A Genetic Algorithm for Marine Spatial Planning with Minimized Conflict Between Planned Regions

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Abstract: To efficiently utilize marine space, numerous experiments have been conducted to optimize marine space. We utilize a genetic algorithm (GA) to develop an optimal spatial plan for the Exclusive Economic Zone (EEZ). The space can be allocated for six different uses, each with its own weight. Conflicts exist among these uses. The objective is to maximize the fitness of the space by evaluating it at the cell level. This involves maximizing the evaluation score, which is determined by the weighted sum of each cell's use, minimizing conflicts, and reducing the number of clusters to ensure continuity of use. The basic allocation model, which achieves the best quality among random solutions within the same running time as our GA, is used for comparison. Experimental results showed that, when our method is compared to the basic model, the evaluation scores increased by approximately 20%, except for one case of use 'ecology'. Additionally, conflicts between zones decreased, and the total fitness improved as the number of clusters decreased.

1 INTRODUCTION

As the population grows and the demand for resources increases, it is important to allocate resources efficiently to meet these demands. In particular, the Food and Agriculture Organization of the United Nations (FAO) predicts that the world's population will reach 9 billion by 2050 (Liu., 2020).

If resources are not efficiently allocated, serious environmental pollution problems and social conflicts may result. The ocean is a repository of food and resources. The ocean covers 70% of the Earth's surface and is home to seven times more marine organisms than land organisms. Therefore, interest in marine spatial planning (MSP) is increasing every year in each country.

MSP is a process and approach used to manage and organize human activities in marine and coastal areas. It involves the systematic and integrated planning of various uses and activities, such as fisheries, tourism, energy development, conservation, and shipping, within the marine environment. The goal of MSP is to achieve sustainable and efficient use of marine resources while minimizing conflicts and negative impacts on the marine ecosystem.

Europe is playing a leading role in the MSP field. In the UK, the Marine and Coastal Access Act 2009 provides the legal basis for MSP. The Act was adopted in 2009 and provides a comprehensive marine planning framework for the protection, management and use of the UK's coastal and marine areas. The law emphasizes the sustainable management and conservation of marine resources and cooperation and coordination among various stakeholders. In addition, in 2014, the EU adopted the Legislation to create a common framework for MSP in Europe. In Asia, the Republic of Korea enacted the Marine Spatial Planning Act in 2018 to establish an MSP process and regulate the utilization of specific marine management areas. Other countries in Asia, such as Thailand, Malaysia, and Indonesia, are also conducting research and development on MSP.

When searching related papers, based on Google Scholar site for the last 5 years, there were 2,110 papers related to MSP modelling. On the other hand, papers related to MSP optimization technology were

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Table 1: Region rate of each use.

	Fishery	Energy	Resource	Marine tour	Harbor	Ecology
Lower Bound	5%	5%	5%	5%	5%	5%
Upper Bound	20%	15%	10%	30%	30%	10%

Table 2: Weights of each use and constraints.

	$w_{conflict}$	$w_{cluster}$	$w_{fishery}$	w_{energy}	$w_{resource}$	$w_{marine\ tour}$	w_{harbor}	$w_{ecology}$
Weight	0.01	10.00	0.30	0.10	0.10	0.10	0.30	0.10

weak with 1,370 papers, and among them, papers using genetic algorithm (GA) accounted for only 2% with 32 papers. Prediction and prevention through simulation and modelling are important, bur further - optimization is required to establish direct policies. Especially, GA excels in global exploration and can be applied to various optimization problems. GAs can be applied to a wide range of problem domains and do not require prior knowledge about the problem structure. They are versatile and adaptable to various types of optimization problems, including continuous, discrete, and combinatorial optimization. Also, GAs have the ability to search the entire solution space, making them suitable for global optimization problems where finding the best possible solution is the objective. They can overcome local optima and escape from stagnant regions in the search space. In addition, since multi-purpose optimization is possible, it is powerful for resource allocation problems that must satisfy various interests.

We try to make the optimal MSP with multiple objectives using a novel GA. In this paper, unlike the existing method, it is unique in that the map is encoded in two dimensions and using block uniform crossover applied to MSP. In addition, by mapping the map for each use, multi-objective optimization considering various uses is possible.

