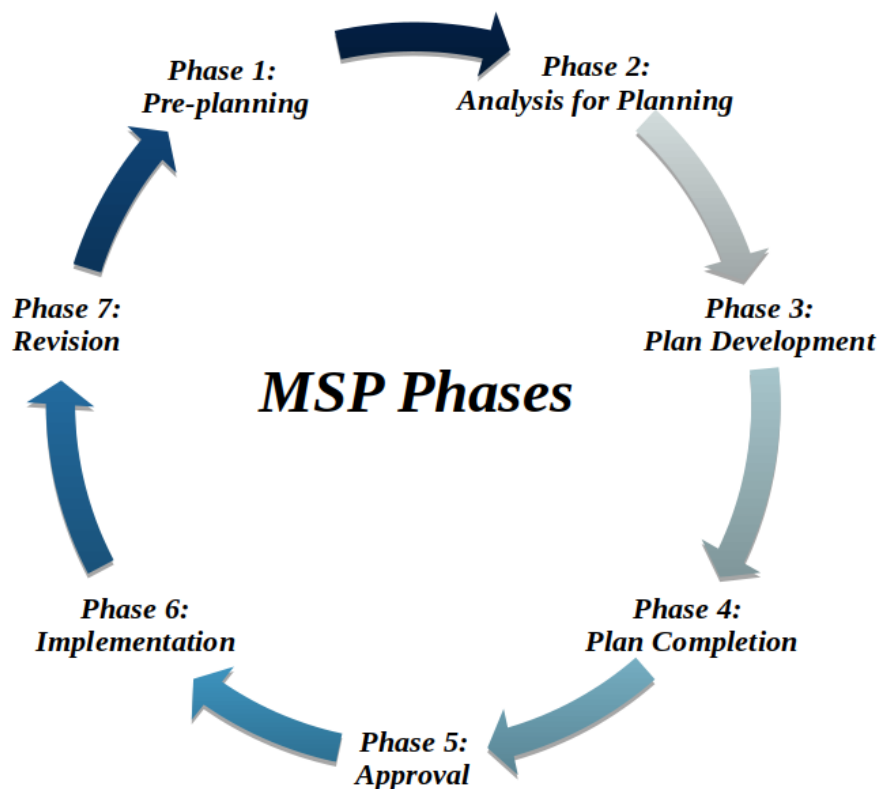


Figure 8: Different phases of MSP

On the other hand, implementation of MSP begins with a *Pre-planning* phase (Phase 1) that includes the definition of planning objectives, conflicting uses, and, very importantly, the organization of stakeholder engagement in the process [ED+09]. *Analysis for planning* (Phase 2) pertains to the definition and analysis of both present (As-Is) and future conditions (To-Be) (e.g., ecological, oceanographic), by collecting and mapping data on existing biophysical conditions and human activities, and identifying corresponding overlaps including conflicts and compatibility. Based on the collected information, having developed and analyzed alternative scenarios according to stakeholders’ preferences, a desired future spatial vision should be selected. In *Management plan development* (Phase 3), while management actions are spatially explicated, an ocean zoning scheme is developed to support their implementation [Aga10; Bas+20]. Ocean zoning should be based, not only on conservation targets but on socio-economic considerations [TT11]. This can be done by incorporating human uses early in the progress, e.g., by optimization algorithms [TT11]. Having the plan completed and approved (Phases 4 and 5), implementing the plan starts (phase 6). Then, evaluating and adopting the plan will make it ready to use (phase 7).

Nonetheless, spatial distribution is a complex issue, as it often involves multiple stakeholders with conflicting goals and objectives. Therefore, much attention has been paid to solving a different range of problems in this domain, like land/marine use allocation problems with MCDM.

Recent research on spatial planning focused on combining MCDM with a GIS. This appears to

be a powerful combination since land/marine use allocation problems both involve multiple objectives and criteria, as well as geographically dependent spatial attributes [Aer02; AH02; Cov99; CC00a; CC00b].

Both GIS and MCDM techniques are derived from relatively technical areas of geography and operations research. Practical use of such techniques often requires a thorough understanding, and non-technical DMs may find using these techniques difficult. However, combined GIS-MCDM techniques can be operationalized for non-technical users by integrating these techniques in Spatial-Decision Support Systems (SDSSs) that are dedicated to a user. A series of SDSSs were built using only GIS-based mapping and visualization tools to provide background information on the planning area. Some SDSSs successfully combined Multi Criteria Analysis techniques (subsets of MCDM) with GIS, enabling the interactive evaluation of spatial land/marine use plans against a pre-defined set of criteria [UJ03; PD93]. The combination of MCDM-GIS can be useful in SDSSs environment when both the alternatives have been clearly defined [RH98].

3.2.2 Zoning in a Geographical Information System Framework

Comprehensive Ocean Zoning (COZ) has the potential to be a powerful tool for integrating marine management at ecosystem scales. In Marine Ecosystem And Management, they look at areas where zoning is used and answer the following questions (for more details, readers could refer [Wil+20]):

1. What exactly is COZ, and what advantages does it offer?
2. What distinguishes zoning at the water from zoning on land?
3. How may zoning be accomplished considering various property-rights regimes?
4. Given the fairly static nature of the zoning technique, how should the dynamics of marine ecosystems be addressed?
5. What are the most difficult aspects of zoning implementation?

However, here we are focusing on the answers to a few numbers of the above questions. Ocean zoning is a collection of regulatory mechanisms used to put MSP into action. Marine spatial plans, like land-use plans, identify authorized uses in all regions of the target habitat or ecosystems. Diverse zones accommodate different purposes or degrees of use, such as fishing, oil drilling, shipping, conservation, and research. Ocean zoning regulations, like municipal zoning regulations, address limitations or approval for such uses. Because the restrictions are area-based, the ZPs are depicted on maps.

Contrary to popular belief, maritime zoning and MSP are not synonymous. According to [ED+09], who led a UNESCO study to examine MSP and its potential to encourage ecosystem-based management, ocean zoning is simply an instrument. Marine planners and environmentalists are increasingly seeing the value in adopting zoning to assist integrate marine management and make it more ecosystem-based. They proposed that COZ could help to resolve conflicts within and across interest groups, including ensuring that these activities have a strong interest in the long-term health of resources.

Today, many nations are at various stages of designing and implementing MSP and marine zoning. While MSP and zoning are increasingly recognized as important ocean resource management measures. Governments in the areas are restricted in their implementation due to a range of capacity, technical, legal, and institutional problems. Furthermore, numerous countries that have already begun to adopt MSP and zoning are having difficulties with enforcement and legislative backing. These measures will be successful only if governments provide the necessary legal instruments to enforce and implement regulations and policies at the national and local levels for inter-agency, multi-sectoral, and transboundary decision-making and coordination.

The first phenomenon mentioned above was made “zoning” another cornerstone of MSP, which, in this thesis, is considered a management tool in the wider context of MSP [Day+12]. Zoning is the process of locating and partitioning a territory into zones that allow or prohibit certain activities to maintain the supply of an overall set of ecosystem services offered by the

zoned area. Zones are often defined utilizing a variety of analytical and decision support techniques (e.g., GIS) [Ade+19]. One of the primary goals of GIS [Mas+21; SP21] is the identification of regions and the partitioning of space using spatial analysis techniques. Zoning is an essential part of MSP and an effective management tool [Day+12; Rah+78b; KOR96; LHF00; Day02; RZ03; SA04; FHCS05; Hal+08; La05]. The ramifications of allowing several conflicting and potentially competing activities to occur at the same site require special consideration during the zoning process. ZPs offer a detailed method for resolving conflicts between activities and identifying trade-offs while balancing opposing interests [Hal+08]. Zoning is used across the world to serve the many goals of marine parks (most notably in Australia's GBR Marine Park [La05]).

Overall, COZ may give advantages over other maritime management approaches. These possible advantages include:

1. Moving management away from fragmented sectoral initiatives and toward integrated, effective EBMs that encompasses all ocean users and consequences;
2. Overcoming the limitations of small-scale protected zones;
3. Recognizing the relative ecological importance and vulnerability of various places;
4. Allowing for compatibility with terrestrial land use and coastal planning; Outlining private sector roles, responsibilities, and market potential; and reducing conflict between incompatible uses.

On one hand, since MSP problems are geographical in nature, they may be organized and handled utilizing GIS features and mathematical models. GIS not only allows for the administration, modification, and spatial analysis of land/marine use data, but it also provides a platform for visualizing, exploring, and assessing different land/marine use scenarios. On the other hand, with developments in GIS and computer technology, several spatial optimization methodologies have been presented for land use planning during the last few decades and less for MSP [YZM18]. Multiple concerns have been considered for different applications in land use planning, including compactness of selected regions, contiguity of equal land use, compatibility of different land uses, and environmental and ecological impacts, among others, which could be used for MSP as well [Aer+03; LCJ08; Sjv04a; Ön+16]. Cartographic representations, for example, which allow for the comparison, superimpose maps, and visualization of siting outcomes, are among the GIS benefits. Figure 9 displays an actual MSP map as well as all competing applications in a given maritime area.

The starting point of spatial planning is geospatial or geographic data, about the geographic location of features and boundaries on the earth's surface, such as natural features, land areas, ocean surfaces, etc. That is, spatial data represents data related to or containing information about locations on the Earth's surface. Spatial data is a foundation of a number of decision problems such as land-use planning [GC20], biodiversity conservation planning [Yan+19], maritime spatial planning [Pin+20], or military planning [LSW03].

3.2.3 Data Modeling in Geographical Information System

As well, we know the importance of data and how the representation of data should be understood in order to achieve better results. Referenced information, especially geographic, is managed, analyzed, and displayed using the GIS, a computer-based tool. Spatial data is a data structure or type available in GIS, and it can be maintained either as raster data or vector data. The relationship of geodata can be easily visualized and understood in the form of maps, charts, and reports, among others, by the utilization of GIS. Raster data is quite useful as it is applicable in a vast range of applications. The main categories under raster data include rasters as basemaps, surface maps, thematic maps, and features attributes. Vector-based files are also commonly used, and sometimes users do not realize it. For instance, font files are widely used, yet some do not realize they are vector graphics. The fonts remain clear even after the text size is increased, either it is to be viewed online or offline, for instance, in a Word document. Raster data and vector data have differences, including the data to be represented and the mode of data representation. The definition, from a GIS perspective, will be divided into three sections: In information theory, a description of the rules by which data is defined, organized, queried, and updated within an

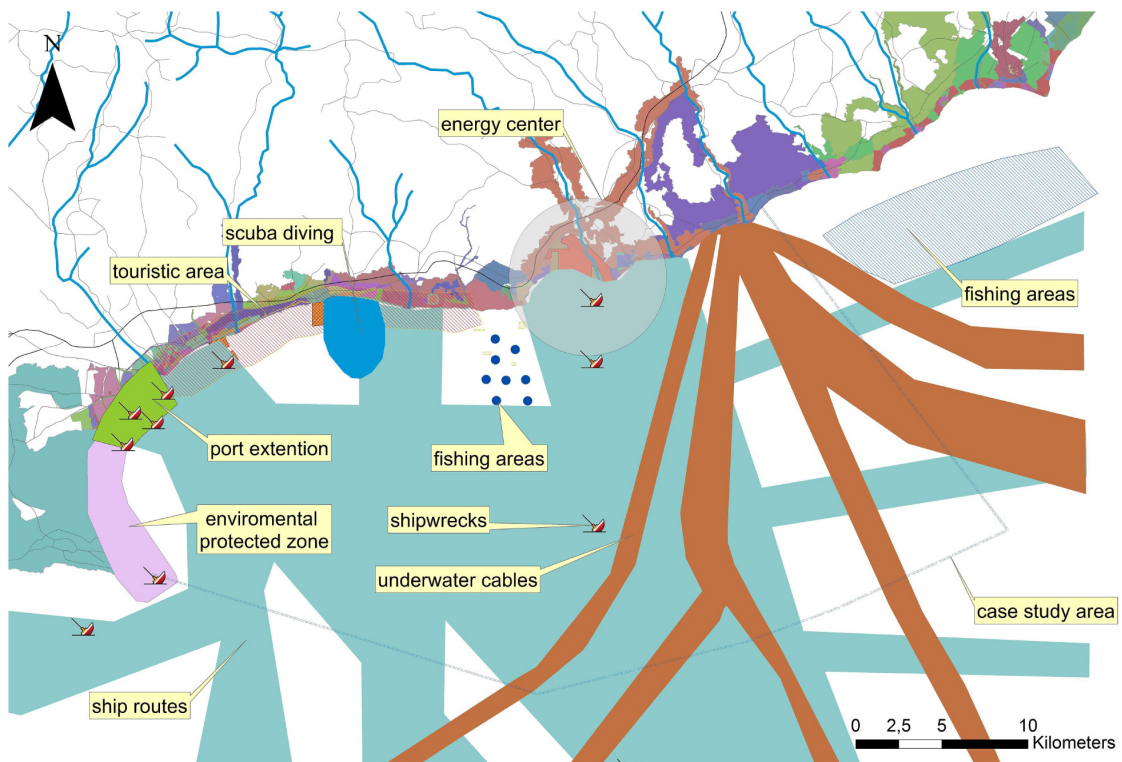


Figure 9: Real MSP map [Bas+21]

information system (usually a database management system). In ArcGIS, a set of database design specifications for objects in a GIS application. A data model describes the thematic layers used in the application (for example, hamburger stands, roads, and counties); their spatial representation (for example, point, line, or polygon); their attributes; their integrity rules and relationships (for example, counties must nest within states); their cartographic portrayal; and their metadata requirements. With respect to the data model, the vector and raster data model are defined as follows as shown in Figure 10:

1. Vector data model: A representation of the world using points, lines, and polygons. Vector models are useful for storing data that has discrete boundaries, such as country borders, land parcels, and streets.
2. Raster data model: A representation of the world as a surface divided into a regular grid of cells. Raster models are useful for storing data that varies continuously, as in an aerial photograph, a satellite image, a surface of chemical concentrations, or an elevation surface.

Raster data is more detailed because it represents square areas. In this case, they describe the interiors in detail rather than the boundaries of their representation, which is the situation with vector data. Vector data are more preferable when storing captured spatial details, while raster data should be applied for analyzing stored data like temperature that vary with location. Satellite imagery and aerial images are also stored in the raster data format in the GIS. When the geospatial data needed is supposed to be more specific, raster data can be used, although it might not apply to all aspects, for instance, the latitudes and longitudes represented in the vector data.

Vector data and spatial data are primary structures of spatial data in the GIS. The nature of the data to be represented should be considered before choosing the structure to apply. Accuracy is a crucial factor as data restructuring in raster data can cause spatial inaccuracies compared to vector data which remains the same and maintains quality even after scaling is done. The representation of raster data is on a grid matrix, while vector data uses vertices or sequential points.

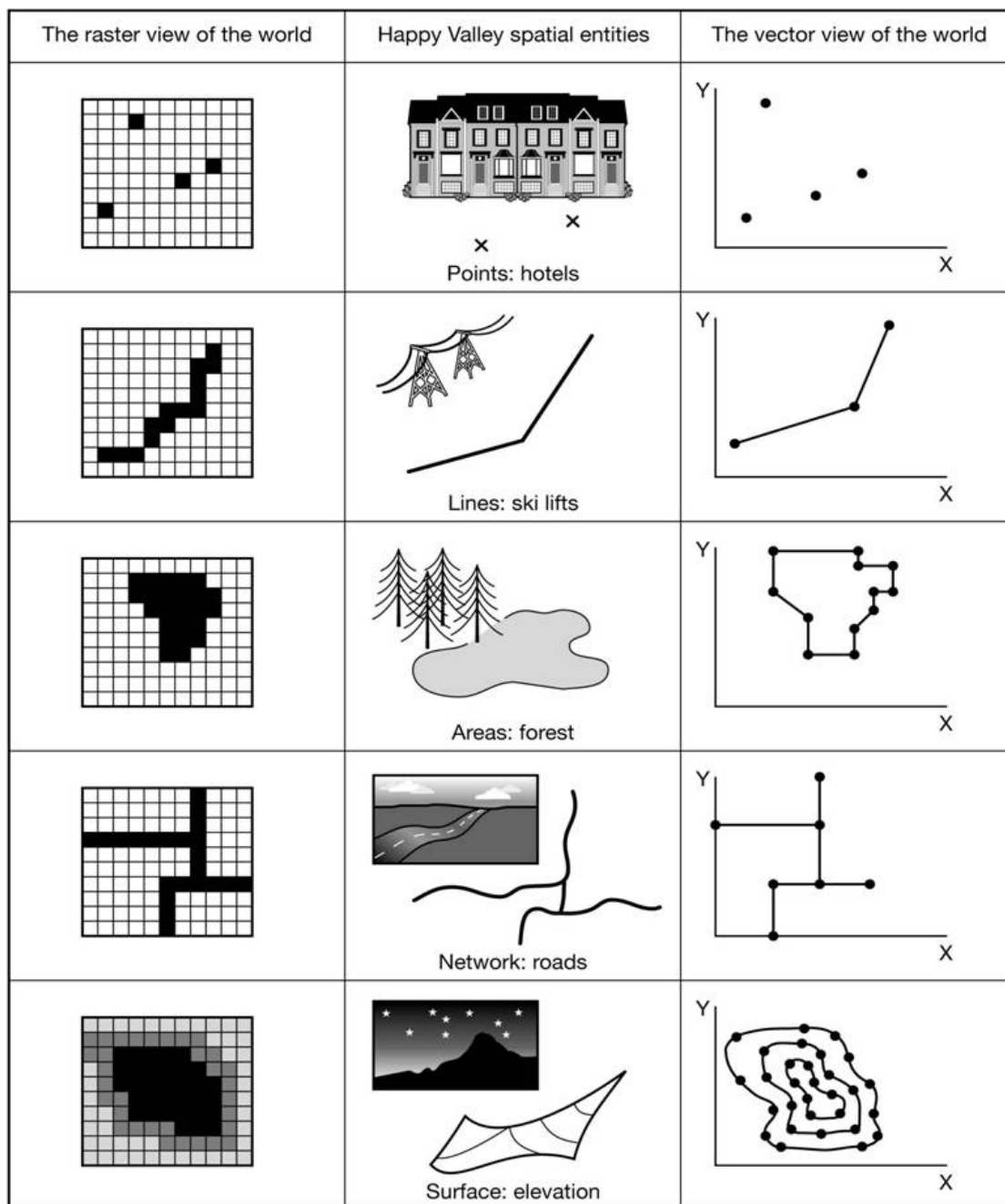


Figure 10: Vector and Raster Data GIS [McC37]

The top-left square of Figure 11 shows a satellite image. The associated raster data could for example represent the vegetation density in each of the pixels. As shown in the top-right grid, the resolution chosen for this example is 1 meter per pixel. The value contained in each of the elements of the raster grid corresponds to an average density measure of the vegetation in each of the cells. It is also possible to assign a color (bottom-right) to each of the cells, through a legend (bottom-left).

Most of these methodologies and applications, however, have depended on raster data structures employing regular grid cells to accomplish them, owing to their simplicity and ease of measuring spatial connections across land grids, such as proximity and adjacency. Except for [CHX09; CY13; MMH13; SJv04a], little work has been done in MSP to use vector data for decision-making units.

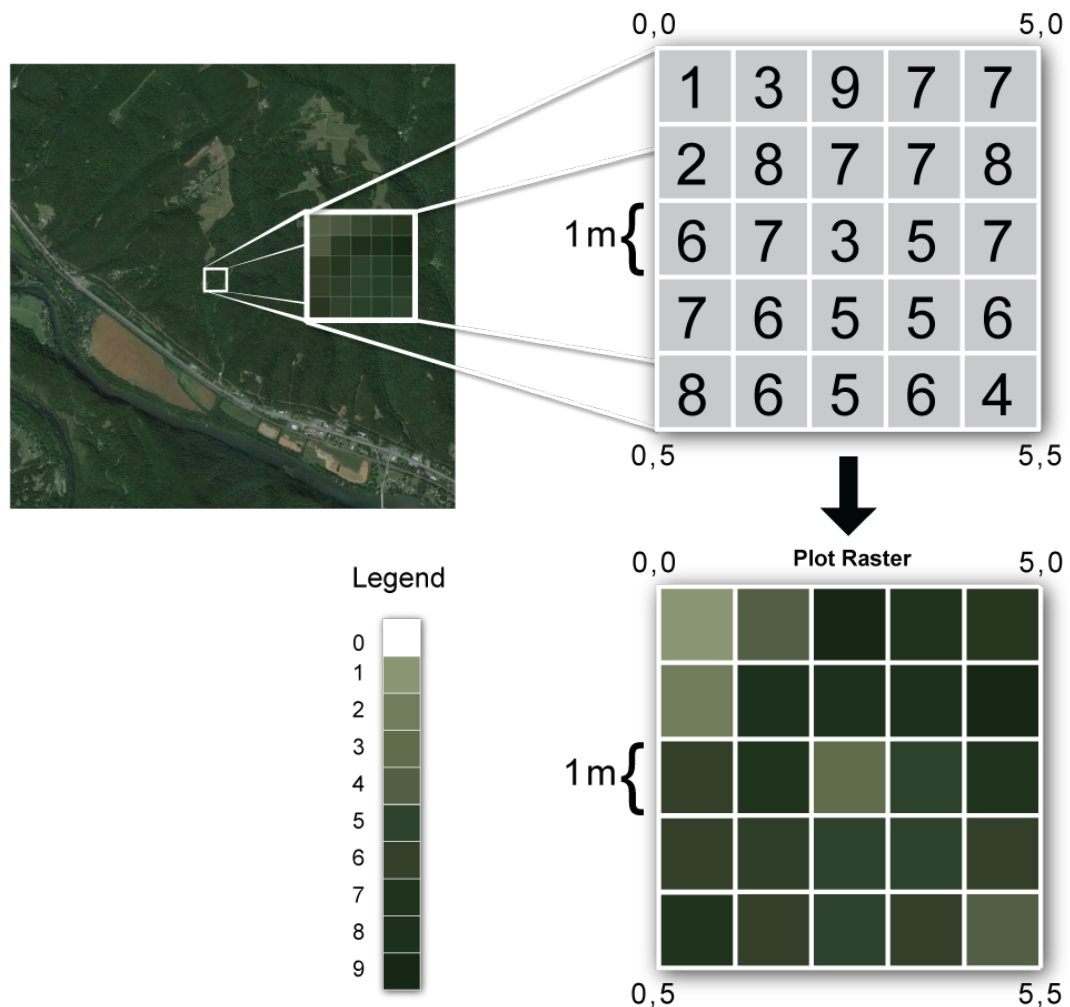


Figure 11: Raster concept [LT92]

3.2.4 Resolution Approaches

The development of integrated **MCDM** and **GIS** approaches appropriate for deployment in **SDSSs** for land/marine use allocation problems remains a challenge. In the absence of other options, optimization techniques (another subset of **MCDM** approaches) can be integrated with **GIS** to help the spatial design of land/marine use allocation plans. In formal terms, all decision problems dealing with related concerns are optimization problems in which we must determine the ideal position and/or form of a spatial region for a specific goal, given certain constraints. Hence, optimization techniques using **GIS** are known as spatial design techniques [Aer02; AH02; SV02].

Exact Methods VS. Approximate Methods

In general, to address an optimization problem, two phases are involved: model formulation and solution. The problem may initially be stated verbally. It is then translated into a set of mathematical equations. These equations tend to involve discrete (integer) as well as continuous decision variables – decision variables are the unknowns whose values determine the solution of the problem under consideration – especially for dealing with indivisible raster elements. A system of such equations is called a **Mixed Integer Programming (MIP)** model. Once a problem is formulated as such, it is solved by either heuristic or exact methods. Heuristic methods are designed to find approximate solutions in reasonable times and are useful for solving large-scale models (as is often the case with raster space). Exact methods, on the other hand, aim to find the best (or optimal) solutions with respect to criteria explicitly considered. If there is no

significant difference between their computational performances, exact methods are preferred. Even when exact methods are not available, good heuristic methods should be able to tell how good the solutions obtained are relative to possible optima. Thus, whether a problem is solved approximately or exactly, for solutions to be correctly evaluated, the problem needs to be formulated exactly. Many region selection criteria have been successfully formulated in MIP format [WRC83; GHR85; BW91; CC00a; Wil02b].

To begin with, all the mentioned phases in MSP problems were addressed initially by using the heuristic approaches [Pre+93; PPD97]. However, later, they were formulated as Mixed Integer Linear Programs (MILP) in the framework of the Set Covering Problem (SCP) and Maximal Covering Problem (MCP) [PCGY01; CR74; CSD96; CB89; Kir83; PCGY01; PBA00; TR73; Und94; WR97]). On the one hand, the most important advantage of using MILP to design MSP is that it can provide a globally optimal solution. On the other hand, an important disadvantage of MILP is related to problem-solving time, which is very likely to have a direct correlation with data size and complexity [O'H09]).

However, the Mathematical Programming of these problems, with the thousand variables, constraints, and multiple objectives, can indeed be solved in seconds or minutes. To do so, solving multiple sub-optimization issues at the same time is a relatively new class of optimization problems, and there has not been much study on it in the literature.

Single Objective VS. Multi-Objective Optimization

Multiple Objective Mathematical Programming (MOMP) is applied, referring to the solution of Mathematical Programming problems with more than one objective function. Given that usually, there is no unique optimal solution (optimizing all objective functions simultaneously), the aim is to find the most preferred among the Pareto optimal solutions [Dem91].

In other words, unlike mono-objective optimization problems, the optimal solution for MOOPs is a group of solutions known as Pareto optimal solutions, rather than a single solution [Cen77; BAJH20]. If it is not feasible to improve one goal without worsening at least another, the solution is Pareto optimal. This set of ideas reflects a compromise between several objectives that are in conflict. The Pareto optimal set and, as a result, the Pareto front are the primary goals of MOOPs resolution [Tal09].

Aside from the foregoing, despite numerous research publications dealing with MSP, the problem has yet to be condensed, since each actor must handle multiple technological, geographical, economic, environmental, and social objectives, as well as restrictions that are typically conflicting. Mathematical models that are integrated into the optimal zoning of these criteria must be more complex and computationally intensive than SCP and MCP formulations. To tackle Mathematical Programming issues with more than one objective function, MOMP is used. Given that there is rarely a single optimum solution (optimizing all objective functions at the same time), the goal is to determine the most favored among the Pareto optimal alternatives [Dem91].

MOMP approaches must mix optimization and decision support to be efficient. The solution procedure may be separated into two steps to handle this issue: The first is the generation of Pareto optimum solutions (all or a subset of them). The second is the decision-subsequent maker's involvement if all the information is available (the so-called MCDM process).

Depending on whether DMs are involved before, during, or after the search, available methodologies for these two stages are often categorized into three ways [CM75; Chi+12]: a priori, interactive, and a posteriori approaches. Among the various techniques in MOMP, the a posteriori method is the most computationally intensive. However, as calculating speed has increased and mathematical programming tools have advanced, the a posteriori method has grown more appealing to today's DMs. Although the best solutions from these formulations are economically efficient, they frequently lack spatial requirements. Spatial criteria might take many shapes [HS09; WS05].

Compactness and connectivity are the most commonly used criteria [FC03; JH13; ÖB03; TM08; WRC83], proximity to selected sites [Bri02; Dis+12; Mil+09; Nal+02; ÖB02; Rot99; Rul+03; Wil08],

habitat fragmentation [ÖB05; ÖB02], contiguity [CP05; Cer+10; CC00a; DCM11; JH13; MRS08; ÖB06; Töt+09; ÖW08; Wil02a; Car+13], existence of buffers and corridors [Con+12; WR96; WR98; WRL05], and accessibility [ÖY07; Rul+03]. .

[CCC15] introduced two MPAs spatial zoning models based on MOILP: a Buffer Cells Model and a External Border Cells (EBC) model. These methods allow MPAs design with multi-objective zones that meet numerous conservation aims while assuring optimal results. Because both neglect buffer cells, the EBC model was chosen for comparison with Marxan with zones. To summarize, the EBC model has significant benefits over Marxan for MPAs spatial zoning. It ensures optimality conditions while giving a compactness/cost trade-off for DMs to explore based on their choices.

[Zen+19] developed a procedure to resolve transboundary water conflicts in the Gaunting reservoir basin based on the theory of a hybrid game and mathematical planning model to optimize water and pollutant discharge while maximizing net aggregate benefit and reducing water supplies and pollution prevention costs.

[Fox+19] used a connectivity-based approach to design the MPAs networks for MOO. The authors developed a MHs algorithm that investigated two marine realistic networks in order to obtain the Pareto optimal set for networks with up to 100 websites.

[ZJK19] used the Ecosystem Service Value calculation to investigate the problems between marine development and exploitation and ecological protection. The findings demonstrate the benefits of optimizing the utilization of the marine area (Dengsha estuary area). They may address the multi-sector conflict issue and provide a new design for optimizing spatial arrangement.

Based on the literature review, the main contributions of this chapter can be summarized as follows:

- **Problem definition:** Since one of the main issues in MSP is to locate and allocate an optimal zone for a new human activity while considering the other existing activities, a new problem in the scope of zoning in MSP is defined and described,
- **Problem formulation:** Given the current state of the art, the most common approach is based on nonlinear multi-objective models, which are usually solved using stochastic search algorithms, resulting in sub-optimal solutions. Working on raster data is chosen, and hence the contribution is to formulate an exact linear model as a MOILP which aims at maximizing the interest of the area of the zone dedicated to one actor while maximizing its spatial compactness.
- **Problem resolution:** To solve this model and determine the optimal solution, two resolution methods are used: a WS of the objectives and AUGMECON2 (an interactive approach based on the classical ϵ -constraint method). Due to a very large number of integer variables and constraints in this MOILP model, the improvement of its resolution by using buffering techniques in a preprocessing phase is implemented.
- **Experimental validation:** A set of artificial datasets is generated to validate the approach and study both the sensitivity of the resolution methods and computation times with respect to various parameters.

3.3 Multi-Objective Single New Marine-Use Zoning Problem in Marine Spatial Planning

The study of the literature in this chapter reveals, among other things, that MSP requires the use of formal techniques to aid decision-making and lead to an overall sustainable strategy for the use of marine resources. As previously stated, we focus on the zoning problem in this chapter, which is a special sub-topic of MSP. To make the linear mathematical formulation possible for this problem, we suppose that a certain number of human activities already exist in a certain maritime region and the best site for a new activity must be established. The existing activities of the area are deemed permanent and cannot be altered. The overall appeal of the new activity's

location is determined by a map that is provided for the entire region and shows the degree to which it is worthwhile or unattractive to carry out the activity at that place.

The existing activities in the area can be classified into 3 categories :

- **shipping lanes** A freight lane is any regular route that a carrier follows. Freight lanes can also be referred to as shipping lanes or trucking lanes. These lanes might connect several cities or transportation centers. They can be direct point-to-point connections, connect numerous points of any form, and go in any direction. Shipping lanes are also known as sea lanes or sea routes, which are routinely utilized as navigable routes for big ships that cannot interfere with new activity. These shipping lanes could also represent underwater cables,
- **ports** (also known as harbors), is a commercial water facility where ships and their goods may unload. A port provides numerous handy amenities for ships since it is equipped with cranes, forklifts, warehouses, and docks. A harbor is a piece of shoreline where ships and other watercraft are anchored or stored.
- **restricted areas** in the ocean, which depict other activities that are incompatible with the new activity. These restricted areas might include maritime protected zones, wind or tidal turbine farms, recreational areas, military bases, and so on. These are sections of the ocean where the government has imposed restrictions on human activities. Many limited places allow individuals to use the region in environmentally friendly ways.

Furthermore, the specific position of the new activity is determined not only by the interest map but also by the distance between the various parts of the three categories of existing activities. In general, in this problem, we will set limitations on the minimum and maximum distances of the new activity from the various existing activities. In other words, the new activity should be situated as follows:

- at a minimum distance of each of the existing activities (depending on each existing activity),
- at a maximum distance of each of the existing activities (depending on each existing activity).

Finally, in this case, it is preferred that the new activity zone be as compact as possible in order to prevent potential conflicts with other new activities that may appear in the region in the future.

The goal of this task is to find the best place for the new activity that optimizes both its interest and its compactness. Meanwhile, it must adhere to set minimum and maximum distances from the existing activities (and therefore without overlapping with them).

Figure 12 depicts this problem description and its numerous aspects in a fictive marine environment. The upper dark gray section of the Figure (with the topographic isolines) shows the mainland, on which four ports are located. The lower half illustrates the marine region where the new activity (e.g., fishing) must be situated and where many other activities already exist: numerous shipping lanes, a windmill farm (restricted area), and a national protected area (restricted area). The amount of interest in the new activity is displayed on the backdrop map in three shades of gray (the more interesting the area, the darker it is). The new activity must be placed within a defined minimum distance of the shipping lanes (d_s^{\geq}), a given minimum and maximum distance of the closest port (d_p^{\geq} and d_p^{\leq}), and a provided minimum distance of restricted areas (d_r^{\geq}). In this problem, the new activity has to be located at a given minimum distance of the shipping lanes (d_s^{\geq}), at a given minimum and a given maximum distance of the closest port (d_p^{\geq} and d_p^{\leq}), as well as at a given minimum distance of restricted areas (d_r^{\geq}). Figure 12 depicts three places for the new activities. A is situated in an area of the sea that is ideal for the new activity. B, on the other hand, is in a less interesting section of the marine region, but C is in a highly interesting part of the maritime area. The star rating represents the three regions' average interest (1 star corresponds to a low interest, 3 stars to a high interest). Furthermore,

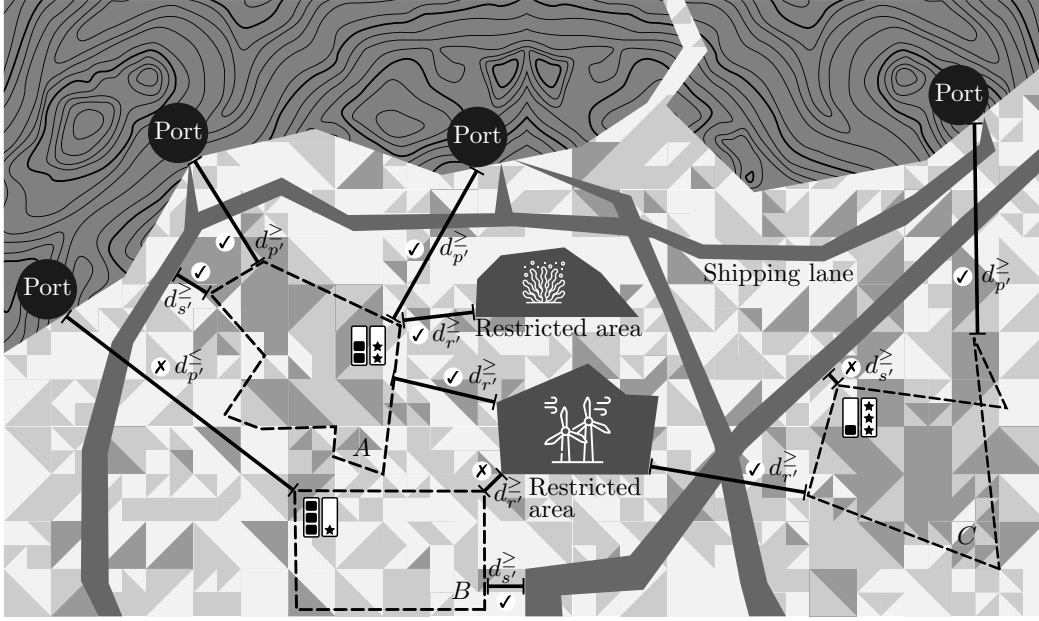


Figure 12: Problem Definition

each of these three sections has a distinct compactness evaluation: B is quite compact since it is a rectangle, A is fairly compact, and C is not very compact. The squares rating on the figure represents this compactness. Choosing between these three locations merely based on their compactness and interest is a challenging task, as none of them surpasses the others on either measure. In addition, the graphic depicts some of the distance constraints. Area A, for example, checks all minimal distance restrictions, but B exceeds a maximum distance constraint to the nearest port (d_p^{\leq}) and a minimal distance requirement to the restricted windmill farm (d_r^{\geq}). Finally, region C violates the minimum distance constraint concerning the shipping lane (d_s^{\geq}). As a result of these constraints violations, B and C are no longer considered for this new activity, and only A is admissible.

3.4 Mathematical Formulation

The beginning point of the problem at hand, as described in Section [3.3], is geospatial data, which represents data connected to or including information about places on the Earth's surface. In this thesis, we used raster data given as a regular grid of cells or pixels. A value is assigned to each pixel in a raster, which reflects some unit of measurement about the underlying geographical area. The quality of raster data is mainly determined by its resolution.

As a result, we assume that the interest map for the new activity is a two-dimensional matrix of uniform cells on a regular grid with n_{row} rows and n_{col} columns, yielding a total of $n_{\text{row}} \cdot n_{\text{col}} = m$ cells. This grid's cells are supposed to have a homogeneous interest value for the particular activity. Let J^{\boxplus} be the set of cells on the grid. Following the problem specification, let \mathcal{L} be the set of n_l shipping lanes, which are represented on the raster grid as a set of cells \mathcal{L}^{\boxplus} . Let \mathcal{P} be a collection of n_p ports represented as a collection of cells \mathcal{P}^{\boxplus} . Finally, consider \mathcal{R} to be a collection of n_r restricted areas (with which the new activity cannot intersect) represented as a set of cells \mathcal{R}^{\boxplus} .

In addition, in order to maintain an interactive process with the numerous stakeholders engaged in the zoning problem, we will not only seek one best spot for the new activity, but will also retain a record of alternative options, leaving the ultimate decision to the DMs. As a result, the optimization process should generate a number of possible zones for the new activity (which we will refer to as the optimization problem's *solutions*). Each solution is constructed around a *central* cell, to which adjacent cells are assigned in order to structure the solution areas.

The notations related to sets, input parameters, and decision variables are described below before giving the formal mathematical formulation.

Sets

- \mathcal{J}^{\square} : The set of m possible cells for the new activity in the ocean
- \mathcal{P} : The set of ports
- \mathcal{P}^{\square} : The set of cells representing the ports
- \mathcal{R} : The set of restricted areas
- \mathcal{R}^{\square} : The set of cells representing all the restricted areas
- \mathcal{S} : The set of shipping lanes
- \mathcal{S}^{\square} : The set of cells representing all the shipping lanes

Parameters

- c : The total number of central cells, referring to the total number of solutions sought
- u : The maximum number of cells around a central cell assigned to a solution
- l : The minimum number of cells around a central cell assigned to a solution
- v_i : The interest value of cell i ($\forall i \in \mathcal{J}^{\square}$), i.e., of each raster cell of the interest map
- d_{ki} : The Euclidean distance between a central cell k and a cell i to be assigned to this central cell ($\forall i, k \in \mathcal{J}^{\square}$)
- d_{pi} : The Euclidean distance between the center of a cell belonging to a port and the center of a cell of the interest map ($\forall p \in \mathcal{P}^{\square}, \forall i \in \mathcal{J}^{\square}$)
- d_{ri} : The Euclidean distance between the center of a cell belonging to a restricted area and the center of a cell of the interest map ($\forall r \in \mathcal{R}^{\square}, \forall i \in \mathcal{J}^{\square}$)
- d_{si} : The Euclidean distance between the center of a cell belonging to a shipping lane and the center of a cell of the interest map ($\forall s \in \mathcal{S}^{\square}, \forall i \in \mathcal{J}^{\square}$)
- $d_{p'}^{\leq}$: The maximum distance of each cell of the new activity to each cell of port p' ($\forall p' \in \mathcal{P}$)
- $d_{r'}^{\leq}$: The maximum distance of each cell of the new activity to each cell of restricted area r' ($\forall r' \in \mathcal{R}$)
- $d_{s'}^{\leq}$: The maximum distance of each cell of the new activity to each cell of shipping lane s' ($\forall s' \in \mathcal{S}$)
- $d_{p'}^{\geq}$: The minimum distance of each cell of the new activity to each cell of port p' ($\forall p' \in \mathcal{P}$)
- $d_{r'}^{\geq}$: The minimum distance of each cell of the new activity to each cell of restricted area r' ($\forall r' \in \mathcal{R}$)
- $d_{s'}^{\geq}$: The minimum distance of each cell of the new activity to each cell of shipping lane s' ($\forall s' \in \mathcal{S}$)

Decision Variables

$$x_{ki} \begin{cases} 1, & \text{if cell } i \in \mathcal{J}^{\square} \text{ is selected and belongs to the area of the new activity} \\ & \text{centred at cell } k \in \mathcal{J}^{\square}, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

$$x_{kk} \begin{cases} 1, & \text{if cell } k \in \mathcal{J}^{\square} \text{ is selected as a central for the new activity} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Objectives:

$$\max \sum_{k=1}^m \sum_{i=1}^m v_i \cdot x_{ki} \quad (3)$$

$$\min \sum_{k=1}^m \sum_{i=1, i \neq k}^m d_{ki} \cdot x_{ki} \quad (4)$$

Subject to:

$$\sum_{k=1}^m x_{kk} = c \quad (5)$$

$$\sum_{i=1}^m x_{ki} \leq u \cdot x_{kk} \quad \forall k \in \mathcal{L}^{\boxplus} \quad (6)$$

$$\sum_{i=1}^m x_{ki} \geq l \cdot x_{kk} \quad \forall k \in \mathcal{L}^{\boxplus} \quad (7)$$

$$\sum_{k=1}^m x_{ki} \leq 1 \quad \forall i \in \mathcal{L}^{\boxplus} \quad (8)$$

$$d_{pi} \cdot x_{ki} \leq d_{p'}^{\leq} \quad \forall p, k, i \in \mathcal{L}^{\boxplus}, \forall p' \in \mathcal{P} \quad (9)$$

$$d_{pi} \cdot x_{ki} \geq d_{p'}^{\geq} \quad \forall p, k, i \in \mathcal{L}^{\boxplus}, \forall p' \in \mathcal{P} \quad (10)$$

$$d_{ri} \cdot x_{ki} \leq d_r^{\leq} \quad \forall r, k, i \in \mathcal{L}^{\boxplus}, \forall r' \in \mathcal{R} \quad (11)$$

$$d_{ri} \cdot x_{ki} \geq d_r^{\geq} \quad \forall r, k, i \in \mathcal{L}^{\boxplus}, \forall r' \in \mathcal{R} \quad (12)$$

$$d_{si} \cdot x_{ki} \leq d_{s'}^{\leq} \quad \forall s, k, i \in \mathcal{L}^{\boxplus}, \forall s' \in \mathcal{S} \quad (13)$$

$$d_{si} \cdot x_{ki} \geq d_{s'}^{\geq} \quad \forall s, k, i \in \mathcal{L}^{\boxplus}, \forall s' \in \mathcal{S} \quad (14)$$

The objective function (3) maximizes the overall interest of a solution. The objective function (4) minimizes the sum of distances from individual cells in each solution to the center cell of that solution. As a result, with this goal, a solution for the new activity is as compact and contiguous as possible. Constraint (5) guarantees that only c central cells (i.e., solutions) are chosen for the new activity. Constraint (6) ensures that if the cell k is chosen as a central cell, i.e., $x_{kk} = 1$, then up to u more cells can be assigned to the solution built around the cell k . Constraint (7) expresses a similar concept as a constraint (6), except that it defines the minimal size of a solution. Constraint (8) states that each cell can belong at most to one solution. Constraints (9), (11), (13) ensure that a solution is not located further than a maximum distance from each port, restricted area, and shipping lane. Similarly, constraints (10), (12), (14) guarantee that a solution is not located closer than a minimal distance from each port, restricted area, and shipping lane.

