Comparative Analysis of Rank and Roulette Wheel Selection Strategies in Genetic Algorithms for Spatial Layout Optimization

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***Abstract*—Autonomous urban planning, facility layout design, and interior design are critical and meticulous tasks that require the optimization of space arrangement. One of the main purposes of space arrangement is to achieve high space utilization with a non-complex arrangement for emergency assistance, particularly to enhance pedestrian safety in panic situations. This study explores the optimization of spatial layouts by employing Genetic Algorithms (GA) due to their robust search capabilities. However, spatial layout size limitations may affect the search capability and significantly impact space arrangement and utilization. Hence, this study presents a comparative study of two GA selection operator methods: Rank Selection (RS) and Roulette Wheel Selection (RWS) for determining the effectiveness in optimizing spatial layout arrangements and space utilization. The results demonstrated significant improvements in crowd flow management, with the RWS method showing the highest fitness value despite slower convergence compared to RS. The study highlighted the impact of different methods on the convergence of the multi-objective fitness value based on space elements such as overlapping and standard walkway distances. While both selection methods proved to be effective in optimizing space utilization, the RWS method demonstrated greater computational efficiency while still adhering to standard layout designs. This efficiency helps to ensure smoother evacuation and ease of movement during emergency situations.**

Keywords*—Genetic algorithm; optimization; spatial layout arrangement; space utilization; urban planning; facility layout design; rank selection; roulette wheel selection

I. Introduction

Pedestrian safety is a critical aspect of urban planning, especially in emergency scenarios. A surging pattern of fatalities due to entrapment incidents in recent years has led to the increased demand for safer building designs and effective emergency protocols. In response, numerous studies have been carried out to uncover the impactful spatial features that significantly influence the pedestrians' movement during the evacuation process. The previous studies have proposed an enhanced spatial layout design that aimed at reducing casualties and improving overall safety [1-6].

Spatial layout arrangement involves the organization and positioning of elements within a given space, serving as a crucial aspect of spatial layout design. This design practice is essential in the planning and construction phases of housing development, ensuring efficient use of space and optimal functionality. The design will outline the blueprint of the layout by assisting in the arrangement of the assigned elements for reaching the suitable order, sorting, grouping, alignment, function, and scale to the layout size. In later times, the spatial layout was designed by employing the manual design method and focusing on the standard design procedure and being influenced by the local demographic structure's culture and current trend [7][8]. However, with the advancement of computer intelligence systems, spatial layout design application tools have been introduced for autonomous spatial layout design [9-11].

The demand for autonomous space arrangements has surged significantly, driven by the need for multi-objective functions in design. However, due to some limitations on the complex computation of the various parameters, the autonomous spatial layout arrangement generated a non-fitness design and constructed a less scalable and less functional floor plan [12]. Traditional autonomous layout designs often fall short in managing crowd movements during panic situations. Ineffective layouts have resulted in numerous entrapment incidents during emergencies [13]. Research by [13] has highlighted the significant impact of optimizing interior resources' allocation and occupancy within the layout. Hence, arrangement and allocation optimality are the new approaches to ensure the traffic flow and the safety of the pedestrians in the layout. This approach can improve the overall quality of life and the environment rather than focusing solely on the layout structure, and functionality.

However, previous research has shown that optimizing layout utilization can lead to several issues, including overlapping objects, low space occupancy, and non-standard layout design [14-23]. Hence, it is necessary for the computer-aided layout design to exploit a suitable optimization method for constructing the high occupancy elements' layout while adapting the architecture building design policy in constructing the space arrangement. This study addresses this gap by proposing an optimized spatial layout that leverages advanced algorithms to enhance safety and efficiency.

The study begins by introducing the optimization method, Genetic Algorithm (GA) as a suitable approach for computing multi-objective functions, and followed by a methodology section, discussing the GA framework, the selection process, and the rank selection techniques adopted in this study. Next, the results section presents the findings, and the conclusion summarizes the key outcomes and suggests directions for future research.