The structure of this paper is as follows: Section 2 introduces related work. Section 3 explains our GA used in MSP. Section 4 analyses the experimental results. And Section 5 concludes.

2 RELATED WORK

Numerous MSP studies have been conducted to efficiently utilize marine space. In (Basirati et al., 2021), the authors proposed a model that can achieve multiple objectives simultaneously through multi-objective integer linear optimization. The authors in (Wang et al., 2022), the authors emphasized the importance of MSP planning based on the collection and analysis of data related to the status of marine aquaculture in Shandong Province. By collecting and analysing data on the location, scale, and types of aquacultures, the study provides insights into the current situation and spatial distribution of marine aquaculture in the region. In (Boussarie et al., 2023), the authors presented a framework for prioritizing offshore wind farms and marine protected areas. In (Janßen et al., 2019), the study discusses the advantages and limitations of MARXAN. MARXAN is a software, which is discrete optimization model. In (Fotakis et al., 2012), the authors presented a study that utilizes a spatial GA to solve the multi-objective optimization problem in forest planning. The algorithm is applied to address the challenges of considering multiple objectives for forest management and conservation. The spatial GA arranges the genetic information of individuals in a spatial manner to explore optimal solutions for the multi-objective goals at hand. In (O'Reilly et al., 2012), the paper focuses on the utilization of a GA to determine optimal locations for offshore wind farm siting. The GA serves as an optimization technique for identifying the best positions to place wind turbines in offshore areas. The study takes into account various factors, including wind resources, water depth, distance from the shore, and environmental constraints. By employing the GA, the researchers aim to maximize energy production while minimizing the environmental impact and other constraints associated with offshore wind farm siting. In (Lubida et al., 2019), the authors focused on land-use planning for achieving sustainable urban development in Africa through a spatial and multi-objective optimization approach. The study proposes a method to plan and optimize land use considering various sustainability-related objectives. It aims to find efficient solutions that take into account economic, environmental, and social factors in urban development. The research contributes to providing sustainable directions for urban development in the African context. The authors in (Gissi et al., 2019), the authors discuss the current state of marine spatial planning.

3 PROPOSED GENETIC ALGORITHM

3.1 Algorithm Design

To evaluate the performance of the spatial planning optimization using GA, I will designate the solution derived from this method as "GA." The population size is 200, and there are 5,000 generations. A steady-state GA is used where one solution replaces another in each generation. The mutation rate is 0.015. The crossover operation applies block uniform crossover, which is an extension of one-point crossover in a 2-dimensional space. The block uniform crossover method is described in Section 3.2. The replacement is performed only when the child has a better fitness than its parent. Figure 1 illustrates the process of a GA.

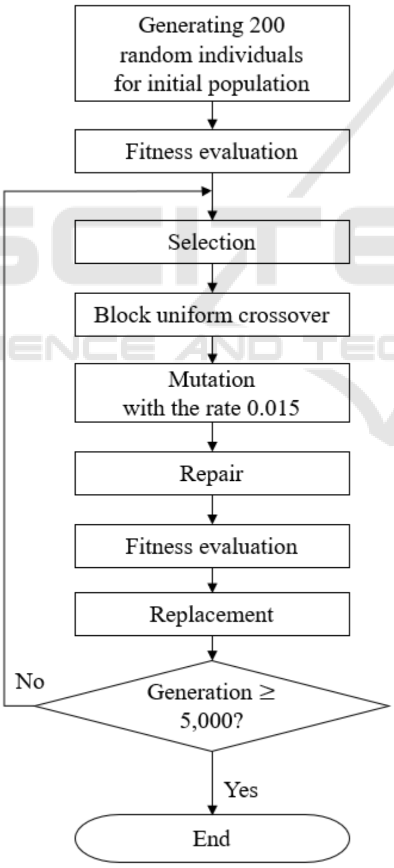


Figure 1: Flowchart of the proposed GA.