3.5 Exact Methods

To solve the proposed MOILP, we investigate two approaches for MOO to achieve the appropriate exact Pareto front: first, an *a priori* method that considers the WS of the two objectives as a single objective function, and second, a *posteriori* method that uses an improved version of the classical ϵ -constraint method (called AUGMECON2 by [MF13]).

Before attempting to solve the program for different issue sizes, it is worth noting that inequations (9) to (14) produce a significant number of constraints involving a big number of integer variables. Each of these inequations, more specifically, provides m^3 constraints associated to m^2 integer variables, where $m = n_{row} \cdot n_{col}$. For a map with a resolution of 100 cells by 100 cells, this equates to 10^{12} constraints and 10^8 integer variables.

To address this challenge, we propose solving the problem in two steps:

1. Reduce the feasible solution space for the mathematical program by deleting areas where no solution can be found using the “buffer” approach described below,
2. Remove the distance constraints (9) to (14) from the program and solve it using one of the two previously suggested strategies.

3.5.1 Buffering Technique

A buffer is an area surrounding a geographic feature that contains locations that are within a certain distance of the feature [LT92; JJ12]. The idea of buffer is used to describe the minimal and maximal distance constraints (9) to (14).

On the one hand, constraints (10), (12), and (14) are utilized to ensure that a solution is not too close to existing ports, activities, or shipping lanes. If we consider a feasible area for the new activity on the interest map, these constraints suggest that these ports, activities, and shipping lanes, as well as the buffers surrounding them, whose radiuses are specified by the d_p^{\geq} , d_r^{\geq} , and d_s^{\geq} parameters should be deleted.

Constraints (9), (11) and (13), on the other hand, ensure that a solution is not located too far away from these existing elements. Again, in terms of the feasible region for the new activity this entails deleting parts that are outside a buffer surrounding the ports, activities, or shipping lanes, the radiuses of which are specified by the d_p^{\leq} , d_r^{\leq} , and d_s^{\leq} parameters.

Figure 13 depicts an exemplary scenario from Section [3.3] in which the buffer approach is used to define the central restricted area. The two white regions of the image show sections of the feasible zone for the new activity that have been excluded due to two distance constraints concerning that specific area (a minimal (12) and a maximal (11) constraints). As a result, solutions B and C are no longer possible since they are not entirely within the remaining feasible zone. The same method is followed for the other locations, ports, and shipping channels until the final feasible zone is discovered.

Once the feasible zone has been reduced using this buffering strategy, the simpler mathematical program (without distance limitations) finally becomes:

Objectives:

$$\max \sum_{k=1}^m \sum_{i=1}^m v_i \cdot x_{ki} \quad (15)$$

$$\min \sum_{k=1}^m \sum_{i=1, i \neq k}^m d_{ki} \cdot x_{ki} \quad (16)$$

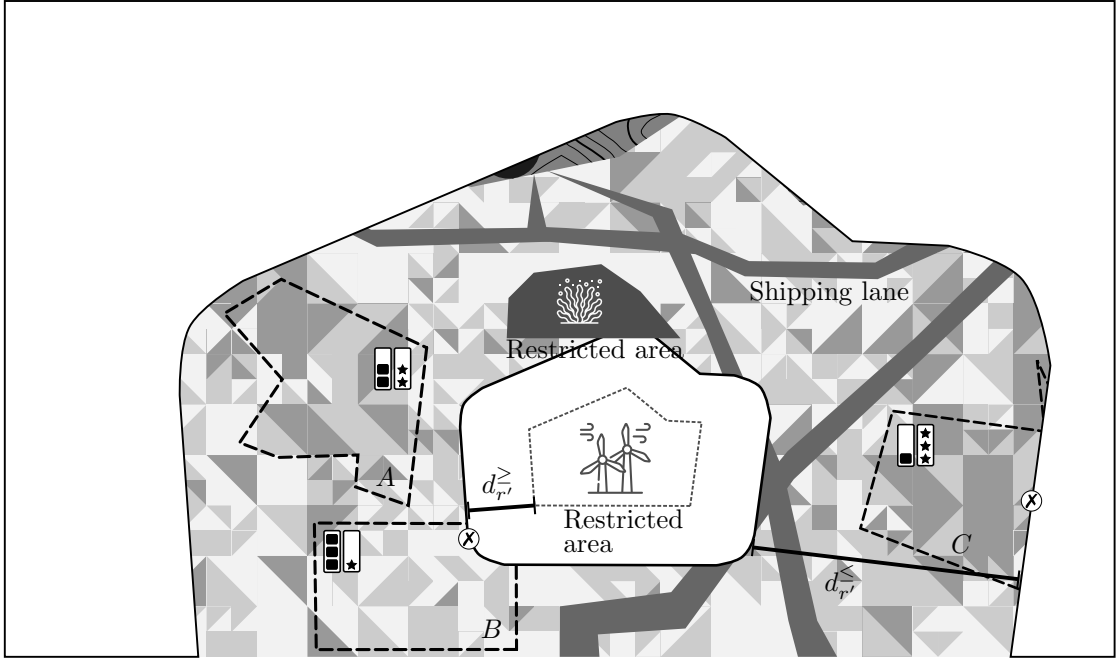


Figure 13: Modification of the feasible region by the buffering technique

Subject to:

$$\sum_{k=1}^m x_{kk} = c \quad (17)$$

$$\sum_{i=1}^m x_{ki} \leq u \cdot x_{kk} \quad \forall k \in \mathcal{L}^{\boxplus} \quad (18)$$

$$\sum_{i=1}^m x_{ki} \geq l \cdot x_{kk} \quad \forall k \in \mathcal{L}^{\boxplus} \quad (19)$$

$$\sum_{k=1}^m x_{ki} \leq 1 \quad \forall i \in \mathcal{L}^{\boxplus} \quad (20)$$

3.5.2 Weighted Sum and AUGMECON2

The simplified model described above can be solved using either the [WS](#) or the AUGMECON2 technique. The first resolution method that is studied in this chapter is the [WS](#), using a linear combination of the two objectives (3) and (4). Therefore, the new objective becomes :

$$\max \left(\lambda \sum_{k=1}^m \sum_{i=1}^m v_i \cdot x_{ki} - (1-\lambda) \sum_{k=1}^m \sum_{i=1, i \neq k}^m d_{ki} \cdot x_{ki} \right), \quad (21)$$

Equation (21) is a [WS](#) formulation, where $\lambda \in [0, 1]$ is a parameter. If $\lambda = 0$, then only the compactness objective is considered, and if $\lambda = 1$, then only the interest objective is used.

AUGMECON2 [[MF13](#)] is the second resolution technique employed. It is an enhancement of the classical ϵ -constraint approach, which is one of the two most common resolution methods for solving multi-objective integer linear systems, together with the previously published [WS](#)

method. It enables the creation of representations of the Pareto front, which is the set of non-dominated solutions. As indicated in [Mav09], the ϵ -constraint technique, together with its improvements, offers several advantages over the WS method, particularly for discrete variables.

[MF13] further reinforced AUGMECON in AUGMECON2 by incorporating a bypass coefficient as well as a form of lexicographic optimization on all objective functions, the order of which was trivial in AUGMECON:

$$\begin{aligned} \max f_1(x) + \epsilon \times \left(\frac{s_2}{r_2} + 10^{-1} \frac{s_3}{r_3} + \dots + 10^{-(p-2)} \frac{s_p}{r_p} \right) \\ \text{Subject to:} \\ f_2(x) - s_2 = e_2 \\ \dots \\ f_p(x) - s_p = e_p \\ x \in S \text{ and } s_i \in \mathbb{R}^+ \end{aligned} \quad (22)$$

In Equation (22), x is the vector of decision variables, and $f_1(x)$, $f_2(x)$, \dots , $f_p(x)$ are the p objective functions. r_k is the range of k^{th} ($k = 2, \dots, p$) objective function obtained from the payoff table. s_k is the slack (or surplus) variables of the respective constraints, ϵ is a small number (usually between 10^{-6} and 10^{-3} , and S is the space of efficient solutions. With this formulation in Equation (22), the solver will find the optimal for $f_1(x)$ and then it will try to optimize $f_2(x)$, then $f_3(x)$ and so on. In the AUGMECON formulation, the sequence of optimizations of $f_2(x)$, \dots , $f_p(x)$ was indifferent, while now in the AUGMECON2, the sequential optimization of the constrained objective functions (in the case of alternative optima) is forced. As it is explained, for each objective function 2, \dots , p , we calculate the objective function range r_k . Then we divide the range of the k^{th} objective function to q_k equal intervals using $(q_k - 1)$ intermediate equidistant grid points. Thus, we have in total $(q_k + 1)$ grid points that are used to vary parametrically the RHS (e_k) of the k^{th} objective function. The total number of runs becomes $(q_2 + 1) \times (q_3 + 1) \times \dots \times (q_p + 1)$. Then the discretization step for this objective function is given as:

$$\text{step}_k = r_k / q_k \quad (23)$$

The RHS of the corresponding constraint in the t^{th} iteration in the specific objective function will be:

$$e_k = \text{fmin}_k + t \times \text{step}_k \quad (24)$$

where fmin_k is the minimum from the payoff table and t the counter for the specific objective function. In each iteration, we check the slack/surplus variable that corresponds to the innermost objective function. Then we calculate the bypass coefficient as:

$$b = \text{int}(s_k / \text{step}_k) \quad (25)$$

Using the bypass coefficient, AUGMECON2 exploits the information provided by the slack/-surplus variables of the constrained objective functions to accelerate solutions by avoiding many redundant iterations, leading to computation time reduction. The jumps in the innermost loop not only make the grid scanning quicker but also allow for decreasing the step of the process and therefore increasing the grid points; by doing so, the exact Pareto set can be identified [Nik+20]. To customize our model with this method, the interest objective function (15) is set as $f_1(x)$ and the compactness objective function (16) as $f_2(x)$ is shifted to the constraints.

3.6 The Experimental Validation

In order to validate the proposals and to study how they behave when confronted with data, three following questions are proposed:

- **validity:** Are the mathematical model and the resolution methods capable of finding the optimal solution?
- **sensitivity:** How do the parameters of the resolution methods influence the solution?
- **complexity:** How do the resolution methods compare w.r.t. to calculation times?

To address these three problems, we first present a geographic data generator capable of producing artificial datasets with varying properties (in terms of interest maps, number, and types of shipping lanes, ports, restricted areas, etc.). The experimental procedure will be described then, followed by the results.

3.6.1 Data Generation

Without losing generality, we construct geospatial raster data in which the raster grid's "bottom row" and "right column" are considered the mainland. This is depicted in Figure 14, where mainland is represented by dark gray cells with no letters or numbers.

As a result, the rest of this data is the marine region in which the new activity must be placed. Each cell in this maritime area has an interest value that reflects how interesting it is to locate the new activity in that cell. The 6 levels of gray linked with 6 levels of interest are illustrated in Figure 14 (1 corresponding to the less interesting cells, and 6 to the most interesting ones).

Let n_p be the number of ports to be generated for a given dataset. For generating these ports, we simply randomly select n_p cells from the mainland cells. In Figure 14 this is represented by the light gray cells marked with a white "P" on the mainland.

The restricted zones are contiguous marine areas where the new activity cannot be found. To create one such region, we first choose a cell at random from the maritime area (the centroid). Then we randomly choose cells from the centroid neighboring cells and allocate them to the restricted area under construction. We next select cells at random from these cells' neighboring cells and repeat this process repeatedly until the area is equal to the desired size.

Two categories of restricted regions are examined for this data: restricted areas that enable shipping lanes to traverse them (e.g., marine protected zones, fishing areas, and so on), and restricted areas that do not allow for junctions with routes (e.g. windmill farms, islands, etc.). For simplicity, the first kind of limited region is referred to as "protected areas", labeling them "A" in Figure 14, and the second type of restricted area as "windmill farms", labeling them "W" in Figure 14. For a particular dataset, let n_a be the number of protected areas and n_w be the number of windmill farms to be created.

With respect to the restricted areas, the following algorithm 1 is applied:

Let n_s be the number of shipping lanes that will be created. Ports are where shipping channels begin and terminate. The shortest path method is employed, which is an adaption of the A^* algorithm [HNR68], to build such a path. The method finds the shortest path between two points, taking into account barriers (the second type of limited region from above, denoted "W" on Figure 14). Figure 14 also depicts three shipping lanes with cells linked by a continuous white line.

By taking all mentioned into account, three types of interest maps could be generated, as shown in Figure 15.

The first technique, called "Totally random", assigns a random integer interest value v_i , $v_i \in \{1, 2, 3, 4, 5, 6\}$, to each cell in the maritime region. In both "controlled" techniques, one or more interesting regions in the feasible region are fixed by setting v_i to its maximum value (6). The **Normalized Discrete Compactness (NDC)** metric, proposed by [LGC13], is a typical

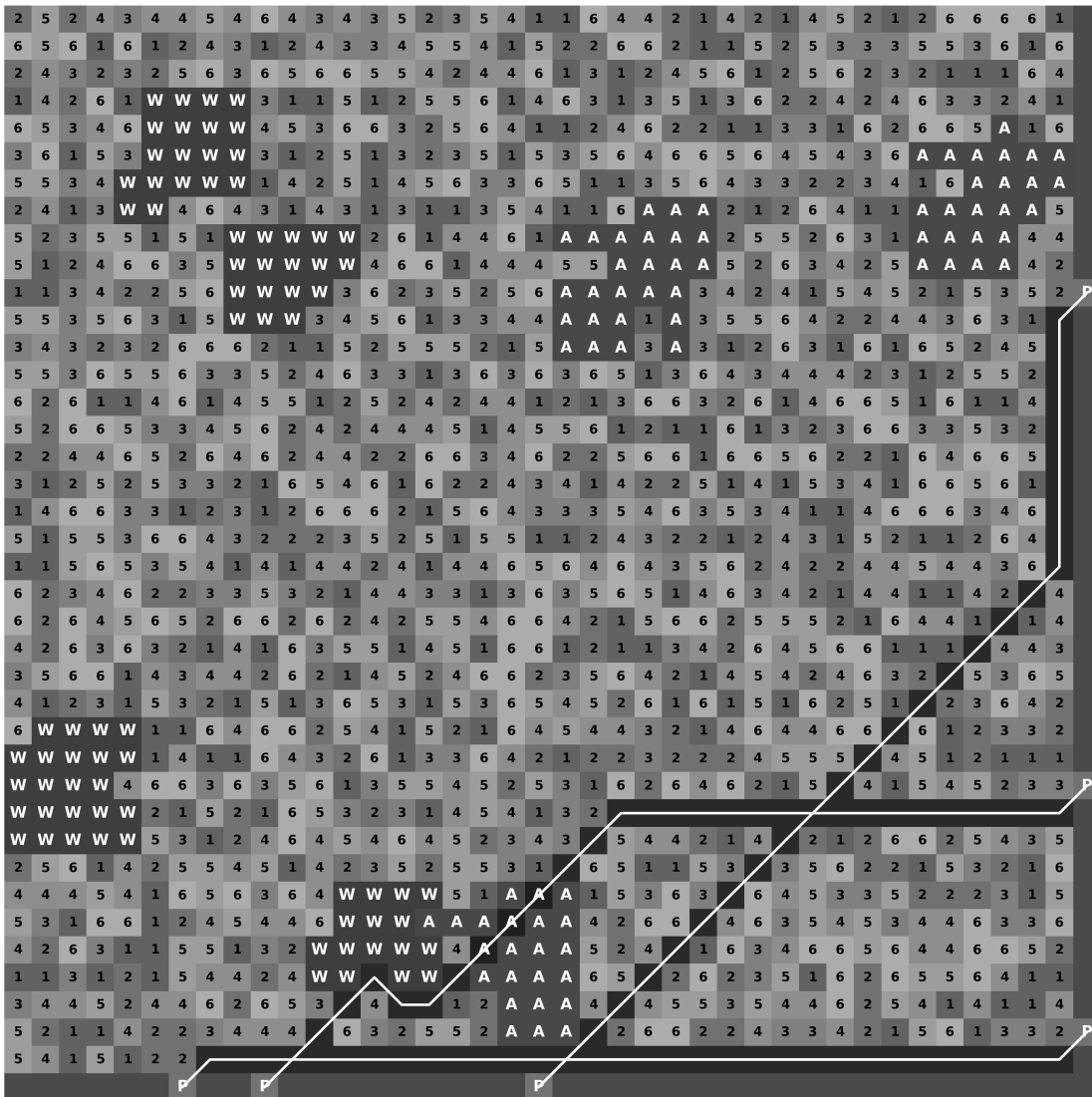


Figure 14: A sample fictive map generated by artificial datasets

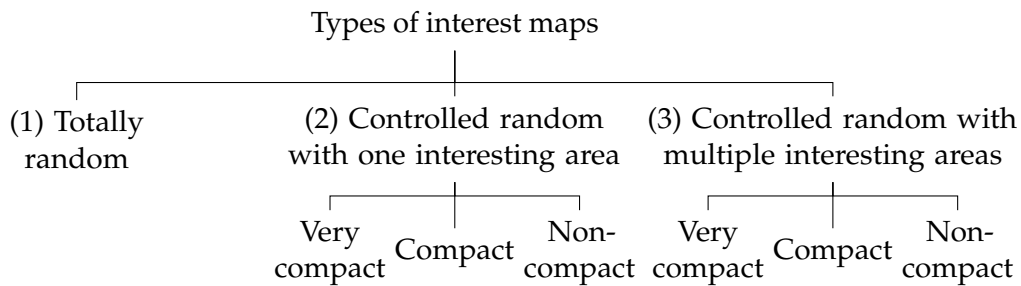


Figure 15: Different types of interest maps

approach for measuring compactness. Because the **NDC** technique is scale-invariant, it can be applied when computing the compactness of shapes with holes on raster datasets.

The concept is to count the number of cell sides L_D shared by pixels representing a shape S , and then compute the measure C_{NDC} . This is stated as Equation (26):

$$C_{NDC} = \frac{L_D - L_{D_{min}}}{L_{D_{max}} - L_{D_{min}}} \quad (26)$$

Algorithm 1 Pseudo-code Restricted Area Generator

```

1: procedure ADJACENT-COLLECTOR( $x, y, \mathcal{R}^{\boxplus}, \text{dirArray}$ )  $\triangleright$  Finding all neighbour cells
2:    $\mathcal{R}^{\boxplus}$  : The set of cells representing all restricted areas
3:    $\mathcal{R}_k^{\boxplus}$  : The list of  $k$  cells randomly selected from  $\mathcal{R}^{\boxplus}$ 
4:    $\text{dirArray}$  : The list of added values sets to cover 8 directions
5:   for  $i$  in  $\text{dirArray}[0]$  do
6:     for  $j$  in  $\text{dirArray}[1]$  do
7:        $\text{allAdj} \leftarrow [(x + i, y + j)]$ 
8:       if  $x, y$  in  $\mathcal{R}^{\boxplus}$  then
9:         Add  $(x, y)$  to the set of possible adjacent cells  $\text{posAdj}$ 
10:        Selecting one random cell from  $\text{allAdj}$  random
11:        for  $i$  in  $\text{dirArray}[2]$  do
12:          for  $j$  in  $\text{dirArray}[3]$  do
13:            for  $d, nd$  in enumerate(random) do
14:              for  $x, y$  in  $[(\text{random}[k][0]+i), (\text{random}[k][1]+j)]$  do
15:                if  $x, y$  in  $\mathcal{R}^{\boxplus}$  then
16:                  Add  $(x, y)$  to the set of possible adjacent cells  $\text{posAdj}$ 
1: procedure RESTRICTED-AREA-GENERATOR( $\mathcal{R}_k^{\boxplus}, \text{dirArray}$ )  $\triangleright$  Make a compact
   restricted zone
2:   for  $i, ci$  in enumerate( $\mathcal{R}_k^{\boxplus}$ ) do
3:      $\mathcal{R} \leftarrow \text{ADJACENT-COLLECTOR}(\mathcal{R}_k^{\boxplus}[i][0], \mathcal{R}_k^{\boxplus}[i][1], \mathcal{R}^{\boxplus}, \text{dirArray})$ 

```

where $L_{D_{\min}}$ and $L_{D_{\max}}$ are the lowest and maximum limits of the number of cell sides that can be shared with the same amount of pixels inside S . Equations (27)-(29) may be produced by defining p as the number of border edges and n as the total number of pixels in S , L_D , $L_{D_{\min}}$ and $L_{D_{\max}}$:

$$L_D = \frac{4n - p}{2} \quad (27)$$

$$L_{D_{\min}} = n - 1 \quad (28)$$

$$L_{D_{\max}} = 2(n - \sqrt{n}) \quad (29)$$

In each case, to compare those interesting areas three degrees of compactness are chosen which are defined as:

- **Very Compact:** contiguous zone with no hole ($0.5 < \text{NDC}$)
- **Compact:** contiguous zone with one hole ($0 < \text{NDC} \leq 0.5$)
- **Not Compact:** not contiguous zone with more than one hole ($\text{NDC} \leq 0$)

The controlled datasets will obviously be utilized for validation, whilst the random ones will help us investigate the differences between the different resolution techniques in terms of solution types as well as complexity/calculation times. In all, this results in the creation of seven different types of fake datasets about the interest map.

Additionally, for each of the seven categories of interest maps, multiple sizes and layouts of the ports, shipping routes, protected areas, and windmill farms have been developed. Table 1 summarizes the data generation parameters.

Table 1: Data generation parameters for exact methods

Parameter name	Possible values	Description
n_{row}	55	number of rows of the raster grid
n_{col}	55	number of columns of the raster grid
n_{p}	4, 6, 10	number of ports
n_{s}	4, 6, 8	number of shipping lanes
n_{a}	2, 3, 4	number of protected areas
n_{w}	1, 3, 5	number of windmill farms
u	20	maximum size of a solution
l	3	minimum size of a solution
(d_i^{\leq}, d_i^{\geq})	(1, 55), (3, 45)	minimal and maximal distance to ports, shipping lanes and restricted areas (windmill farms and protected areas), $i \in \{p', s', r'\}$

In terms of problem-specific parameters, we modify the lowest and maximal distance constraints to the various existing ocean activities, as indicated in Table 1. The total number of artificial datasets generated is $7 \times 3^4 \times 2 = 1134$.

3.6.2 Experimental Protocol

Algorithms Configuration and Metrics

The *WS* resolution approach requires a fixed parameter (λ) that provides the trade-off between the two objectives under consideration. During some pre-tests, we examined the influence of 11 various values (between 0 and 1) of the λ parameter on the *WS* of the objectives on a sample of 21 datasets, and we discovered that it varied linearly with λ . As a result, for our more extensive experiments, we determined that three λ values are adequate, as shown in Table 2.

Table 2: *WS* parameter

Parameter name	Possible values	Description
λ	0.25, 0.50, 0.75	tradeoff between the two objectives (compactness and interest)

The AUGMECON2 parameters are set to create three optimum Pareto front solutions. Multiple metrics could be observed for each algorithm configuration, and the following will be presented in the results section [3.7]:

- **Computation times** (separately for the buffering technique and the optimization part)
- **Location of the optimal solution**
- **Characteristics of the optimal solution**
 - Compactness
 - Number of cell candidates

To address the first question about **validation**, the algorithms are run with their different parameter configurations on the controlled random datasets. For each run and each dataset, we check if the obtained solution is equal to or included in the (or one of the) best artificially generated locations of the interest maps.

Then, to answer the **sensitivity** question, we use the totally random datasets. We first measure the compactness of the solutions with respect to the variations of the algorithms' parameters, as well as the influence of the distance parameters on the compactness. Then we compare the outputs of the algorithms to check if they produce the same or different solutions. In the second

case, we also check if the solutions are intersecting, included one in the other, or totally disjoint. The effect of the distance parameters is also studied on the compactness of the solutions and their sizes.

Finally, to answer the **complexity** question, we evaluate the effect of the distance parameters on the resolution methods, by separating the buffer generation time from the optimization time.

Implementation

The **MOILP** model is implemented in Python, version 3.8, by using the PuLP module, an LP modeler written in Python which calls an optimization software tool (CPLEX) as a solver. All experimental tests are implemented on a laptop with AMD Ryzen 5 PRO 2500u w/ Radeon Vega Mobile GFX 2.598GHZ processor with 16 GB RAM running Linux/Ubuntu 20.04.1 LTS.

Statistical Methods

Statistical tests were performed to examine the significance of the data in order to support the conclusions stated in this chapter. To be more explicit, a Fisher-Snedecor approach was used to examine the difference between the various sub-samples. At a 95% level of confidence, all the provided results are significant.

3.7 Computational Results

After completing all validation, sensitivity analysis, and computing time tests, the primary results are as follows:

■ Validation : (On controlled data)

As previously stated, to demonstrate the model's validity, we must demonstrate that 100% of the attained solution is equivalent to or contains the (or one of the) artificially constructed optimal locations of the interest maps using controlled random regions. Concerning the various forms of interest maps for controlled datasets shown in Figure 15, we choose three as examples to demonstrate how the validity is validated: extremely compact and compact controlled random with one interesting region, and non-compact of that with several interesting areas. Figure 16 depicts a geospatial raster-based map, in which the controlled random region and the best solution are represented with white and dark gray raster cells in the maritime area.

As observed, the white cells correspond to both the ideal zone and a portion of the controlled random region, while the other two dark gray cells round out the rest of the random area. Because of two holes in the regulated area, we classify it as "not very compact". In general, the restricted region encompasses the whole optimal solution; that is, the ideal solution is located exactly within that area. It is worth noting that in all three circumstances, the model returns not only the smallest but also the most interesting answer. According to the tests, we may infer that the given answer is either %100 equivalent to or contained in the controlled random generated zone.

■ Sensitivity Analysis : (On the random data)

1. Compactness:

The compactness metric was averaged across all setups for the two distinct buffer levels. First, raising the λ for **WS** increases the weight of the interest function while lowering the weight of compactness. As a result, in the presented findings, the bigger the λ , the less compact the solutions. Figure 19 represents the box plots for both resolution methods w.r.t compactness for different λ values in **WS** in subplot 19b and different solutions in **AUGMECON2** in subplot 19a. Figure 19 depicts the link between the compactness of the solution and the algorithm parameters. Figure 19b demonstrates that raising the λ causes **WS** to move from compact to non-compact solutions.

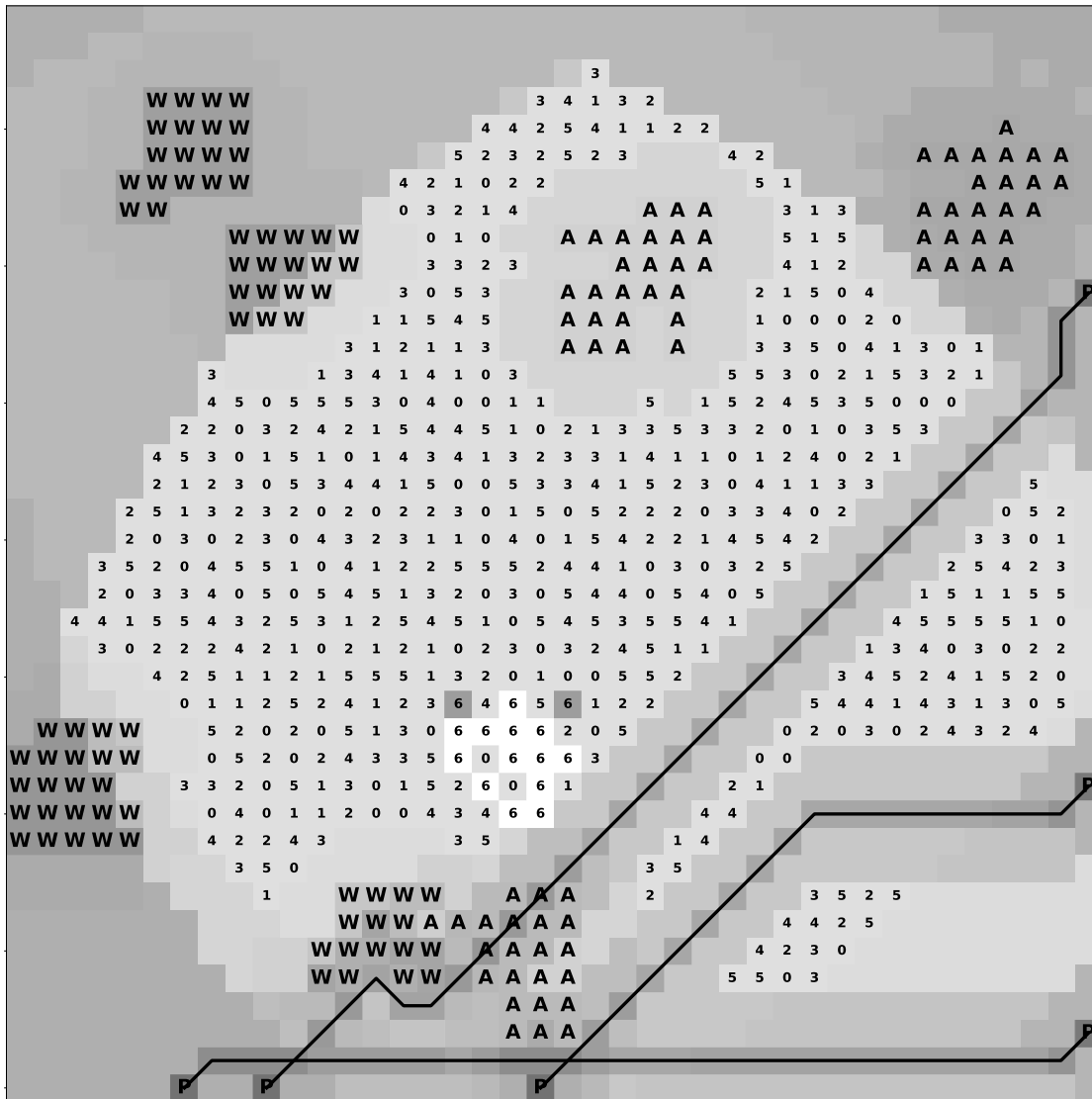


Figure 16: The sample validity map with one compact area

While, the sensitivity of AUGMECON2 to the compactness requirement is different. Figure 20 shows the convergence of two objective functions by highlighting an example of Pareto-optimal solutions produced by the AUGMECON2 technique.

The objective function (4) is related to the minimum distance between the center cell of the solution and the candidate cells around it. As can be seen in Pareto-front Figure 20, by increasing this objective function (4) which is shifted into constraints, we are relaxing this constraint and going toward the maximum value of the objective function (3) which represents the interest. However, since the algorithm has to satisfy both objective functions at the same time, it tries to return different shapes by keeping nearly the same compactness, instead of giving less compact solutions. Therefore, the more objective function (4) (solution), the less the variability, illustrated in Figure 19a. On the other hand, increasing the objective (4) shifts the algorithm’s focus to the maximum interest value by selecting more and more cells, but the size constraint, which has the highest value, imposes another limitation on the algorithm, forcing it to find fewer different solutions with varying compactness.

2. Number of candidate cells:

Figure 21 represents the box plots for both resolution methods w.r.t the average candidate cells. Figure 21 shows that the average number of candidate cells in the solution for WS is unaffected by buffer size, whereas AUGMECON2 is. The method

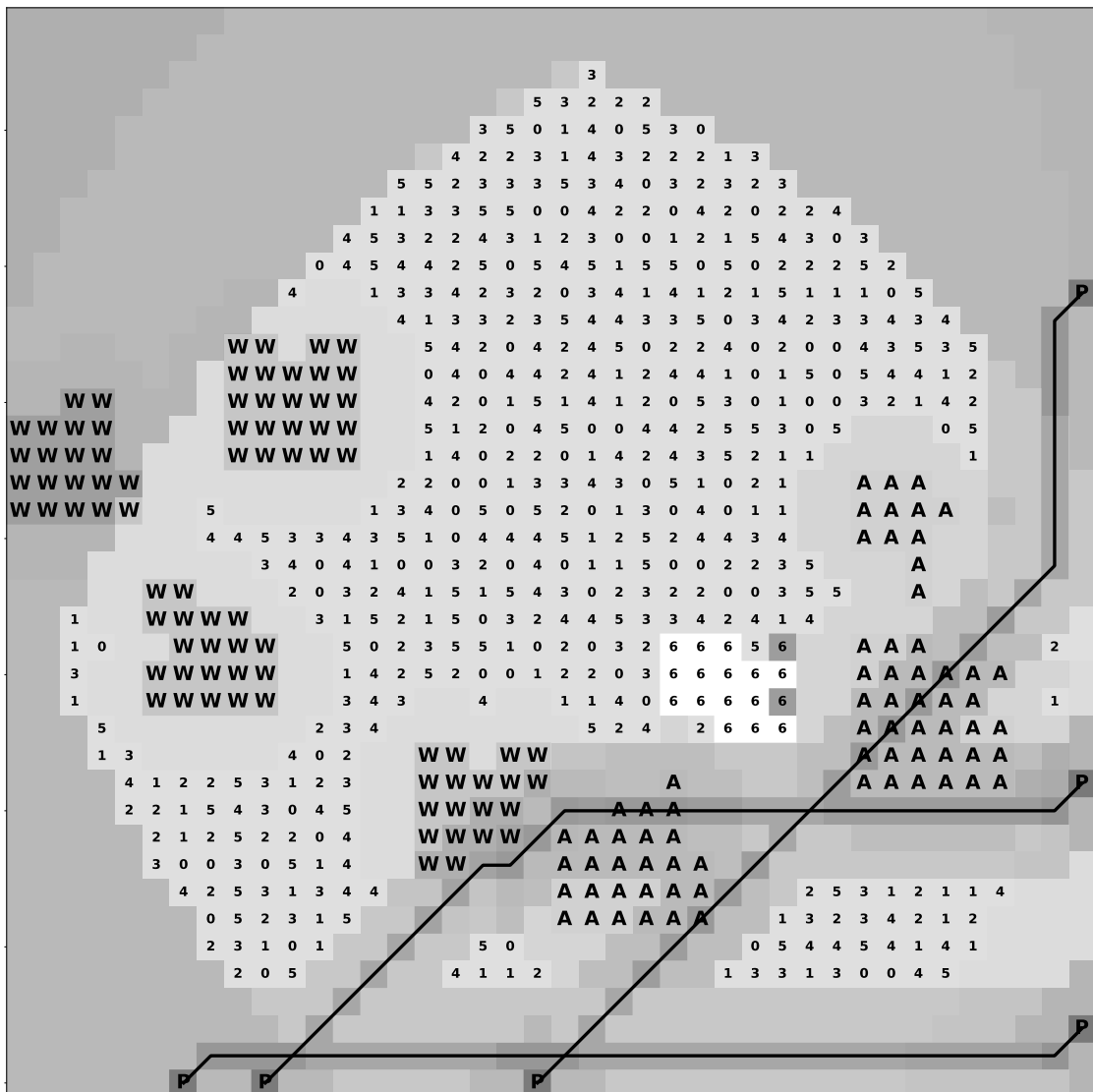


Figure 17: The sample validity map with one very compact area

returns fewer candidate cells when the buffer size is increased. Significant statistical tests ($p\text{-value} < 0.05$) confirm these results. One probable explanation is that the difference between the two buffers under consideration is not great enough to have a worldwide influence on the number of **WS** candidate cells, but AUGMECON2 is quite sensitive to the buffer and the solution space.

■ Computation Time : (On the random data)

Figure 22 represents the box plots for both resolution methods w.r.t the computation time. The sum of the optimization and buffer times yields the overall computing time. Figure 22 shows the difference in overall computing time between **WS** and AUGMECON2. As demonstrated, the **MOILP** model is solved in less time for both **WS** and AUGMECON2 for a smaller feasible region (*i.e.* greater buffer size) than for a larger solution space (*i.e.* smaller buffer size). We see a longer computation time for AUGMECON2 with a smaller buffer ($p\text{-value} < 0.05$). However, because of its buffer size sensitivity, AUGMECON2 becomes more efficient with a bigger buffer ($p\text{-value} < 0.05$).