II. Genetic Algorithm

In [24], the authors show that the optimization with multi-objective functions can be inspired by the principles and inspiration of biological evolution. Numerous studies have been proposed in layout design optimization using bio-inspired algorithms for applications such as optimal job scheduling, structural design, cost minimization, flow control, and space occupancy. For example, research by [25] explored the use of Genetic Algorithm (GA), Differential Evolution (DE), Artificial Bee Colony (ABC), Charge Search System (CSS), and Particle Swarm Optimization (PSO) algorithms to optimize robot workcell layout in manufacturing systems, focusing on optimizing layout area and robot operation time. Meanwhile, research by [26] proposed optimal design solutions for planar trusses in structural roof articulations using Elitism-Based Genetic Algorithm (EBGA), Ant Colony Optimization (ACO), Artificial Honey Bee Optimization (AHBO), and PSO, with an emphasis on minimizing truss weight. Research by [27] explored the optimization of construction layout arrangements to reduce transportation costs, comparing the performance of PSO, ABC, and Symbiotic Organisms Search (SOS) algorithms. Additionally, research by [28] applied a GA to garden landscape design, aiming to adhere to the fundamental principles of landscape and urban design while meeting people's needs, showing improvements over traditional methods. Research by [13] utilized GA for resource allocation to enhance spatial layout design, and research by [29] employed GA to optimize land use for sustainable land resource management. These studies highlight that only a small number of works focus on indoor design and spatial element arrangement, despite the growing use of bio-inspired algorithms in layout optimization. Building on this foundation, the focus of this study is to evaluate and compare the effectiveness of GA, PSO, ACO, and ABC specifically for optimizing spatial layout arrangements in the context of urban planning and design.

One of the suitable bio-inspired algorithms is Genetic Algorithm (GA). GA is the adaptation of the natural evolution process inspired by Charles Darwin's theory of genetic evolution for the survival of the fittest genes. Genetic evolution is based on the genetic structure, and the natural selection operation carried out for the genes' transformation and modification for the next generation [30] [31]. The principles of Darwinian natural selection are based on heredity, variation, and selection. In selecting a GA for optimizing spatial layout arrangements, its flexibility and adaptability make it a compelling choice. GA is particularly effective for complex problems with large solution spaces. The ability to perform global searches and avoid local optima makes GA well-suited for layout optimization, where multiple variables and constraints must be balanced. Additionally, GA can be easily modified and combined with other techniques to enhance its performance and tailor it to specific problem domains, such as spatial layout optimization. This adaptability, combined with their proven success in various domains, makes GA a suitable and powerful method for optimizing spatial layout arrangements, ensuring efficient use of space while meeting design criteria.

GA has three operators: 1) Selection, 2) Crossover, and 3) Mutation. These operators will converge the genes to find the best fitness function to generate the fittest final offspring. The GA process will begin with the initialization of the random production of N number of chromosomes, with each chromosome containing an array of gene bits. The objective function will be assigned for determining the fitness values of the chromosomes. There are many types of selection schemes that can be used for discriminating the fittest values and the lowest values of the spatial layout design solutions; 1) Rank Selection (RS), 2) Roulette Wheel Selection (RWS), 3) Tournament Selection (TS), 4) Stochastic Universal Sampling (SUS), and many more.

The RWS is the proportionate fitness selection that represents the circular wheel that is divided based on the probability of the fitness value from the whole values and represented in the circle's degree value (the ratio of individual fitness value and the total fitness of overall individuals in the population). The fittest individual will have a bigger degree region in the circle and have a greater chance of being selected during the spinning process. Hence, the probability of being the fittest individual is high. A fixed point will be generated randomly to represent the real roulette wheel spinning. The fitness values selected by the fixed point will be selected as the parents. The RWS is also implemented in SUS. However, in SUS selection, there are multiple fixed points marked as the random stochastic selection, and the parents can be obtained in a single spin. This setup will be able to encourage the highly fit parents to be selected at once.