3.1.1 Block Uniform Crossover

The order of block uniform crossover is as follows: First, a cutting line is randomly selected from the row of the generated array(solution). Second, pick one cutting line from the column. The location of the cutting line is arbitrarily determined whenever an intersection operation is performed. Third, child solutions are generated by performing copying from the parent solutions alternately for the four regions thus created (Anderson et al., 1991). Block uniform crossover is widely used in two-dimensional problems (Im, C. H et al.,2003, Paik, K., 2011). Please refer to the appendix for detailed explanations.

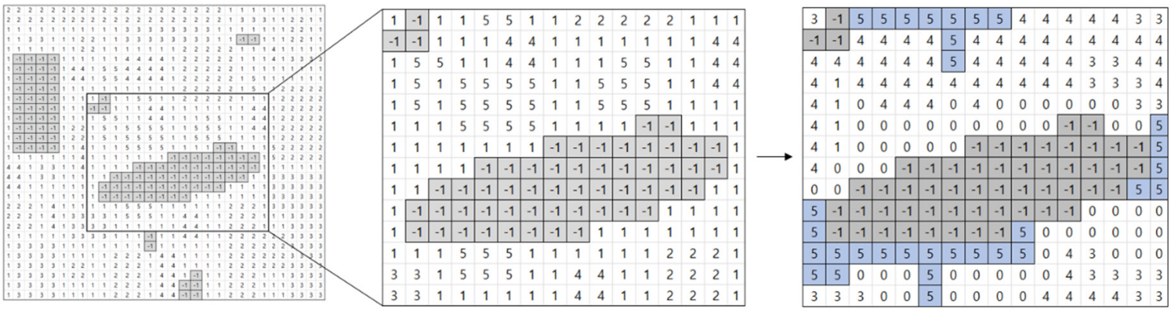
3.2 Experimental Design

In this experiment, the uses of marine space are divided into six categories: fishery, energy, resource, marine tour, harbour, and ecology. Each use has minimum and maximum area ratios defined in Table 1. If these ratios are violated, repair operations are conducted to adjust the area occupied within the appropriate ratio. And each use is assigned a number from 0 to 5. And we will call it as use number. The weights for each use are determined based on expert opinion, and that are presented in Table 2.

A domain map indicates feasible and infeasible regions. A constraint matrix representing the degree of conflict between different area use. Each use has a use map. And in the use map, each cell is assigned an evaluation number from 1 to 5. Note that it is different from use number. The higher evaluation number, the more appropriate the area for the use. For example, if a cell is assigned a value of 5 on the ecology map, that cell is an area very suitable for ecology. In Figure 2(a), ecology's use map is represented.

To calculate fitness, first, the domain map is checked to determine if the cell is available for use. Unavailable cells are indicated as -1 in the domain map. If a cell is available, use number is assigned to the cell. It is a generated solution. For each use, a solution, add up the evaluation number specified in the use map. It becomes the evaluation score for that each use. For example, if there are 3 cells assigned ecology, use number 5, to the solution, and the evaluation number at the ecology use map for each cell is 1, 5, 3 the ecology evaluation score is 9. Total evaluation value is obtained by summing the product of the evaluation score and the weight.

The conflict number is assigned to 6 by 6 matrix. Conflict score is obtained by add up conflict numbers when other uses are adjacent. Conflict value is obtained by multiplying the conflict score by the conflict weight.



(a) An example use map, ecology

(b) A plot that magnifies a section of the ecology use map

(c) A result map of our final solution highlights the ecology regions in blue

Figure 2: An example map of ecology.

Table 3: Experimental results

		Fitness	Conflict	#Clusters	Fishery	Energy	Resource	Marine Tour	Harbour	Ecology
R(200)	Best	−3852.84	2443.46	411.00	305.00	223.00	124.00	443.00	457.00	172.00
	Ave	−4009.83	2498.22	427.00	276.30	184.13	104.00	358.63	405.73	155.37
	SD	62.08	38.41	6.26	18.09	22.45	10.96	26.64	30.18	7.47
R(5200)	Best	−3579.91	2383.62	386.00	314.00	227.00	138.00	432.00	472.00	176.00
	Ave	−3848.54	2453.16	411.13	279.40	176.57	99.73	367.47	410.57	159.63
	SD	65.41	34.07	6.47	26.69	19.23	15.00	30.57	28.14	7.01
GA	Best	202.93	927.92	17.00	469.00	266.00	143.00	568.00	610.00	178.00
	Ave	152.71	1057.67	22.37	417.43	199.87	102.10	492.83	565.00	127.40
	SD	22.37	63.28	2.27	25.14	29.83	19.52	32.95	27.69	25.93

*Best : the highest value obtained among the 30 experiments.
*Ave : the average value obtained among the 30 experiments.
*SD : the standard deviation of the values from the 30 experiments.
*R(200) : the quality of the best among initial population of the GA.
*R(5200) : the best quality of random solutions achieved in the same time as in our GA.