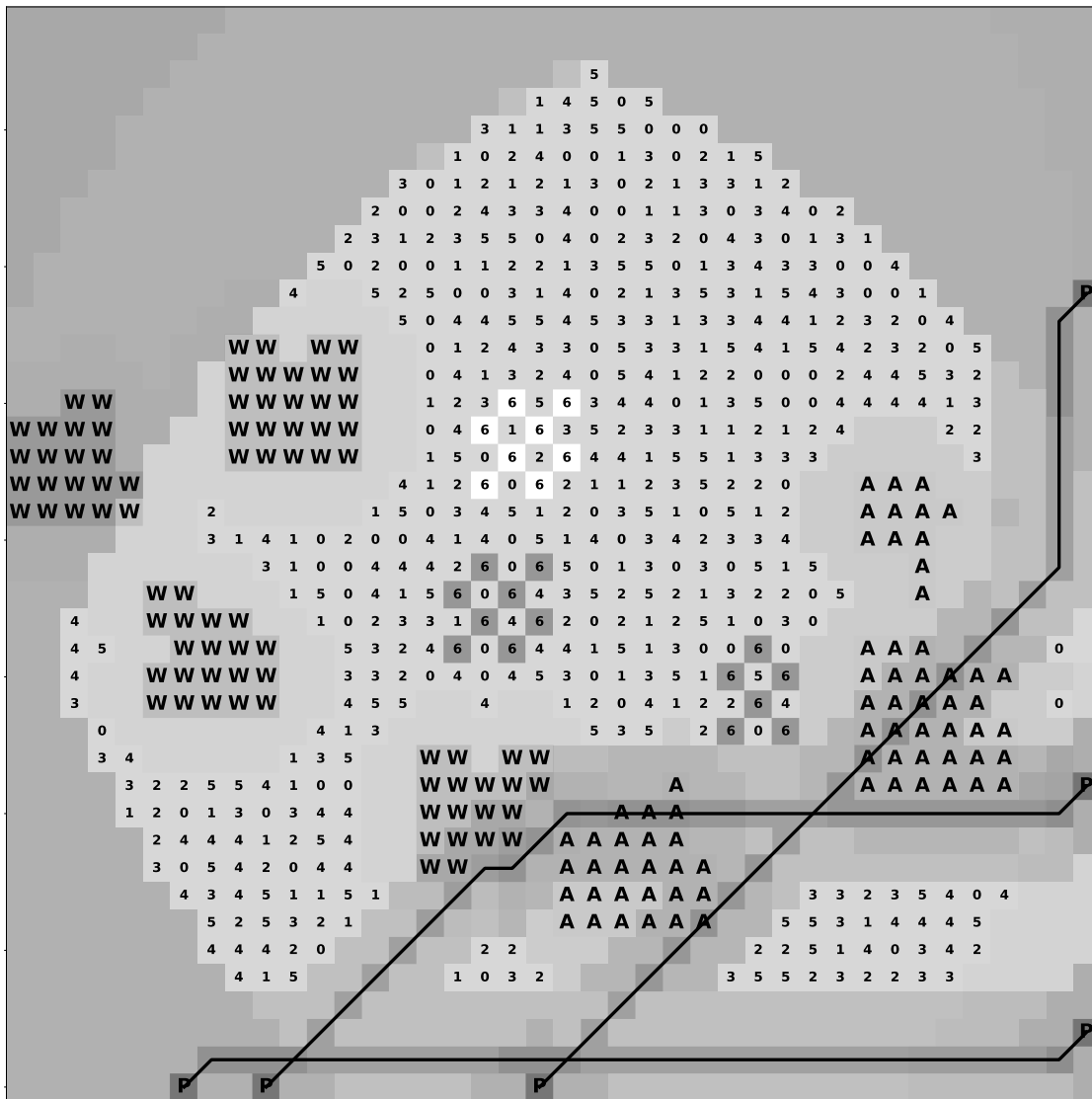


Figure 18: The sample validity map with multiple non-compact areas

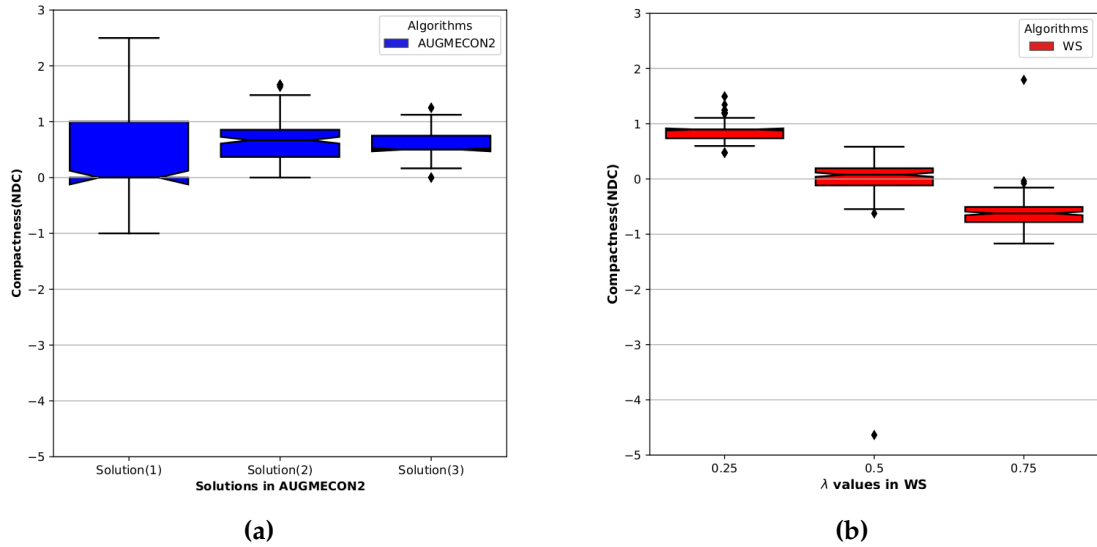


Figure 19: The Average Compactness Comparison between WS and AUGMECON2: (a) 3 Pareto-optimal solutions of AUGMECON2 with increasing the objective function (4); (b) that of WS w.r.t λ

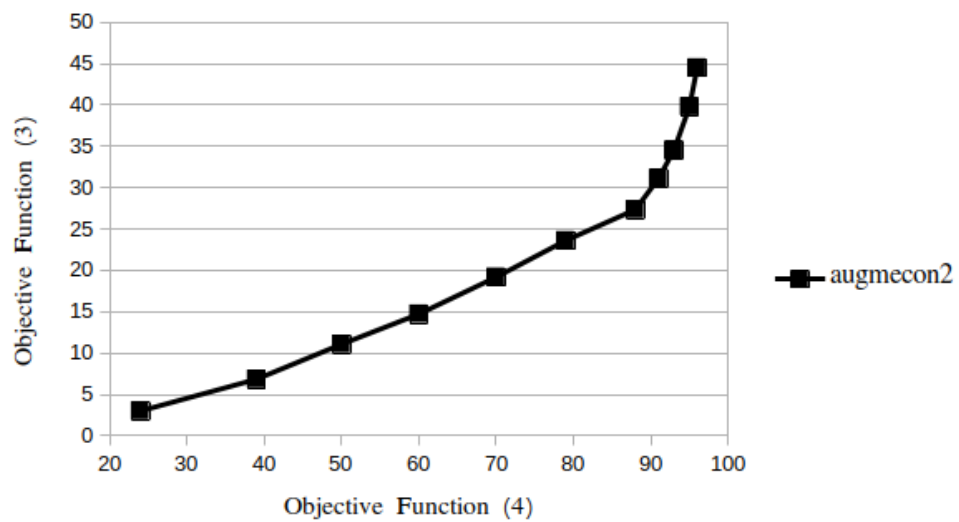


Figure 20: The Pareto Front of AUGMECON2

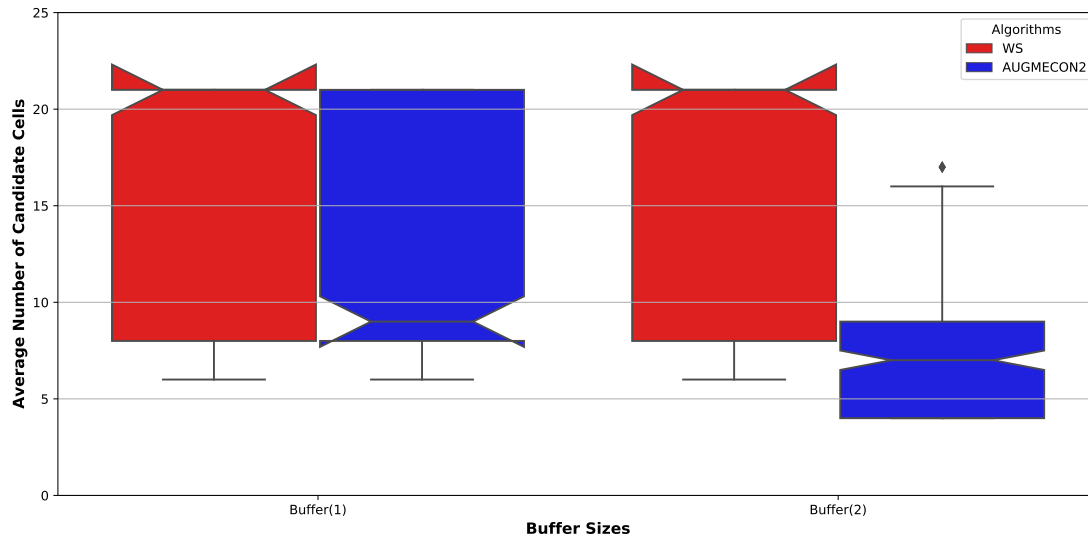


Figure 21: The Average Candidate Cells of all Configurations for each Buffer Size between WS and AUGMECON2

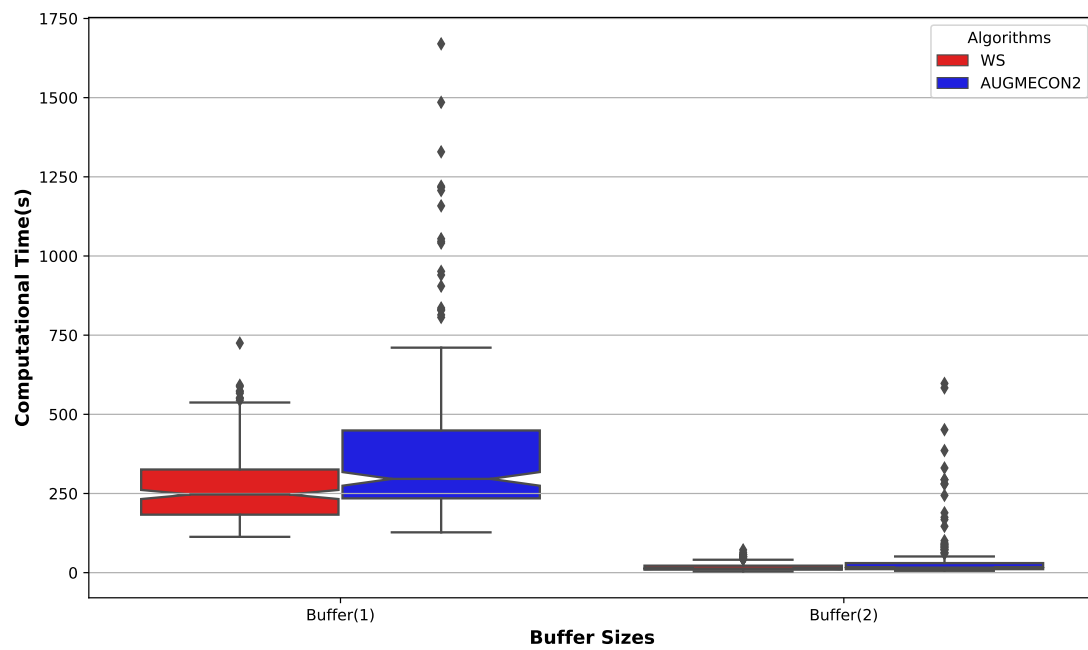


Figure 22: The Average Time Comparison of all Configurations for each Buffer Size between WS and AUGMECON2

3.8 Conclusion

In this chapter, a novel multi-objective mathematical model is proposed to solve the problem of locating and allocating a new human activity optimally in a given marine area. The proposed approach highlights an exact resolution of the problem. To solve it, we analyzed two resolution methods, a *WS* of the objectives and AUGMECON2, an enhanced version of the classical ϵ -constraint method. Empirical study based on synthetic data proves the ability of both methods to yield optimal solutions.

Our study shows also that AUGMECON2 represents the most promising approach in terms of relevance and diversity of the solutions, compactness, and computation time. Indeed, AUGMECON2 is able to exploit almost every run to produce a different solution. It also offers the possibility to easily control the number of generated solutions. On the opposite, *WS* provides less balanced solutions between the two objectives of interest and compactness, while being less sensitive to the buffering technique.

The next challenge is to scale up the problem resolution to larger problems. This objective is achieved in the next chapter by developing MHs that are faster while providing solutions that are close to optimality. To be more compatible with reality, another extension of this work would concern the determination of the best location for multiple new activities at the same time.

Chapter 4

Extensions to Evolutionary Approaches for Zoning Management in Marine Spatial Planning

Contents

4.1	Introduction	52
4.2	Literature Review	53
4.2.1	Meta-Heuristics	53
4.2.2	Single-Solution Based VS. Population-Based Meta-Heuristics	54
4.2.3	Hybrid Meta-Heuristics	57
4.3	Multi-Objective Evolutionary Algorithms	59
4.3.1	Solution Encoding Schema	59
4.3.2	Synchronous Hypervolume-Based Non-dominated Sorting Genetic Algorithm-II	61
4.3.3	Hybrid Synchronous Hypervolume-based Non-dominated Sorting Genetic Algorithm-II Using Local Search (Memetic Algorithm)	62
4.3.4	Search Components	63
4.3.5	Evaluation and Selection Operators	72
4.3.6	Stop Condition of Multi-Objective Evolutionary Algorithms	73
4.4	Tuning Parameters	74
4.4.1	Multi-Response Surface Methodology Optimization	75
4.4.2	Final Tuned Parameters	82
4.5	Experimental Validation	82
4.6	Computational Results	83
4.7	Conclusion	86

ABSTRACT

In Chapter [3], an exact MOILP model for the spatial zoning management in MSP is developed as an optimization model and validated by experimental studies. However, due to the computing complexity of MOILP models, the findings of Chapter [3] are limited to small scale and do not support the given problem with real-world application on a large scale. Therefore, this chapter presents and compares the results of two MOEAs, SH-NSGA-II, which is an extension of NSGA-II, and an MA in which SH-NSGA-II is enhanced with a local search. These proposed algorithms are used to solve the multi-objective spatial zoning optimization problem, which seeks to maximize the zone interest value assigned to the new activity while simultaneously maximizing its spatial compactness. We introduce several innovations in these proposed algorithms to address the problem constraints and to improve the robustness of the traditional NSGA-II and MA approaches. Unlike traditional ones, a different stop condition, multiple crossover, mutation, and repairing operators, and also a local search operator, are developed. We present a comparative study of the results obtained using both algorithms. To guarantee robust results for both algorithms, their parameters are calibrated and tuned using the Multi-Response Surface Methodology (MRSM) method. The effective and non-effective components, as well as the validity of the regression models, are determined using Analysis Of Variance (ANOVA). Although SH-NSGA-II has revealed good efficiency, its performance can still be improved by using a local search scheme within SH-NSGA-II, which is specially tailored to the problem characteristics.

4.1 Introduction

Spatial management planning is a resource location-allocation strategy described as the process of locating and allocating distinct human activities or uses to the specified units of areas on the Earth's surface [Doo+18; GK17]. One of the first and foremost prerequisites for properly MSP is spatial data, often known as geospatial or geographic data. That is, data about the geographic position of features and boundaries on the Earth's surface, such as natural features, land regions, ocean surfaces, and so on. Coordinates and topologies are commonly used to map and store spatial data [SE21; Bas+21]. A wide range of decision problems in the spatial planning strategy, such as land-use planning [GC20], and MSP [Bas+21] make use of spatial data.

Formally, MSP decision problems are optimization problems in which we must identify the optimal position and form of a spatial region for a new activity, given certain restrictions. Solving these two sub-optimization issues at the same time is a relatively new class of optimization problem, and there has not been much study on it in the literature [Cen77; BAJH20]. The majority of spatial zoning approaches are expressed as multi-objective non-linear optimization models, which are frequently solved using stochastic search techniques, resulting in sub-optimal solutions [SP22]. Nevertheless, in Chapter [3], we offered an exact mathematical zoning model for MSP as an MOILP problem [Bas+21].

Difficulties arise, however, when an attempt is made to increase the size of the problem. The main limitations in the exact solvers for generating the optimal solutions are referred to as their high computational cost and computational hardness¹ [Lok+18]. Therefore, to reach good enough solutions in practice, using evolutionary-based approaches like heuristic or MHs algorithms is typically sufficient for real MOOPs case studies on a large scale [Sjv04b; LBR19].

As a result, a challenge in this chapter lies in developing and implementing different MHs to solve the given MOOPs, the spatial zoning problem in MSP. To do so, two novel population-based MOEAs are proposed. To increase the reliability of measures, the experimental tests are

¹A computational hardness assumption in computational complexity theory is the assumption that a certain problem cannot be solved effectively (where efficiently typically means "in polynomial time"). It is unknown how to show the (unconditional) hardness of practically any important problem. Instead, computer scientists use reductions to formally link the hardness of a new or complicated problem to a computational hardness assumption about a better-understood problem [Wik21]

designed and validated. Finally, the comparative analysis among MOEAs and the exact results in small size and between both MOEAs in large size is studied.

The chapter is structured as follows. Section [4.2] provides a review of the literature on the topic and a summary of the contributions. In Section [4.3], we propose the MOEAs algorithms for the problem at hand to find the optimal solutions. In Section [4.4], we describe an experimental design to tune the parameters of the proposed algorithms, while in Section [4.5], we explain the experimental validation metrics. In Section [4.6] we propose the computational results on artificially generated synthetic instances. We draw conclusions in Section [4.7]. It is worth noting that this chapter is based on an accepted conference paper and an under-review journal article, which are mentioned in the publications list at the end of the manuscript.

4.2 Literature Review

As already explained, land-use planning [GC20], biodiversity conservation planning [Yan+19], MSP [Bas+21], and military planning [LSW03] are only a few of the decision issues in the spatial planning strategy that employ spatial data. Due to competing goals and restrictions in the mentioned problems, selecting the optimum zone(s) or area(s) for a certain purpose using geographical data may be challenging. In contrast to land-use planning, maritime activities were not handled for many years, since the sea was thought to be unbound and its resources inexhaustible [DC+09; Bas+21]. Today, protecting the global marine environment has become critical, and the MSP strategy is a central tool for developing sustainable human activities in the ocean, taking into account the interactions between different activities and stakeholders [Aga15].

In MSP, decision issues are optimization problems in which we must determine the best location and/or shape of a geographic region for a certain activity, given certain constraints. Two sub-optimization difficulties here are the appropriate location and shape of a spatial region.

The complexity of a problem indicates the difficulty of the problem. It is also necessary to understand the *size* of input instances that the method is expected to solve. Even though a problem is NP-hard, an exact approach may be used to address small instances. Furthermore, the *structure* of the instances is important. Exact algorithms may solve some medium- or even large-size instances with a specified structure in the optimization problem. Finally, the search time required to solve a particular problem is a significant consideration when choosing an optimization technique [Tal09]. When there are efficient, exact methods available, it is inappropriate to apply MHs to solve issues. The P class of optimization issues is an example of this type of problem. MHs are worthless when the exact algorithms provide an “acceptable” search time to solve the target cases. For example, one should not utilize MHs to discover the shortest path or minimal spanning tree in a graph. There are known polynomial-time exact algorithms for these issues. As a result, MHs are rarely applied for simple optimization issues. So the first step in solving a problem is to assess its complexity.

Despite progress in reformulating our MOILP model and the invention of more efficient techniques, such as the buffering technique, our MOILP problem continues to be difficult to solve in an acceptable time for moderate and large cases. To deal with this issue, implementing MOEAs such as single Solution-Based Metaheuristics (S-metaheuristics) or Population-Based Metaheuristics (P-metaheuristics) can be applied [SJv04b; LBR19]. Unlike exact approaches, MHs enable the handling of large-scale issue instances by providing adequate solutions in a reasonable amount of time. There is no certainty that global optimum or even bounded solutions will be found.

4.2.1 Meta-Heuristics

In the class of approximate methods, two subclasses of algorithms may be distinguished: approximation algorithms and heuristic algorithms. Unlike heuristics, which usually find reasonably “good” solutions in a reasonable time, approximation algorithms provide provable solution quality and verifiable run-time bounds. Heuristics find “good” solutions to large-scale problem instances. They allow obtaining acceptable performance at an acceptable cost in a wide range of problems. In general, heuristics do not have an approximation guarantee on the solutions they

get. They may be classified into two families: specific heuristics and **MHs**. Specific heuristics are tailored and designed to solve a specific problem and/or instance. **MHs** are general-purpose algorithms that can be applied to solve almost any optimization problem. They may be viewed as general upper-level methodologies that can be used as a guiding strategy in designing underlying heuristics to solve specific optimization problems [Tal09]. The word *heuristic* has its origin in the old Greek word *heuriskein*, which means the art of discovering new strategies (rules) to solve problems. The suffix *meta*, also a Greek word, means “upper-level methodology”. The term **MHs** was introduced by *F. Glover* in the paper [[Glo86]]. **MHs** search methods can be defined as upper level general methodologies (templates) that can be used as guiding strategies in designing underlying heuristics to solve specific optimization problems.

In the last 20 years, **MHs** have grown in prominence. Using **MHs** to solve **MOOPs** has been a particularly active research and development topic in recent years. Their employment in a variety of applications demonstrates their efficiency and efficacy in resolving huge and complicated issues, like;

- Engineering design, topology optimization, and structural optimization in electronics and VLSI, aerodynamics, fluid dynamics, telecommunications, autonomy, and robotics are some fields where **MHs** are used.
- Data mining and machine learning in bioinformatics and computational biology, as well as finance.
- Control, signal, and image processing; system modeling, simulation, and identification in chemistry, physics, and biology.
- Routing problems, robot planning, scheduling and production issues, logistics and transportation, supply chain management, and so on.

Optimization is omnipresent; optimization issues are frequently difficult, and then there are **MHs** everywhere. Even in the scientific community, the number of **MHs**-related sessions, seminars, and conferences is increasing considerably. The pedigree of multiple **MHs** is depicted in Figure 23 [PC04] proposed the heuristic concept for solving optimization issues in 1945. [Dan51] developed the simplex method in 1947 as a local search algorithm for linear programming problems. [Edm71] published the greedy heuristic in the combinatorial optimization literature for the first time in 1971. The following **MHs** initial references are based on their application to optimization and/or machine learning problems: **Ant Colonies Optimization (ACO)** [Dor92], **Artificial Immune Systems** [BV90; FPP86], **Bee Colony** [See09; YK96], **Cultural Algorithms** [Rey94], **Co-Evolutionary Algorithms** [Hil90; Hus91], **Covariance Matrix Adaptation Evolution Strategy** [HO96], **Differential Evolution** [PRI94; SP97], **Estimation of Distribution Algorithms** [Bal94], **Evolutionary Programming (EP)** [Fog62], **Evolution Strategies (ES)** [RTE65], **Genetic Algorithms (GAs)** [Hol62; Hol75], **Great Deluge Algorithm** [Due93], **Guided Local Search** [Vou98; VT95], **Genetic Programming (GP)** [Koz+92], **Greedy Adaptive Search Technique** [FR89], **Iterated Local Search** [MOF91], **Noisy Method** [CH93], **Particle Swarm Optimization (PSO)** [KE95], **Simulated Annealing (SA)** [Cer85; KGJV83], **Smoothing Method** [GM86], **Scatter Search (SS)** [Glo77], **Threshold Accepting** [DS90], **Tabu Search (TS)** [Glo86; Han86], **Variable Neighborhood Search (VNS)** [MH97].

4.2.2 Single-Solution Based VS. Population-Based Meta-Heuristics

Regardless, when the **MHs** are used, the objective is to generate a Pareto optimum approximation that has two properties: convergence to the Pareto optimal front and consistent diversity. The first condition ensures that near-optimal Pareto solutions are generated, while the second property indicates that the acquired solutions are well distributed on the Pareto optimal front, ensuring that no valuable information is lost [CH08]. Exploring the search space (*diversification*) and exploding the best solutions identified (*intensification*) are two contradictory criteria to consider when building an **MH**, as seen in Figure 24. In general, basic S-metaheuristics are more exploitation oriented, whereas basic P-metaheuristics are more exploration oriented. The acquired “good” solutions help identify promising areas. Intensification involves digging deeper into promising areas in the hope of discovering more effective solutions. Non-investigated

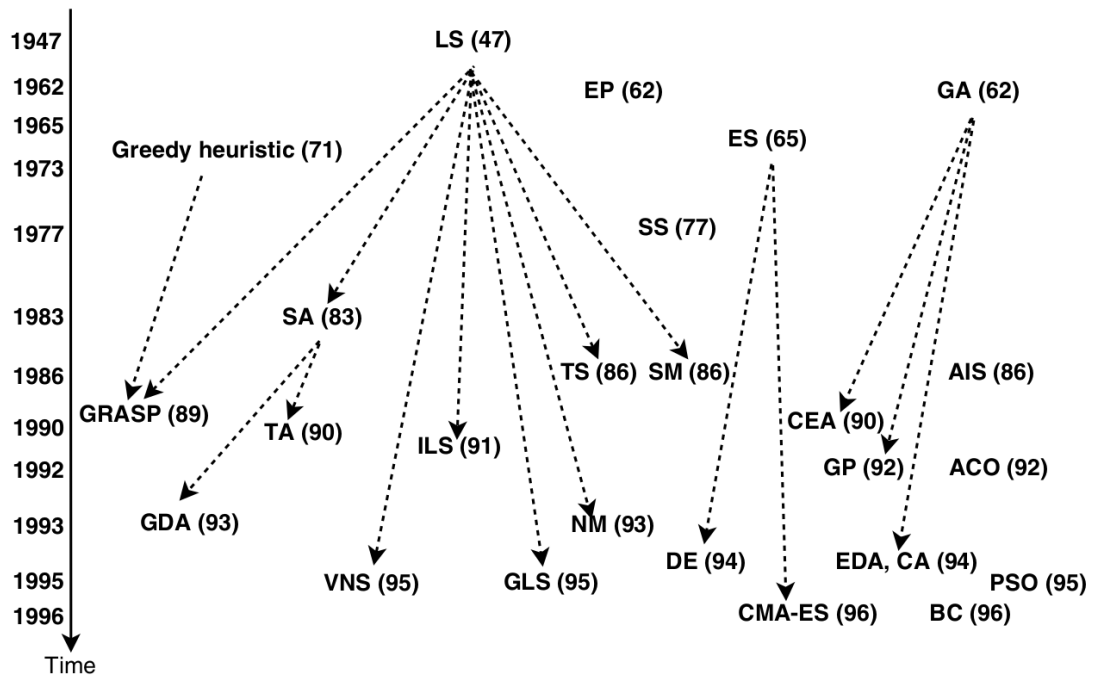


Figure 23: MHs ancestry. As per the original date, the application to optimization and/or machine learning is considered. [Tal09].

parts of the search space must be visited during diversification to ensure that all regions of the search space are equally explored and that the search is not limited to a few regions. In terms of exploration (resp. exploitation) in this design space of Figure 24, random search algorithms are the most extreme (resp. iterative improvement local search). At each iteration of the random search, a new random solution is generated in the search space. At each iteration of the basic steepest local search algorithm, the best adjacent solution that improves the results is selected.

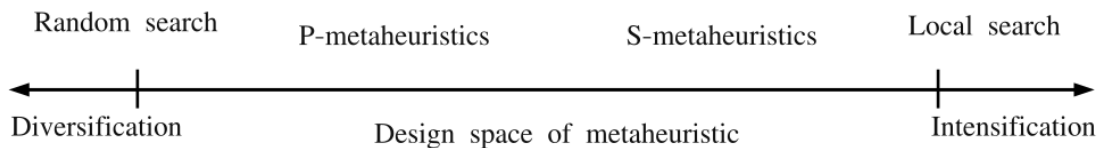


Figure 24: Two conflicting criteria in designing MHs: exploration (diversification) versus exploitation (intensification) [Tal09].

In other words, during the search, S-metaheuristics (such as local search and SA) control and transform a single solution, whereas P-metaheuristics (such as PSO and Evolutionary Algorithms (EAs)) evolve an entire population of solutions. S-metaheuristics are exploitation-focused; they can increase the search in small regions. Exploration-oriented MHs are P-metaheuristics that allow for more variety throughout the whole search space. As a result, utilizing some strategies in these algorithms that enhance the underestimated local search section might be useful to empower P-metaheuristics.

As mentioned above, solving the multi-objective decision issues in MSP entails developing a collection of Pareto optimum solutions that satisfy the conditions of convergence to the true Pareto front and uniform diversity. The majority of research on MHs for MOO focuses on P-metaheuristics, such as EAs, which are more suited to solving MOOPs [CLVV+07; Deb01]. The creation of MHs that allow the approximation of the Pareto front in addressing MOP issues is our primary focus.

Figure 25 provides the number of research documents using MOEA algorithms in the spatial

optimization field from 2010 to 2022 (Scopus). As already mentioned, MOEA algorithms are popular choices for solving complex large-scale spatial optimization problems. There have been several MHs algorithms, such as NSGA-II [WH+21], Strength Pareto Evolutionary Algorithms (SPEA, SPEA-II) [FLT21], PSO [CPP17], SA [Gon+21], Multi-Objective Genetic Algorithm [LWM08], ACO [Wan+21b], Harmony Search [Wan+21a], Hill Climbing [Liu+06], TS [LC08], and Greedy Algorithms (GA) [XGS21].

Figure 25 shows that NSGA-II has recently been widely used in solving complex, large-scale spatial optimization problems.

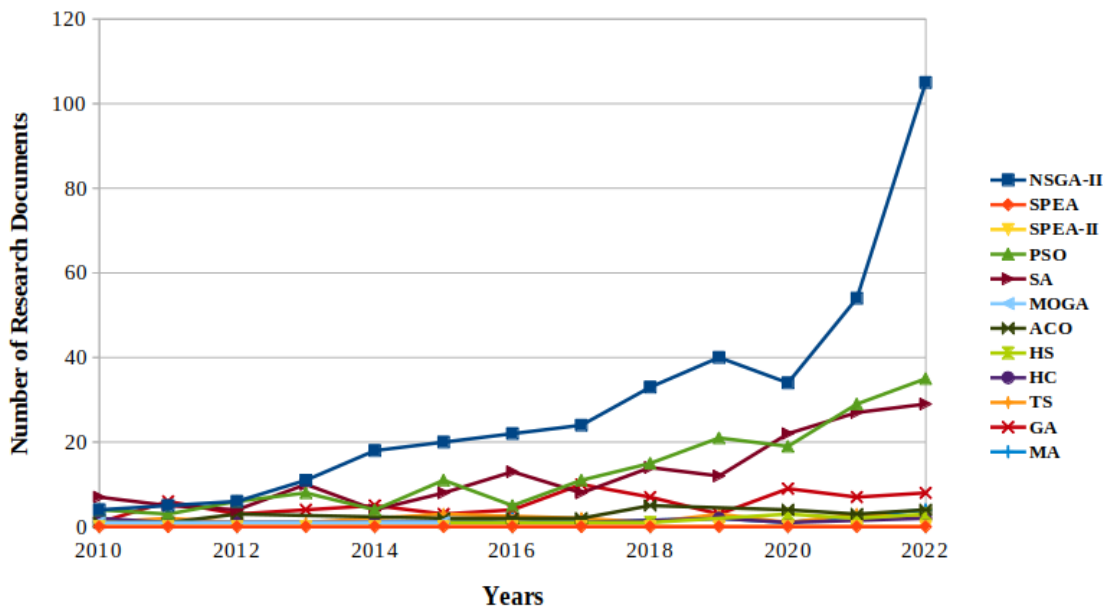


Figure 25: The trend of MOEAs in spatial optimization during recent 13 years

For example, in 2019, [Fox+19] applied a connectivity-based method for MOO to the design of MPA networks. The authors developed the MHs algorithm to find the Pareto optimal set for networks up to 100 sites by examining two real-world marine networks.

[Aer+03] used SA to solve the spatial goal programming for the land use allocation problem. This work determines the multi-site allocation between different land uses, which is a kind of partitioning problem without considering the existing elements as constraints.

[Yao+19] highlights the prominent sustainability concerns in land use planning and suggests a generalized multi-objective spatial optimization model facilitates conventional planning. They developed an evolutionary-based algorithm to solve the land use optimization problem. One limitation of this work, however, is that it focuses on the simple partitioning problem without considering the influence of the land uses on each other. Moreover, the developed heuristic algorithm is a traditional GA.

According to [SJ14], an improved land use optimization model is proposed for land use planning with a new spatial component. A GA is developed to solve the optimization problems. The context relates to interactive decision support for land use planning, in which the data is stored in a vector-based GIS, which is the extension of earlier work by the authors for a grid (raster) structure. However, again, the weaknesses of this work concern the mathematical formulation, which is nonlinear, and it is a kind of partitioning problem solved by a traditional GA, which is not compared with any other algorithm.

In the research of [WC04], an intelligent GIS-based spatial zoning system with a multi-objective hybrid MHs algorithm was developed to draw territory lines for geographical or spatial zones for space control. In this method, a GIS and a hybrid MHs (i.e., TS and SS algorithms) were used to generate non-dominated alternatives.

[Li+11] attempted to use the urban cellular automata coupled with ACO to solve a zoning

problem of the protected natural area in a changing landscape. The performance of this method against three traditional optimization algorithms, i.e., SA, Iterative Relaxation, and Density Slicing, has been tested and confirmed in the metropolitan region of Guangzhou, China, using Geographical Simulation and Optimization System software.

In 2017, [KZ+17] offered a spatial zoning approach simulating the long-term expansion of Mashhad city in Iran. In this method, a mix of external and internal variables for predicting urban growth was considered. In addition, this spatial zoning method differentiates the local-scale urban dynamics in districts from the socio-economic characteristics. First, Thiessen polygons were used in this method to identify districts with different morphology and functional attributes. Urban growth was then simulated for each district using a multi-layer perceptron neural network and Markov chains analysis. Finally, the multi-layer perceptron and Markov chains algorithms were used to derive transition maps from non-urban to urban use of land and to determine the spatial evolution of built-up areas at the metropolitan scale.

4.2.3 Hybrid Meta-Heuristics

In the field of optimization, interest in hybrid MHs has grown significantly in recent years. Hybrid algorithms produce the best results for many real-world or classical optimization problems [Tal02]. P-metaheuristics, S-metaheuristics, mathematical programming, Constraint Programming, and machine learning approaches have been used to create very strong search algorithms.

As stated above, the design of MHs is guided by two competing goals: exploration and exploitation. Exploration is required to guarantee that every area of space is sufficiently examined to offer an accurate estimate of the global optimum. Exploitation is vital since refining the present solution typically results in a better solution. P-metaheuristics (e.g., EAs, SS, particle swarm, Ant Colonies) are effective in exploring the search space but ineffective in implementing the solutions identified. As a result, the most efficient P-metaheuristics have been combined with S-metaheuristics such as local search, SA, and TS, all of which are effective optimization approaches in terms of exploitation. The strengths and disadvantages of the two kinds of algorithms are complementary. The S-metaheuristics attempt to optimize locally, whereas the P-metaheuristics attempt to optimize worldwide. In Low-Level Teamwork Hybrid (LTH), MHs are incorporated in a P-metaheuristic² (Figure 26). This type of hybrid method is widely common and has been successfully applied to a wide range of optimization problems. The majority of cutting-edge P-metaheuristics merge into S-metaheuristics.

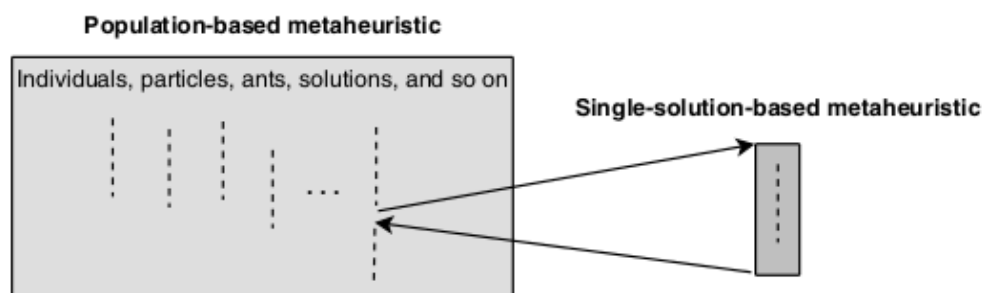


Figure 26: A combination of LTH. P-metaheuristics contain S-metaheuristics [Tal09].

In the research of [Lu+19], MA was used to solve the multiple **Traveling Repairman Problem with Profits (TRPP)**. In this MA, a randomized greedy construction method for initial solution generation, a VNS for local refinement, and a dedicated route-based crossover operator for solution recombination were combined. The effectiveness of the developed MA was demonstrated in solving an extensive set of instances of TRPP.

[EK20] developed another MA with optimal recombination for the asymmetric traveling salesman problem. In this MA, a crossover operator based on an exact algorithm was used to solve the optimal recombination problem on cubic digraphs, and a mutation operator was

²This class of hybrid MHs includes MAs

employed to make random jumps in 3-opt or 4-opt neighborhoods. In addition, a greedy constructive heuristic was used in this MA to generate the initial population.

[Hua+19] proposed a so-called niching MA for multi-solution traveling salesman problem. In this MA, a niche preservation technique to enable the parallel search, an adaptive neighborhood strategy to balance the exploration and exploitation, a critical edge-aware method to provide effective guidance to the reproduction, and a local search strategy to improve the search efficiency were proposed. Comprehensive experiments were conducted to confirm the effectiveness of the proposed MA.

[YATZ19] proposed an MA for closed-loop supply chain network design. In this MA, a priority-based encoding/decoding method based on a flexible combinatorial neighborhood search strategy was developed. Moreover, a technique to convert the discrete representation to a continuous one was proposed to avoid the time-consuming repair process in the discrete solution representation. Finally, a multi-start simulation annealing is integrated into the MA to enhance the search performance. The outperformance of the proposed MA, compared to commercial solvers and GA, was validated in various test problems ranging from small size to large size.

For the hub location and routing problem with the distinct collection and delivery tours, [YBD19] proposed a MILP model and the related MA to solve it. For scheduling and planning problems with a single objective, [RCR20; Ala+19; YK20; Jin+20] have developed various versions of MA to them.

For MOO, there have been a number of research works using MA, such as [Gon+19; Dec+19; Abe+20; ZWY20; STJ19; PL19; Sun+19].

MA has been used to solve many other optimization problems such as gene selection problem in microarray data [Gho+19a], training recurrent neural networks for the energy efficiency problem [RCP19], preventing epidemic spreading in networks [Wan+20], medical data classification [Bal+19], feature selection for handwritten word recognition [Gho+19b], composing distributed data-intensive Web services [SMC19], the 3-D protein structure prediction problem [LCD20], etc.

Following the reviewed studies in this field, the major knowledge gap addressed in this chapter is designing the efficient MOEAs to be able to:

1. solve spatial zoning optimization problems, which is more than a simple partitioning problem.
2. be applicable for any real spatial zoning problems in large-scale maps.
3. converging to good enough solutions in a reasonable computing time.
4. be compatible with the raster data.

On the basis of the knowledge gaps identified, this chapter presents the following contributions.

1. **Problem resolution:** We present two different population-based MOEAs (SH-NSGA-II and MA), which are Pareto-based techniques, to address the computational hardness issue of the exact method for the large-scale spatial zoning optimization problem in MSP. Initialization, stop condition, chromosome encoding, crossover, mutation, check and repair operators, constraint management methodologies, and algorithm structure in raster data are all suggested as innovations. The proposed MOEAs are used to simultaneously optimize the interestingness and compactness objectives of the new activity zone.
2. **Experimental validation:** MRSM for parameter tuning: we set up an Design Experiment (DOE) as Box-Behnken Design (BBD), which implements a multi-response regression model for three different map sizes of the problem in order to determine the optimal value of the algorithm parameters. Moreover, the effectiveness of all models is validated by ANOVA.
3. **Comparison Analysis:** To compare two MOEAs, different performance measures are indicated and calculated for better characterization of the Pareto solutions, resulting in a more precise analysis of two algorithms for small- and large-scale problems. To guarantee

all conclusions, the significance value of the **Wilcoxon Signed-Rank Test (WSRT)** (paired samples) tests of all performance measures for the exact method, **SH-NSGA-II**, and **MA**, in the three problem size levels are calculated and compared.

4.3 Multi-Objective Evolutionary Algorithms

[Wei91] was the first to establish the baselines of heredity from parents to offspring in the nineteenth century. The idea of evolution was then proposed by [Dar59] in his renowned book *On the Origin of Species* in 1859. These theories of the emergence and development of new species prompted computer scientists to develop **EAs** in the 1980s. During the last 40 years, three main schools of **EAs** have evolved independently: **GAs**, primarily developed in Michigan, USA, by [Hol62; Boo+05]; **ES**, developed in Berlin, Germany, by [RTE65; Hun76] and [Sch95]; and **EP**, developed in San Diego, USA, [Fog62; Fog98]. [Koz+92] later suggested **GP** around the end of the 1980s.

EAs are stochastic P-metaheuristics that have been successfully applied to a wide range of real-world and complicated issues. They are the most studied P-metaheuristics. Their effectiveness in addressing tough optimization problems in a variety of fields has given rise to the subject known as Evolutionary Computation [BFM18]. **EAs** are built on the concept of *competition*. They are a type of iterative optimization technique that simulates species evolution (Figure 27). They are based on the evolution of a population of individuals.

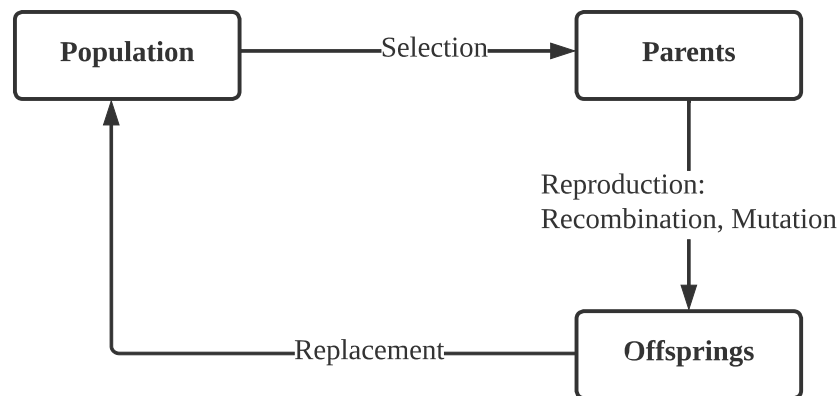


Figure 27: A generation in EAs

All the studies reviewed so far confirmed using the P-metaheuristics and **LTH** like **MA** as the suitable choices to solve the spatial zoning optimization problem described precisely in Section [3.3]. Therefore, in this section, we propose two **MOEAs**; **SH-NSGA-II** and **MA**. At their core, two P-metaheuristics are lied, based on the well-known high-level template for **NSGA-II** endowed with novelties in problem-specific coding, decoding, and recombination operators. The aim is to compare the efficiency of the two **MOEAs** based on the randomly generated datasets for the problem. In this context, the **DMs**, finally, are intended to find the most preferred solutions called the Pareto optimal set or Pareto frontier. In this section, both **MOEAs**, along with all their common components, are explained in detail.

4.3.1 Solution Encoding Schema

One of the first tasks in successfully implementing **MHs** is to choose the solution representation. In the spatial planning, the problem solution representation could involve geographic location dimensions (“cells”, “patches”, or “grids”).

To randomly produce a feasible initial population of solutions, we must consider various constraints while solving **MOOPs**. For the spatial zoning optimization problem, there is a set of

constraints as follows:

- The size of each solution is a fixed number of cells (the required solution size).
- Intersections between the solutions and other existing activities are not permitted.
- No hole is accepted in each solution because if a zone is closed and bounded, then it is compact [Bas22; Veb04].
- The solution's layout and structure should be uninterrupted, that is, without a break in continuity to make a solution compact.

Figure 28 depicts a mapping between the space of solution and the space of encoding. On the left of Figure 28, a raster reflects a specified zone of an activity on a map. This raster-based zone includes a regular grid of cells or pixels. Each raster cell contains a single value, and the coordinate of each raster cell relates to the center of the cell $((x_i, y_i)$ in Figure 28). Each cell can be defined by a cell dimension, such as the width and height of the cell. As cells in a raster are frequently square, their width and height will be the same.

In the GAs, the term “chromosome” is used to represent one single solution, while the term “population” is used for a given number of chromosomes. Therefore, the chromosome shown on the right of Figure 28 illustrates the encoded solution as a chromosome.

In Figure 28, the direction of generating a chromosome in a raster starts from the south-west of the map shown by the numbers 1 to 15 as an example (1 is located in the first cell and 15 in the last one, that is, the order of their selection). However, our proposed algorithms lead to a Pareto front including multiple different chromosomes (solutions) on the map for one specific activity, one of those is illustrated in Figure 28. Therefore, if we translate and gather multiple chromosomes all together in one matrix, we will reach the matrix of population 30 (Pop_{list}). By doing so, the solution representation in this chapter is a multi-dimensional matrix $(m \times n)$, in which m shows the number of rows of the matrix and n declares the number of columns. In other words, n reveals the size of each chromosome, that is, the total number of cells in its equivalent zone, while m is the given population size in the proposed algorithms (N_{pop}).

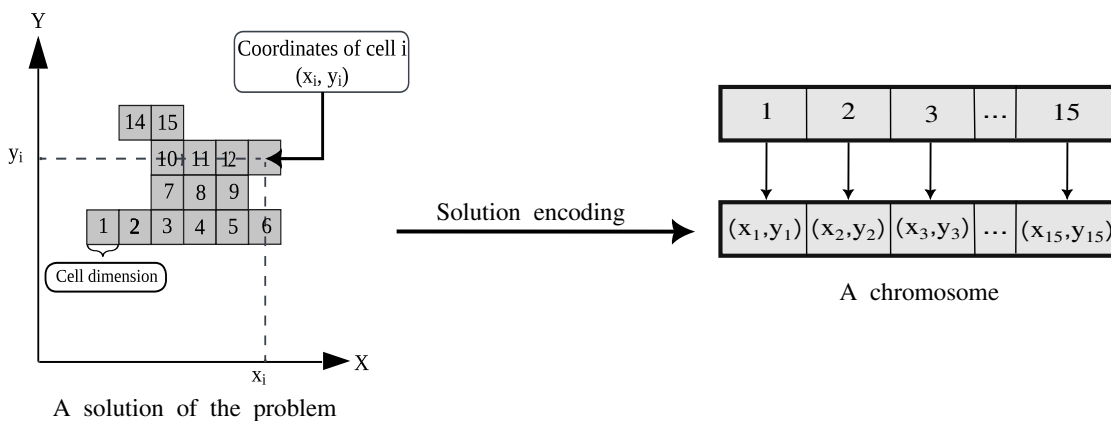


Figure 28: Mapping between the space of solution and the space of encoding.

$$Pop_{list} = \begin{bmatrix} (x_{11}, y_{11}) & \cdots & (x_{1j}, y_{1j}) & \cdots & (x_{1n}, y_{1n}) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ (x_{i1}, y_{i1}) & \cdots & (x_{ij}, y_{ij}) & \cdots & (x_{in}, y_{in}) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ (x_{mi}, y_{mi}) & \cdots & (x_{mj}, y_{mj}) & \cdots & (x_{mn}, y_{mn}) \end{bmatrix}_{m \times n} \quad (30)$$

4.3.2 Synchronous Hypervolume-Based Non-dominated Sorting Genetic Algorithm-II

MOEAs optimize two or more conflicting objectives by considering a collection of Pareto optimum solutions. [Deb+00] presented one of the efficient approaches to achieving Pareto frontiers, called NSGA-II. The key challenges in MOEAs are (1) computing complexity and (2) non-elitism approach, to name a few. To deal with computational complexity, NSGA-II employs a fast non-dominated sorting strategy. To address constrained MOOPs, NSGA-II employs an effective constraint-handling approach. It also explains how to use an elite approach to prevent losing out on the best answer and to increase the robustness of the system.