The total cluster value is determined by multiplying the number of clusters formed by the allocated regions with the cluster weight. Regions of the same area use are not considered as a single cluster if they are not contiguous.

Finally, the fitness is calculated by subtracting the conflict value and the cluster value from the evaluation value. Figure 2(c) displays a fitness map that highlights the areas in blue where ecology is allocated. Equations (1) – (4) summarizes this process.

$U = \{fishery, energy, resource, marine\ tour, horbour, ecology\}$

$$V_e = \sum_{i \in U} w_i \times S_i \tag{1}$$

$$V_{conflict} = w_{conflict} \times S_{conflict} \tag{2}$$

$$V_{cluster} = w_{clusters} \times \#clusters \tag{3}$$

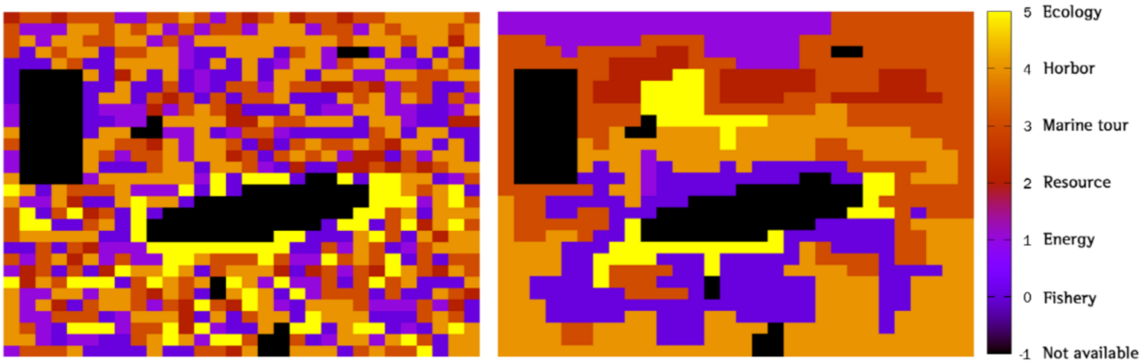
$$fitness = V_e - V_{conflict} - V_{cluster} \tag{4}$$

where V_e is evaluation value, S_i is evaluation score for use $i \in U$, $V_{conflict}$ is conflict value, $S_{conflict}$ is conflict score, and $V_{cluster}$ is cluster value.

4 EXPERIMENTAL RESULTS

All the experiments are conducted using a computer with processor AMD Ryzen Threadripper 2990WX 32-Core @ 1.75GHz with 64 GB of RAM. And OS is Ubuntu 18.04.6 LTS. C++ is used to implement the source code.

To make a comparison, the best solution obtained from the pool of 5,200 solutions, each of which entails randomly assigning zones. It will be denoted as "R(5200)". To demonstrate that the solution derived from the 5,200 solutions outperforms a smaller subset, I will label the best solution from the initial 200 random solutions as "R(200)". This comparison



(a) R(5200) (b) Our genetic algorithm

Figure 3: Result maps.

will showcase the superiority of the obtained solution from the larger set. The experiment was performed 30 times for each case. It took 516.32 seconds to complete the optimization process for 5000 generations. It depends on the number of generations. The optimization process took place in Jeju Island, located in South Korea. The unit of measurement used in the experiment corresponds to cells, with each cell representing $3' \times 3'$ as latitude $\times$longitude, where 60' means 1 degree.

Comparing the results of the GA and R(5200) in Table 3's average, it can be observed that the GA achieved a reduction of approximately 57% in conflict compared to Random. The evaluation scores for most area use showed an increase. On the other hand, despite the decrease in the evaluation score for ecology, these exceptions can be seen as positive factors for maintaining a balanced overall performance. This is because the conflict value decreased, and the overall fitness increased. Additionally, Figure 3(a) demonstrates a significantly larger number of clusters compared to Figure 3(b), indicating that optimization has not been achieved. According to Table 3, the number of clusters exhibited a reduction rate of approximately 95% upon completion of the optimization. The fitness of the Random solution appears as negative, which is a result of being penalized for a higher number of clusters and conflict levels. In conclusion, based on Figure 4, it is evident that the fitness of the "GA" results obtained through GA is significantly higher, indicating that the optimization of zone allocation through GA can be effectively utilized in MSP process.

5 CONCLUSIONS

This study successfully optimized MSP with multiple objectives using GA. The objective of optimization is to maximize the overall fitness value. The experiments showed higher fitness values compared to random allocation of area use. By successfully applying GA to MSP, it has become possible to achieve optimal and automated planning that takes into account various constraints. In this paper, the weights of each area use were determined based on expert opinions, but it is also possible to optimize by considering the weights based on the expertise. In the future, we plan to observe trade-off graphs between different area use. Given the potential for environmental changes and social policy modifications, spatial re-planning may be necessary. Therefore, collaboration with monitoring technologies that can incorporate such factors will be crucial.

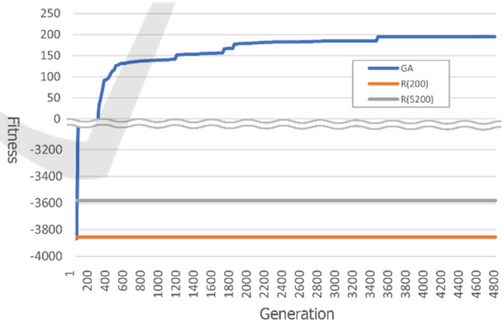


Figure 4: Fitness plot of our GA.

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APPENDIX

Comparing Methods with Respect to Each Score and the Number of Clusters that Constitutes Fitness

The graph presented in Figure 5(a) showcases the comparison of experimental results, highlighting the superiority of our GA. It focuses on two key parameters: the conflict score and the number of clusters. In this graph, lower values are considered better, indicating improved performance.

Figure 5(b) displays the performance scores of each use case. Higher values in this graph indicate better overall performance.

Together, these two figures provide a comprehensive visual representation of how our GA outperforms other approaches in terms of conflict resolution, cluster numbers, and overall evaluation scores.

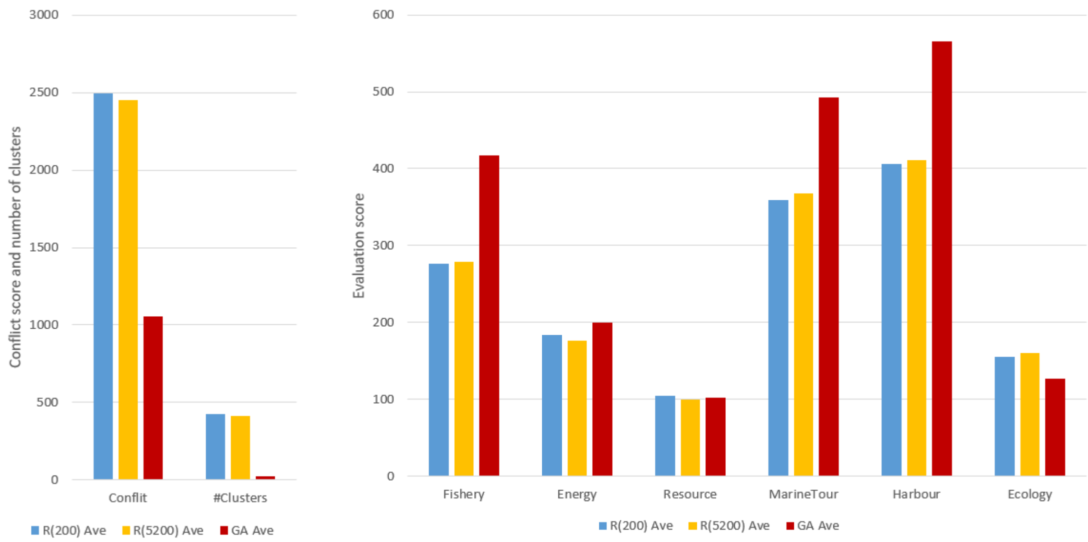
Block Uniform Crossover in Our Genetic Algorithm