Figure 29 is a graphical depiction of NSGA-II. Figure 29 provides how the given set of five solutions (F_1 - F_5) are classified into three non-dominated fronts (P_{t+1}). As can be seen on the left of Figure 29, P_t is a population that NSGA-II randomly generates with respect to population size N_p . Following that, O_t is the chosen chromosomes by the selection operator for the offspring population, with regard to a crossover rate P_c and a mutation rate P_m . As shown in the first rectangle on the left of Figure 29, NSGA-II then combines P_t and O_t to generate R_t , which it then sorts into numerous non-dominated fronts F_i based on coverage and fitness function. These sorted F_i s, which are shown in the next rectangle, give rise to the next population, P_{t+1} as the last rectangle on the right, in which the best F_i s form P_{t+1} . Because the size of P_{t+1} should be the same as that of P_t , all elements of F_i may not be in P_{t+1} like F_4 and F_5 marked as “Rejected” in the figure. As a result, crowding sorting is used to complete P_{t+1} by adding an incomplete front in the crowding distance technique, in which the required population is created by the top of the front elements, such as F_1 , F_2 , and F_3 in Figure 29, without sacrificing good solutions (elitism). NSGA-II generates O_{t+1} from P_{t+1} similarly as O_t . It then iterated the preceding processes to achieve the best Pareto solutions while keeping a stopping criterion in mind. For further information on NSGA-II, readers might consult [Deb11; Deb+00]. The chromosomes in P_t are then sorted into numerous fronts of non-dominated solutions.

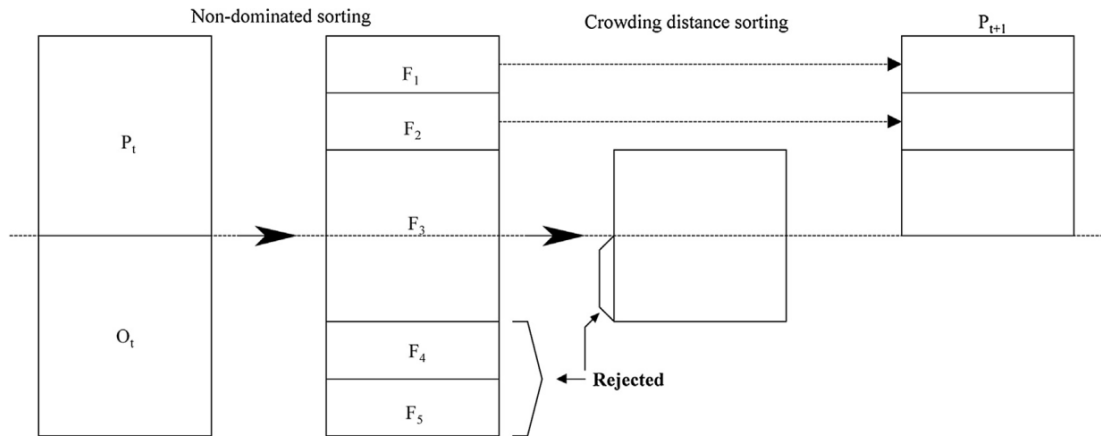


Figure 29: Graphical representation of NSGA-II [Deb11]

In this chapter, we propose the SH-NSGA-II architecture for solving the spatial zoning optimization problem. Compared to the typical NSGA-II, the suggested one employs a different initialization approach, stop criterion, four crossover operators, and three mutation operators throughout the search phase [Deb+00]. Furthermore, offspring chromosomes, which are produced by the four crossovers and three mutations, may compete with parent chromosomes for survival from generation to generation. Furthermore, the proposed SH-NSGA-II includes a check and repair mechanism that prevents the search process from being trapped in local optima. In other words, the proposed SH-NSGA-II is capable of preventing repeating solutions by producing solutions with various structures and without discarding non-feasible solutions: it can fix those that require minimal changes to make them feasible/acceptable. The suggested SH-NSGA-II components will be described in depth in the following sections.

In Figure 30, the flowchart of the SH-NSGA-II is presented. This flowchart starts with the

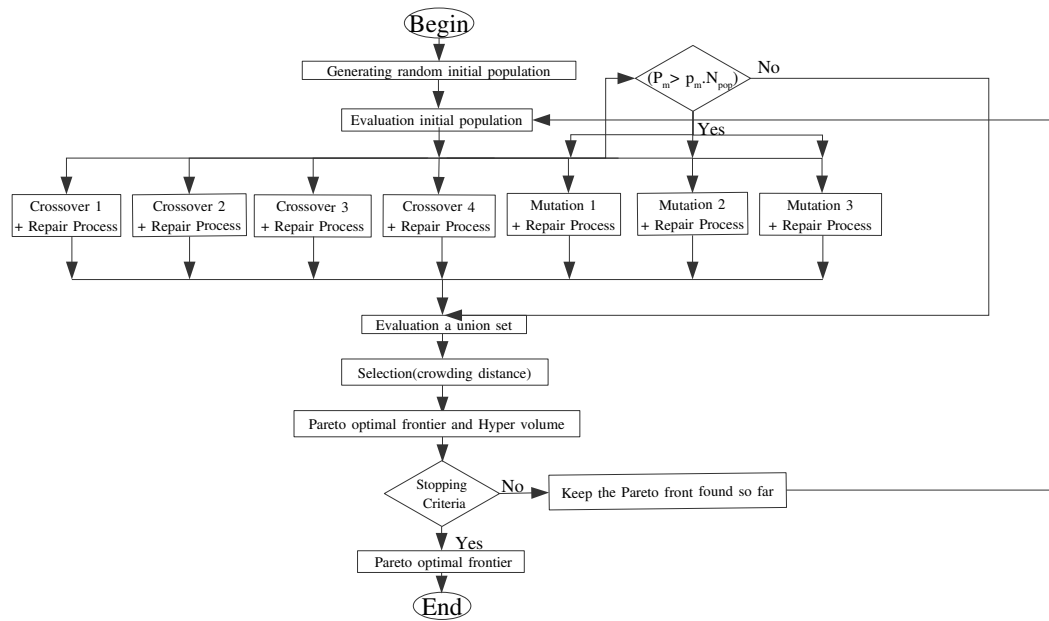


Figure 30: The flowchart of SH-NSGA-II for spatial zoning optimization problem

first randomly generated set of non-dominated populations. Next, the set of current initial zones is assessed by computing their objective functions. By doing so, the main loop of the algorithm launches. One of four crossovers is chosen at random in the initial phase to create non-iterative and acceptable offspring, and this random selection is repeated until the crossover rate is reached. On the other hand, if the probability of mutation is satisfied, the same procedure as a random selection in the crossover is repeated for three mutation operators to produce offspring. Following that, all populations and the achieved offspring are grouped to form a union set, which is then evaluated. Because the size of a union set should be the same as the beginning population, all zones may not be included in a union set at this point. As a consequence, the crowding distance approach is utilized to complete it by adding an incomplete front, in which the needed population is formed by the top of the front components without losing good solutions (elitism). Furthermore, it must attain the Pareto front in each iteration in order to compute the stop criteria, which is the number of non-improved **Hyper-Volume (HV)** values and will be explained in detail in Subsection 4.3.6. As a result, if this stop requirement is not met, the final selected solution set is saved, and the next generation begins. Otherwise, the final Pareto front is stated. The pseudo-code 10 presents **SH-NSGA-II** in more detail shown in Appendix B.

4.3.3 Hybrid Synchronous Hypervolume-based Non-dominated Sorting Genetic Algorithm-II Using Local Search (Memetic Algorithm)

As mentioned, applying some strategies to empower the local search ability in **MOEAs** helps to reduce the likelihood of premature convergence. Therefore, we propose another MOEA as a hybrid **SH-NSGA-II** using local search (MA) to enforce and compare with the proposed **SH-NSGA-II**. The **MA** combines an evolutionary search-based optimization algorithm with a problem-specific local search to balance the exploration and exploitation of the algorithm and therefore improve the quality of the solution [DW17; Dec+18]. **MA** has recently been shown to be useful and powerful in tackling difficult large-scale optimization issues [Gon+19; PRV18; ZBW20].

As can be seen in the flowchart of **MA** Figure 31, the **MA** starts similarly to **SH-NSGA-II** with a population that is formed with respect to a predefined population size. The main difference between the two is concerning to extra local search operator. Unlike the **NSGA-II**, no binary tournament is used in the selection process. It should be noted that three notations p_m and p_l in Figure 31 represent the probability of mutation and the probability of local search, respectively. In addition, the details of the proposed **MA** components will be presented in the subsequent

Sections.

The pseudo-code 2 describes our proposed MA to solve the spatial zoning optimization problem. In this pseudo-code, two different colors, red and black, are used. The red lines are added to SH-NSGA-II in black to make the MA algorithm. Unlike the traditional MA [Deb+00], the proposed one employs four crossover operators, three mutations, and a local search operator during the search process. The proposed MA added a local search strategy to SH-NSGA-II to improve its search efficiency.

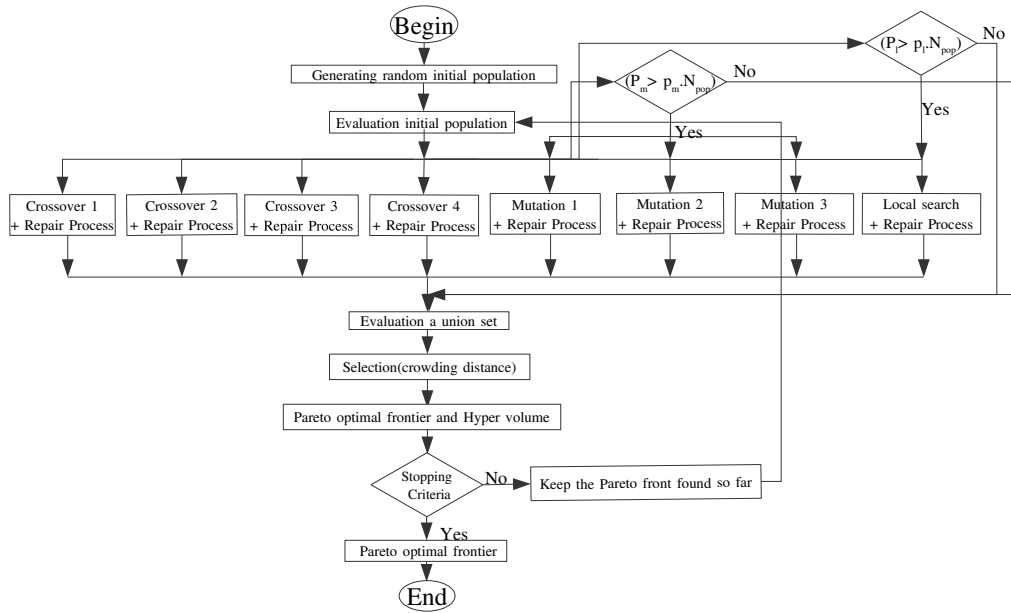


Figure 31: The flowchart of MA for the spatial zoning optimization problem

As can be seen in the pseudo-code 2, the start point for both algorithms is similar, that is generating a random population with respect to the predefined population size (N_{pop}), and then it is evaluated. To begin with, all three groups of populations, including crossover, mutation, and local search indicated by pop_{cross} , $pop_{mutation}$, pop_{local} in order, will start with the initial population. Afterward, on the basis of the crossover rate, this operator begins to make a list of new offspring. In each turn, up to the crossover rate, a crossover (i) is randomly selected between four different crossover operators. In case of not being in the offspring list, the feasible generated offspring would be added. After making the offspring list of crossover, the mutation loop will be started by meeting the mutation probability. The initial population would be mated by three different mutation operators (i) which are selected randomly iteratively. Then, the output of them would be saved in the offspring list of mutation if it is not already there. Following that, the local search process would be launched by local probability. Unlike SH-NSGA-II, no binary tournament is used in the local search operator selection process. Instead, a lower selective pressure is applied to select a number of the population. By doing so, it ensures that each chromosome in the selected population gets an opportunity to pass on its genes to the next generation, promoting variety and avoiding premature convergence. Then, a union set would be updated by combining all gathered offspring from the crossover, mutation, and local search operators. Next, using the crowding distance, the union set is adjusted to a certain size. Finally, the stop condition which is the number of non-improved HV values (K) which will be explained in detail in Subsection 4.3.6, is calculated, and all population lists along with their evaluations are updated to check if to continue or stop the main loop.

4.3.4 Search Components

MOEAs employ different common search components (e.g., selection, variation operators (mutation and recombination³), and replacement) as their major mechanism to carry out the evolution-

³Also called crossover and merge.

Algorithm 2 Pseudo-code MA

```

1: procedure MA( $N_{pop}, R_c, R_m, P_m, R_l, P_l$ )
2:   pop  $\leftarrow$  random_population( $N_{pop}$ )     $\triangleright$  Create a random initial population set
3:   F  $\leftarrow$  evaluation_Fitness(pop)         $\triangleright$  Evaluate the initial population
4:   popcross, popmutation, poplocal  $\leftarrow$  pop
5:   Fcross, Fmutation, Flocal  $\leftarrow$  F
6:   while not stop criterion(counter < K) do
7:     while not crossover rate do
8:       Ci  $\leftarrow$  crossoveri(popcross, Fcross)     $\triangleright$  For  $i^{th}$  crossover of 4
9:       Offspringcrossi  $\leftarrow$  non_repeat(Ci)  $\triangleright$  Clearing and Collecting offspring
10:    if mutation probability then
11:      while not mutation rate do
12:        Mi  $\leftarrow$  mutationi(popmutation, Fmutation)  $\triangleright$  For  $i^{th}$  mutation of 3
13:        Offspringmutationi  $\leftarrow$  non_repeat(Mi)  $\triangleright$  Clearing and Collecting
offspring
14:    if local probability then
15:      Offspringlocal  $\leftarrow$  local_search(poplocal, Flocal)
16:    pop  $\leftarrow$  insert(pop, popcross, popmutation, poplocal)  $\triangleright$  Create a union set
17:    F  $\leftarrow$  evaluation_Fitness(pop)           $\triangleright$  Evaluate union set
18:    Fpareto, Npareto  $\leftarrow$  pareto_front_finding(F, Npop)  $\triangleright$  Finding the pareto
front
19:    hv  $\leftarrow$  HV(Fpareto, Npareto)             $\triangleright$  Calculating HV
20:    counter  $\leftarrow$  count(hvlist)            $\triangleright$  Counting the non-improved HV value
21:    pop  $\leftarrow$  selection(Npop, pop, F)       $\triangleright$  Do selection among union set
22:    F  $\leftarrow$  evaluation_Fitness(pop)
23:    Updating popcross, popmutation, poplocal, Fcross, Fmutation, and Flocal
24:    Reporting the final Pareto front based on the Crowding Distance

```

ary process. This section explains all the operators used in [SH-NSGA-II](#) and [MA](#).

The Initialization Operators

The Pareto front can be generated more rapidly and produce more possible solutions with well-initialized populations, but the process is less efficient if the starting answers are poorly chosen. In spatial planning optimization issues, maps including existing activities and feasible areas to be found as the new activity should be incorporated into the iteration process, and initialization operators should generate 100% random solutions. Instead of checking distances on all possible grids, the utilized technique for generating the random population is similar to circle filling on a grid by bounding box, in which we save a lot of time by examining a much smaller region without looking at the rest of the grid. Compared to other basic algorithms, this may be able to construct compact zones with sufficient diversity that match all the restrictions listed in Section [4.3.1](#).

The following is a summary of the steps in this algorithm:

1. The square bounding box must be defined first
2. Getting all the cells in this box together
3. Choosing cells that match all the following criteria:
 - Starting with radius 1, being within the circle (if it is less or equal than the radius, then mark it)
 - Being feasible
 - Being non-repetitive
4. Step 3 is repeated until the upper-bound solution size is reached, and the radius is increased to the maximum preset radius in each iteration (8)

As can be seen in [Figure 32](#), it is a sample of circular fill of radius 3.5 with a bounding box. The values shown in [Figure 32](#) are the centroid distances of the grid from the center yellow point. The bounding box is defined by the four bounds; left, right, bottom, and top. Having gathered all feasible cells within this rectangle, the checking approach begins. Here, we select the number of cells with respect to the solution size, starting with radius 1. Among all the inside gathered (x, y) s, those are marked that not only meet the maximum radius distance restriction but also have yet-to-be selected (as shown in dark green). In order to increase the variety structure of the generated zones, another algorithm is used in which, instead of filling the circle, the square surrounding this circle (the bounding box) is considered.

Crossover Operators

Two proposed [MOEAs](#) utilize four crossovers, namely [Crossover-1 \(4.3.4\)](#), [Crossover-2 \(4.3.4\)](#), [Crossover-3 \(4.3.4\)](#), and [Crossover-4 \(4.3.4\)](#), which are explained in details in this section. They are applied to three separate sections of the chromosome, to thoroughly investigate the search space of the problem. We must choose two parents as inputs for this operator for each crossover. As a result, binary tournament selection is chosen as a selection method for picking two selective parents [[Deb+00](#)]. The chromosomes of both parents are then encoded and sorted according to x-coordinate/y-coordinate.

Having selected a random crossover i as mentioned on line 8 of the pseudo-code [2](#), the parent populations go through the tournament selection and two of them are selected. The selected parents are mated by the selected crossover operator and generate maximum two offspring after passing the check and repair operator. The parents of the remained offspring are deleted from the parent population list. The updated parent list will be returned to the crossover loop, and this action is iterative until the crossover rate is reached.

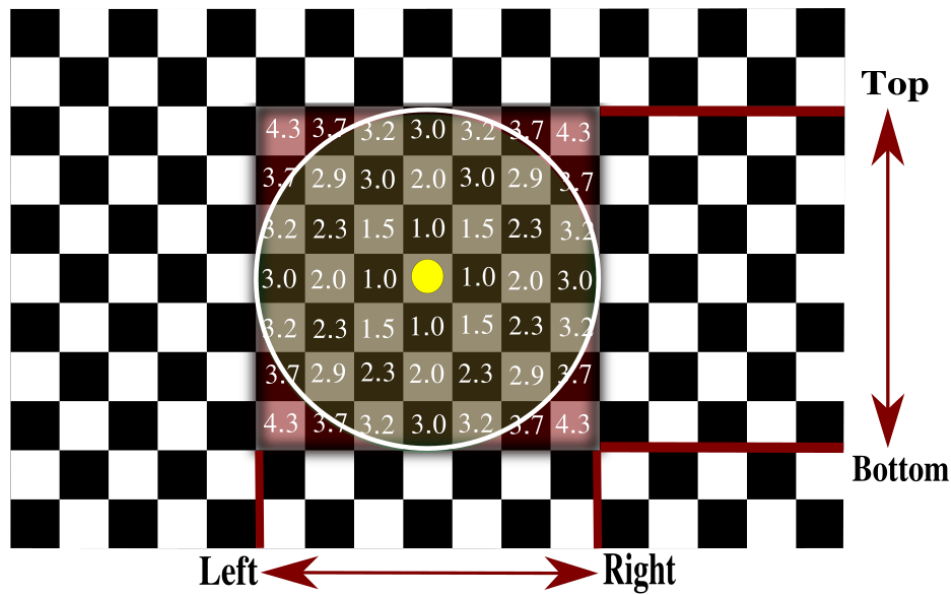


Figure 32: Random population using circle filling on a grid by bounding box

Single-Point Vertical Cutting Crossover (Crossover-1)

In this crossover, two parents representing two zones, together with their encoded chromosomes, are represented in purple and yellow in Figure 33. Then, as shown in Figure 33, a cut-point cell is chosen at random along the length of each chromosome. The next step is to create the center cell of these two cut-point cells, which is labeled “C” in red. As a result, each parent is split into three sections: before cut-point, cut-point, and after cut-point.

This split is done vertically since both parents are ordered based on the x-coordinate to begin with, which is why this crossover is named “Single-Point Vertical Cutting Crossover”. After locating the middle cell, the other two parts are vertically swapped and transformed to the new center point, i.e., the “left-hand” side of “Parent-1” and the “right-hand” side of “Parent-2” are shifted to the middle cell that forms “Offspring-1”.

The “left-hand” side of “Parent-2” and the “right-hand” side of “Parent-1” are substituted with the identical middle cell, resulting in another offspring, “Offspring-2”.

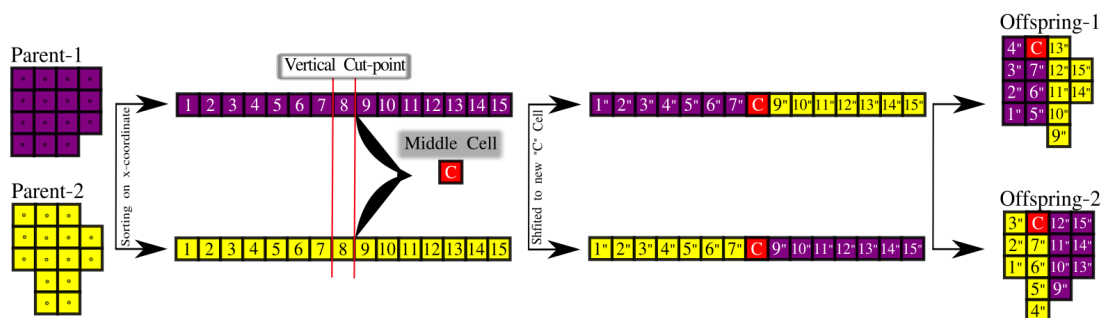


Figure 33: Single-point vertical cutting crossover (Crossover-1)

Figure 33 shows different numbers in the offspring chromosomes than those of parents because the coordinates of parent cells are changed by the new center point to other locations on the map. The output of each crossover is two offspring (children). By implementing this crossover leading to replacement through the map, some offspring may become infeasible due to the violation of certain constraints of the spatial zoning optimization problem. Therefore, it is needed to check and repair all offspring chromosomes to ensure their feasibility. This check and repair operator is explained in detail in Section 4.3.4. It is noted that four crossovers are not related, and they

usually have different inputs but always unique outputs.

For more clarification, line 8 of pseudo-code 10 and 2 for **SH-NSGA-II** and **MA**, is explained in detail hereafter. Algorithm 3 is proposed for implementing Crossover-1.

Algorithm 3 Pseudo-code Crossover-1

- 1: **procedure** CROSSOVER-1($\text{pop}_{\text{cross}}, F_{\text{cross}}$)
 - 2: $P_1, P_2 \leftarrow \text{binary_tournament_selection}(\text{pop}_{\text{cross}}, F_{\text{cross}})$ \triangleright Select two parent chromosomes
 - 3: $P_1, P_2 \leftarrow \text{sort_x}(P_1, P_2)$ \triangleright Sorting parent chromosomes based on x-coordinate
 - 4: $\text{cut_point} \leftarrow \text{rand}(1, 15)$ \triangleright Determining one random cut-point
 - 5: $x_{P_1[\text{cut_point}]} < x_{P_2[\text{cut_point}]}$ \triangleright Defining the order of the cut-point x-coordinate between parents
 - 6: $\text{middle_cell} \leftarrow \text{average}(P_1[\text{cut_point}], P_2[\text{cut_point}])$ \triangleright Finding the middle cell
 - 7: $P'_1, P'_2 \leftarrow \text{transform}(P_1, P_2, \text{middle_cell})$
 - 8: $\text{Offspring}_1 \leftarrow \text{insert}(P'_1[: \text{middle_cell}], P'_2[\text{middle_cell} :])$
 - 9: $\text{Offspring}_2 \leftarrow \text{insert}(P'_2[: \text{middle_cell}], P'_1[\text{middle_cell} :])$
 - 10: Check and repair both offspring chromosomes
 - 11: **Outputs** : $\text{Offspring}_1, \text{Offspring}_2$ maximum two acceptable offspring chromosomes
-

Single-Point Horizontal Cutting Crossover (Crossover-2)

The cutting direction is switched from vertical to horizontal, unlike Crossover-1. To put it another way, the y-coordinate is used to arrange two parent chromosomes. As shown in Figure 34, it should be noted that the random cut point in this example is the cell number (5). The graphical representation of this crossover is shown in Figure 34. Next, the middle cell of these two cut-point cells (number 5) is made, which is called “C” in red. Each parent is divided into three parts; before cut-point, cut-point, and after cut-point, respectively. As both parents are sorted based on the y-coordinate, this division is done horizontally, that is the reason why this crossover is called “**Single-Point Horizontal Cutting Crossover**”. Having found the middle cell, the other two parts are horizontally swapped and transformed to the new center point, that is, “**bottom**” of “**Parent-1**” and “**top**” of “**Parent-2**” are shifted to the middle cell that forms the “**Offspring-1**”. On the other side, “**bottom**” of “**Parent-2**” and “**top**” of “**Parent-1**” are replaced to the same middle cell making another offspring, “**Offspring-2**”.

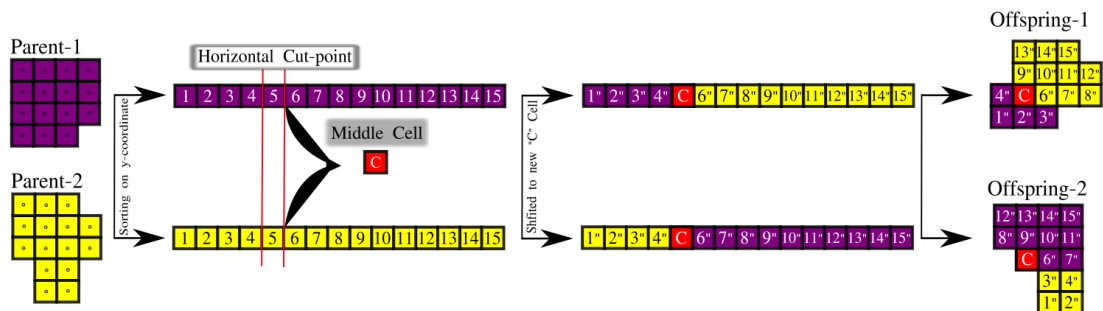


Figure 34: Single-point horizontal cutting crossover (Crossover-2)

As in line 8 of pseudo-code 10 and 2 for **SH-NSGA-II** and **MA** mentioned each crossover, Algorithm 11 is presented in Appendix B for implementing Crossover-2.

Semi-Proportional Vertical Single-Point Cutting Crossover (Crossover-3)

The structure (shape and size) and position of each zone are the two fundamental concerns in the spatial zoning optimization problem, as far as can be deduced. That is why the fundamental goal of the two first crossovers is to create well-diversified offspring in the parent neighborhoods from a structural standpoint. However, the goal of the following two crossovers is to produce well-diversified offspring in proximity to the parents. Therefore, Crossover-3 and Crossover-4 are built to focus on positioning the new activity in highly interesting zones. Therefore, the cutting type in Crossover-3 and -4 is the same as Crossover-1 (vertical single-point cutting).

However, after selecting the cutting cells at random in the parents, the new rule is used to locate the cell “C” among the offspring. The method for locating the cell “C” is based on the first objective function, which is the interestingness value of parents.

However, after randomly selecting the cutting cells in the parents, the new rule is applied to find the cell “C” in the offspring. The approach to finding the cell “C” is based on the first objective function, namely, the interestingness value of parents.

The difference between the initial objective function values of two parent chromosomes is calculated using the indicator “**proportion**” in Crossover-3. Following the proportional value, three situations are considered:

1. **Zero proportion:** When both parents’ first objective function values are equivalent, the middle cell in the distance between the parents’ selected cutting cells ($1/2 \times A$) is picked as the new “C” cell. The cells of the offspring are created by modifying the parent chromosomes, depending on the sort of cutting used here, which is vertical.
2. **Negative proportion:** When the initial objective function value of “**Parent-1**” is smaller than “**Parent-2**”, a new “C” cell is drawn toward the “**Parent-2**” placed in the distance ($2/3 \times A$) from the “**Parent-1**”, resulting in one of the offspring. The other offspring, on the other hand, is formed in the middle distance as previously. The rest of the procedure is identical to that of a zero proportion.
3. **Positive proportion:** The direction of the movement of the “C” cell is exactly the opposite of the negative proportion. Because the objective value of “**Parent-1**” is greater than that of the other. As a result, one of the children is drawn to the first parent, while the other stays in the center. The rest of the procedure remains unchanged.

For example, in Figure 35, the negative proportion is shown. As this crossover is called semi-proportional single-point vertical cutting crossover, the first offspring stays in the middle, and the other goes toward the parent with a higher first objective function (interestingness value).

Algorithm 12 in AppendixB is proposed for implementing Crossover-3.

Full-Proportional Vertical Single-Point Cutting Crossover (Crossover-4)

The only difference between Crossover-3 and -4 is that in the case of positive and negative proportions, both offspring intend to get closer toward the parent with higher objective function. Therefore, we could call it as full-proportional vertical single-point cutting crossover. All 4 crossovers are implemented iteratively through a loop. In each iteration, the check and repair operator checks the feasibility of the offspring (explained in Section 4.3.4). If each offspring is validated, it will be added to the list of offspring. This insertion will continue until the crossover rate is reached.

Algorithm 13 in AppendixB is proposed for implementing Crossover-4.

Mutation Operators

Vertical and horizontal reconfiguration of the solutions are examined to employ well-diversified solutions around the parent chromosomes, as demonstrated in the crossover operators. Three mutation operators, on the other hand, are utilized to better explore the problem’s search space. After a certain number of iterations within the main loop of the suggested MOEAs, the mutation operators will randomly be chosen. The proposed MOEAs employ three mutation operators, namely Mutation-1, Mutation-2, and Mutation-3. These operators start to be applied to each

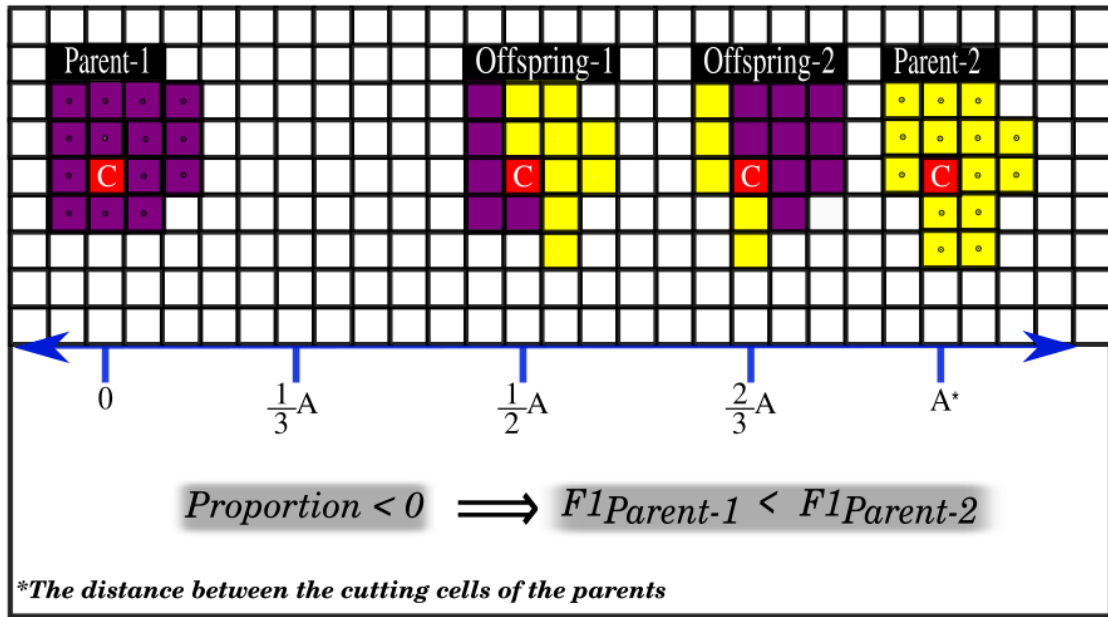


Figure 35: Semi-proportional vertical single-point cutting crossover Crossover-3

chromosome. The structure of mutations is based on a mix of four-directional motions (right, left, up, and down) and rotational symmetry of the solution across solution space (90° , 180° , 270°). Each mutation has two parent chromosomes as inputs, just like the crossover operators in Section 4.3.4 (binary tournament selection). Each chromosome is shifted to the other side of the search space in Mutation-1, Algorithm 4, with each parent's moving step between the list of four directions chosen at random. On the one hand, each gen coordinate (x, y) in each parent chromosome should be rotated counterclockwise by a specified angle around a given origin in Mutation-2, Algorithm 5, in addition to the 4-direction movement. In Mutation-3, Algorithm 6, however, the rotation process is the only factor that affects each parent chromosome. There could only be two offspring chromosomes after confirming the feasibility and correcting the result of each mutation.

Algorithm 4 Pseudo-code Mutation-1

- 1: **procedure** MUTATION-1($pop_{mutation}, F_{mutation}$)
- 2: $P_1, P_2 \leftarrow$ **binary_tournament_selection**($pop_{mutation}, F_{mutation}$) \triangleright Select two parent chromosomes
- 3: $m_1, m_2 \leftarrow$ **rand**($move_list$) \triangleright Moving step value for each chromosome
- 4: $Offspring_1 \leftarrow$ **move**(P_1, m_1)
- 5: $Offspring_2 \leftarrow$ **move**(P_2, m_2)
- 6: Check and repair both offspring chromosomes
- 7: **Outputs** : $Offspring_1, Offspring_2$ maximum two acceptable offspring chromosomes

Check and Repair Operators

Some challenges may arise throughout the solution development process. One challenge is that new solutions must be generated inside the possible solution space, not outside of it or in conflict with existing activity. Another challenge is recreating the solutions in a compact manner (*i.e.* without any hole). Two distinct check and repair operators, “**check-and-repair**” and “**compact-improver**”, are employed to fix these difficulties. Three potential situations for the first issue and one scenario for the second issue might occur as follows:

- Scenarios pertaining to the first problem are as follows:

Algorithm 5 Pseudo-code Mutation-2

```

1: procedure MUTATION-2( $\text{pop}_{\text{mutation}}, F_{\text{mutation}}$ )
2:    $P_1, P_2 \leftarrow \text{binary\_tournament\_selection}(\text{pop}_{\text{mutation}}, F_{\text{mutation}})$   $\triangleright$  Select two
   parent chromosomes
3:    $m_1, m_2 \leftarrow \text{rand}(\text{move\_list})$   $\triangleright$  Moving step value for each chromosome
4:    $\text{point}_1, \text{point}_2 \leftarrow \text{rand}(\text{point\_list})$   $\triangleright$  Selecting randomly the rotation origin
   point
5:    $\text{angle}_1, \text{angle}_2 \leftarrow \text{rand}(\text{angle\_list})$   $\triangleright$  Selecting randomly the rotation angle
6:    $\text{Offspring}_1 \leftarrow \text{move\_rotate}(P_1, m_1, \text{point}_1, \text{angle}_1)$ 
7:    $\text{Offspring}_2 \leftarrow \text{move\_rotate}(P_2, m_2, \text{point}_2, \text{angle}_2)$ 
8:   Check and repair both offspring chromosomes
9:   Outputs :  $\text{Offspring}_1, \text{Offspring}_2$  maximum two acceptable offspring chromo-
   somes

```

Algorithm 6 Pseudo-code Mutation-3

```

1: procedure MUTATION-3( $\text{pop}_{\text{mutation}}, F_{\text{mutation}}$ )
2:    $P_1, P_2 \leftarrow \text{binary\_tournament\_selection}(\text{pop}_{\text{mutation}}, F_{\text{mutation}})$   $\triangleright$  Select two
   parent chromosomes
3:    $\text{point}_1, \text{point}_2 \leftarrow \text{rand}(\text{point\_list})$   $\triangleright$  Selecting randomly the rotation origin
   point
4:    $\text{angle}_1, \text{angle}_2 \leftarrow \text{rand}(\text{angle\_list})$   $\triangleright$  Selecting randomly the rotation angle
5:    $\text{Offspring}_1 \leftarrow \text{rotate}(P_1, \text{point}_1, \text{angle}_1)$ 
6:    $\text{Offspring}_2 \leftarrow \text{rotate}(P_2, \text{point}_2, \text{angle}_2)$ 
7:   Check and repair both offspring chromosomes
8:   Outputs :  $\text{Offspring}_1, \text{Offspring}_2$  maximum two acceptable offspring chromo-
   somes

```

1. The chromosomes are not included inside the solution space (map).
 2. The chromosomes are located within the solution space, but they overlap with the activities that already exist.
- Scenarios related to the second issue:
 1. Holes or discontinuities can be seen in the chromosomes.

The following are some possible solutions for each scenario.

- The following is the recommended solution for the first issue, which uses the “**check-and-repair**” operator:
 1. A random population generator generates and replaces a completely new chromosome.
 2. Counting the number of overlapping cells; if there are less than 5, the search procedure continues to look for alternatives in nearby cells while maintaining or expanding the compactness; otherwise, the cell is completely deleted. The overlapping cell’s feasible and non-iterative 4-direction $((-1, 0), (0, 1), (0, -1), (1, 0))$ neighbors are collected.
- The following is the proposed solution for the second issue, which employs the “**compactness-improver**” operator:
 1. The “0-1” solution matrix is bound by the number “2”.
 2. Examining the rows and columns for any “1” or solitary “0” completely encircled by “1”.
 3. Removing the zero detected rows/columns and replacing the single encircled element “0” in the outer layer of the matrix with one of the possible elements “1”.

The solutions mentioned for “**check-and-repair**” are coded as explained in pseudo-code 7 to repair infeasible chromosomes to meet all the constraints and requirements of the spatial zoning optimization problem. In pseudo-code 7, the first proposed solution is coded in red and the second one in blue. In line 16 of this algorithm, all feasible and non-iterative 4-direction $((-1, 0), (0, 1), (0, -1), (1, 0))$ neighbors of the overlapped cell are gathered.

Figure 36 is a given example to better understanding how the “**compactness-improver**” operator works. In Figure 36, one achieved solution with one hole and interruptions is shown in the shape “1”. The “**compactness-improver**” first bounds the matrix of solution with value “2”. Next, the operator starts detecting the rows and columns without “1” like the green row in matrix “2”. After deleting all zero rows and columns, the initial solution turned into the shape “3” with a hole. Afterward, the operator makes a list of zeros with 2×1 or 4×1 connected components in their neighbors. Like blue zero in matrix “4” which is surrounded by 4×1 in red. Next, the zero is changed to 1 in orange as shown in matrix “5” and from the outer layer, one of the ones is changed to 0 in purple. Finally, the repaired shape is “6” which is well-compact.

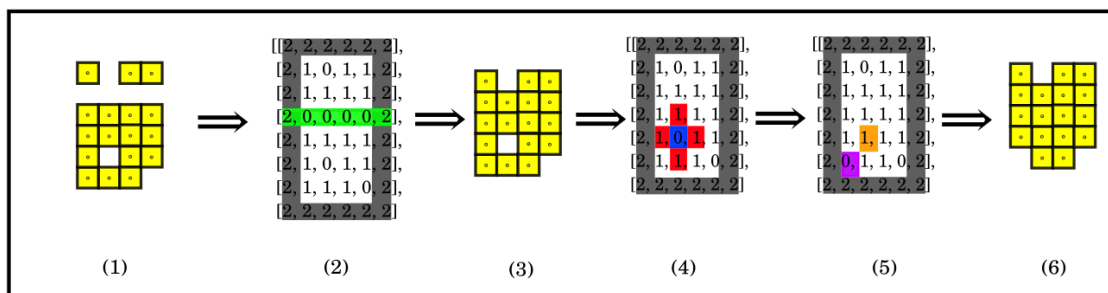


Figure 36: Compactness improver operator

All crossover, mutation, and local search operators include these two repairing operators in their bodies.

Algorithm 7 Pseudo-code Check-and-Repair

```

1: procedure CHECK-AND-REPAIR(pop, area, feasible_cells)
2:   counter  $\leftarrow$  0
3:   remove_list  $\leftarrow$   $\emptyset$ 
4:   check_list  $\leftarrow$   $\emptyset$ 
5:   for i in pop do
6:     for j in i do
7:       if j not in area then
8:         i  $\leftarrow$  random_population(Npop)  $\triangleright$  Replacing the new chromosome
9:       else if j not in feasible_cells then
10:        counter  $\leftarrow$  counter + 1
11:        check_list  $\leftarrow$  j
12:        if 1  $\leq$  counter  $\leq$  4 then
13:          for k in check_list do
14:            neighbour  $\leftarrow$  get_adjacent(Npop)
15:            if neighbour  $\neq$   $\emptyset$  then
16:              One of neighbor which leads to a more compact solution is chosen
17:            else
18:              remove_list  $\leftarrow$  i
19:          else
20:            remove_list  $\leftarrow$  i
21:   pop  $\leftarrow$  delete(pop, remove_list)  $\triangleright$  Deleting the remove_list from the population list

```

Local Search Operator

In addition to the crossovers and mutations which are used in both MOEAs, the suggested MA utilizes a local search operator that performs a tiny modification on a given solution to extensively search the neighborhood of that solution and boost the spatial zoning optimization problem convergence speed to the optimality. Using tournament selection, the parent chromosomes of the local search are chosen from the population with the size of the local search rate, and the offspring chromosomes are provided following the repair process.

This operator focuses on improving the interestingness values of the cells whose values are 2 units lower than the maximum value. Therefore, it starts to search for the best replacements in the neighbors of these cells. In this replacing process, the priority is on the higher value neighbors. However, it is noted that only if the 4-direction neighbors of the considered parent's gen are not in the parent chromosome, this replacement would be done. In other words, removing the selected gene bounded by other cells in the parent chromosome would result in the non-compactness and hole in the offspring chromosome. Next, among these neighbors, one of them is randomly selected as the replacement. The offspring chromosome of the local search may be infeasible because some constraints can be violated after employing the local search operator. Therefore, the local search requires employing the repair process.

The pseudo-code of the proposed local search operator is presented in Algorithm 8.

4.3.5 Evaluation and Selection Operators

Two different objective functions are used to calculate the fitness value of each chromosome (solution quality). The first objective function is obtained by adding the interest values of the zone cells, and the compactness value is determined using the NDC metric, proposed by [LGC13].

Each time, the population is classified into distinct non-dominance levels through the selection procedure. The fitness of any solution is equal to its level of non-dominance ("1" will be ascribed to the first non-dominated front). This procedure is for the minimization problems, but otherwise,

Algorithm 8 Pseudo-code Local_Search

```

1: procedure LOCAL_SEARCH( $\text{pop}_{\text{local}}, R_l, \text{param}_v$ )
2:    $P\_list \leftarrow \text{tournament\_selection}(\text{pop}_{\text{local}}, F_{\text{local}}, R_l)$        $\triangleright$  Select the parent
   chromosomes
3:   for  $i$  in  $P\_list$  do
4:     for  $j$  in  $i$  do
5:        $\text{condition} \leftarrow \text{feasibility\_check}(j)$        $\triangleright$  Checking the feasibility of the
       selected parent's gen
6:       if  $\text{param}_v[j] \leq (\max(\text{param}_v) - 2)$  and  $\text{condition}$  then
7:         while  $C \leq (\max(\text{param}_v) - \text{param}_v[j] - 2)$  do
8:            $\text{selected\_neighbours} \leftarrow \text{get\_adjacent\_higher}(j)$   $\triangleright$  Starting with
            $(\max(\text{param}_v) - C)$  value
9:           if  $\text{selected\_neighbours} \neq \emptyset$  then
10:             $j \leftarrow \text{choice}(\text{selected\_neighbours})$ 
11:          else
12:             $C \leftarrow C + 1$ 

```

the maximization problems could be altered to minimization by multiplying by “-1”.

This approach allows for simultaneous non-dominated sorting and filling of population steps based on crowding distance until the population size requirement is reached. As a consequence, each time, a non-dominated front finding operator was used to determine if the acquired solution could be included in the Pareto set. Otherwise, there is no reason to continue sorting. If the number of identified solutions exceeds the population size, the excess will be removed using the crowding-distance metric from the previous front that could not be fully accommodated.

When two solutions are compared, the crowded comparison operator gives the tournament winner. The winner is determined by two factors in the population: the non-dominance ranking r_i and the local crowding distance d_i . The search space surrounding a i^{th} solution in its front (marked with solid circles) that is not filled by any other solution in the population is measured by the crowding distance attribute of that solution. The perimeter of the cuboid produced by employing the nearest neighbors as vertices (solid circles $(i - 1)$ and $(i + 1)$) is estimated as d_i , shown in Figure 37 by the dashed box (called the crowding distance). The binary crowding tournament selection operator, which is based on r_i and d_i , operates as follows: A solution i wins a tournament over a solution j if any of the following criteria are true:

1. If $r_i < r_j$, the chosen solution is on a better non-dominated front.
2. If $r_i = r_j$ and $d_i > d_j$ (When both solutions are on the same front and the criteria above cannot be met, this is used; in this situation, the solution that is located in a less congested region and has a bigger d_i , wins).

4.3.6 Stop Condition of Multi-Objective Evolutionary Algorithms

Different termination criteria may be utilized in MOEAs, including 1) a predetermined amount of iterations, and 2) convergence to a solution of a specified quality [Tal09; Sid+12]. We created a novel stop criterion that may alleviate some shortcomings of duplicate generations while also lowering the ratio of solution quality to processing time. This condition is used to halt the operation after the algorithm has completed a particular number of iterations without improving. It is based on the HV value, MOEAs Pareto sets diversity and convergence control measure, over a set of iterations. For multi-objective issues, HV is a well-known performance metric. It adheres to the Pareto principle and is based on the volume difference between a predetermined reference point and the solution offered. As a result, the HV necessitates the establishment of a reference point that is greater than the Pareto front's maximum value named by r in figure 38 [CSR15]. It determines the area/volume dominated by the set of solutions provided in relation to a reference point [Pdq+22; GMF21].

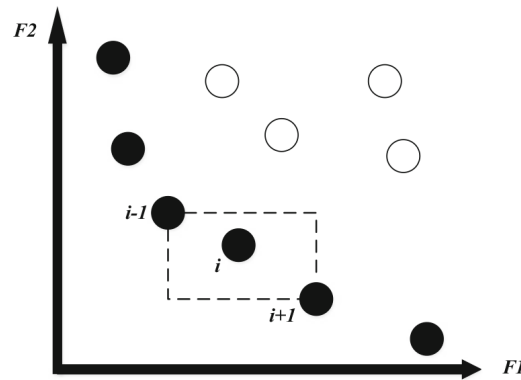


Figure 37: Crowding-distance calculation. Points marked in filled circles are solutions of the same non-dominated front [BAJH20]

The figure 38 depicts a two-objective example, in which the area dominated by a set of points ($p^{(1)}$, $p^{(2)}$, and $p^{(3)}$) is shown in gray. Whereas the goal with this metric is to increase the distance to the reference point, to maximize its performance. The more HV value, the less distance to the Pareto front is.

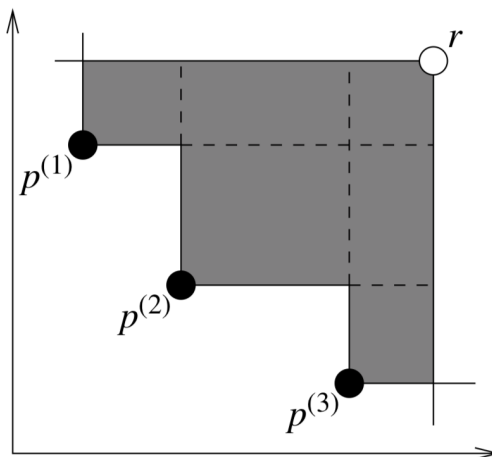


Figure 38: HV indicator for a non-dominated approximation set of solutions [FPLI06]

This metric is also used for the stop criterion in the proposed MOEAs algorithms. That is, at the end of each iteration in both algorithms, the HV of the optimal Pareto front is calculated and compared with that of the previous iteration. Then, the number of non-improved HV values in each iteration is determined. If this number violates the predefined maximum bound, the main loop of each MOEA will be stopped and the optimal Pareto front will be returned. The approach to defining this upper bound is explained in Subsection 4.3.6.

4.4 Tuning Parameters

To compare the performance of the two MOEAs, it needs to tune their parameters. However, before that, a DOE approach is used to explore the impacts of the components. Next, the MOEAs parameters, which have a substantial influence on the quality of the solution explored and then optimized by using the Response Surface Methodology (RSM). RSM contributes to the improvement and optimization of processes by creating an analytical link between the input and result variables in experiments. However, most previous RSM-based solutions focused on single-response problems, with multi-response scenarios receiving fewer attention [TTW+10].

Therefore, in this section, the appropriate tuning approach for our problem is explained (4.4.1) and the final obtained values of tuned parameters are reported (4.4.2).

4.4.1 Multi-Response Surface Methodology Optimization

According to research, the optimal factor settings for one performance feature are not always consistent with those for other performance qualities. Finding compromising circumstances in input variables that are moderately favorable to all responses might be addressed in more general situations [Kök08]. More details on RSM related design and optimization of response surfaces are given in [Kle08] and [Mye+04].

In order to determine the substantial factors, MRSM developed a special type of Fractional Factorial Experiments to reduce the large number of experiments required in it [Kar+19]. BBD with one central point is used to run the experiments, even though the responses may have curvature over the search ranges of the factors [Mye+04]. There are $k = 4$ factors for SH-NSGA-II and $k = 6$ factors for MA, each with three levels, i.e. low, medium, and high, and each signed by $-1, 0,$ and $+1,$ respectively. The data generation parameters of the spatial zoning optimization problem are summarized in Table 3. We vary these problem-specific parameters in three different levels (low, medium, and high) for three different map sizes ($55 \times 55, 300 \times 300, 1000 \times 1000$) as shown in Table 3. The total number of artificial datasets for each map size that have been generated is $3^4 = 81$. Among 81 datasets, 8 of them are randomly selected to be used in all evaluations for each map size. Moreover, the anonymous link where anyone with the link can view all coded algorithms along with all data is provided in the repository [Bas22].

Using the data in Table 3, the coded MOEAs were executed based on the BBD for four factors in three levels with one center point for SH-NSGA-II and six factors in three levels with one center point for MA, shown in Table 4.

Table 3: Data generation parameters for MOEAs

Parameter Names	Possible Values	Description
n_{row}	55, 300, 1000	Number of rows of the raster grid
n_{col}	55, 300, 1000	Number of columns of the raster grid
n_p	6, 8, 10	Number of ports
n_s	6, 7, 8	Number of shipping lanes
n_a	3, 4, 5	Number of protected areas
n_w	2, 3, 4	Number of windmill farms

Table 4: Search range of algorithm parameters

Algorithm	Actual Values	Coded Values	Low(-1)	Medium(0)	High(+1)
SH-NSGA-II	Population_size (N_{pop})	x_1	100	150	200
	Crossover_rate (R_c)	x_2	0,4	0,6	0,8
	Mutation_rate (R_m)	x_3	0,1	0,4	0,7
	Mutation_probability (P_m)	x_4	0,25	0,5	0,75
MA	Population_size (N_{pop})	x_1	100	150	200
	Crossover_rate (R_c)	x_2	0,4	0,6	0,8
	Mutation_rate (R_m)	x_3	0,1	0,4	0,7
	Mutation_probability (P_m)	x_4	0,25	0,5	0,75
	Local_rate (R_l)	x_5	0,1	0,5	0,8
	Local_probability (P_l)	x_6	0,45	0,6	0,8

Multi-Response Optimization Problems (MROPs) have been examined from a variety of perspectives and can be divided into three groups:

- **Desirability viewpoints:** in this category, researchers try to aggregate the information of all responses into one response, and then an optimization method is performed on a single objective called the total desirability function.

- **Priority based methods:** some cases have responses with different importance degrees, in such problems, we must consider the most important response for optimization and if the solutions were not unique, then get the best solution by comparing the status of other responses with alternative solutions and the aforesaid steps are repeated till all the responses are considered or a unique optimal solution is found.
- **Loss function:** in this category, based on the Taguchi loss function, all response values are aggregated and converted to a single one. A wide range of research has been studied to develop and generalize the Taguchi loss function concerning the special trait of its cases [Hej+12].

The third category of **MRSM** achieves a balance between resilience and optimization for multiple response issues by incorporating some well-established methods in it, such as GA, Artificial Neural Network, the Taguchi loss function, and desirability function. So, we create a hybrid technique that uses the Taguchi method's loss function to compact and calculate multi-responses. In this chapter, all response values (multi-objectives) of **MROPs** are aggregated and converted to a single one using the Taguchi loss function.

The proposed approach has the following steps:

- Identifying the experimental variables, and parameters, affecting the solution as considerable factors and responses.
- Applying a proper design, running experiments, and fitting the response surfaces.
- Getting information about the importance weights of response variables by implementing some feature selection methods.
- Forming a multi-response model.
- Solving the model to achieve the optimal combination of factors, which is the stationary point in the original units in **RSM**.

There are two types of factors in the loss function of the Taguchi method; noise factors N , and controllable factor S . Since **MOEAs** have multiple runs to obtain better solutions, the signal-to-noise ratio (S/N) is used in this research to analyze the results. The signal-to-noise ratio measures how the response varies relative to the nominal or target value under different noise conditions.

Three metrics are used to assess **MOEAs** in this chapter: **HV**, **Number of Pareto Solutions (NPS)**, and **Best Solution (Best Sol)**. **NPS** metric presents the number of Pareto optimal solutions that are obtained by each algorithm. For each set of solutions, the values of both objective functions, each weighted 0.5, are put together to identify the best solution. After that, **Best Sol** is picked as the best answer, the maximum (similar to how the **Simple Additive Weighting Algorithm (SAWA)** in **MCDM** handles [Zan+98]). Because the goal is to maximize efficiency, the higher the **HV**, **NPS**, and **Best Sol** values, the better.

There are four different formulations to calculate signal-to-noise ratios [Hec+02]. Following the objective of our experiment, we selected the first type in which for the signal-to-noise ratio, the larger is better, whose aim is to get the maximum S/N determined in Equation 31:

$$\frac{S}{N} = -10 \log\left(\frac{1}{n} \sum_{i=1}^n \frac{1}{\text{sum}_i^2}\right) \quad (31)$$

Where sum_i is the response in the Taguchi method, and n is the number of replications ($n = 3$). S/N is the **MRSM** response. Since the largest S/N value corresponds to the optimal combination of parameter values, this response should be maximized. A regression equation can be used to determine the relevance of individual process factors and their interactions. It calculates the relationship between the response and the parameters of the input process.

To compute the S/N , the resulting metrics are merged into a single value (using **SAWA** in the **MCDM** approach with equal weight). As an example, Table 5 shows the values of the metrics for **SH-NSGA-II** obtained based on different combinations of parameters after meeting the stop

criteria of the [SH-NSGA-II](#) execution for one dataset. The last column, namely, Sum, is the summation of the four metrics that will be used as the response of the loss function (S/N) in the Taguchi method. Note that the highest Sum is the best value in evaluating [MOEAs](#) in terms of the merged metrics using the [SAWA](#) method.

Table 5: Results of metrics for SH-NSGA-II

N_{pop}	R_c	R_m	P_m	HV	NPS	Best Sol	Sum
100	0,4	0,4	0,5	5,782	3	0,520	9,302
200	0,4	0,4	0,5	5,718	2	0,518	8,236
100	0,8	0,4	0,5	5,709	4	0,517	10,226
200	0,8	0,4	0,5	5,545	3	0,505	9,049
100	0,6	0,1	0,5	5,706	3	0,516	9,222
200	0,6	0,1	0,5	5,718	2	0,518	8,236
100	0,6	0,7	0,5	5,788	5	0,520	11,308
200	0,6	0,7	0,5	5,532	4	0,517	10,049
100	0,6	0,4	0,25	5,699	4	0,514	10,214
200	0,6	0,4	0,25	5,709	2	0,517	8,226
100	0,6	0,4	0,75	4,566	2	0,502	7,069
200	0,6	0,4	0,75	5,189	2	0,519	7,709
150	0,4	0,1	0,5	5,627	2	0,511	8,138
150	0,8	0,1	0,5	5,414	2	0,506	7,919
150	0,4	0,7	0,5	5,709	4	0,516	10,225
150	0,8	0,7	0,5	5,785	4	0,519	10,304
150	0,4	0,4	0,25	5,709	3	0,517	9,226
150	0,8	0,4	0,25	5,718	2	0,518	8,236
150	0,4	0,4	0,75	5,709	3	0,517	9,226
150	0,8	0,4	0,75	4,934	3	0,5	8,434
150	0,6	0,1	0,25	5,706	5	0,516	11,222
150	0,6	0,7	0,25	5,712	3	0,517	9,229
150	0,6	0,1	0,75	5,019	3	0,506	8,525
150	0,6	0,7	0,75	5,715	3	0,517	9,232
150	0,6	0,4	0,5	5,718	2	0,518	8,236

The design points, along with the results of the experiments for small size of [SH-NSGA-II](#), is represented in [Table 6](#). The small size of MA and the other map size for both algorithms are represented in [Tables 20–24](#) in the [Appendix A](#), respectively.

Table 6: Computational results obtained for the tuning parameters of SH-NSGA-II for small map size.

Run Order	x_1	x_2	x_3	x_4	Signal_Noise
1	-1	-1	0	0	19,269
2	-1	1	0	0	19,234
3	1	-1	0	0	19,265
4	1	1	0	0	19,605
5	0	0	-1	-1	20,687
6	0	0	-1	1	20,923
7	0	0	1	-1	20,034
8	0	0	1	1	19,867
9	-1	0	0	-1	19,098
10	-1	0	0	1	18,205
11	1	0	0	-1	18,965
12	1	0	0	1	19,741
13	0	-1	-1	0	20,641
14	0	-1	1	0	20,398
15	0	1	-1	0	19,390
16	0	1	1	0	20,369
17	-1	0	-1	0	20,840
18	-1	0	1	0	19,229
19	1	0	-1	0	19,624
20	1	0	1	0	20,043
21	0	-1	0	-1	19,454
22	0	-1	0	1	19,876
23	0	1	0	-1	19,852
24	0	1	0	1	19,183
25	0	0	0	0	19,529

To estimate the response functions, the developed algorithms and experimental DOE tests are programmed in Python 3.8 and R version 4.1.2, respectively. I did all experimental tests on an OpenStack virtual machine running Linux/Ubuntu 20.04.1 LTS with 20 VCPU, 10 GB disk, and 30 GB RAM.

Then, the response function is estimated and optimized using MRSM. Furthermore, for each MOEAs in each size, the design should fit the second-order regression model (a quadratic model), that is, the one containing squared terms, the product of two factors, linear terms, and an intercept. To find the subset of variables in the dataset resulting in the best performing model, that is, a model that lowers prediction error, the feature selection technique is applied to iteratively add and remove predictors in the predictive model.

In this chapter, we employed a feature selection strategy for all regression models that combined stepwise regression and cross-validation to produce the highest-performing model. All final models are solved using the coded parameters, and the algorithm finds the best combination of parameters (a stationary point in the original units). The summary table and ANOVA results of the best regression functions are reported in Tables 7–27 for SH-NSGA-II and MA, respectively.

ANOVA on the proposed multi-response optimization models was performed to estimate the coefficients of the polynomial equation in Equation 32.

$$Y = \beta_0 + \sum_{i=1}^k \beta_i x_i^2 + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i=1}^k \sum_{j=i+1}^k \beta_{ij} x_i x_j \quad (32)$$

Table 7: Summary table SH-NSGA-II for small map size

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	19.564	0.141	138.581	<2.2e-16 ***	
x ₁	0.113852	0.108	1.0559	0.3088910	
x ₂	-0.105908	0.108	-0.9822	0.343	
x ₃	-0.180506	0.108	-1.674	0.116	
x ₄	-0.024356	0.108	-0.226	0.824	
x ₁ ²	-0.382	0.156	-2.451	0.0279735 *	
x ₃ ²	0.734	0.156	4.708	0.0003359 ***	
x ₁ :x ₃	0.507455	0.187	2.717	0.0166845 *	
x ₁ :x ₄	0.417154	0.187	2.234	0.0423352 *	
x ₃ :x ₂	0.305370	0.187	1.635	0.1242988	
x ₄ :x ₂	-0.272812	0.187	-1.461	0.1661494	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Multiple R-Squared: 0.81, Adjusted R-Squared: 0.68					
F-statistic: 5.98 on 10 and 14 DF, p-value: 0.001417					
ANOVA	Df	Sum Sq	Mean Sq	F value	Pr(>F)
FO(x ₁ , x ₂ , x ₃ , x ₄)	4	0.688	0.172	1.2333	0.341
PQ(x ₁ , x ₃)	2	5.2575	2.629	18.842	0.000107
x ₁ :x ₃	1	1.030	1.030	7.383	0.016684
x ₁ :x ₄	1	0.696	0.696	4.989	0.042335
x ₃ :x ₂	1	0.373	0.373	2.673	0.124299
x ₄ :x ₂	1	0.297	0.297	2.133	0.166149
Residuals	14	1.953	0.139		
Lack of fit	14	1.953	0.139		
Pure error	0	0.0			
Stationary point of response surface:					
	x ₁	x ₂	x ₃	x ₄	
	0.149	0.00	0.13	0.00	
Stationary point in original units:					
	N _{pop}	R _c	R _m	P _m	
	157.45	0.60	0.44	0.50	
rsm(formula=Signal_Noise~ FO(x ₁ , x ₂ , x ₃ , x ₄)+(x ₁ :x ₃)+(x ₁ :x ₄)+ +(x ₂ :x ₃)+(x ₂ :x ₄) + PQ(x ₁ , x ₃), data = BBD)					

Statistical significance was checked by F-value and p-value (significant probability value). Terms whose p-value is less than 0.05 have a significant effect on the response. Based on the ANOVA results, the equations of the response surface models, which relate the significant factors to responses, were obtained, as shown in Equation (33).

$$\begin{aligned} \frac{S}{N} = & 19.564140 + x_1 + x_2 + x_3 + x_4 + 0.113852 x_1 - 0.105908x_2 - 0.180506 x_3 \\ & - 0.024356 x_4 - 0.382041 x_1^2 + 0.733790 x_3^2 + 0.507455 x_1 \times x_3 \\ & + 0.417154 x_1 \times x_4 + 0.305370 x_3 \times x_2 - 0.272812 x_4 \times x_2 \end{aligned} \quad (33)$$

The quality of fit of the polynomial model was evaluated by the determination of coefficients R-Squared, adjusted R-Squared, p-value, and acceptable stationary point in original units. These coefficients imply that the models are adequate for representing the relationship between the factors and response (S/N). As can be seen in Table 7, all these coefficients are promising for SH-NSGA-II of small map size, and the established response surface models are reliable and capable of expressing the relationship between important factors and response accurately. The results for other map size for both algorithms are represented in Appendix A in Tables 25–27, respectively.

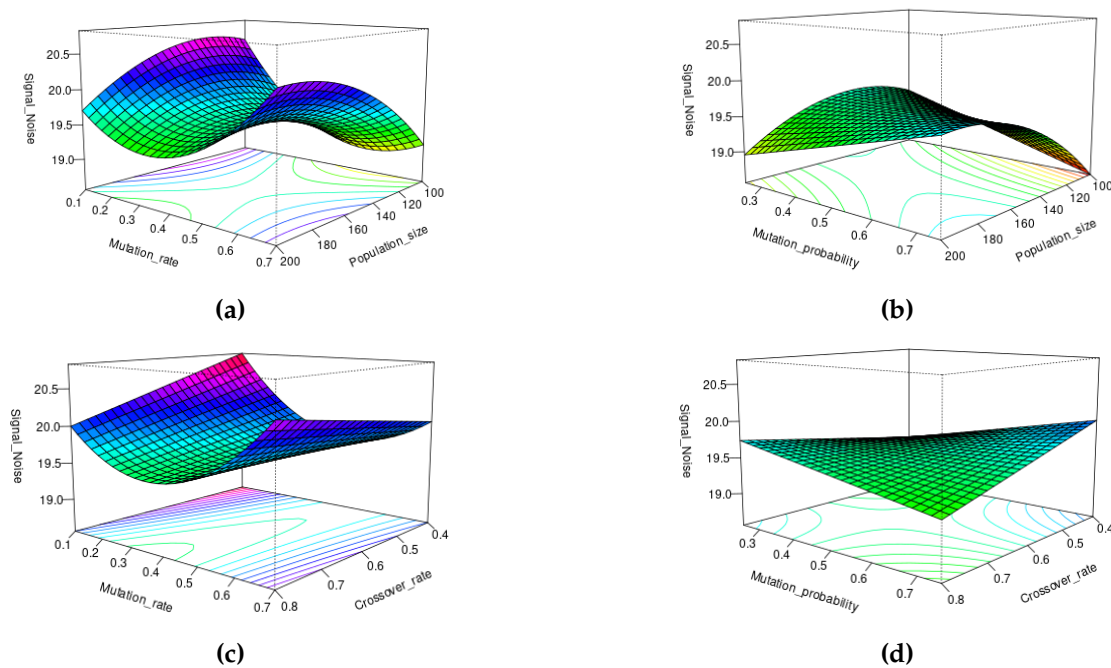


Figure 39: The response surface 3D plots of interaction of important factors on S/N : (a) interaction of population size and mutation rate; (b) interaction of population size and mutation probability; (c) interaction of mutation rate and crossover rate; (d) interaction of mutation probability and crossover rate

By means of best fitted regression models, the interactions of important factors on the response surface were evaluated. Finally, the optimal combination is obtained, which is the stationary point based on the generated response surface model. One caution about DOE and MRSM is related to the extrapolation of the stationary point, that is, whether this point is outside the experimental space or not? In other words, since a quadratic model will always show an optimum point, its accuracy depends on the accuracy of the model. Therefore, to validate the best MRSM model, it is necessary to make a balance between the accuracy of the optimal point and the regression model at the same time. Figure 39 and 40 represent an example of response surface 3D plots between population size and mutation rate, population size and mutation probability, mutation rate and crossover rate, and mutation probability and crossover rate for the SH-NSGA-II algorithm for small size maps. The graphs show the significant impact on S/N .

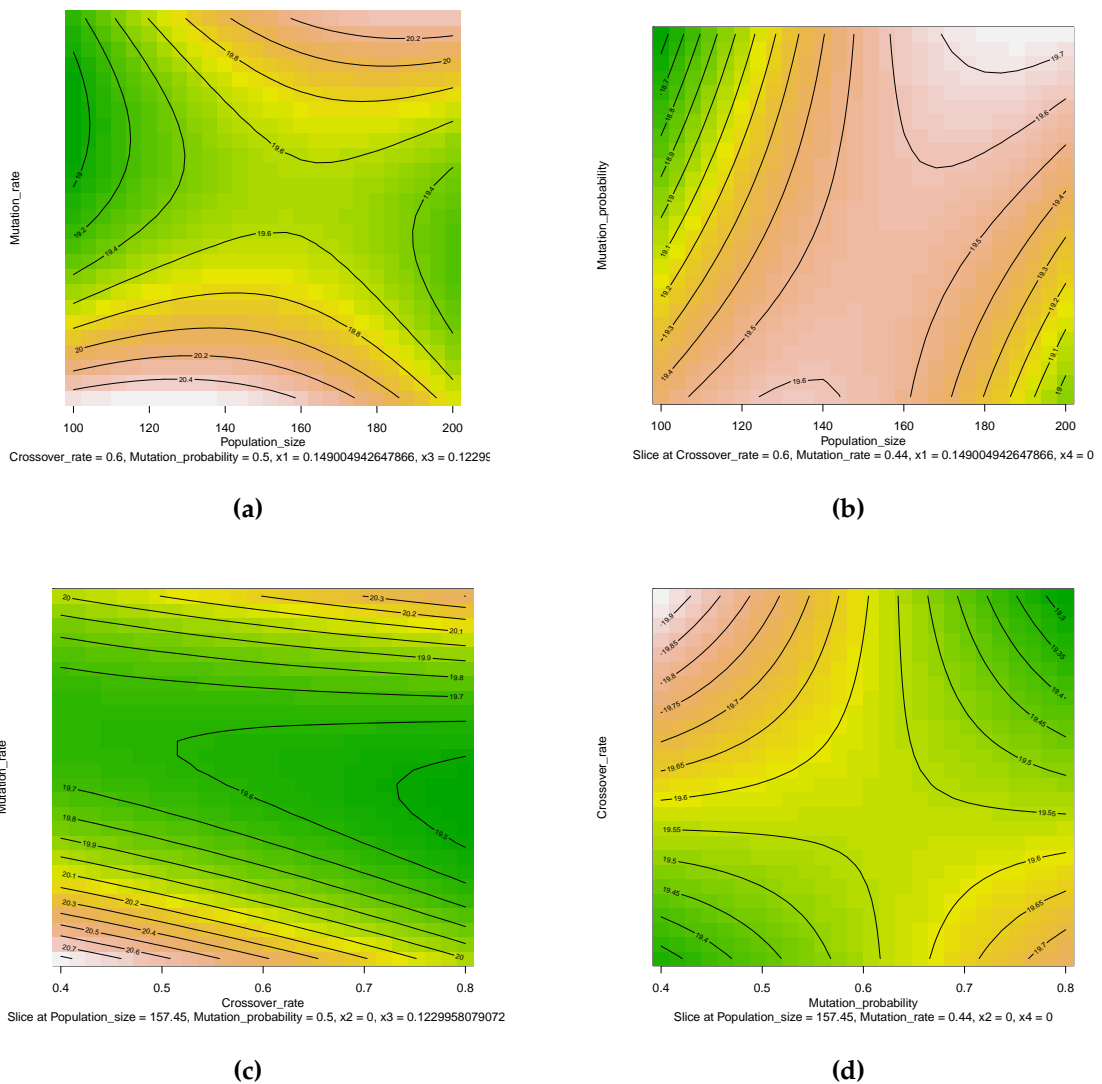


Figure 40: The response surface 3D plots of interaction of important factors on S/N : (a) interaction of population size and mutation rate; (b) interaction of population size and mutation probability; (c) interaction of mutation rate and crossover rate; (d) interaction of mutation probability and crossover rate

For example, from Figure 39a, the contour plot shows that the mutation rate around 0.4 and population size between 150 and 160 led to the best value for S/N . By doing so for all other three plots, we can easily figure out that the obtained stationary point is driven correctly, and it is compatible with and in the range of all interactions between important factors.

4.4.2 Final Tuned Parameters

The optimal values of the parameters related to the stationary point are tuned as shown in Table 8 after finding the best fitted **MRSM** regression model for three distinct map sizes for each **MOEAs**. The parameter setting may vary depending on the magnitude of the challenge in terms of the size of the map. As a result, we fit a distinct **MRSM** model to each map size, resulting in various adjusted parameters.

Table 8: Tuned parameters for SH-NSGA-II and MA

Solving Methodologies	Parameters	Size		
		Small	Medium	Large
SH-NSGA-II	N_{pop}	157	179	150
	R_c	0,6	0,67	0,69
	R_m	0,44	0,43	0,46
	P_m	0,5	0,5	0,5
MA	N_{pop}	150	163	124
	R_c	0,55	0,6	0,6
	R_m	0,4	0,5429	0,4
	P_m	0,5	0,5	0,583
	R_l	0,776	0,586	0,4
	P_l	0,667	0,625	0,64

As we divided our spatial zoning optimization problem into three different size levels, for each of them, this stop criterion should be defined. To discover the ideal value for these criteria, we run 8 various problems with a set number of repetitions 3000 to examine the trend of **HV** value for estimating each size of both methods. The average number of repetitions without improvement for each size is then used as a stop condition. Table. 9 declares the stop condition value for the **MOEAs** in each size.

Table 9: Stopping Condition for SH-NSGA-II and MA

Solving Methodologies	Size		
	Small	Medium	Large
SH-NSGA-II	600	600	600
MA	400	500	500

4.5 Experimental Validation

Once the parameters have been tuned, the goal is to compare the performances of **SH-NSGA-II** vs. **MA**. To evaluate both methods, 8 different randomly selected datasets are used, as presented in Table 3. Then, to evaluate a much more robust comparison, each instance is implemented 30 times, and each reported value is the median of 30 runs of each problem with its respective method. Before presenting the results, the selected performance metrics are presented.

The fact that the result of the optimization process is a set of solutions representing an approximation of the Pareto front, rather than a single solution, is a major challenge in **MOO** assessment. Because of the conflicting nature of the Pareto set solutions, we need to utilize certain performance measurements to evaluate the given methods [BD20]. We cannot tell if the algorithm has converged to the exact optimum until we know the Pareto-front. However, we can see when the algorithm has made the most progress during optimization and, as a result, whether the number of iterations should be reduced or increased. Additionally, the measurements allow the two

algorithms to be compared to each other. To assess the performance of different, multi-objective **MHs**, non-dominated sets of solutions must be compared [Tal09]. Although various measures for non-dominated sets have been proposed, there is no universally acknowledged performance evaluation standard. To categorize quality indicators, many attributes can be employed.

The quality indicators are listed in the order in which they meet two separate performance goals: 1) convergence to the ideal Pareto front and 2) diversity of alternatives along the front. They are usually based on metrics of cardinality, distance, or volume. Cardinality-based indicators necessitate a limited approximation of the Pareto set. In general, distance-based indicators are sensitive to the scope of the objectives. As a result, all objective magnitudes must be standardized. It should be noted that relying solely on one quality indicator is invariably insufficient. From each class of measurements, at least one indicator must be chosen. Therefore, in addition to the metrics outlined in Section 4.4.1, iteration number and three other performance metrics are used in order to evaluate and compare both **MOEAs** algorithms. *NPS*, *BestSol*, and *HV* are the diversity-based, convergence-based, and hybrid categories of quality indicators, respectively.

The higher the three other performance criteria, the greater the quality of the solution we have.

Mean Ideal Distance (MID):

This measure depicts the proximity of the Pareto solution to the ideal point (0, 0), which is a convergence-based indicator as given in Equation 34:

$$\text{MID} = \frac{\sum_{i=1}^n c_i}{n} \quad (34)$$

where n is the number of the non-dominated set and $c_i = \sqrt{f_{1i}^2 + f_{2i}^2}$, and f_{1i}, f_{2i} are the value of the non-dominated solution of i^{th} for the first and second objective functions, respectively.

Spread of Non-Dominance Solution (SNS):

A diversity-based metric that analyzes the uniformity of the generated solution distribution in terms of dispersion and extension is the spread of a non-dominance solution. The formula for this indicator may be found in Equation 35.

$$\text{SNS} = \sqrt{\frac{\sum_{i=1}^n (\text{MID} - c_i)^2}{n - 1}} \quad (35)$$

The Rate of Achievement to two objectives Simultaneously (RAS):

The balance in reaching to objective functions is another convergence-based quality metrics. In the following Equation (36) $F_i = \min(f_{1i}, f_{2i})$.

$$\text{RAS} = \frac{\sum_{i=1}^n \left| \frac{f_{1i} - F_i}{F_i} \right| + \left| \frac{f_{2i} - F_i}{F_i} \right|}{n} \quad (36)$$

4.6 Computational Results

Therefore, this section investigates the effectiveness of the proposed **MA** algorithm using defined indicators. To analyze these two **MOEAs** with respect to each indicator, we did the **WSRT** (paired samples) tests to check the null hypothesis that the **MA** algorithm works better than **SH-NSGA-II** with respect to each indicator. These conclusions are supported by significant Wilcoxon tests ($p - \text{value} < 0.05$).

The **WSRT** tests the null hypothesis that two related paired samples come from the same distribution. In particular, it tests whether the distribution of the differences ($x - y$) is symmetric about zero. It is a non-parametric version of the paired T-test.

To prove the validity of the algorithms, we need to show the gap between the optimal and **MOEAs** solutions. As the solutions for the small size from the exact method are available, we could do the validation for this size. Table 10 shows the performance indicators with respect to the exact methods and the two **MOEAs**. As shown in Table 10 according to each measure, although both **MOEAs** achieved promising values and are pretty well close to exact solutions, **MA** has less gap than **SH-NSGA-II** with exact and optimal solutions in small size. In Figures 41, the differences between all three methods are shown.

Table 10: The comparison between **MOEAs** and the optimal solution

Problems	Map Size	HV			Best Sol			MID			SNS			RAS		
		Exact	SH-NSGA-II	MA	Exact	SH-NSGA-II	MA	Exact	SH-NSGA-II	MA	Exact	SH-NSGA-II	MA	Exact	SH-NSGA-II	MA
1	Small	5,866	5,5173	5,7448	0,563	0,5315	0,5462	78,859	76,0040	76,4613	3,038	2,215	2,984	0,995	0,9903	0,9913
2		6,310	5,7088	6,3004	0,557	0,5210	0,5570	85,126	79,5036	83,0024	4,936	1,730	4,455	0,996	0,9909	0,9940
3		6,313	5,6567	6,3004	0,558	0,5205	0,5570	84,002	79,0040	83,1690	6,725	1,368	4,627	0,995	0,9904	0,9940
4		6,310	5,7088	6,3034	0,557	0,5214	0,5570	85,112	79,1463	83,0024	5,039	1,891	4,553	0,996	0,9904	0,9940
5		6,316	5,7119	6,3004	0,557	0,5220	0,5570	85,126	79,3371	83,3357	4,814	2,060	4,455	0,996	0,9901	0,9940
6		6,313	5,7149	6,3004	0,557	0,5205	0,5570	85,751	79,3374	83,3357	5,158	1,869	4,502	0,996	0,9904	0,9940
7		6,310	5,6299	6,3004	0,558	0,5205	0,5570	85,223	79,0040	83,0023	5,606	2,060	4,231	0,996	0,9901	0,9939
8		6,310	5,7149	6,3004	0,557	0,5181	0,5570	85,112	79,3368	83,0024	5,314	2,079	4,293	0,996	0,9901	0,9939
Average		6,2556	5,6704	6,2313	0,5580	0,5219	0,5557	84,2891	78,8342	82,2889	5,0789	1,9090	4,2625	0,9958	0,9903	0,9936

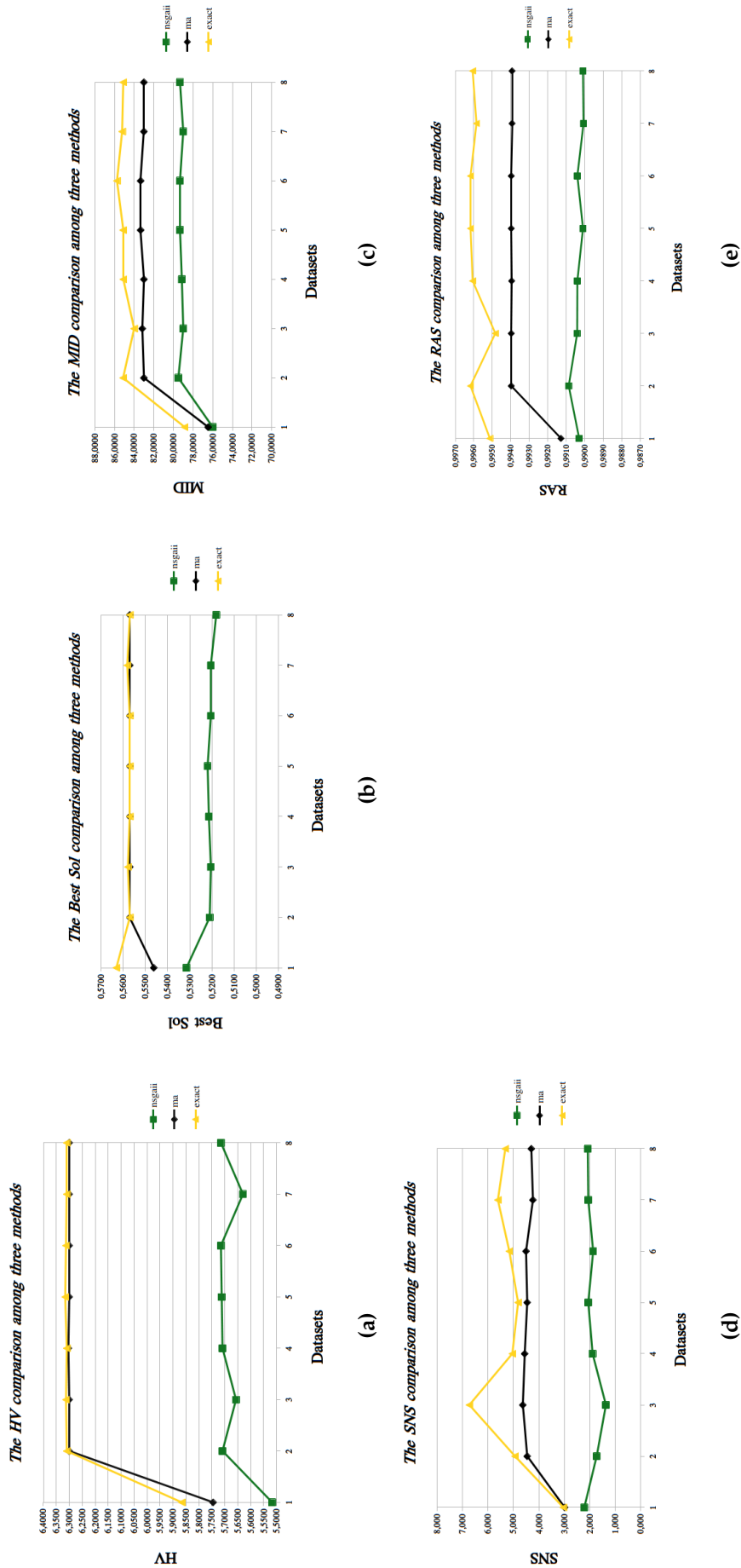


Figure 41: The comparison among MOEAs algorithms and exact optimal solutions for small size: (a) Comparison based on HV performance metric; (b) Comparison based on Best Sol performance metric; (c) Comparison based on MID performance metric; (d) Comparison based on SNS performance metric; (e) Comparison based on RAS performance metric

Finally, besides the small size, for the other two problem sizes, the results of both MOEAs regarding the performance metrics are shown in Table 11. For each set of problems, seven performance metrics are investigated which show execution improvement through the MA algorithm. MA outperforms SH-NSGA-II by taking all mentioned metrics into account.

Table 11: The result of MOEAs

Problems	Map Size	HV		Best Sol		MID		SNS		RAS	
		SH-NSGA-II	MA	SH-NSGA-II	MA	SH-NSGA-II	MA	SH-NSGA-II	MA	SH-NSGA-II	MA
1	Medium	5,7088	6,1241	0,5163	0,5441	78,4038	81,6018	0,8989	2,6722	0,9901	0,9946
2		5,7088	5,8651	0,5196	0,5330	77,8921	78,2774	1,5506	2,1082	0,9901	0,9897
3		5,7088	6,1287	0,5172	0,5450	78,3789	81,2689	0,8721	2,9073	0,9901	0,9937
4		5,7057	6,1333	0,5154	0,5450	78,4323	81,0321	0,8692	2,9057	0,9901	0,9932
5		5,7057	6,1272	0,5154	0,5450	78,4038	81,4758	0,9147	2,8806	0,9901	0,9940
6		5,8636	5,8513	0,5356	0,5255	78,4328	77,3799	2,5409	1,6422	0,9898	0,9888
7		5,7057	6,1303	0,5154	0,5450	78,3675	81,2245	0,8647	2,9648	0,9899	0,9938
8		5,6451	6,1015	0,5163	0,5436	78,3789	80,7083	0,8421	2,8663	0,9899	0,9934
Average		5,7190	6,0577	0,5189	0,5408	78,3363	80,3711	1,1691	2,6184	0,9900	0,9927
1	Large	5,8958	6,1704	0,5129	0,5215	80,6714	82,8363	1,2377	2,0048	0,9901	0,9911
2		5,9640	6,1187	0,5145	0,5201	80,6714	81,2543	1,4120	1,3426	0,9897	0,9902
3		5,8881	6,0367	0,5168	0,5198	80,2547	81,2951	1,1655	1,5255	0,9895	0,9905
4		5,8881	6,2283	0,5155	0,5364	80,6714	83,1792	1,2235	2,6565	0,9894	0,9911
5		5,8138	6,1126	0,5054	0,5254	80,6463	82,2531	0,4633	1,9388	0,9888	0,9914
6		5,8850	6,0065	0,5129	0,5211	80,3623	80,8038	1,0260	1,7866	0,9895	0,9910
7		5,8942	6,3204	0,5103	0,5570	81,0039	81,8038	1,0945	2,7866	0,9900	0,9940
8		5,8881	5,9352	0,5103	0,5235	80,5050	80,9838	0,8421	1,7966	0,9897	0,9906
Average		5,8896	6,1161	0,5123	0,5281	80,5983	81,8012	1,0581	1,9798	0,9896	0,9912

Additionally, for small-, medium-, and large-scale problems, we compare the results of both algorithms w.r.t the computational time. For small-, medium-, and large-scale problems, the computational time MA is almost 50%, 29%, and 17% faster than SH-NSGA-II with higher solution convergence quality. That is, MA not only gets to the optimal Pareto front faster, but its Pareto front also contains solutions with higher interesting values.