Figure 6 depicts the concept of block uniform crossover, which serves as an extension of one-point crossover into two dimensions. This technique involves the following steps:

1. Random Selection: A row cutting line and a column cutting line are randomly selected within the solution space.
2. Division of Solution Space: The selected cutting lines divide the solution space into four distinct regions.
3. Offspring Generation: The offspring is generated by performing alternating parent copy operations within each of the four regions. This means that for each region, the genetic material from one parent is copied into the offspring, while the other parent's genetic material is copied into the next region, and so on.

The benefits of block uniform crossover are twofold. First, it allows for the exploration of a broader solution space by creating diverse combinations of genetic material from the parents. This increases the chances of discovering novel and potentially superior solutions. Second, by incorporating genetic material from both parents, block uniform crossover helps to preserve and combine beneficial traits, potentially leading to offspring with enhanced performance.

Overall, block uniform crossover serves as a valuable tool within the GA framework, particularly in two-dimensional problem domains.



(a) Conflict scores and the numbers of clusters (the lower, the better)

(b) Evaluation scores of uses (the higher, the better)

Figure 5: Visual comparison of our experiments (values from Table 3).

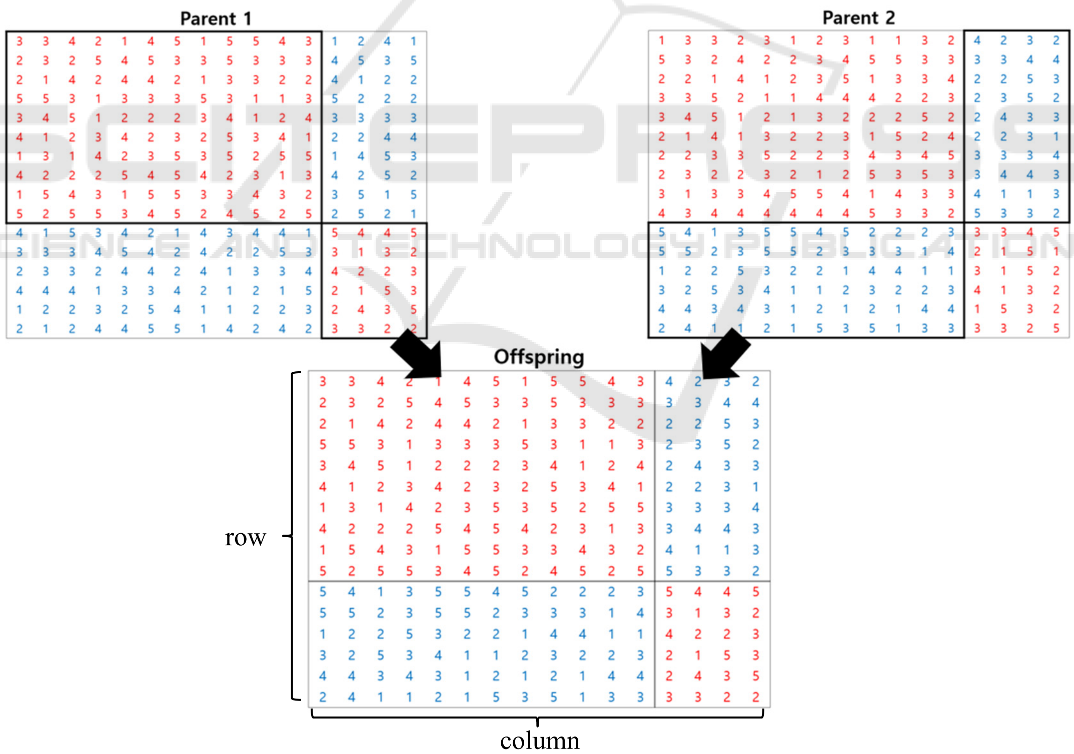


Figure 6: Example of the block uniform crossover with one cutting line on each dimension.