When MOEAs are used to solve a problem, they generate a set of Pareto solutions from which DMs can choose the best one. Because this decision is like those made in Multi-Attribute Decision-Making problems, one method used in them is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), which is similar to an ideal solution [JV14], the fuzzy hierarchical TOPSIS [WCH09], Simple Additive Weighting (SAW) [Meh14], the fuzzy SAW [LW13], and the linear programming technique for multidimensional analysis.

4.7 Conclusion

Two novel P-metaheuristics based on GA have been developed to solve the spatial zoning optimization problem (SH-NSGA-II and MA). To demonstrate the outperformance of the proposed MOEAs, 24 test cases with 30 times replications were used. The results show that, on average, the proposed MA provided better solutions in less computational time, and that, when compared to SH-NSGA-II, the proposed MA has a better consistency. Finally, a set of (24 × 30) WSRT revealed that the proposed MA outperforms the SH-NSGA-II significantly. Although these findings have gone some ways toward solving the given specific problem on a large scale, more improvements could be possible to reduce the computational time while increasing the convergence speed. Moreover, some improvements in population generator operators could help in this regard to diminishing the need for repairing operators. A further study could assess and develop more MOEAs to compare with the current proposed ones. Finally, we will investigate the spatial zoning optimization problem's applicability in the real world and test the robustness of the proposed MA on more complex spatial data with multi-agents in the future.

Chapter 5

Cooperative Multi-Objective Multi-Agent Zoning Management for Marine Spatial Planning

Contents

5.1	Introduction	88
5.2	Multi-Agent Systems and Their Properties	90
5.2.1	Environment	91
5.2.2	Interactions	92
5.2.3	Cooperation VS. Non-Cooperation	93
5.2.4	Negotiation Heuristics	95
5.3	Multi-Agent Systems Applied to Spatial Zoning Management Planning 96	
5.3.1	Selected Literature Review	96
5.3.2	Research Gaps and Objectives	99
5.4	A Cooperative Multi-Objective Multi-Agent System	99
5.4.1	Initialization	101
5.4.2	Compatibility	102
5.4.3	Communication	102
5.4.4	Illustrative Example of Multi-Objective Multi-Agent System . .	104
5.5	Experimental Validation	105
5.5.1	Scenarios and Parameters Setting	105
5.5.2	Ranking Methods	107
5.6	Computational Results	108
5.7	Discussion	110

ABSTRACT

Even though this thesis up to now did partially substantiate the spatial zoning management for a single new activity by having semi-cooperative relationship with other activities in Chapters [3] and [4], it does not still address the second objective posed in Chapter [1] about negotiation. This chapter presents a formal and executable approach to resolve a conflict in MOMAS of spatial zoning management by negotiation. MOMAS modeling provides a powerful framework for simulating the multi-level decision-making processes of marine use optimization allocation in a collaborative, decentralized decision-aiding process. The decision levels include the agent-to-optimizer and the agent-to-agent collaborative mechanism. We develop a heuristic negotiation-based system that classifies MOMAS settings on the basis of a chaining negotiation structure. This strategy is carried out after running the MA algorithm for each agent and gathering their Pareto optimal solutions. Different negotiation strategies for CR are also presented, tested, and ranked using the Condorcet aggregation method. Results highlight how agents can arrive at good solutions by using the above strategies.

5.1 Introduction

Most coastal and marine regions throughout the world are multi-use zones where many human activities occur. Coastal and marine environments attract a range of competing uses, which can overlap and have adverse effects on each other (user-user conflicts) or have an influence on the coastal marine environment (user-environment conflicts). As a result, several governments are trying to control conflicts among marine and coastal resource users while also preventing damage to the ecosystem. In MSP, different institutional, economic, and social actors compete for maritime resources and have conflicting objectives and contradictory preferences. In such spatial conflicts, the challenge is to choose an appropriate allocation strategy within a wider spatial decision-making process, where marine users interact with each other to reach a spatial allocation agreement.

Classically, centralized decision-making processes are employed in such complex systems, i.e., a single Decisional Center is acquainted with all information of the system [Mar+17]. Figure 42 illustrates the classical centralized decision-making process with a downstream level that can still be decomposed into further subsystems. As shown in Figure 42, the central node is in charge of the system planning and owns the power to manage the operations performed by all the sub-elements, or agents. This central node also performs the decision-making by optimizing the objectives of the entire system [HAR08; Ale+11]. Such centralized decision processes mostly ignore the interaction between the subsystems.

Through the 4th industrial revolution and due to the emergence of the Internet-of-Things paradigm, decisional processes have moved toward decentralized decision-making models, where each individual element of the system makes its own decisions, trying to optimize its own objectives [Mar+17]. Depending on the collaboration degree, the elements will more or less take into account the decisions of the other agents. In order to work smoothly, such a system necessitates collaborative mechanisms to coordinate the agents' decisions and exchange information and preferences between the various agents. In a decentralized decision-making process, each independent agent has its own objective functions that could conflict with the objectives of the other agents and which are subject to the specific constraints of that element. Inter-agent constraints may also be incompatible, and the responsibility of the collaborative mechanism is to overcome and settle down these incompatibilities. In addition, other agents' decisions and the flows of information between the levels often influence the decision variables for each agent. To manage such interdependent relationships in a decentralized decision-making process, it is necessary to define a decision framework that is capable of coordinating the decisions made by the different agents, as well as information they exchange. Figure 43 shows a collaborative decentralized decision-making process, where agents make independent and collaborative decisions at the same time.

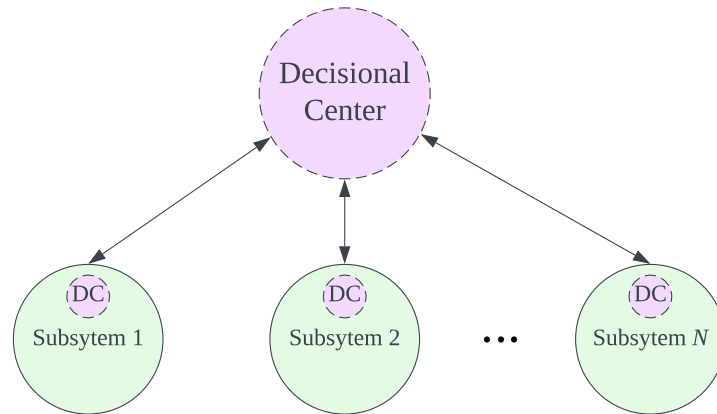


Figure 42: Centralized decision-making process with no collaboration between subsystems

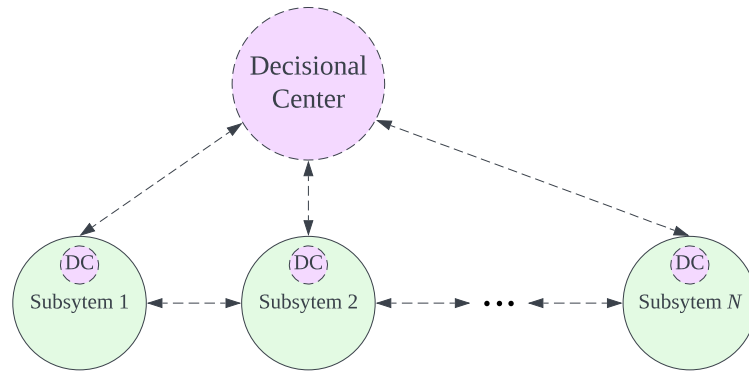


Figure 43: Decentralized decision-making process with collaboration between subsystems

Our current mentioned real-world problem in *MSP* (and many others) contains three aspects that make them impossible to be solved by classical centralized decision-making processes and existing commercial optimization software all around the world. Firstly, they are *MOOPs*, where solving the problem for each objective leads to a different solution. Accordingly, an approach is required to find a set of mathematically “equal” solutions called Pareto optimal solutions. Secondly, they can be modeled as multi-agent problems, where the preferences of all possible agents should be incorporated into the decision process. Therefore, an interactive optimization approach is required that effectively takes the agent preferences and finds a compromise optimal decision accordingly. This agent-to-optimizer interaction helps the agents learn about the problem and allows them to modify and change their preferences progressively. The third aspect is the interdependency between the agents who affect their decisions. This issue necessitates a collaborative mechanism between agents to share information or even to handle conflicting preferences and constraints. Through this agent-to-agent collaboration mechanism, agents can modify their preferences in terms of solutions and constraints and finally update their decisions.

Therefore, this methodology can solve such a multi-objective multi-agent optimization problem by providing the agent-to-optimizer and the agent-to-agent collaborative mechanism. Figure 44 shows the structure of such a multi-objective multi-agent collaborative-interactive decentralized decision-aiding process.

The contribution proposed in this chapter aims at tackling the following research questions:

1. How could we develop an optimizer that solves a multi-objective problem to find a

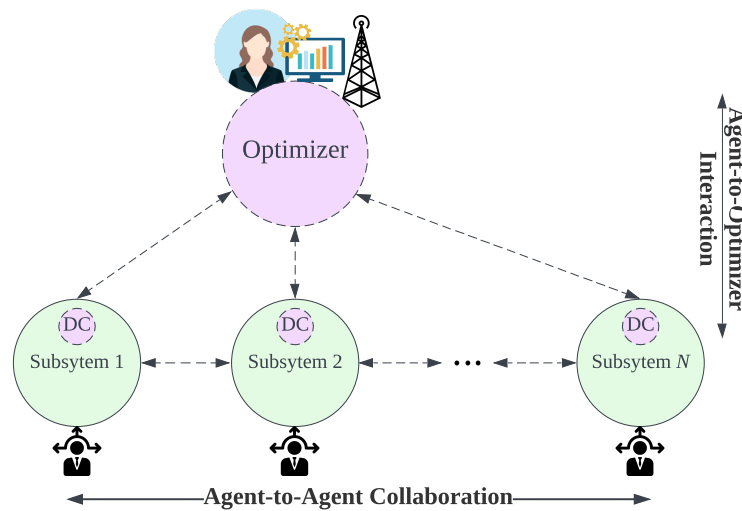


Figure 44: Multi-objective multi-agent collaborative-interactive decentralized decision-making process

compromise optimal solution and provides a mechanism where agents effectively interact with the optimizer and not only learn about the problem but also guide the optimization process by modifying their preferences?

2. How could we develop a mechanism where the agents effectively collaborate to share information and learn the preference of the other agents, as well as modify their own preferences accordingly. In case of facing a conflict, how do we develop a negotiation-based mechanism to reach a spatial allocation agreement through their conflicting objectives?

To address the first question, an idea is to develop one or more **MOEAs**. This question is answered in Chapter [4], by validated MOEA, MA. Then, an agent-to-optimizer interaction mechanism is developed using labeling methods to determine the compatibility relations between the Pareto set of different agents.

To deal with the second question, first, the preferences of different agents are characterized by the assumption of a priority order between different agents. By considering the compatibility matrix between all agents, an agent-to-agent collaboration mechanism is designed by gathering agents with compatible, compatible under certain conditions, and conflicting preferences/constraints. Next, they share their preferences to either translate the constraints to buffer technique (if possible) and modify their decisions or start the negotiation-based mechanism. The interactions could be designed with different scenarios depending on the level of agents' cooperation.

The chapter is structured as follows. In section 5.2, we describe the theoretical framework of **MAS** and some relevant concepts that have guided our work, In Section 5.3, we review the state-of-the-art with a focus on **MAS** applied to spatial zoning. In Section 5.4, we propose our multi-agent negotiation-based model for the spatial zoning problem. In Section 5.5, we describe an experimental design to test the proposed algorithms, while in Section 5.6, we propose the computational results on artificially generated synthetic instances. Conclusions and discussions are drawn in Section 5.7. It is worth noting that this chapter is based on an under-review journal article, which is mentioned in the publications list at the end of the manuscript.

5.2 Multi-Agent Systems and Their Properties

The first notion of **MAS** was discovered in the 1980s, namely in the **Distributed Artificial Intelligence (DAI)** research field. The intelligence in those systems was spread across many entities:

the **agents**. According to [WJ95; Fer99], an agent is a software or physical entity like robots, humans, or human teams that:

- is autonomous,
- is located in an environment and is able to interact with it,
- has communication abilities with other agents,
- has skills.

“**Perception - Decision - Action**” is the common triptych used to describe the **life cycle** of an agent. The agent **perceives** information from its environment in the first stage. The agent decides what action to take based on its observations in the **decision** stage. Finally, in the last phase, the agent does the previously determined **action(s)**. This life cycle enables the agent to adjust its behavior in response to dynamic events. There are several agent implementations. They differ in the location of the intelligence on the agent. We might think of reactive or cognitive agents as examples [Gle11]. A reactive agent responds to changes in its environment. Reactions, like reflexes, are determined by senses and internal states rather than memory. A cognitive agent, on the other hand, is more complicated. Such an agent has an explicit representation of its surroundings as well as the other agents in the system. A cognitive agent also has a complex communication strategy. Cognitive agents are often used in systems with a few agents (~ 10) whereas reactive agents are used in large systems (~ 100). Other characteristics include **located agents**, whose perceptions are determined by their location in the environment, and **communicative agents**, which can communicate with other agents regardless of their location. They are autonomous in the sense that they determine what action to take, whereas objects are execution units that do what is asked of them. Thus, agents are **proactive**, but objects are **reactive**: if no one asks them, they do nothing. Objects are implementation strategies in the realm of **MAS**.

Now that we have defined an agent, we can answer the question “What is a **MAS**?” Formally, [Fer99] proposes to define the **MAS** as a system that has the following characteristics:

- set of entities E , located into an environment ENV ,
- set of agents A such as $A \in E$,
- set of actions ACT , that agents can perform in ENV ,
- communication systems.

A **MAS** is a group of agents that are placed in an environment and interact with one another to achieve a local goal. **MAS** are naturally intriguing for solving **decentralized** problems. Indeed, knowledge and competencies are **distributed** among the agents in such a system. Furthermore, a **MAS** might be **close** or **open**. A close **MAS** suggests the agents are the same throughout the execution, whereas an open **MAS** allows the agents to appear and disappear. Agents in such a **MAS** can be added by humans or formed directly by existing agents. External operators or a suicide ability might possibly be to blame for the disappearance. Finally, **MAS** agents may or may not be unique. Thus, **MAS** can be classified as **homogeneous** if all agents follow the same pattern, or as **heterogeneous** if individuals have diverse models.

5.2.1 Environment

As previously stated, **MAS** is a system that exists in an environment in which agents evolve concurrently. This environment encompasses anything that is not part of the system. As a result, agents will interact with and modify it. Thus, the system and its environment are coupled together. The system acts on the environment, which answers using feedback. Figure 45 represents such a feedback loop.

As the system and the agents, the environment is often characterized using the following properties ([Bre96; Lin01]):

- **Accessible / Inaccessible**

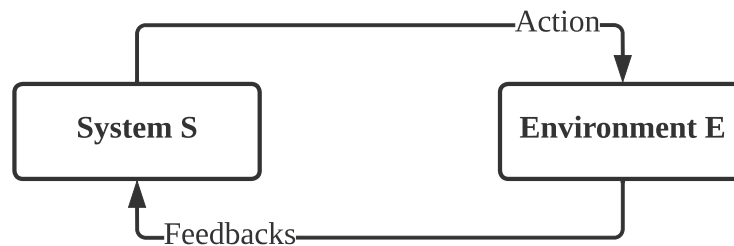


Figure 45: The feedback loop

- **Accessible:** the system can have complete, updated, and true information on its environment,
- **Inaccessible:** only partial information is available,
- **Continuous / Discrete**
 - **Continuous:** number of possible actions and perceptions is infinite,
 - **Discrete:** actions and perceptions are distinct and clearly defined,
- **Deterministic / non-deterministic**
 - **Deterministic:** each action has a single effect on the environment: the current state of the environment determines the next one,
 - **Non-deterministic:** an action has no guaranteed effect,
- **Dynamic / Static**
 - **Dynamic:** environment states depend on system actions but also on actions of different processes. External events can produce effects on the environment, but those changes cannot be predicted,
 - **Static:** environment cannot evolve without system actions.

5.2.2 Interactions

A **MAS** is a sophisticated system made up of numerous interacting elements, known as agents, that have basic and local behaviors. Each agent is autonomous and not managed at the macro level. Furthermore, no entity has complete control over the system. Interactions between agents generate the emergent property: the system function. Thus, the key to designing **MAS** that perform the desired function is to identify appropriate local interactions and implement agents that follow those rules. The theory of **MOMAS** [VMPP98] proposes a theoretical framework to design such complex systems. These techniques are built on agent interactions and the concept of **cooperation**.

According to [Jen99], there are three types of interactions: **antinomic**, **neutral**, and **cooperative**. An entity has an antinomic interaction when its action interferes with another entity ability to complete its activity. The interaction is neutral if the activity does not disrupt yet does not benefit either party. Finally, if the conduct of one entity benefits the behavior of another, the relationship between them is **cooperative**. System classification is also possible. Thus, the system is in a cooperative state if all interactions between the system and its environment are cooperative; otherwise, the system is in a **non-cooperative** state if interactions are neutral or antinomic.

From the agent's standpoint, cooperation is defined as their ability to collaborate in order to achieve their goals. To enable cooperative interactions, four properties must be met [Gli01]:

- **Sincerity:** an agent is sincere, which implies that it never lies,
- **Willingness:** a request is always satisfied if it is coherent with the agent state and if it has the skills to perform it.
- **Fairness:** when it is possible, the agent with the lowest level of non-satisfaction degree is favored to be satisfied.
- **Reciprocity:** all agents know those properties and respect them.

5.2.3 Cooperation VS. Non-Cooperation

A major MAS idea is cooperation [CMS88; DM91; DLC89; Fer97]. Four generic goals for agent collaboration have been proposed by [DL89]: (1) increase task completion rates through parallelism; (2) increase the number of concurrent tasks by sharing resources (information, expertise, devices, etc.); (3) increase task completion chances through duplication and the ability to use different modes of realization; (4) reduce task interference by avoiding negative interactions. Cooperation in agent-based systems, on the other hand, is at best ambiguous and at worst very inconsistent, which will be assessed through reviewing the research studies.

Cooperative agents are made up of many modules that reflect a division of their physical, cognitive, and social abilities (Figure 46). During the agent's life cycle, each module represents a distinct resource.

- Agent interactions are managed by two modules: perception and action modules,
 - the perception module represents the inputs the agent receives from its environment,
 - the action module represents the output and the way the agent can act on its environment,
- the skill module concerns the knowledge that enables the agents to realize their local function,
- the representation module concerns the beliefs an agent has on its environment and includes the representation of other agents,
- the aptitude module contains generic and external tools an agent needs to accomplish its treatment,
- the cooperation module concerns all cooperative attitudes of the agent. It manipulates the skills and representations modules, in order to anticipate or detect and repair **Non-Cooperative Situation (NCS)**.

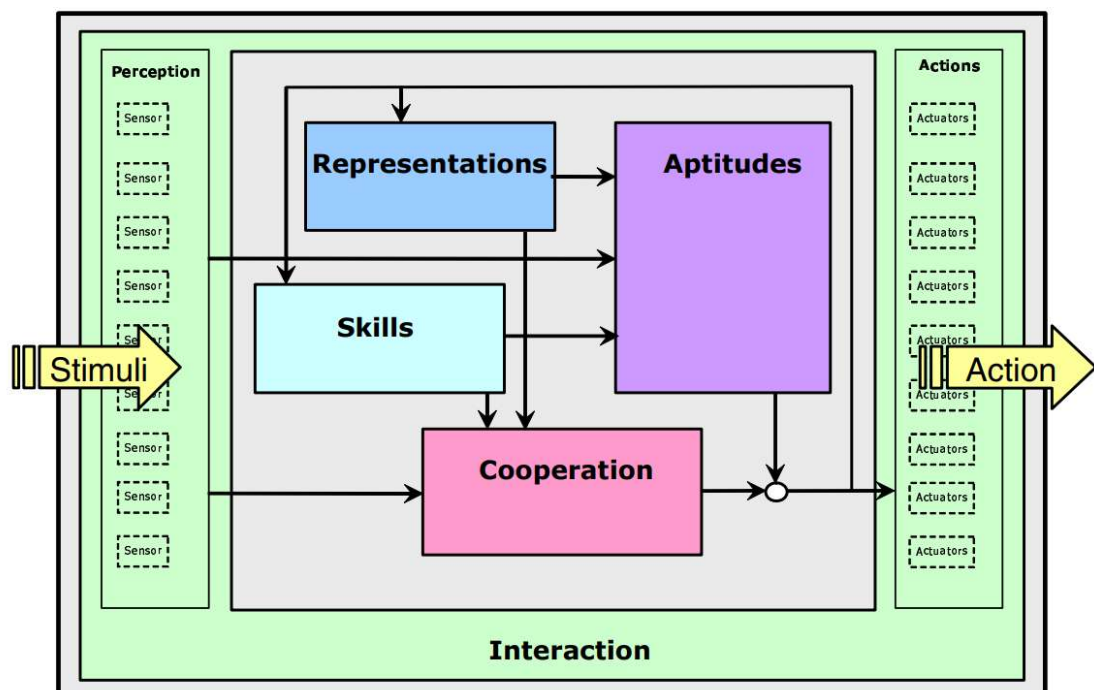


Figure 46: The different modules of a cooperative agent [GPB04]

The preceding section suggests that when a system is cooperative, the appropriate function is created. As a result, a system is never completely cooperative. Certain NCS scenarios may arise. Agents may have competing goals or might not understand each other. Seven NCS scenarios have been found in [Gle11].

- **Incomprehension:** the agent does not understand the message it has received,
- **Ambiguity:** a single message can be understood in different ways,
- **Incompetence:** an agent has no skill to treat information it has perceived,
- **Unproductivity:** even if the agent has understood the message, it cannot get useful information,
- **Conflict:** the action performed by an agent will be discordant with one performed by another agent,
- **Concurrence:** an action chosen by an agent puts it in concurrence with another one,
- **Uselessness:** the agent produces an action that is not useful for the system.

Figure 47 depicts the seven scenarios and their occurrences during the agent life cycle. Thus, ambiguity and incomprehension are associated with the perception stage, incompetence, unproductivity with the decision step, and ultimately concurrence, conflict, and uselessness with the action step.

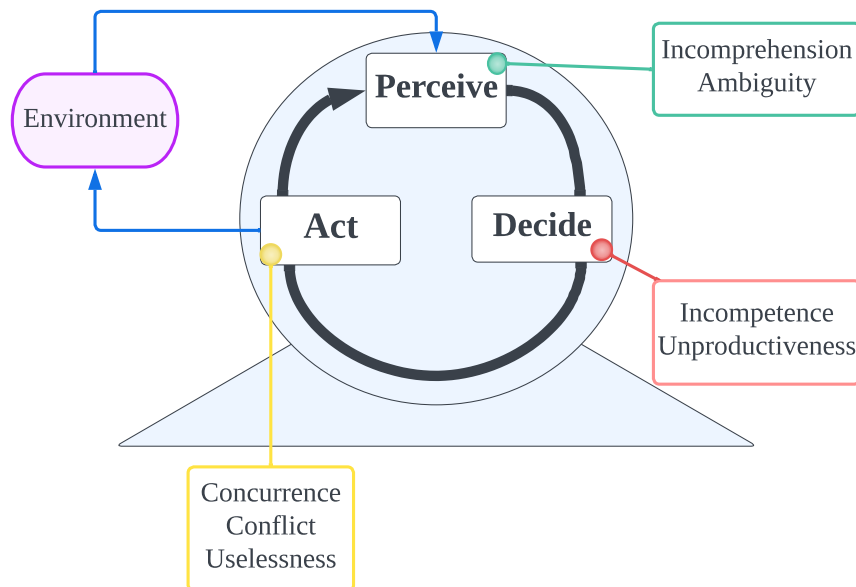


Figure 47: NCS in the agent life-cycle

In MOMAS, agents must try to be cooperative to avoid NCS. They must possess mechanisms to anticipate and detect them and to act in consequence. Thanks to those mechanisms, an agent is able to self-adapt its behavior, and so to modify its interactions. Thus, cooperation is the key to the self-organization of the system. We can describe the algorithm of a cooperative agent in a conflict situation as follows: if an NCS is detected, the agent uses the negotiation mechanisms to come back to a cooperative state, where it performs its nominal behavior. Thus, to solve a problem using MOMAS, the cooperation of all the agents is the key. As a cooperative entity, a cooperative agent spontaneously communicates its relevant information to its neighbors and helps its neighbor that encounters more difficulties.

5.2.4 Negotiation Heuristics

Various protocols for negotiation exist in the MAS literature. In [RRR01], three different techniques are presented for complex negotiations. These include: (i) negotiation through an arbitrary leader - in this method, an arbitrary leader is selected to arbitrate the conflict (interference) resolution process between the agents, (ii) negotiation through chaining - in this method, a ranked order assigned to each agent based on when they join the group is used for CR, and (iii) negotiation through cloning - in this method, each agent creates a “restricted” clone (agent for negotiation) and passes them to every other agent in the group. In this method, we assign a rank to each of the agents based on their pre-defined priorities. On one hand, through designing a negotiation protocol, certain normative requirements and circumstances must be satisfied, some of which are presented in Table 12, based on the literature [LWJ03; SW03; LF15].

Table 12: Requirements for a negotiation protocol

1	Incentive Compatibility	A protocol should be incentive compatible, meaning that the agents expose some private information in accordance with the protocol design.
2	Individual Rationality	Participation in the negotiation must be profitable; otherwise, an agent would not participate if it would result in a loss.
3	Behavioral Stability	A protocol should provide incentives to encourage agents to behave predictably.
4	Guaranteed Success	Under all circumstances, a protocol should find consensus.
5	Simplicity	The best agent technique should be simple to understand and implement.
6	Privacy	The agents should be required to give as little information as possible.
7	Scalability	A protocol should be scalable in terms of computation for numerous problems and agents.

In the social sciences, there are two main approaches to the formulation of negotiation theorems. The formal theory of bargaining is the first approach. This formal game-theoretic technique provides an explicit analysis of numerous circumstances as well as precise results on which strategy a negotiator should employ. However, it necessitates creating tight assumptions and requiring the agents to adhere to stringent negotiating protocols, which are not always viable in real-world situations. The second approach, which we call the negotiation guides approaches, comprises informal theories that aim to suggest possible strategies for a negotiator and assist him in reaching good results [Kra97; GK96; FU81]. This negotiating guide does not take into account the strict constraints and assumptions offered by game-theory models. Because no formal theory or strategies can be employed, applying these methods to the hybrid of MCDM and Artificial Intelligence (AI) problems is more challenging than utilizing the first approach. These methods, on the other hand, can be used in domains where people engage with one another and with automated agents, as well as scenarios where automated agents interact in surroundings with no pre-defined rules.

These informal models can be used as guidance to develop negotiation heuristics [KL95] or as a foundation to develop a logical negotiation model [KNS93]. Heuristics for collaboration and coordination among multi-agent, based on successful human cooperation and interaction strategies, may be effective in non-structured and unpredictable environments. From any Operational Research point of view, despite the fact that relevant data are frequently accessible,

companies may not be able to address their planning challenges optimally due to time or computational resource restrictions. That is why approximation techniques and heuristics are routinely used instead of optimal computations. In many situations, heuristic techniques are recognized to produce satisfactory, near-optimal results in a short amount of time [BR03].

5.3 Multi-Agent Systems Applied to Spatial Zoning Management Planning

The purpose of this section is to review recent research concerning the use of MAS in the field of spatial zoning management in Subsection[5.3.1]. Then, we will end up with the research gaps and objectives for this issue in Subsection[5.3.2].

5.3.1 Selected Literature Review

One major barrier to MSP is that the science for assessing and communicating tradeoffs among human uses of the ocean, as well as identifying strategies to mediate these tradeoffs, has been slow to catch up with policy opportunities emerging from efforts to implement ecosystem-based management, MSP, and MPAs [Les+13]. All of these management approaches are primarily about making decisions that affect trade-offs across multiple sectors [ATJ09]. However, because trade-offs are rarely addressed directly or transparently, they frequently go unmet or are poorly judged. One key reported advantage of MSP is that it makes trade-offs clear; nonetheless, this requires analytical tools for analyzing spatial conflicts and synergies among sectors. Despite numerous pieces of research implementing different approaches for successful marine spatial allocation to stakeholders, it is still a non-straightforward issue, as many parameters should be considered: technological, spatial, economic, environmental, and social, wherein stakeholders are in conflict. In particular, the identification of a permitted area of the sea for zoning each marine use, as well as allocation of such area, is a complex geographical and multi-criteria decision problem.

Overall, in a situation where several activities/agents compete for limited resources and each of them has different economic, environmental, and social objectives to be optimized, we can implement it based on MOMAS. Despite the fact that many real-world problem domains are intrinsically multi-objective, the bulk of MAS implementations tries to optimize agents' policies with regard to a single objective. MOMAS clearly analyzes the potential trade-offs between opposing objective functions. In MOMAS, the agents have different preferences regarding each objective and different (possibly contradictory) constraints (technical, economic, geographical, etc.). In addition, they have no information about the other activities and may not have enough knowledge about the problem and possible outcomes. In addition to MSP, another application of such a situation is a production system, in which different subsystems (i.e., a machine, a workstation, a workshop, a department, or even higher aggregated levels) compete for limited production resources while jointly generating a unique overall outcome.

Intelligent decision-making models and systems, however, have seen recent advancements. Businesses typically face complex decisions involving large amounts of data. In recent years, MCDM and AI techniques have been successfully applied to aid decision-making on a wide range of complex real-world issues. The use of MCDM and AI together brings up new options for organizing complex decision issues in both static and distributed contexts. Large data volumes, ill-structured data modeling, advanced decision models, and effective computational optimization strategies for issue resolution are just a few examples [HAR08]. The goal of DAI research is to better comprehend information and reasoning procedures required for intelligent coordination, as well as to embody and evaluate this understanding in computer systems [Als+07].

Meanwhile, MAS have gained significant interest in the past two decades [SCV04; Qin+16; FND18; Wan+16]. Technological advances have enabled the deployment of multi-agent networks to many engineering applications from commercial to military uses [Hua+21; CLS04; BH20; McA+07]. Other major issues arise as a result of decentralization, such as conflicts between agents and their distinct agendas. This is due to the fact that each agent's information may be

inadequate, and agents' interests may contradict. As a result, in MAS, CR is a significant and implicit issue [Als+07].

Several requirements often regulate agents interactions in MAS such as cooperation, competition, or co-existence [Als+07; Cd95; BG14] to collaboratively complete a necessary task or reach a certain objective.

In MAS, interactions between agents are justified by their dependency in these three dimensions [Als+07]: I) Objectives Compatibility, that is, the MAS challenge is to establish whether the various agents in the system have compatible goals. II) Agent Capacity, i.e., task completion via agent interaction, is the MAS issue. The MAS challenge is the discovery and resolution of agent conflicts (III) Resource Relationships.

CR entails the detection of conflicts, the search for solutions, and the communication with agents to establish an agreement on the CR option to pursue. CR is a regular occurrence in MAS due to its fundamental properties [AMK00; LJ95]. Knowledge and skill are often spatially, functionally, or temporally decomposed in application areas where MAS technology is applicable.

However, most of the methods suffer from some serious limitations on the idea of a negotiation/cooperation in CR to reach spatial allocation agreements between agents through their conflicting objectives. Most studies in the field of spatial zoning management planning have only focused on the theoretical point of view in negotiation strategies, not the practical.

In the following, we will take a look at some of these studies.

[Wat+09a; Ven+21] describe Marxan with Zones, an extension of Marxan that provides land-use zoning options in geographical regions for biodiversity conservation. The major new element in the decision problem is the ability to assign any parcel of land or sea to a specific zone, rather than just reserved or unreserved. Each zone can then choose its own actions, objectives, and constraints, with the flexibility to define each zone's contribution to meeting targets for pre-specified features (e.g. species or habitats). The goal is to keep the total cost of implementing the zoning plan as low as possible while meeting a variety of conservation and land-use objectives. Moreover, in [Cho+22; Han+22], the *prioritizr R package*, MILP techniques are used to provide a flexible interface for developing and solving conservation planning problems. It supports a wide range of conservation planning objectives, constraints, and penalties that can be used to tailor conservation planning problems to the specific needs of a conservation planning exercise. As mentioned, these pieces of software are focusing on conservation planning, which is totally different from the spatial zoning problem defined in this thesis. They are trying to prioritize different conservation zones by using partitioning techniques. Partitioning is focusing on the allocation, not location-allocation problem. The other issue which is not considered through them is negotiation and collaboration possibility between different zones or actors. Specially those who are in conflict or have some special constraints. Even having the optimal solutions/zones for each actor could be likely to face some conflicts between some actors. The compatibility relationship between different actors is one of the most important elements but has received less attention. The primary advantage of the agent-based negotiation system is its flexibility to control multiple agents at the same time, which is over one simple zoning problem. As a result, the concept of a negotiation/cooperation in CR to reach spatial allocation agreements between agents with competing objectives is not included in these pieces of software.

[Kyr+17] developed a decision-making procedure based on cooperative game theory to distribute disputed areas of specific size among heterogeneous players of the Dogger Bank Special Area of Conservation in the North Sea, which involves three totally or partially conflicting activities, namely, fishing, nature conservation, and wind farm development. The authors tested a given set of alternatives that are fair enough between shareholders but not with the optimization algorithm. Moreover, the problem is not modeled as MOOPs.

[Mas+14] applied a methodology based on a combination of GIS, MCDM, and an optimization algorithm to efficiently install a marine energy farm in a suitable area. Integration of GIS and MCDM is at the core of the search process for the best-suited marine areas, taking into account geographical constraints, such as human activity and technological opportunities. The optimization step of the approach evaluates the most appropriate technologies and farm configurations

in order to maximize the quantity of energy produced while minimizing the cost of the farm. However, there has been no CR in this problem.

[Ale+12] developed a method to facilitate the implementation of the EA by locating offshore renewable energy devices. Using a real-time interactive mapping device (touch-table) and stakeholder workshops, the authors gathered data and facilitated the negotiation of spatial trade-offs at a potential site for tidal renewable energy off the Mull of Kintyre (Scotland). Conflicts between the interests of tidal energy developers and commercial and recreational users of the area were identified, and the preferences and concerns of stakeholders were highlighted. However, no negotiation or cooperative mechanism is presented to overcome these conflicts.

[TSR14] applied MSP to manage conflicts in a multi-use coastal area of Kenya. Their approach includes several steps supported by GIS, MCDM, and optimization. GIS was used to identify overlapping coastal uses and map conflict hotspots. MCDM was used to incorporate the preferences of user groups and managers into a formal decision analysis procedure. Optimization was applied to generate optimal allocation alternatives to competing uses. However, this problem is neither MOOPs, nor spatial zoning. Moreover, no CR or negotiation mechanism is suggested.

[Zen+19] suggested an Hybrid Game Theory and Mathematical Programming Model (HGT-MPM) is for resolving trans-boundary water conflicts in the Guanting Reservoir Basin between two cities in north China (Zhangjiakou and Beijing). A water allocation model is constructed that takes into account both water quality and quantity to optimize water consumption and pollutant discharge in the two cities, maximizing net aggregate benefits and lowering costs for water delivery and pollution treatment. By solving the proposed HGT-MPM with reciprocal benefit claim restrictions, the strategy spaces of the two players are demarcated. To determine the equilibrium of bargaining, the Rubinstein bargaining solution approach is used. The findings not only give a foundation for allocating trans-jurisdictional water and pollutant discharge rights equitably and efficiently, but also provide some inspiration for management policy enhancement, such as the establishment of water rights trading system. However, no negotiation or cooperative mechanism is presented to overcome these conflicts.

Multiple agents and stakeholders with differing viewpoints and interests are frequently involved in urban planning. [Fas+20] presents a decision-analytic approach for analyzing stakeholder disputes in urban planning. First, the stakeholders express their preferences for actions using a set of criteria and assign a weight to each criterion. Then, for each action, a conflict index and overall value are calculated. Then, by solving an optimization problem with varying levels of conflict as a resource constraint, a collection of effective Pareto portfolios of actions is constructed. Finally, the actions are subjected to a sensitivity analysis. Real-world survey data from the municipality of Upplands Väsby, Sweden, is used to show the concept. However, no negotiation or cooperative mechanism is presented to overcome these conflicts.

When considering these conflicting objectives, ZPs give an explicit strategy for resolving conflicts between activities and calculating trade-offs. Zoning is used to support the numerous aims of marine parks all over the world [Wat+09b]. To tackle spatial multiple-use difficulties, MSP is required, but first, all current uses, restrictions, and conflicts must be identified and mapped. In a multiple-use Brazilian estuary, [Pre+16] suggested usage conflicts connected to multi-legislative government, disregard for fishermen's concerns, and increasing industrial expansion due to economic development were identified. The overlaps between the places that are now used for fishing and the areas where this activity is prohibited were examined. A GIS dataset was used to collect and superimpose information on legislation creating no-fishing zones, the most significant fishing spots, and fishing records. However, no negotiation or cooperative mechanism is presented to overcome these conflicts.

[Kra97] suggested that combining AI approaches with methods and techniques from a variety of multi-agent domains, including game theory, operations research, physics, and philosophy, is advantageous in addressing the difficulty of developing coordinated and cooperated intelligent agents. To back up this assertion, they have used an interdisciplinary approach with great success. They explained the advantages of using multi-agent techniques, as well as the adjustments, tweaks, and extensions required to solve DAI challenges. In such situations, all the agents work together toward the satisfaction of a joint goal, not multi-objectives.

[AMM12] introduces a multi-unit combinatorial auction and the winner determination issue is addressed using an efficient novel algorithm. Making no assumptions about the number of activities, shared resources, or agents, the suggested technique may tackle complicated large-scale multi-agent situations. Furthermore, their strategy allows for the release of agents at random times as they come dynamically along the planning horizon. They proposed a novel distributed MAS using the auctions-based negotiation (DMAS/ABN) approach for resolving resource conflicts and allocating multiple different types of shared resources amongst multiple competing agents. The DMAS/ABN is put through its paces on a regular set of issue scenarios. The findings are compared to three cutting-edge decentralized algorithms, as well as two current centralized approaches. However, this problem neither is solved by the optimization algorithm, nor is modeled as MOOPs.

5.3.2 Research Gaps and Objectives

Taken together, the reviewed studies were either theoretically proposing some strategies to address CR in MAS, or practically solving the problems which were not MOOPs. Moreover, some of them were out of the current study field. In one hand, difficulties arise, however, when an attempt is made to implement the policy to find a set of Pareto optimal solutions through the conflicting objectives in MOOPs. On the other hand, the possibility of finding a compromise optimal decision which not only incorporates all preferences of multi-agents but also resolves the conflict between non-compatible ones, should be evaluated. Therefore, these mentioned issues are some limits to how far the idea of CR in MOMAS can be taken.

Therefore, in a much more systematic study of this chapter, we propose how to address the problem of constructing linked and collaborative intelligent agents in the given application by merging AI approaches with methodologies and techniques from a number of multi-agent areas, such as operations research, agent-based modeling, and MCDM. We show how to adopt multi-agent methodologies for the spatial zoning application in MSP, as well as the changes, tweaks, and extensions that are required to tackle this specific intelligent decision-making problem. In sum up, the main objective of this chapter is to develop a decentralized decision-aiding system for cooperative multi-objective multi-agent spatial zoning management for MSP that:

- helps multiple agents with different economic, environmental, and social objectives and preferences to solve their various types of MOOPs,
- provides the agent-to-optimizer interaction mechanism, where the agents learn the problem, modify/change their preferences (if necessary), and guide the optimization process toward a most preferred solution,
- provides an agent-to-agent collaboration mechanism, where the agents collaborate/negotiate with other agents for sharing information and handling conflicting preferences/constraints, and finally to relax/change/modify their constraints and decisions.

5.4 A Cooperative Multi-Objective Multi-Agent System

In Chapter [4], we presented two promising MOEAs for single marine use to employ for a decision-making problem known as the multi-objective spatial zoning optimization problem [Bas+21]. The algorithms lead to agent-goal allocation, and they eventually converge on solutions in which a single marine use fulfills all the goals and constraints. Moreover, we have shown that computing complexity is negligible, and there is no need for explicit communication. In addition to these characteristics, we have shown that the proposed algorithms are close to optimal.

However, in real life, it is clear that multiple marine uses would often result into conflicts that need to be solved. Our contribution aims at proposing a negotiation-based algorithm in order to add cooperation to our decision support system. Figure 48 shows the cooperative MOMAS diagram for spatial zoning management in MSP. This diagram is made of three different phases; Initialization, Compatibility, and Communication.

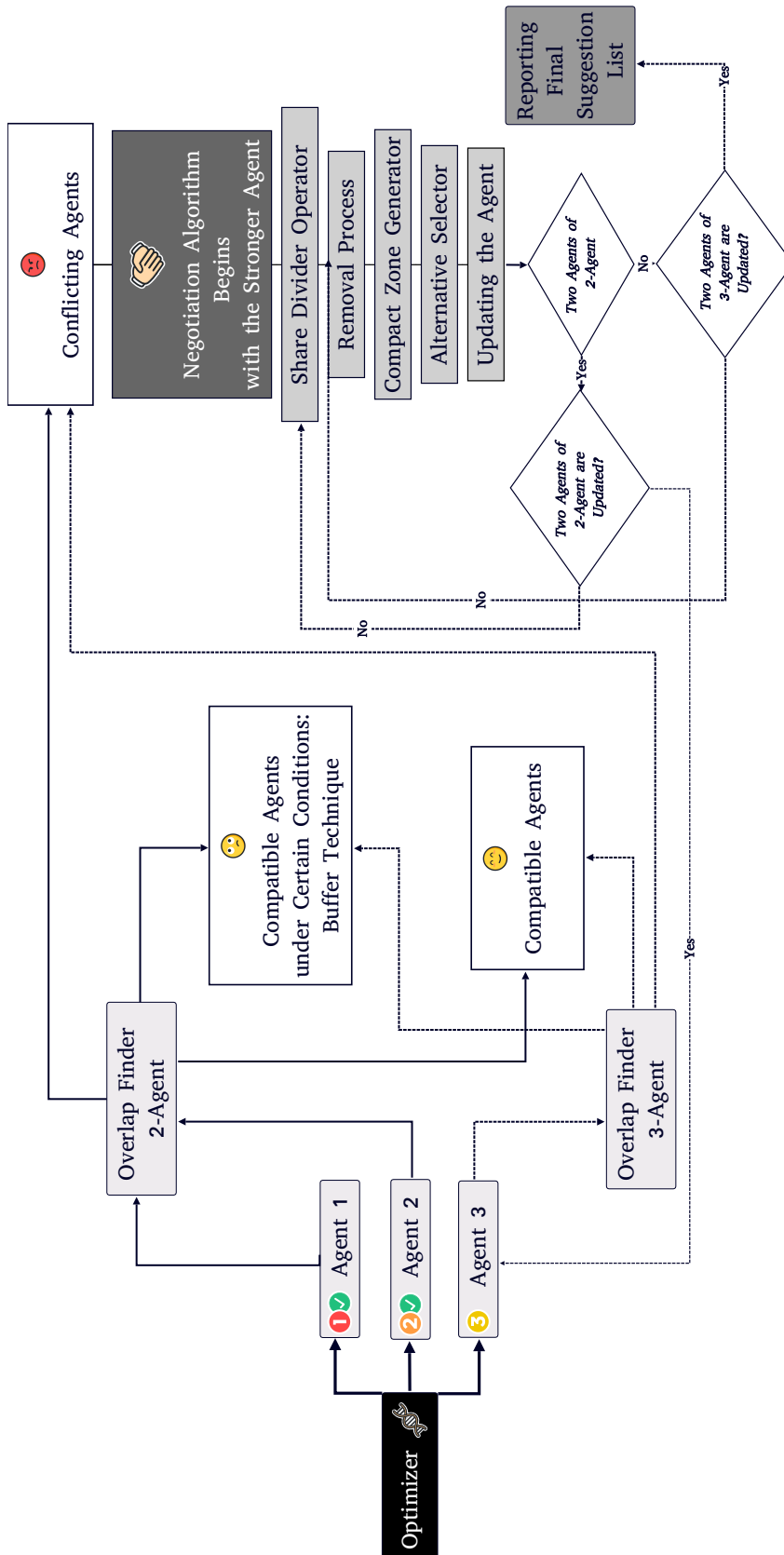


Figure 48: The diagram of the negotiation-based MOMAS for spatial zoning management in MSP

Following the **MAS** properties explained in Section [5.2], hypotheses considered in this proposed cooperative **MOMAS** are represented in Table 13. The diagram is encoded by the pseudo-code 9 hereafter. The details of this pseudo-code are explained in this section.

Table 13: Assumptions of MOMAS

Agents	homogeneous, communicative, and proactive
MAS	decentralized, close, multi-objective, and cooperative
Environment	continuous, deterministic, and static

Algorithm 9 Pseudo-code MOMAS for Spatial Zoning Management

- 1: **procedure** MULTI-AGENT(agent₁, agent₂, agent₃,
feasible_matrix₁, feasible_matrix₂)
 - 2: pop₁ ← **MA**(agent₁) ▷ Initialization step by achieving the Pareto set with the agent-to-optimizer connection
 - 3: pop₂ ← **MA**(agent₂)
 - 4: pop₃ ← **MA**(agent₃)
 - 5: agent₁ > agent₂ > agent₃ ← Ranking agents based on the chaining protocol
 - 6: pop_{Compatible}, pop_{semi-Compatible} ← Labelling the agents based on *Compatibility Matrix* by three terms (*Compatible*, *semi-Compatible*, and *Conflicting*).
 - 7: suggestion_list₁₋₂ ← (pop_{Compatible}, pop_{semi-Compatible}) ▷ Adding pop_{Compatible} and pop_{semi-Compatible} to the feasible solution list
 - 8: binary_matrix₁₋₂ ← **overlap_finding**(pop₁, pop₂)[0] ▷ Determining if two solutions of pop₁ and pop₂ are overlapped or not by True or False
 - 9: cord_matrix₁₋₂ ← **overlap_finding**(pop₁, pop₂)[1] ▷ Saving the coordinates of the overlapped cells
 - 10: suggestion_list₁₋₂ ← **check_repair_2agent**(pop₁, pop₂, feasible_matrix₁, feasible_matrix₂, binary_matrix₁₋₂, cord_matrix₁₋₂) ▷ Checking and repair each overlapped solutions of pop₁ and pop₂
 - 11: binary_matrix₁₋₃ ← **overlap_finding**(suggestion_list₁₋₂, pop₃)[0] ▷ Determining if two solutions of repaired pop₁ and pop₃ are overlapped or not by True or False
 - 12: cord_matrix₁₋₃ ← **overlap_finding**(suggestion_list₁₋₂, pop₃)[1] ▷ Saving the coordinates of the overlapped cells
 - 13: suggestion_list₁₋₃ ← **check_repair_3agent**(suggestion_list₁₋₂, pop₃, feasible_matrix₁, feasible_matrix₃, binary_matrix₁₋₃, cord_matrix₁₋₃) ▷ Checking and repair each overlapped solutions of pop₁ and pop₃
 - 14: binary_matrix₁₂₋₃ ← **overlap_finding**(suggestion_list₁₋₂, suggestion_list₁₋₃)[0] ▷ Determining if two solutions of repaired pop₂ and pop₃ are overlapped or not by True or False
 - 15: cord_matrix₁₂₋₃ ← **overlap_finding**(suggestion_list₁₋₂, suggestion_list₁₋₃)[1] ▷ Saving the coordinates of the overlapped cells
 - 16: suggestion_list₁₂₋₃ ← **check_repair_3agent**(suggestion_list₁₋₂, suggestion_list₁₋₃, feasible_matrix₂, feasible_matrix₃, binary_matrix₁₂₋₃, cord_matrix₁₂₋₃)[0] ▷ Checking and repair each overlapped solutions of pop₂ and pop₃
-

5.4.1 Initialization

As shown in Figure 48, there are one optimizer and three different agents; Agent₁, Agent₂, and Agent₃. It should be noted that the number of agents as three is considered here as an example,

convenient for presentation purpose. Otherwise, it is quite straightforward to generalize the approach for multi-agents. Following the flowchart depicted in figure 48, the process starts with the activation of the agent-to-optimizer link, which is the first part of the decentralized decision-aiding system. In this initialization phase, each agent connects directly to the optimizer to achieve nearly optimal allocation solutions that guarantee Pareto efficiency. Following the outperformed MOEA in Chapter [4], the MA algorithm is selected as an optimizer. According to the life-cycle presented in Figure 47, this phase represents the *Perception* module of the agents. That is, agents perceive their environment by connecting to their optimizer. The optimizer helps them learn about the problem, providing them with the Pareto optimal sets. This step is described in lines 2-4 of the pseudo-code 9.

5.4.2 Compatibility

Next, two agents should be selected to determine their compatibility relation. An assumption here is to adopt a ranking approach and to assume that all actors will accept this priority list. Then, according to the chaining protocol, the agents are ranked and the first two ranked are selected as mentioned in line 5 pseudo-code 9. As shown in Figure 48, Agent₁ and Agent₂ are selected by the green checked-in circle. The compatibility matrix of the selected agents is developed using the **overlap finder 2-Agent** operator.

This operator labels the compatibility relation between each couple of agents by three terms; I) **compatible**, II) **compatible under certain conditions**, and III) **conflicting** agents.

If two agents are compatible, it means that in the case of having an intersection between their zones, they can keep on with their activities without any issue. For some agents, this situation could be possible, provided their constraints are met. That is, they are compatible under certain conditions. However, for two agents in conflict, this situation is impossible. These three compatibility relation statuses are shown in Figure 48 by three stickers; happy, sad, and angry. This module is encoded in the line 6 pseudo-code 9.

5.4.3 Communication

Having the compatibility statuses between two agents clarified, the conflicting agents start to communicate. The communication module plays the role of agent-to-agent interconnection in the decentralized decision-aiding system. This module lets agents negotiate, cooperate, collaborate, and communicate with each other to reach a compromise.

The procedure of this module is encoded in lines 7-16 of the pseudo-code 9. This module includes two different processes called *2-agent* and *3-agent*. The former deals with the negotiation mechanism when we have two agents. However, the latter handles the issues when another agent is added to the previous two agents.

Hereafter, the details of these lines are explained as follows:

1. Having the agents labeled by three different terms in line 6 pseudo-code 9, the assessment of the first two ranked agents begins in line 8-9 of the pseudo-code 9. The *compatible* solutions of them are added to the *suggestion_list₁₋₂* as mentioned in line 7 pseudo-code 9. This list contains possible solution combinations for these two agents. However, regarding the second category of the solutions called *compatible solutions under condition*, one suggesting algorithm could be *buffer technique* as mentioned in Figure 48. we suppose one of the main constraints for these agents could be the distance. The details of this technique are explained in Subsection 3.5.1. This technique translates the minimal and maximal distance constraints into buffers around each solution. By doing so, it reduces the feasible solution space for agents by deleting areas where no solution can be found. By doing so, first, the constraints of the agents are met, then the refreshed solutions can be rechecked to determine their status. It is worth mentioning that the conflicting agents have already agreed to solve their conflict through the negotiation process. Therefore, these agents are loyal by standing on their commitments.
2. In the case of conflict (*binary_matrix == True*), the coordinates of the overlapped cells are saved in a matrix called *cord_matrix*. In this step, the agents decide by which *share*

percentage the *Share Divider Operator* divides the overlapped cells between them. By doing so, the *decision* module of the agent life cycle is defined here. The *share percentage* is one of the decisions that should be made by the agents in this MOMAS. Here, as an example, we imagine that they select an equal number (50%-50%). For each agent, 50% of the cells are kept called *fixed cells*, and the rest 50% should be replaced called *incomplete cells*. This selection gives an equal chance to both agents through their negotiation.

3. The *repairing process* starts with the agent by higher order Agent₁ in line 10 pseudo-code 9. In the *Removal Process*, the 50% fixed cells of Agent₁, first, is removed from its *possible cells set*. The *possible cells set* is a set that includes the feasible cells to choose for a new agent.

The agents decide to consider **equilibrium** hypothesis or not. This hypothesis, in addition to the *fixed cells* of Agent₁, removes the *fixed cells* of Agent₂ from *possible cells set* of Agent₁ before its repairing. This hypothesis tries to empower the decentralized system by balancing the fairness between agents. This hypothesis is equally carried out for Agent₂ before its repairing. This hypothesis is another *decision* module of the agent life cycle. Following these decisions, the agents apply some measurements. The *Removal Process* and *Share Divider Operator*, therefore, are defined as the *actions* of the agent life cycle. Then, to the remaining 50% cells, using the initialization operators 4.3.4, alternative compact zones will be generated.

Having calculated their objective functions, the minimum first objective function among these alternatives would be selected and added to Agent₁. As mentioned in Chapter [3], the first objective function maximizes the overall interest of a solution. The reason why only this objective function is considered is that the second one would be already met by using the initialization operator. Moreover, the incomplete part of each agent after removing the overlapped cells is already compact.

For Agent₂, the *fixed cells* of Agent₁ and the *incomplete cells* of Agent₂ would be removed from the *possible cells set* of Agent₂. The same process as Agent₁ to find the best combination for the lack number of cells would be repeated for Agent₂. Then, this process would be repeated for all two solutions of Agent₁ and Agent₂ which are in conflict.

4. Then, the repaired solutions for both agents are added to suggestion_list₁₋₂ in line 10 pseudo-code 9. So far, the *2-agent* process is done.
5. Each solution of Agent₃ is checked with the solutions of Agent₁ in suggestion_list₁₋₂, to see whether or not they are in conflict. Now, the *3-agent* process initiates in line 11-12 of the pseudo-code 9.
6. If a conflict occurs, through the *Removal Process*, the agents decide to consider the **equilibrium** hypothesis or not. If yes, the solution of Agent₂ in the current set of suggestion_list₁₋₂, the *fixed cells* of Agent₁, and Agent₃ are removed from *possible cells set* of Agent₁. Then, by using the *compact square zone generator* algorithm 4.3.4, different alternative compact zones will be generated. The minimum one with respect to the first objective function would be selected and added to Agent₁. Next, for repairing Agent₃, the solutions of Agent₁, Agent₂, and its *fixed cells* are removed from *possible cells set* Agent₃. Next, the mentioned algorithm will find the best alternative to repair its solution. These solutions are saved in the suggestion_list₁₋₃ in line 13 pseudo-code 9.
7. Next, this process will be repeated to check the current solutions of Agent₃ with its equivalent solution of Agent₂ in the suggestion_list₁₋₃ in line 14-15 of the pseudo-code 9.
8. In the end, the final suggestion_list₁₂₋₃ in line 16 pseudo-code 9, including different combinations of the solutions of all three agents, would be proposed to the *DMS* to select the best choice from their point of view.

All the mentioned modules, through the agent life cycle, work together, communicate, and exchange information to obtain all the common global constraints and the target of all agents.

5.4.4 Illustrative Example of Multi-Objective Multi-Agent System

Figure 49 shows the graphical CR between three agents as an example of how to solve their conflicts using the proposed negotiation-based MOMAS.

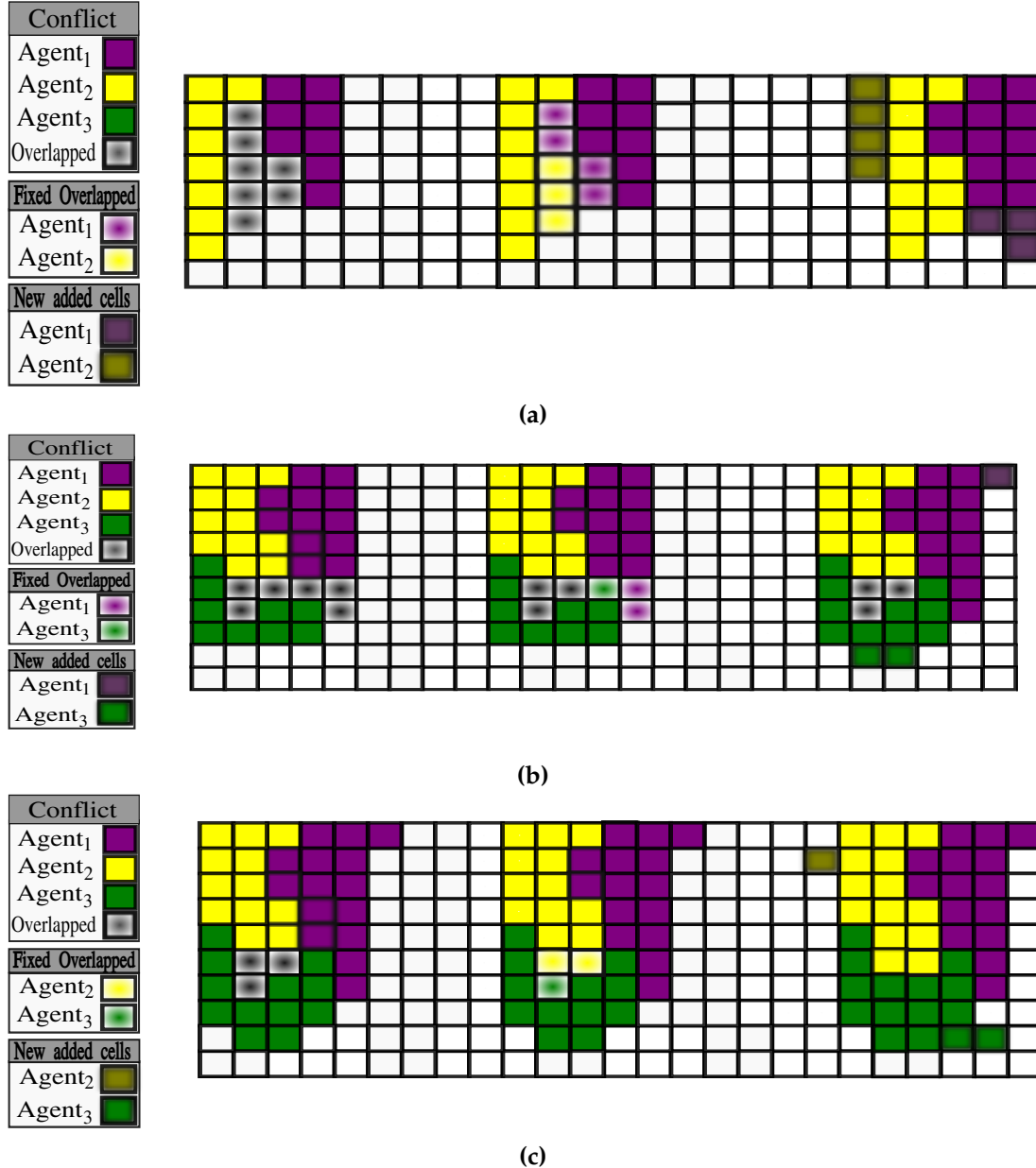


Figure 49: The graphical CR between three agents: (a) the conflict between Agent₁ and Agent₂; (b) the conflict between Agent₁ and Agent₃; (c) the conflict between Agent₂ and Agent₃

As can be seen in Figure 49, three different agents which are in conflict start the negotiation process. Following the chaining structure between them, the order of rank is Agent₁, Agent₂, and Agent₃ sequentially. To begin with, in Figure 49a, the *share percentage* determines how many overlapped cells (in gray) should be allocated to each agent (here it is 50% - 50%). Then, Agent₁ will start the process by finding the alternatives for its overlapped cells. Meanwhile, all the cells of Agent₂ have already been deleted from the *possible cells set* of Agent₁. That is, the *equilibrium hypothesis* is considered. Having found the best alternative for this agent, the *fixed cells* are removed from the *possible cells set* of Agent₂. The local search operator will start to find the best alternative for Agent₂. In Figure 49b, after fixing the first two agents, the third agent is added. In the case of a conflict, the CR will start with Agent₁ and Agent₃. Among gray-overlapped

cells, those related to these two agents are determined. The same conflict-resolving process as explained will repeat for these two. However, in this step, the cells of Agent₂ and Agent₃ will be deleted from the *possible cells set* of the Agent₁. After finding and fixing the cells of both agents, the resolving process will start for the Agent₂ and Agent₃, as shown in Figure 49c. In this process, the fixed solution of Agent₁ should be removed from the *possible cells set* of other agents. By doing so, the conflict between all three agents is solved, and they reached the compromises which are proposed as a list of possible combinations between all agents.

5.5 Experimental Validation

For the collaborative MOMAS, meeting some requirements could influence the quality and satisfactory level of different agents through the negotiation process [Kra97]. Therefore, in this section, we study the effect of these requirements on our MOMAS model in Subsection[5.5.1]. Then, we compare all the proposed negotiation models by ranking methods in Subsection[5.5.2].

5.5.1 Scenarios and Parameters Setting

The parameter setting of different scenarios are designed in Table 14.

Table 14: Experimental protocol

Scenario	Actual Values	Coded Values
Scenario-1 (Share Percentage)	(0%, 100%)	SH0
	(30%, 70%)	SH1
	(50%, 50%)	SH2
	(70%, 30%)	SH3
	(100%, 0%)	SH4
Scenario-2 (Equilibrium)	Without equilibrium	NE
	With equilibrium	E
Scenario-3 (Cooperation Level)	Non-cooperative	NC
	cooperative	C

- Scenario(1): Negotiation process with different share percentages**
 For this scenario, five different probabilities are considered as the degree of collaboration between agents, in which the first number in each set declares the *share percentage* of the strongest agent and the second one that of the weaker agent. This scenario is shown by notation SH from 0 to 4.
- Scenario(2): Negotiation process without equilibrium rule**
 In this scenario, including regulation, the equilibrium rule is considered by applying the removal process for both agents at the same time. That is, before the compact zone generator starts looking for alternatives to the stronger agent, the remained cells of the weaker agent would be removed from the possible cells set of the stronger one. On the other hand, for the weaker agent, it would remove the confirmed zone of the stronger agent from its possible cells set. This scenario is shown by the notation NE for non-equilibrium and E for equilibrium.
- Scenario(3) : Non-cooperative Negotiation process**
 In this scenario, the communication and computational costs are studied. Instead of starting with the Pareto optimal set for each agent, we will start the process with the Pareto set for the stronger agent. For example, Agent₁, Agent₂, and Agent₃ are in descending order. First, we will run the MA algorithm for the Agent₁. Next, having saved all Pareto solutions for each solution of Agent₂, first, its equivalent agent-solution has to be deleted from the possible cells set of Agent₂. By considering this updated set of possible cells, the MA algorithm will generate the optimal solutions for the Agent₂. Again, for Agent₃, each set of solutions, including Agent₁ and Agent₂, is removed from the possible cells set

of Agent₃. Then, for each combination, the MA algorithm should run. This scenario has not only a higher computational time but also less equilibrium and cooperation between agents. Therefore, it is more likely not to ensure the collective gains from cooperation. This scenario is shown by the notation NC for non-cooperative and C for cooperative.

All possible negotiation models, including the combination of three scenarios, are coded in Table 15.

Table 15: The coded negotiation models

Model		Problem							
		1	2	3	4	5	6	7	8
MA + SH0	E + C	11	12	13	14	15	16	17	18
	NE + C	21	22	23	24	25	26	27	28
MA + SH1	E + C	31	32	33	34	35	36	37	38
	NE + C	41	42	43	44	45	46	47	48
MA + SH2	E + C	51	52	53	54	55	56	57	58
	NE + C	61	62	53	64	65	66	67	68
MA + SH3	E + C	71	72	73	74	75	76	77	78
	NE + C	81	82	83	84	85	86	87	88
MA + SH4	E + C	91	92	93	94	95	96	97	98
	NE + C	101	102	103	104	105	106	107	108
MA +	NC	111	112	113	114	115	116	117	118

As shown in Table 15, the “model” column includes two sub-columns. The first sub-column starts with MA, which is referred to as the optimizer name, and + the share percentage scenario, SH. In the second sub-column, all possible combinations of equilibrium scenarios with cooperative assumptions are written. The first and second sub-columns together make the name of the negotiation model, for example, MA + SH0 + E + C. The “problem” column refers to the artificial datasets. We summarize the data generation parameters of the spatial zoning optimization problem in Table 17. We vary these problem-specific parameters at two different levels (low and high) for two different map sizes (55×55 and 1000×1000) as shown in Table 17. The total number of generated artificial datasets is $2^5 = 32$. Among 32 datasets, 8 of them are randomly selected to be used in all evaluations for each model.

Table 17: Data generation parameters for MOMAS

Parameter names	Possible values	Description
n_{row}	55, 1000	Number of rows of the raster grid
n_{col}	55, 1000	Number of columns of the raster grid
n_p	6, 10	Number of ports
n_s	6, 8	Number of shipping lanes
n_a	3, 5	Number of protected areas
n_w	2, 4	Number of windmill farms
n_{sol}	15	The number of cells assigned to a solution (solution size)

v_i	(1-6), (7-12), (13, 20)	The interest value of each cell of the interest map for each agent
-------	-------------------------	--

The output value for each model with respect to each dataset is a matrix as shown in Equation (37). The length of this matrix (m) is the multiplicity of the number of Pareto sets of the three agents (NPS_1 , NPS_2 , and NPS_3). In f_{ij}^1 , f^1 refers to the first objective function value in the problem (interestingness objective) and ij indicates the number of Pareto sets and number of agents in order.

$$F = \begin{bmatrix} f_{11}^1 & f_{12}^1 & f_{13}^1 \\ \vdots & \vdots & \vdots \\ f_{i1}^1 & f_{ij}^1 & f_{i3}^1 \\ \vdots & \vdots & \vdots \\ f_{m1}^1 & f_{mj}^1 & f_{m3}^1 \end{bmatrix}_{m \times 3} \quad (37)$$

$$m = (NPS_1 \times NPS_2 \times NPS_3) \quad (38)$$

To calculate the matrix mentioned in Equation (37) for each proposed negotiation model, the following steps should be carried out:

- First, $2^5 = 32$ artificial datasets are generated and 8 of them are selected randomly. They are used in the MA algorithm to achieve the optimal Pareto set of each agent. It is worth noting that, in each run, the dataset of all agents is considered the same, only with respect to their interestingness value.
- Second, the solutions achieved are evaluated by each negotiation model.
- Third, to evaluate a much more robust comparison between different negotiation models, each instance is implemented 20 times by each model, and each digit is the median of 20 runs of each problem.

However, for a sake of clarity, in Table 15, instead of writing the solution list of each model for each dataset, the coded value of each list is named by using the row number (model) and the column number (dataset) as shown. For example, in 12, 1 refers to the first scenario (MA + SH0 + E + C) and 2 refers to the second dataset.

5.5.2 Ranking Methods

In order to compare different developed negotiation models, aggregation methods are needed first to report the best solution on the Pareto front of each dataset.

For each dataset, we used the WS method to aggregate the values of the first normalized objective function for the three agents. For normalization, we used Equation (39). Then, for each agent, the normalized objective functions are aggregated (y_i in Equation 41) with the same weight shown in Equation (40). The highest value of y_i (Equation 41) for each negotiation model ($1 \leq m \leq 11$) is selected as the best y_m^* for each dataset (Equation (42)). Finally, by including all datasets, the matrix of the final table could be shown as Equation (43) in which n is equal to 8 datasets.

$$f_{ij}^* = f_{ij}^1 / \sqrt{\sum_{i=1}^m (f_{ij}^1)^2} \quad (39)$$

$$W = \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \quad (40)$$

$$y_i = \sum_{j=1}^3 w_j f_{ij}^* \quad (41)$$

$$y_m^* = \left\{ \max_i y_i \quad \forall 1 \leq m \leq 11 \right\} \quad (42)$$

$$Y = \begin{bmatrix} y_{11}^* & \cdots & y_{1j}^* & \cdots & y_{1n}^* \\ \vdots & \vdots & \vdots & & \vdots \\ y_{i1}^* & \cdots & y_{ij}^* & \cdots & y_{in}^* \\ \vdots & \vdots & \vdots & & \vdots \\ y_{m1}^* & \cdots & y_{mj}^* & \cdots & y_{mn}^* \end{bmatrix}_{m \times n} \quad (43)$$

Having prepared the normalized aggregated values for each dataset, the ranking process will start.

The Condorcet winner technique is selected to rank different negotiation models made up of the following stages.

1. Make a list of all possible head-to-head matchups between the candidates (negotiation models).
2. With each matchup, go through all the table columns and award all the voters in that column to the matchup's favorite candidate.
3. The Condorcet winner is the candidate who has defeated all other candidates in matchups.

The main advantage of the Condorcet ranking method in comparison with the other methods, like Borda, is in removing the effect of arbitrary voting value.

The developed algorithms and experimental tests have been programmed in Python3.8.. All experimental tests have been carried out on an OpenStack virtual machine running Linux/Ubuntu 20.04.1LTS with 20VCPU, 10GBdisk, and 30GBRAM.

5.6 Computational Results

As explained in the previous section, the normalized value of the aggregated objective functions for each dataset and model is calculated in Table 18.

Then, for each dataset, the values of y^* are ranked in ascending order (the smallest value is ranked as 1) and their ranks are written $r(y^*)$ as shown in Table 19.

By comparing all pairs of models, the model that beats the others, with respect to the given award in the total datasets, would be the winner and would be ranked down again as the last rank shown in the last column of Table 19.

According to the final Condorcet ranking, it should be concluded the results of MA + SH2 + E + C is the most efficient, the results close to MA + SH2 + NE + C as jointly efficient, the outcomes close to MA + SH0 + NE + C as socially fair. The first main result is that the configurations with cooperation (C) performed considerably better than without cooperation (NC) in terms of the first objective function performance. MA + SH4 + E + C is not significantly better than MA + NC in terms of Pareto results. The higher *share percentage* for the weaker agent is supposed to increase the welfare of that, especially with a lower equilibrium in the removal process. The combination of both might lead to better negotiation result. The use of a non-cooperative model does not lead to significant Pareto improvement without sharing; however, with cooperation, they lead to significantly better Pareto results. SH0 + C with NE is better compared to SH0 + C with E, but vice versa for SH2 + C. In the case of a NC model, only the general model is free

Table 18: Aggregated normalized value of the first objective functions

<i>Model</i>		y_{i1}^*	y_{i2}^*	y_{i3}^*	y_{i4}^*	y_{i5}^*	y_{i6}^*	y_{i7}^*	y_{i8}^*
<i>MA + SH0</i>	E + C	0,30654	0,19662	0,61223	0,08211	0,06770	0,54783	0,24783	0,54783
	NE + C	0,32466	0,22391	0,69639	0,14477	0,22027	0,43784	0,37836	0,73784
<i>MA + SH1</i>	E + C	0,29037	0,30509	0,59155	0,24986	0,05878	0,57695	0,27695	0,51695
	NE + C	0,31626	0,04752	0,69513	0,75690	0,18255	0,72449	0,32449	0,62449
<i>MA + SH2</i>	E + C	0,33888	0,45310	0,81233	0,66119	0,23506	0,52601	0,42601	0,82601
	NE + C	0,32262	0,39013	0,70518	0,52116	0,28614	0,76444	0,36444	0,66444
<i>MA + SH3</i>	E + C	0,28233	0,38467	0,45891	0,10841	0,02375	0,43163	0,23163	0,43163
	NE + C	0,29019	0,12065	0,45460	0,68820	0,08060	0,66603	0,36603	0,46603
<i>MA + SH4</i>	E + C	0,26920	0,40648	0,34281	0,50199	0,02408	0,34966	0,14966	0,34966
	NE + C	0,28056	0,01372	0,36600	0,32444	0,08974	0,41141	0,21141	0,41141
<i>MA +</i>	NC	0,27706	0,00372	0,26600	0,12440	0,13974	0,45141	0,11141	0,30141

Table 19: Finalized Condorcet rank

<i>Model</i>		$r(y_{i1}^*)$	$r(y_{i2}^*)$	$r(y_{i3}^*)$	$r(y_{i4}^*)$	$r(y_{i5}^*)$	$r(y_{i6}^*)$	$r(y_{i7}^*)$	$r(y_{i8}^*)$	Condorcet Rank
<i>MA + SH0</i>	E + C	7	5	7	1	4	7	5	7	6
	NE + C	10	6	9	4	9	4	10	10	3
<i>MA + SH1</i>	E + C	6	7	6	5	3	8	6	6	7
	NE + C	8	3	8	11	8	10	7	8	4
<i>MA + SH2</i>	E + C	11	11	11	9	10	6	11	11	1
	NE + C	9	9	10	8	11	11	8	9	2
<i>MA + SH3</i>	E + C	4	8	5	2	1	3	4	4	8
	NE + C	5	4	4	10	5	9	9	5	5
<i>MA + SH4</i>	E + C	1	10	2	7	2	1	2	2	10
	NE + C	3	2	3	6	6	2	3	3	9
<i>MA +</i>	NC	2	1	1	3	7	5	1	1	11

of other assumptions. However, it not only increases the computational time substantially but worsens the performance through cooperation. For one set of solutions in a problem with three agents, the average computational time of the cooperative models is almost 63% faster than the non-cooperative ones, with higher solution quality by less loss of optimality.

Taken together, one bullet point that should be paid attention to is that the higher the *share percentage* of the weaker agent, the better rank we achieve. In the *share percentage*, the first percentage belongs to the stronger agent and the second one to the weaker one. Therefore, the stronger agent already has one bonus over the weaker one. We could interpret the way how they try to balance and compensate for this inequality under different circumstances.

When the agents decide on the non-equal *share percentage*, they prefer to compensate for their inequality by having more options to select in their *repairing process*. By selecting the NE, the fewer removed cells from the solution space, the more possibilities are given to them to repair their incomplete cells. Moreover, the higher the *share percentage* is given to the weaker agent, the higher the rank would be given to the model.

Therefore, that is the reason why NE is better for SH0, SH1, and SH3 sequentially. However,

when they decide on the equal *share percentage*, they do not still compensate the priority bonus of the stronger agent for the weaker one in their first decision. So, the second decision could be E instead of NE. If they select NE, the stronger agent will have more chances in the *repairing process* than the weaker one as the starting agent. Finally, that is why E is placed in higher rank than NE for SH2. In our ranking process, we tested the Borda Count method, but due to the arbitrarily given value to each candidate, the Condorcet method is selected. Although the main disadvantage of the Condorcet method is facing the cycle in pairs comparison, in case of not happen, it leads to a promising ranking. In our comparisons, we had not faced this issue, that is the reason why we reached the promising final ranking by this method.

5.7 Discussion

The goal of this chapter was to create a generic model that would aid in the resolving conflict in **MOMAS** of spatial zoning management in the **MSP**. When agents understand they may be in conflict with each other based on their existing perceptions and decision modules, they adopt a cooperative strategy. In our system, agents always choose one or more actions in a negotiation to obtain the greatest possible compromise (in terms of preferences) while avoiding deadlocks. Because the quantity of exchanged messages is minimal, and it is not required for agents to communicate all information about them, the communication cost of negotiation is low. The results confirm that the negotiation mechanism is effective when agents are in conflict. To be able to solve the conflict between different agents, the optimality would be a bit attacked. However, in this algorithm, by doing a local search around the remaining part of the optimal solution of each agent and finding the most interesting zone, this loss would be diminished. The use of the *compact zone generator* to perform the local search avoids the proposal of non-compact zones.

However, in addition to the mentioned merits, a number of limitations need to be considered. First, considering a priority order between agents is a strong assumption that needs to be refined in future work. Even though the decision about a *share percentage* by agents gives a chance to deal with this issue and enter a win-win negotiation, an *a priori* hierarchy between actors is not always available in real life.

Another limitation lies in the fact that the approach is designed only for two objective functions for each agent. Two other options that could be considered are: first, considering equal to or more than two different objective functions for each agent, and second, considering more than two general objective functions the same for all agents. Finding the most appropriate optimization method for this type of problem would be challenging. Moreover, this **MOMAS** is considered a closed system, not an open one. In an open system, it could be possible for the agents to appear and disappear during the process. This assumption will allow the integration of new agents throughout the process. Third, the interaction between the environment and the system by feedback is not considered. However, a future study could assess if the agents could be back in their optimizer environment during the negotiation by giving their preferences as feedback during or at the end of the negotiation. Fourth, meeting the constraints of the agents at the same time in **CR** is not studied. Another perspective deals with the extension of the **MOMAS** model, currently based on raster data, to vector data.

The last but not the least perspective could tackle this issue with a reasonable approach, like a hybrid of reinforcement and preference learning with optimization techniques for **CR** in **MOMAS**. Nevertheless, such approaches would need a significant amount of realistic synthetic or real-world data in order to prove their efficiency. Having access to concrete datasets remains a future challenge for research in **MSP**.

Chapter 6

Conclusions and Perspectives

Contents

6.1	Summary of the Contributions	112
6.2	Limitations and Perspectives	113

The notable goal of this thesis is to create a spatial decision support system for locating and allocating areas of marine space to various stakeholders, despite possibly competing objectives and constraints.

To overcome this issue, we focus on three distinct needs in this thesis:

1. Defining and modeling the problem in a realistic GIS environment, as well as developing a mathematical model to handle it,
2. Being capable of providing solutions to large-scale problems,
3. Developing a cooperative decision-making framework to assist many stakeholders in settling potential conflicts through negotiation.

6.1 Summary of the Contributions

All in all, to address the mentioned objectives, this thesis offers a MOMAS. This approach has gone some way toward representing the multi-level decision-making processes of spatial zoning management for marine uses, with the following contributions:

- **Formulation and modeling of the zoning problem:**

Though since locating and allocating an optimal zone for a new human activity while keeping other present activities in mind is one of the key issues in the MSP, a new problem in the scope of zoning management in the MSP is identified and discussed. Chapter [2] has given an account of the reason for the widespread use of spatial planning by reviewing the relevant literature. To model this problem, the most prevalent technique is based on nonlinear multi-objective models, which are often solved using stochastic search algorithms, resulting in sub-optimal solutions. Hence, the first contribution here leads to formulating an exact linear model as a MOILP which aims at maximizing the interest of the area of the zone dedicated to one marine activity, while maximizing its spatial compactness. Second, to make the model close to reality rather than vector data, working on raster data is chosen, which fully covers the geospatial data of the areas. In Chapter [3], a novel multi-objective mathematical model is proposed to solve the problem.

- **Exact resolution:**

Two resolution approaches are utilized to solve the MOILP model and establish the best solution: WS and AUGMECON2. Because of the huge number of integer variables and constraints in this MOILP model, the resolution is improved in a preprocessing step by applying the buffering technique. This study, presented in Chapter [3], supports the results that AUGMECON2 is the most promising technique in terms of solution relevance and variety, compactness, and computing time. Indeed, AUGMECON2 can be used practically in every run to provide a unique answer. It also allows us to simply regulate the number of solutions created. WS delivers less balanced solutions between the two goals of interest and compactness while being less sensitive to the buffering approach. Overall, these specific approaches are limited to a small scale and do not support the concerning issue on a large scale. To evaluate all methodologies and analyze the sensitivity of the resolution methods and computation times concerning various parameters, a set of artificial datasets is established for all experimental assessments.

- **MHs:**

Barriers may result, meanwhile, when an attempt is taken to enlarge the problem. These barriers are the high computational cost and computational hardness of the exact solvers for large-scale cases of the problem. In Chapter [4], from an analysis of the limitations in Chapter [3], new methods to manage these barriers of the MOILP model using MOEAs are described. After an introduction to MHs, we put focus on two novel P-metaheuristics based on GA developed to solve the spatial zoning optimization problem (SH-NSGA-II and MA). Several innovations and contributions are suggested and applied in initialization, stop condition, chromosome encoding, crossover, mutation, check and repair operators, constraint management methodologies, and algorithm structure based on raster data.

These MOEAs are aimed to optimize not only the interestingness but also the compactness of the new activity zone. To tune the parameters of MOEAs, we use MRSM. We set up a DOE as BBD, which implements a multi-response regression model for three different map sizes of the problem to determine the optimal value of the MOEAs parameters. Moreover, the effectiveness of all models is validated by ANOVA. Different performance metrics are suggested and calculated for better characterization of the Pareto solutions in order to compare the two MOEAs. Doing so results in more efficient and effective analysis of two algorithms from small- to large-scale issues. The significant value of the WSRT tests of all performance metrics for the exact method, SH-NSGA-II, and MA in the three problem size levels is evaluated and compared to validate all findings. 24 test cases with 30 times replications are utilized to illustrate the outperformance of the suggested MOEAs. The results show that, on average, the proposed MA provided better solutions in less computational time and has a higher consistency than SH-NSGA-II. Finally, a series of (24×30) WSRT indicated that the suggested MA greatly outperforms the SH-NSGA-II.

- **CR:**

To address the third need of the thesis goal, the assumption of cooperation between multiple competing interests should be added. This requirement guides us to developing a CR framework in the cooperative decision-making process using MAS and heuristics methods in Chapter [5]. This method set out to support the claimants with a compromise in which they are provided with alternatives that maximize the allocated benefit to them and guarantee fairness and a highly satisfactory level for long-term cooperation. The agent-to-optimizer and agent-to-agent collaborative mechanisms make up the decision levels in MOMAS. We propose a heuristic negotiation-based method for classifying MOMAS properties using a chaining negotiation structure. First, at the agent-to-optimize decision level, the agents complete their perception module. Having the MA algorithm run on each agent and their Pareto optimum solutions collected, the agent-to-agent decision level is implemented. In this technique, agents in a negotiation always make one or more decisions and take one or more actions in order to reach the optimum reasonable compromise while avoiding bottlenecks. Negotiation communication costs are minimal because the number of messages transmitted is limited and agents are not required to disclose all information about them. Various CR negotiating scenarios are also described, evaluated, and rated using the Condorcet aggregation approach. The findings demonstrate how agents can arrive at good solutions by employing the aforementioned techniques.

6.2 Limitations and Perspectives

The limitations and perspectives of this thesis could be listed as follows:

1. In our MOILP model, we cover the global constraints and do not dig deeper into the constraints of each activity. For example, in the real world, one of the challenging constraints for some marine activities, such as shipping, is time scheduling. This issue comprises determining the arrival, departure, and waiting times of each ship to each port to serve the cargo. Therefore, time windows (hard or soft) could be added to the constraints for the ship routing and scheduling problems. Although considering more constraints makes the MOILP model more complex, it is more likely to make the negotiation mechanism easier in the end. Since most of the conflict comes up from these restrictions, relaxing them by the agents' decisions through the negotiation could help them reach the compromise.
2. In our MOILP model, we define the global objective functions, which are only two. They are the global objective functions for all considered marine uses. Adding some more objective functions could help to cover more criteria and preferences of the actors. Therefore, some other objective functions could be added, like minimizing the cost of allocation of the located zones to each marine use while maximizing total profit for each of them.

Improving the exact model by considering more than two objective functions could be assessed by two ideas through future research. For example, one idea could consider the global objectives as general ones and use the bi-level optimization methods for each actor.

By doing so, the objectives of each actor nested within the global ones would be met first and then help to optimize the general ones.

Another choice includes having equal to or over two different objective functions for each agent. Accordingly, finding the applicable resolution methods like [MHs](#) could be challenging for these ideas.

3. In our [MOILP](#) model, which is a semi-cooperative spatial zoning problem, one new human activity is to be located and allocated by fixing other human activities. Therefore, an issue that is not addressed is modeling exact mathematical programming by location-allocation of multiple new marine uses at the same time. Developing the mathematical programming for this type of problem ([MOMAS](#)) might change the model from linear to non-linear and much more complicated. Having the mathematical model of [MOMAS](#) could help to catch up with the optimal solutions, not approximate ones for all actors. This idea needs more research and investigation.
4. In resolution methods, although [MOEAs](#) findings have gone some way toward solving the given specific problem on a large scale, more improvements could be possible to reduce the computational time while increasing the convergence speed. For instance, some improvements in population generator operators could help in this regard by diminishing the need for repair operators, since a remarkable time in our [MOEAs](#) is dedicated to these operators.

Moreover, assessing and developing more [MOEAs](#) to compare with the current proposed ones could help to find the fastest [MOEAs](#) for this problem. This perspective could be reachable with a piece of extension in the current algorithm.

Another method for the future research we could investigate is the *Matheuristics* algorithms. They are heuristic algorithms made by the interoperation of [MHs](#) and mathematic programming techniques, would be interesting. This method could mix the current [MOILP](#) model with [MOEAs](#) in a way.

5. The [MOEAs](#) and [MOILP](#) models, in our research, are based on raster data. However, the current research is not designed to evaluate these models based on vector data. Although considering the raster data increases the precision of our solutions and is more preferable to the marine companies, the vector data reduces the computational cost and hardness of our algorithms.

Therefore, developing a non-linear model based on the polygon to make the transformation easier while using the vector data rather than raster data could be evaluated in future work.

6. The current thesis has only examined certainty in the parameters without involving uncertainty in them. The uncertainty of input data, particularly when the input data statistically incorporates many distributions, and the dynamicity of the input data are two essential challenges to address in real-world optimization problems. To make the methods more compatible with the real world, considering the uncertainty hypothesis could help. For example, one intriguing research approach for data uncertainty might be to use ML techniques such as clustering algorithms (e.g., k-means, SOM) to cluster the input data with the goal of differentiating data with various distributions. These data classes can then be used/integrated to address the optimization challenge at hand.

Robust optimization or stochastic programming could be an idea. There are two main factors that distinguish them:

- In stochastic optimization, it is nearly always assumed that we know the probability distribution (possibly in the form of discrete probabilities of each scenario) of the random parameters. In robust optimization, it is usually (but not always) assumed that we do not know the distribution.
- In stochastic optimization, the goal is usually to optimize the expected value of the objective function (min expected cost, max expected profit, etc.). In robust optimization, because we do not know the probabilities, we instead optimize some other measure. Common measures are to optimize the worst-case outcome – e.g., minimize the maximum cost, maximize the minimum profit, etc. – sometimes over

only a subset of the possible scenarios. There are lots of other common objectives, too.

For data dynamicity, Machine Learning (ML) approaches may be used to monitor/predict the development of the input data, and when a new evolution is identified, the optimization variables are changed suitably.

7. The **MOMAS** is considered a closed system, not an open one. The open system lets the new agents integrate seamlessly throughout the process. By doing so, it could be possible for the agents to appear and disappear during the process. Therefore, this assumption could make the negotiation mechanism more flexible for the agents while reducing unnecessary communication between them. Therefore, it could lead to a reduction in negotiation complexity and costs.

This idea should be implemented through the new negotiation heuristic.

8. The interaction between the environment and the system by feedback is not considered. Adding the feedback assumption to **MOMAS** could help the agents reach the best compromised solution. For example, the agents might return to their optimizer environment during the negotiation by providing feedback throughout or at the end of the negotiation. By doing so, the interactive communication between the optimizer and agents could keep the optimizer updated regarding the solution changes.

This idea should be implemented through the new negotiation heuristic.

9. Some other techniques to address **CR** analysis for multi-uses, which should help address the zoning management in **MSP**, could be as follows. This perspective could define as new research. These directions also open other research questions that are worthy for further investigations.

- assessing the mixing of reinforcement learning or deep learning with optimization techniques. However, such techniques would require a considerable amount of accurate synthetic or real-world data to show their efficacy. Access to actual datasets is a future concern for **MSP** research.
- investigating the Hybrid Learning-Based Multi-Objective Polyhedral and Hierarchical Optimization for **MOMAS**. This method might help meet not only global constraints and objectives but also the specific ones for each of them.
- mixing the agent-based simulation-based models and optimization techniques (Using AnyLogic optimization which is built on top of the OptQuest Optimization Engine, one of the most flexible and user-friendly optimization tools on the market). Although Anylogic is proprietary software, which is not usable for research study, it could be applied for real-case use in the industry.

Publications

The scientific achievements of this research work have been presented to the community through several journal articles (under review and published) and oral presentations in national and international conference.

Journal Articles:

- *Chapter[3]* is related to:
Basirati, Mohadese, Romain Billot, Patrick Meyer, and Erwan Bocher. "Exact Zoning Optimization Model for Marine Spatial Planning (MSP)." *Frontiers in Marine Science* 8 (2021).

Submitted Journal Articles:

- *Chapter[5]* is related to:
Basirati, Mohadese, Romain Billot, and Patrick Meyer. "An Agent-Based Heuristic Algorithm for Conflict Resolution in Zoning Management for Marine Spatial Planning" *Expert Systems with Applications* (2022).
- *Chapter[4]* is related to:
Basirati, Mohadese, Romain Billot, and Patrick Meyer. "Two Parameter-Tuned Multi-Objective Evolutionary-Based Algorithms for Zoning Management in Marine Spatial Planning." *Annals of Mathematics and Artificial Intelligence* (2022).

Conference Presentations:

- *Chapter[4]* is related to:
Basirati, Mohadese, Romain Billot, Patrick Meyer, and Erwan Bocher. An Extension of NSGA-II for scaling up Multi-Objective Spatial Zoning Optimization. The 16th Learning and Intelligent Optimization Conference (LION16), Jun 2022, Milos Island, Cyclades, Greece.
- **Basirati, Mohadese**, Romain Billot, Patrick Meyer, and Erwan Bocher. Developing an Exact Zoning Optimization Model for Marine Spatial Planning(MSP). 31st European Conference on Operational Research (EURO 2021), Jul 2021, Athens, Greece.
- **Basirati, Mohadese**, Romain Billot, Patrick Meyer, and Erwan Bocher. Developing a Novel Exact Model of Zoning Optimization for Marine Spatial Planning. INFORMS Annual Meeting 2021, Oct 2021, Anaheim, United States.
- **Basirati, Mohadese**, Romain Billot, Patrick Meyer, and Erwan Bocher. "A hybrid multi-objective evolutionary-based and multi-criteria decision-making approach for negotiation in marine spatial planning." The International Virtual Summer School on Metaheuristics (MESS2020+1) Catania, Italy, June 2021.
- **Basirati, Mohadese**, Romain Billot, Patrick Meyer, and Mehrdad Mohammadi. "A hybrid multi-objective evolutionary-based and multi-criteria decision-making approach for cooperative marine spatial planning (MSP)." In ROADEF 2020: 21st Annual Conference of the French Society of Operations Research and Decision Aiding, February 2020, Montpellier, France: 19-21.

Appendix A

Tables

Table 20: Computational results obtained for the tuning parameters of SH-NSGA-II for medium map size in Subsection [4.4.1]

Run Order	x_1	x_2	x_3	x_4	Signal_Noise
1	-1	-1	0	0	20,199
2	-1	1	0	0	21,106
3	1	-1	0	0	20,804
4	1	1	0	0	23,267
5	0	0	-1	-1	19,756
6	0	0	-1	1	20,890
7	0	0	1	-1	20,491
8	0	0	1	1	22,035
9	-1	0	0	-1	21,079
10	-1	0	0	1	21,534
11	1	0	0	-1	20,827
12	1	0	0	1	20,840
13	0	-1	-1	0	20,361
14	0	-1	1	0	21,482
15	0	1	-1	0	21,025
16	0	1	1	0	20,456
17	-1	0	-1	0	20,684
18	-1	0	1	0	20,279
19	1	0	-1	0	20,107
20	1	0	1	0	22,062
21	0	-1	0	-1	20,495
22	0	-1	0	1	20,994
23	0	1	0	-1	20,722
24	0	1	0	1	20,706
25	0	0	0	0	22,294

Table 21: Computational results obtained for the tuning parameters of SH-NSGA-II for large map size in Subsection [4.4.1]

Run Order	x_1	x_2	x_3	x_4	Signal_Noise
1	-1	-1	0	0	19,422
2	-1	1	0	0	17,823
3	1	-1	0	0	18,792
4	1	1	0	0	20,042
5	0	0	-1	-1	18,693
6	0	0	-1	1	18,245
7	0	0	1	-1	18,854
8	0	0	1	1	19,025
9	-1	0	0	-1	19,809
10	-1	0	0	1	19,560
11	1	0	0	-1	17,949
12	1	0	0	1	17,755
13	0	-1	-1	0	17,173
14	0	-1	1	0	18,553
15	0	1	-1	0	19,556
16	0	1	1	0	21,042
17	-1	0	-1	0	17,080
18	-1	0	1	0	17,473
19	1	0	-1	0	19,366
20	1	0	1	0	18,725
21	0	-1	0	-1	19,532
22	0	-1	0	1	19,041
23	0	1	0	-1	17,413
24	0	1	0	1	18,001
25	0	0	0	0	18,520

Table 22: Computational results obtained for the tuning parameters of MA for small map size in Subsection [4.4.1]

Run Order	x_1	x_2	x_3	x_4	x_5	x_6	Signal_Noise
1	-1	-1	0	0	0	0	6,0738
2	1	-1	0	0	0	0	5,9897
3	-1	1	0	0	0	0	5,8388
4	1	1	0	0	0	0	6,1284
5	-1	0	-1	0	0	0	5,6148
6	1	0	-1	0	0	0	5,7023
7	-1	0	1	0	0	0	5,9356
8	1	0	1	0	0	0	6,2064
9	-1	0	0	-1	0	0	5,9291
10	1	0	0	-1	0	0	6,1875
11	-1	0	0	1	0	0	5,5990
12	1	0	0	1	0	0	5,9862
13	-1	0	0	0	-1	0	5,9112
14	1	0	0	0	-1	0	6,0874
15	-1	0	0	0	1	0	5,9913
16	1	0	0	0	1	0	5,9983
17	-1	0	0	0	0	-1	5,8264
18	1	0	0	0	0	-1	6,1187
19	-1	0	0	0	0	1	5,7696
20	1	0	0	0	0	1	6,0717

Table 22 continued from previous page

21	0	-1	-1	0	0	0	5,5075
22	0	1	-1	0	0	0	6,1086
23	0	-1	1	0	0	0	6,3044
24	0	1	1	0	0	0	6,1880
25	0	-1	0	-1	0	0	5,8952
26	0	1	0	-1	0	0	6,0828
27	0	-1	0	1	0	0	5,7706
28	0	1	0	1	0	0	5,9275
29	0	-1	0	0	-1	0	5,952
30	0	1	0	0	-1	0	6,1481
31	0	-1	0	0	1	0	6,0383
32	0	1	0	0	1	0	6,1187
33	0	-1	0	0	0	-1	6,1096
34	0	1	0	0	0	-1	5,9573
35	0	-1	0	0	0	1	6,0490
36	0	1	0	0	0	1	5,9113
37	0	0	-1	-1	0	0	5,8748
38	0	0	1	-1	0	0	6,3023
39	0	0	-1	1	0	0	5,5594
40	0	0	1	1	0	0	5,8613
41	0	0	-1	0	-1	0	5,7685
42	0	0	1	0	-1	0	6,2078
43	0	0	-1	0	1	0	5,9467
44	0	0	1	0	1	0	6,0555
45	0	0	-1	0	0	-1	6,112
46	0	0	1	0	0	-1	5,9037
47	0	0	-1	0	0	1	5,5400
48	0	0	1	0	0	1	5,9878
49	0	0	0	-1	-1	0	6,1911
50	0	0	0	1	-1	0	5,8647
51	0	0	0	-1	1	0	6,0778
52	0	0	0	1	1	0	5,8252
53	0	0	0	-1	0	-1	6,1218
54	0	0	0	1	0	-1	5,7822
55	0	0	0	-1	0	1	6,2058
56	0	0	0	1	0	1	5,9441
57	0	0	0	0	-1	-1	6,2225
58	0	0	0	0	1	-1	5,5603
59	0	0	0	0	-1	1	5,9229
60	0	0	0	0	1	1	5,9453
61	0	0	0	0	0	0	5,9826

Table 23: Computational results obtained for the tuning parameters of MA for medium map size in Subsection [4.4.1]

Run Order	x_1	x_2	x_3	x_4	x_5	x_6	Signal_Noise
1	-1	-1	0	0	0	0	5,6378
2	1	-1	0	0	0	0	5,6342
3	-1	1	0	0	0	0	5,4515
4	1	1	0	0	0	0	5,6007
5	-1	0	-1	0	0	0	5,6748
6	1	0	-1	0	0	0	5,6505
7	-1	0	1	0	0	0	5,5797
8	1	0	1	0	0	0	5,7132
9	-1	0	0	-1	0	0	5,6864
10	1	0	0	-1	0	0	5,6490

Table 24: Computational results obtained for the tuning parameters of MA for large map size in Subsection [4.4.1]

Run Order	x_1	x_2	x_3	x_4	x_5	x_6	Signal_Noise
1	-1	-1	0	0	0	0	5,5069
2	1	-1	0	0	0	0	5,7999
3	-1	1	0	0	0	0	5,7164
4	1	1	0	0	0	0	5,7134
5	-1	0	-1	0	0	0	5,3670
6	1	0	-1	0	0	0	5,7984
7	-1	0	1	0	0	0	5,6145
8	1	0	1	0	0	0	5,6678
9	-1	0	0	-1	0	0	5,8562
10	1	0	0	-1	0	0	5,8804
11	-1	0	0	1	0	0	5,5735
12	1	0	0	1	0	0	5,933
13	-1	0	0	0	-1	0	5,657
14	1	0	0	0	-1	0	5,7651
15	-1	0	0	0	1	0	5,6800
16	1	0	0	0	1	0	5,7498
17	-1	0	0	0	0	-1	5,5157
18	1	0	0	0	0	-1	6,0049
19	-1	0	0	0	0	1	5,8153
20	1	0	0	0	0	1	5,7693
21	0	-1	-1	0	0	0	5,5509
22	0	1	-1	0	0	0	5,8061
23	0	-1	1	0	0	0	5,5889
24	0	1	1	0	0	0	5,6754
25	0	-1	0	-1	0	0	5,7666
26	0	1	0	-1	0	0	5,6816
27	0	-1	0	1	0	0	5,2774
28	0	1	0	1	0	0	5,8137
29	0	-1	0	0	-1	0	5,5858
30	0	1	0	0	-1	0	5,7544
31	0	-1	0	0	1	0	5,7651
32	0	1	0	0	1	0	5,7241
33	0	-1	0	0	0	-1	5,6344
34	0	1	0	0	0	-1	5,5069
35	0	-1	0	0	0	1	5,5509
36	0	1	0	0	0	1	5,7589
37	0	0	-1	-1	0	0	5,7651
38	0	0	1	-1	0	0	5,595
39	0	0	-1	1	0	0	5,4506
40	0	0	1	1	0	0	5,8122
41	0	0	-1	0	-1	0	5,4628
42	0	0	1	0	-1	0	5,9168
43	0	0	-1	0	1	0	5,7651
44	0	0	1	0	1	0	5,5904
45	0	0	-1	0	0	-1	5,9593
46	0	0	1	0	0	-1	5,6237
47	0	0	-1	0	0	1	5,6662
48	0	0	1	0	0	1	5,590
49	0	0	0	-1	-1	0	5,8076
50	0	0	0	1	-1	0	5,7651
51	0	0	0	-1	1	0	5,616
52	0	0	0	1	1	0	5,6616
53	0	0	0	-1	0	-1	5,8440
54	0	0	0	1	0	-1	5,7482

Table 25: Summary table SH-NSGA-II for medium map size in Subsection [4.4.1]

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	22.293804	0.511	43.585	1.77e-15 ***	
x ₁	0.543194	0.148	3.679	0.002781 **	
x ₂	0.405784	0.148	2.748	0.016598 *	
x ₃	0.166822	0.148	1.130	0.278985	
x ₄	0.016797	0.148	0.114	0.911171	
x ₁ ²	-0.468	0.304	-1.539	0.147876	
x ₂ ²	-0.593	0.304	-1.948	0.073293 .	
x ₃ ²	-0.895	0.304	-2.941	0.011461 *	
x ₄ ²	-0.781	0.304	-2.565	0.023522 *	
x ₁ :x ₂	0.389	0.256	1.520	0.152325	
x ₂ :x ₃	-0.4220	0.256	-1.6512	0.122626	
x ₂ :x ₄	0.590	0.256	2.3067	0.038183 *	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Multiple R-Squared: 0.768, Adjusted R-Squared: 0.571					
F-statistic: 3.903 on 11 and 13 DF, p-value: 0.01136					
ANOVA	Df	Sum Sq	Mean Sq	F value	Pr(>F)
FO(x ₁ , x ₂ , x ₃ , x ₄)	4	5.85	1.463	5.59	0.0076
PQ(x ₁ , x ₂ , x ₃ , x ₄)	4	2.67	0.667	2.55	0.089
x ₁ :x ₂	1	0.605	0.604	2.312	0.152
x ₂ :x ₃	1	0.713	0.713	2.727	0.123
x ₂ :x ₄	1	1.392	1.392	5.3208	0.038
Residuals	13	3.401	0.261		
Lack of fit	13	3.401	0.261		
Pure error	0	0.000			
Stationary point of response surface:					
	x ₁	x ₂	x ₃	x ₄	
	0.58	0.34	0.09	0.01	
Stationary point in original units:					
	N _{pop}	R _c	R _m	P _m	
	178.99	0.67	0.43	0.50	
rsm(formula=Signal_Noise~FO(x ₁ , x ₂ , x ₃ , x ₄) + (x ₁ :x ₂) + (x ₂ :x ₃) + (x ₂ :x ₄) + PQ(x ₁ , x ₂ , x ₃ , x ₄), data = BBD					

Table 26: Summary table SH-NSGA-II for large map size in Subsection [4.4.1]

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	5.726	0.034	168.698	<2.2e-16 ***	
x ₁	0.037	0.018	2.03	0.059 .	
x ₂	0.065	0.018	3.59	0.0024 **	
x ₃	0.030	0.018	1.69	0.11	
x ₄	-0.0027	0.018	-0.154	0.879	
x ₂ ²	-0.070	0.028	-2.47	0.0259 *	
x ₃ ²	-0.070	0.028	-2.48	0.025 *	
x ₄ ²	-0.084	0.028	-2.957	0.009 **	
x ₂ :x ₃	0.050	0.031	1.597	0.130	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Multiple R-Squared: 0.682, Adjusted R-Squared: 0.523					
F-statistic: 4.293 on 8 and 16 DF, p-value: 0.006382					
ANOVA	Df	Sum Sq	Mean Sq	F value	Pr(>F)
FO(x ₁ , x ₂ , x ₃ , x ₄)	4	0.078	0.019	4.968	0.0085
PQ(x ₂ , x ₃ , x ₄)	3	0.047	0.016	3.97	0.027
x ₂ :x ₃	1	0.01	0.01	2.55	0.1297
Residuals	16	0.063	0.004		
Lack of fit	16	0.063	0.004		
Pure error	0	0.00			
Stationary point of response surface:					
	x ₁	x ₂	x ₃	x ₄	
	0.00	0.46	0.21	-0.017	
Stationary point in original units:					
	N _{pop}	R _c	R _m	P _m	
	150.0	0.69	0.46	0.5	

```
rsm(formula = Signal_Noise ~FO(x1, x2, x3, x4) + (x2:x3) + PQ(x2, x3, x4),
data = BBD)
```


Table 27: Summary table MA for small map size in Subsection [4.4.1]

	Estimate	Std. Error	t value	Pr(> t)		
(Intercept)	5.922	0.020	289.154	<2.2e-16 ***		
x ₁	0.099	0.024	4.124	0.0001503 ***		
x ₂	0.036	0.024	1.492	0.1424554		
x ₃	0.161	0.024	6.679	2.509e-08 ***		
x ₄	-0.137	0.024	-5.704	7.536e-07 ***		
x ₅	-0.036	0.024	-1.494	0.1419021		
x ₆	-0.018	0.024	-0.762	0.4498483		
x ₂ ²	0.072	0.030	2.390	0.0209104 *		
x ₅ ²	0.055	0.030	1.8343	0.0729486 .		
x ₁ :x ₂	0.093	0.054	1.734	0.0894593 .		
x ₂ :x ₃	-0.179	0.054	-3.330	0.0016981 **		
x ₃ :x ₅	-0.083	0.054	-1.534	0.1317846		
x ₃ :x ₆	0.164	0.054	3.046	0.0037986 **		
x ₅ :x ₆	0.171	0.054	3.178	0.0026234 **		
Signif. codes: 0 '***' 0.001 '**'			0.01 '*' 0.05 '.' 0.1 ' ' 1			
Multiple R-Squared: 0.7522,			Adjusted R-Squared: 0.6837			
F-statistic: 10.98 on 13 and 47 DF,			p-value: 3.159e-10			
ANOVA	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
FO(x ₁ , x ₂ , x ₃ , x ₄ , x ₅ , x ₆)	6	1.151	0.192	16.532	3.919e-10	
PQ(x ₂ , x ₅)	2	0.089	0.045	3.843	0.029	
x ₁ :x ₂	1	0.035	0.035	3.007	0.090	
x ₂ :x ₃	1	0.129	0.129	11.086	0.0017	
x ₃ :x ₅	1	0.028	0.027	2.352	0.132	
x ₃ :x ₆	1	0.108	0.108	9.276	0.0038	
x ₅ :x ₆	1	0.117	0.117	10.099	0.0026	
Residuals	47	0.545	0.012			
Lack of fit	47	0.545	0.012			
Pure error	0	0.000				
Stationary point of response surface:						
	x ₁	x ₂	x ₃	x ₄	x ₅	x ₆
	0.00	-0.25	0.00	0.00	0.328	0.00
Stationary point in original units:						
	N _{pop}	R _c	R _m	P _m	R _l	P _l
	150.0	0.5497	0.40	0.50	0.56	0.625
rsm(formula = Signal_Noise ~FO(x ₁ , x ₂ , x ₃ , x ₄ , x ₅ , x ₆) + (x ₁ :x ₂) +(x ₂ :x ₃) + (x ₃ :x ₅) + (x ₃ :x ₆) + (x ₅ :x ₆) + PQ(x ₂ ,x ₅), data = BBD)						

Table 28: Summary table MA for medium map size in Subsection [4.4.1]

	Estimate	Std. Error	t value	Pr(> t)		
(Intercept)	5.73	0.022	255.803	<2.2e-16 ***		
x ₁	0.022	0.016	1.35	0.182		
x ₂	0.0012	0.017	0.07	0.94462		
x ₃	0.030	0.017	1.85	0.07 .		
x ₄	-0.009	0.016	-0.55	0.58		
x ₅	0.027	0.016	1.67	0.10		
x ₆	-0.082	0.0169	-5.0774	6.190e-06 ***		
x ₁ ²	-0.041	0.022	-1.89	0.06474 .		
x ₂ ²	-0.094	0.022	-4.278	8.961e-05 ***		
x ₃ ²	-0.032	0.022	-1.4469	0.15443		
x ₅ ²	-0.035	0.02	-1.5561	0.12626		
x ₂ :x ₃	-0.0463	0.036	-1.27	0.21043		
x ₂ :x ₅	-0.079	0.036	-2.188	0.03367 *		
Signif. codes: 0 '***' 0.001 '**'			0.01 '*' 0.05 '.' 0.1 ' ' 1			
Multiple R-Squared: 0.5445,			Adjusted R-Squared: 0.4306			
F-statistic: 4.781 on 12 and 48 DF,			p-value: 4.309e-05			
ANOVA	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
FO(x ₁ , x ₂ , x ₃ , x ₄ , x ₅ , x ₆)	6	0.172	0.029	5.39	0.00025	
PQ(x ₁ , x ₂ , x ₃ , x ₅)	4	0.099	0.025	4.67	0.0029	
x ₂ :x ₃	1	0.009	0.009	1.6113	0.21	
x ₂ :x ₅	1	0.025	0.025	4.7817	0.034	
Residuals	48	0.255	0.005			
Lack of fit	48	0.255	0.005			
Pure error	0	0.00				
Stationary point of response surface:						
	x ₁	x ₂	x ₃	x ₄	x ₅	x ₆
	0.27	0.006	0.48	0.00	0.39	0.00
Stationary point in original units:						
	N _{pop}	R _c	R _m	P _m	R _l	P _l
	163.32	0.60	0.543	0.50	0.59	0.625
rsm(formula = Signal_Noise ~FO(x ₁ , x ₂ , x ₃ , x ₄ , x ₅ , x ₆) + (x ₂ :x ₃) +(x ₂ :x ₅) + PQ(x ₁ , x ₂ , x ₃ , x ₅), data = BBD)						

Table 29: Summary Table MA for large map size in Subsection [4.4.1]

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.60	0.034	165.05	<2.2e-16 ***
x ₁	0.074	0.025	2.97	0.0049 **
x ₂	0.065	0.025	2.600	0.013 *
x ₃	0.023	0.025	0.92	0.36
x ₄	-0.044	0.024	-1.83	0.07 .
x ₅	0.0189	0.025	0.75	0.45
x ₆	-0.013	0.025	-0.53	0.60
x ₁ ²	0.07	0.033	2.173	0.035 *
x ₄ ²	0.067	0.033	2.060	0.046 *
x ₅ ²	0.062	0.0333	1.84	0.07 .
x ₆ ²	0.073503	0.0333	2.20	0.034 *
x ₁ :x ₂	-0.074	0.054	-1.36	0.179
x ₁ :x ₃	-0.095	0.054	-1.74	0.089 .
x ₁ :x ₄	0.084	0.054	1.55	0.129
x ₁ :x ₆	-0.130	0.054	-2.39	0.021 *
x ₂ :x ₄	0.155	0.054	2.87	0.0065 **
x ₂ :x ₆	0.077	0.054	1.44	0.157
x ₃ :x ₄	0.133	0.054	2.45	0.018 *
x ₃ :x ₅	-0.164	0.054	-3.047	0.004 **
x ₆ :x ₅	-0.090	0.054	-1.68	0.099 .
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Multiple R-Squared: 0.6456, Adjusted R-Squared: 0.4813				
F-statistic: 3.93 on 19 and 41 DF, p-value: 0.0001194				

ANOVA	Df	Sum Sq	Mean Sq	F value	Pr(>F)
FO(x ₁ , x ₂ , x ₃ , x ₄ , x ₅ , x ₆)	6	0.28	0.047	4.03	0.0029
PQ(x ₁ , x ₄ , x ₅ , x ₆)	4	0.11	0.027	2.26	0.0787
x ₁ :x ₂	1	0.022	0.022	1.86	0.179
x ₁ :x ₃	1	0.036	0.036	3.04	0.089
x ₁ :x ₄	1	0.030	0.028	2.40	0.13
x ₁ :x ₆	1	0.068	0.067	5.71	0.02
x ₂ :x ₄	1	0.097	0.096	8.21	0.006
x ₂ :x ₆	1	0.024	0.024	2.07	0.157
x ₃ :x ₄	1	0.071	0.071	6.01	0.0186
x ₃ :x ₅	1	0.11	0.109	9.28	0.004
x ₆ :x ₅	1	0.03	0.033	2.84	0.0995
Residuals	41	0.48219	0.01176		
Lack of fit	41	0.48219	0.01176		
Pure error	0	0.00000			

Stationary point of response surface: x₁ x₂ x₃ x₄ x₅ x₆
-0.52 0.0 0.0 0.33 -0.15 0.09

Stationary point in original units: N_{pop} R_c R_m P_m R_l P_l
123.78 0.60 0.40 0.58 0.397 0.64

rsm(formula = Signal_Noise ~FO(x₁, x₂, x₃, x₄, x₅, x₆) + (x₁:x₂) + (x₁:x₃) + (x₁:x₄) + (x₁:x₆) + (x₂:x₄) + (x₂:x₆) + (x₃:x₄) + (x₃:x₅) + (x₅:x₆) + PQ(x₁, x₄, x₅, x₆), data = BBD)

Appendix B

Pseudo-code

Algorithm 10 Pseudo-code SH-NSGA-II in Subsection[4.3.2]

```

1: procedure SH-NSGA-II( $N_{pop}, R_c, R_m, P_m$ )
2:    $pop \leftarrow \mathbf{random\_population}(N_{pop})$     ▷ Create a random initial population set
3:    $F \leftarrow \mathbf{evaluation\_Fitness}(pop)$         ▷ Evaluate the initial population
4:    $pop_{cross}, pop_{mutation} \leftarrow pop$ 
5:    $F_{cross}, F_{mutation} \leftarrow F$ 
6:   while not stop criterion(counter < K) do
7:     while not crossover rate do
8:        $C_i \leftarrow \mathbf{crossover}_i(pop_{cross}, F_{cross})$     ▷ For  $i^{th}$  crossover of 4
9:        $Offspring_{cross_i} \leftarrow \mathbf{non\_repeat}(C_i)$  ▷ Clearing and Collecting offsprings
10:    if mutation probability then
11:      while not mutation rate do
12:         $M_i \leftarrow \mathbf{mutation}_i(pop_{mutation}, F_{mutation})$  ▷ For  $i^{th}$  mutation of 3
13:         $Offspring_{mutation_i} \leftarrow \mathbf{non\_repeat}(M_i)$  ▷ Clearing and Collecting
        offsprings
14:         $pop \leftarrow \mathbf{insert}(pop, pop_{cross}, pop_{mutation})$     ▷ Create a union set
15:         $F \leftarrow \mathbf{evaluation\_Fitness}(pop)$     ▷ Evaluate union set
16:         $F_{pareto}, N_{pareto} \leftarrow \mathbf{pareto\_front\_finding}(F, N_{pop})$     ▷ Finding the pareto
        front
17:         $hv \leftarrow \mathbf{HV}(F_{pareto}, N_{pareto})$     ▷ Calculating HV
18:        counter  $\leftarrow \mathbf{count}(hv_{list})$     ▷ Counting the non-improved HV value
19:         $pop \leftarrow \mathbf{selection}(N_{pop}, pop, F)$     ▷ Do selection among union set
20:         $F \leftarrow \mathbf{evaluation\_Fitness}(pop)$ 
21:        Updating  $pop_{cross}, pop_{mutation}, pop_{local}, F_{cross}, F_{mutation},$  and  $F_{local}$ 
22:        Reporting final Pareto front based on the Crowding Distance

```

Algorithm 11 Pseudo-code Crossover-2 in Subsection[4.3.4]

```

1: procedure CROSSOVER-2( $\text{pop}_{\text{cross}}, F_{\text{cross}}$ )
2:    $P_1, P_2 \leftarrow \text{binary\_tournament\_selection}(\text{pop}_{\text{cross}}, F_{\text{cross}})$   $\triangleright$  Select two parent
   chromosomes
3:    $P_1, P_2 \leftarrow \text{sort\_y}(P_1, P_2)$   $\triangleright$  Sorting parent chromosomes based on y-coordinate
4:    $\text{cut\_point} \leftarrow \text{rand}(1, 15)$   $\triangleright$  Determining one random cut-point
5:    $y_{P_1[\text{cut\_point}]} < y_{P_2[\text{cut\_point}]}$   $\triangleright$  Defining the order of the cut-point y-coordinate
   between parents
6:    $\text{middle\_cell} \leftarrow \text{average}(P_1[\text{cut\_point}], P_2[\text{cut\_point}])$   $\triangleright$  Finding the middle
   cell
7:    $P'_1, P'_2 \leftarrow \text{transform}(P_1, P_2, \text{middle\_cell})$ 
8:    $\text{Offspring}_1 \leftarrow \text{insert}(P'_1[: \text{middle\_cell}], P'_2[\text{middle\_cell} :])$ 
9:    $\text{Offspring}_2 \leftarrow \text{insert}(P'_2[: \text{middle\_cell}], P'_1[\text{middle\_cell} :])$ 
10:  Check and repair both offspring chromosomes
11:  Outputs :  $\text{Offspring}_1, \text{Offspring}_2$  maximum two acceptable offspring chromo-
   somes

```

Algorithm 12 Pseudo-code Crossover-3 in Subsection[4.3.4]

```

1: procedure CROSSOVER-3( $\text{pop}_{\text{cross}}, F_{\text{cross}}$ )
2:    $P_1, P_2 \leftarrow \text{binary\_tournament\_selection}(\text{pop}_{\text{cross}}, F_{\text{cross}})$   $\triangleright$  Select two parent
   chromosomes
3:    $P_1, P_2 \leftarrow \text{sort\_x}(P_1, P_2)$   $\triangleright$  Sorting parent chromosomes based on x-coordinate
4:    $\text{cut\_point} \leftarrow \text{rand}(1, 15)$   $\triangleright$  Determining one random cut-point
5:    $x_{P_1[\text{cut\_point}]} < x_{P_2[\text{cut\_point}]}$   $\triangleright$  Defining the order of the cut-point x-coordinate
   between parents
6:    $\text{middle\_cell} \leftarrow \text{average}(P_1[\text{cut\_point}], P_2[\text{cut\_point}])$   $\triangleright$  Finding the middle
   cell
7:    $F1_{P_1}, F1_{P_2} \leftarrow F_{\text{cross}}(P_1, P_2)$   $\triangleright$  The first objective values of parents
8:    $\text{Proportion} \leftarrow (F1_{P_1} - F1_{P_2})/F1_{P_1}$ 
9:   if  $\text{proportion} = 0$  then
10:     $\text{mid\_cell}_1, \text{mid\_cell}_2 \leftarrow \text{middle\_cell}$ 
11:   if  $\text{proportion} < 0$  then  $\triangleright$  That means  $F1_{P_1} < F1_{P_2}$ 
12:     $\text{added\_value} \leftarrow ((\text{middle\_cell}/3) * \text{abs}(\text{proportion}))$   $\triangleright$  The movement
    value toward higher parent
13:     $\text{mid\_cell}_1 \leftarrow \text{middle\_cell}$   $\triangleright$  Fixed at the middle cell
14:     $\text{mid\_cell}_2 \leftarrow \text{transform}(\text{middle\_cell}, \text{added\_value})$   $\triangleright$  Get closer to the
    cutting cell of  $P_2$ 
15:   if  $\text{proportion} > 0$  then  $\triangleright$  That means  $F1_{P_1} > F1_{P_2}$ 
16:     $\text{added\_value} \leftarrow ((\text{middle\_cell}/3) * \text{abs}(\text{proportion}))$   $\triangleright$  The movement
    value toward higher parent
17:     $\text{mid\_cell}_1 \leftarrow \text{transform}(\text{middle\_cell}, \text{added\_value})$   $\triangleright$  Get closer to the
    cutting cell of  $P_1$ 
18:     $\text{mid\_cell}_2 \leftarrow \text{middle\_cell}$   $\triangleright$  Fixed at the middle cell
19:    $P'_1 \leftarrow \text{transform}(P_1, \text{mid\_cell}_1)$ 
20:    $P'_2 \leftarrow \text{transform}(P_2, \text{mid\_cell}_2)$ 
21:    $\text{Offspring}_1 \leftarrow \text{insert}(P'_1[: \text{mid\_cell}_1], P'_2[\text{mid\_cell}_2 :])$ 
22:    $\text{Offspring}_2 \leftarrow \text{insert}(P'_2[: \text{mid\_cell}_2], P'_1[\text{mid\_cell}_1 :])$ 
23:  Check and repair both offspring chromosomes
24:  Outputs :  $\text{Offspring}_1, \text{Offspring}_2$  maximum two acceptable offspring chromo-
   somes

```

Algorithm 13 Pseudo-code Crossover-4 in Subsection[4.3.4]

```

1: procedure CROSSOVER-4( $\text{pop}_{\text{cross}}, F_{\text{cross}}$ )
2:    $P_1, P_2 \leftarrow \text{binary\_tournament\_selection}(\text{pop}_{\text{cross}}, F_{\text{cross}})$   $\triangleright$  Select two parent
   chromosomes
3:    $P_1, P_2 \leftarrow \text{sort\_x}(P_1, P_2)$   $\triangleright$  Sorting parent chromosomes based on x-coordinate
4:    $\text{cut\_point} \leftarrow \text{rand}(1, 15)$   $\triangleright$  Determining one random cut-point
5:    $x_{P_1[\text{cut\_point}]}$  <  $x_{P_2[\text{cut\_point}]}$   $\triangleright$  Defining the order of the cut-point x-coordinate
   between parents
6:    $\text{middle\_cell} \leftarrow \text{average}(P_1[\text{cut\_point}], P_2[\text{cut\_point}])$   $\triangleright$  Finding the middle
   cell
7:    $F_{1P_1}, F_{1P_2} \leftarrow F_{\text{cross}}(P_1, P_2)$   $\triangleright$  The first objective values of parents
8:    $\text{Proportion} \leftarrow (F_{1P_1} - F_{1P_2})/F_{1P_1}$ 
9:   if  $\text{proportion} = 0$  then
10:     $\text{mid\_cell}_1, \text{mid\_cell}_2 \leftarrow \text{middle\_cell}$ 
11:   if  $\text{proportion} < 0$  then  $\triangleright$  That means  $F_{1P_1} < F_{1P_2}$ 
12:      $\text{added\_value} \leftarrow ((\text{middle\_cell}/3) * \text{abs}(\text{proportion}))$   $\triangleright$  The movement
     value toward higher parent
13:      $\text{mid\_cell}_1, \text{mid\_cell}_2 \leftarrow \text{transform}(\text{middle\_cell}, \text{added\_value})$   $\triangleright$  Get
     closer to the cutting cell of  $P_2$ 
14:   if  $\text{proportion} > 0$  then  $\triangleright$  That means  $F_{1P_1} > F_{1P_2}$ 
15:      $\text{added\_value} \leftarrow ((\text{middle\_cell}/3) * \text{abs}(\text{proportion}))$   $\triangleright$  The movement
     value toward higher parent
16:      $\text{mid\_cell}_1, \text{mid\_cell}_2 \leftarrow \text{transform}(\text{middle\_cell}, \text{added\_value})$   $\triangleright$  Get
     closer to the cutting cell of  $P_1$ 
17:    $P'_1 \leftarrow \text{transform}(P_1, \text{mid\_cell}_1)$ 
18:    $P'_2 \leftarrow \text{transform}(P_2, \text{mid\_cell}_2)$ 
19:    $\text{Offspring}_1 \leftarrow \text{insert}(P'_1[: \text{mid\_cell}_1], P'_2[\text{mid\_cell}_2 :])$ 
20:    $\text{Offspring}_2 \leftarrow \text{insert}(P'_2[: \text{mid\_cell}_2], P'_1[\text{mid\_cell}_1 :])$ 
21:   Check and repair both offspring chromosomes
22:   Outputs :  $\text{Offspring}_1, \text{Offspring}_2$  maximum two acceptable offspring chromo-
   somes

```

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Titre : Gestion du zonage dans l'aménagement de l'espace marin : Optimisation multi-objectifs et résolution de conflits basée sur des agents

Mots clés : Système Multi-Agents Multi-Objectifs, Gestion du Zonage, Algorithmes Basés sur l'évolution, Planification de l'espace Marin, Résolution des Conflits, Système d'aide à la Décision.

Résumé : Le défi de cette thèse est de développer un système d'aide à la décision spatiale pour localiser et allouer des zones d'espace marin à de multiples acteurs, malgré des objectifs et des contraintes initiaux potentiellement conflictuels.

Pour répondre à cette question, dans cette thèse, nous nous concentrons sur trois exigences différentes comme suit : 1) Modéliser le problème dans un cadre Système d'Information Géographique réaliste et formuler un modèle mathématique pour le résoudre, 2) Être capable de proposer des solutions pour des problèmes à grande échelle, 3) Développer un processus de prise de décision qui aide les multiples acteurs à résoudre les conflits possibles en parvenant à un compromis.

En fonction de ces objectifs, cette thèse propose un Système Multi-Objectifs Multi-Agents qui simule les processus décisionnels multi-niveaux de la gestion

du zonage spatial des usages marins avec trois contributions principales : 1) Programmation Linéaire Multi-Objectifs Entiers, 2) Algorithmes Évolutionnaires Multi-Objectifs, 3) Processus de décision coopératif avec des Systèmes Multi-Agents et des méthodes heuristiques.

Cette thèse propose une approche formelle et exécutable pour traiter le problème de gestion du zonage de l'espace avec des objectifs et des acteurs multiples. En cas de conflit, différents scénarios de coopération sont comparés et classés. Les résultats expérimentaux sur des jeux de données synthétiques mettent en évidence le fait que de bons compromis peuvent être atteints lorsque les acteurs acceptent de coopérer. Les travaux proposés ouvrent la voie à de futurs outils d'aide à la décision en ligne appliqués à des cas réels.

Title : Zoning Management in Marine Spatial Planning: Multi-Objective Optimization and Agent-Based Conflict Resolution

Keywords : Multi-Objective Multi-Agent System, Zoning Management, Evolutionary-Based Algorithms, Marine Spatial Planning, Conflict Resolution, Decision-Aiding System

Abstract : The challenging issue of this thesis is to develop a spatial decision support system for locating and allocating areas of marine space to multiple actors, despite potentially conflicting initial objectives and constraints.

To address this issue, in this thesis, we focus on three different requirements as follows: 1) Modeling the problem in a realistic Geographic Information System (GIS) framework and formulating a mathematical model to solve it, 2) Being able to propose solutions for large-scale problems, 3) Developing a decision-making process that helps multiple actors to resolve possible conflicts by reaching a trade-off.

According to these objectives, this thesis proposes a Multi-Objective Multi-Agent System (MOMAS) that simulates the multi-level decision-making processes

of marine use spatial zoning management with three main contributions: 1) Multi-Objective Integer Linear Programming (MOILP), 2) Multi-Objective Evolutionary Algorithms (MOEAs), 3) Cooperative decision-making process with Multi-Agent Systems (MAS) and heuristics methods.

This thesis proposes a formal and executable approach to address the spatial zoning management problem with both multiple objectives and actors. In the case of conflict, different cooperation scenarios are compared and ranked. The experimental results on synthetic datasets highlight the fact that good tradeoffs can be reached when the actors agree to cooperate. The proposed work paves the way for future online decision support tools applied to real-world cases.