RS ranks individuals based on fitness values and applies a roulette-wheel-like method for parent selection, where each individual has an equal share (same probability) of being selected as the parents. The selection sometimes will make poor selections of parents who have a possibility of selecting the least fit solutions for reconstructing the fitter individuals. TS is the selection strategy that selects the k-number of solutions from the whole available solutions and comparing the fitness values among them. The fittest candidates among the k-individuals will be passed on to the next-gen. The probability of the selection is based on the candidate's likelihood in the tournament group. The tournament size will be able to affect the selection process as the less fit solution will have a low possibility of being selected in the large tournament group as it must compete with the stronger candidate with a high fitness solution. Based on the type of selection schemes, RS and RWS have been selected to be compared as one of the selected selection methods in comparing the spatial layout designs to find the higher fitness parents for the recombination and diversification of the offspring. This selection scheme has been selected due to its ability to contribute to the high convergence rate, as the fittest parents are able to construct better offspring with fitter fitness values.

TS and SUS selection methods are also able to give a high possibility of convergence rate. However, the random selection for the first step of the methods will contribute towards the divergence of the parents and will have a high possibility of not being able to construct the offspring that have the best inheritance from the parents. Whereas both RS and RWS are able to create a great balance between convergency and divergence of the offspring construction as there will be a high possibility of the selection approach to select the fittest parents, and there are also chances of selecting less fit parents but with low possibility. Therefore, this research focuses on utilizing RS and RWS for the parent selection phase in GA.

In light of the research problem, the goal is to transform spatial layouts into safer, more navigable spaces during emergencies. In contrast to existing studies that focus solely on layout efficiency or cost-based metrics, this study offers a novel comparative analysis of GA selection strategies using RS and RWS for managing the integration of multi-objective functions that include crowd flow safety and layout efficiency. The aim is to achieve autonomous high occupancy space arrangements that comply with spatial design standards and improve pedestrian movement flow, particularly during evacuation processes.

III. METHODOLOGY

Genetic Algorithms (GA) are powerful optimization tools inspired by the process of natural selection. In the context of constructing a spatial layout, GA facilitates the generation of optimized solutions through iterative processes. This research study focuses on comparing two selection methods; Roulette Wheel Selection (RWS) and Rank Selection (RS). Both methods are evaluated using a consistent approach involving uniform crossover and bit flip mutation to ensure a fair comparison.

A. *Genetic Algorithm (GA) Framework*

The three fundamental phases need to be highlighted for constructing a spatial layout based on GA's design; 1) the selection phase, 2) the crossover phase, and 3) the mutation phase. Fig. 1 shows the fundamentals of genetic evolution processing for optimizing genetic fitness.

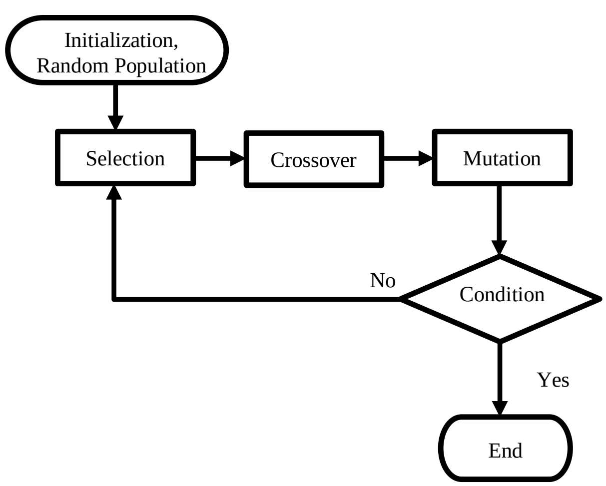


Fig. 1. Fundamental genetic evolution process

The optimized spatial layout arrangement is constructed based on the adaptation of the binary GA as shown in Fig. 2.

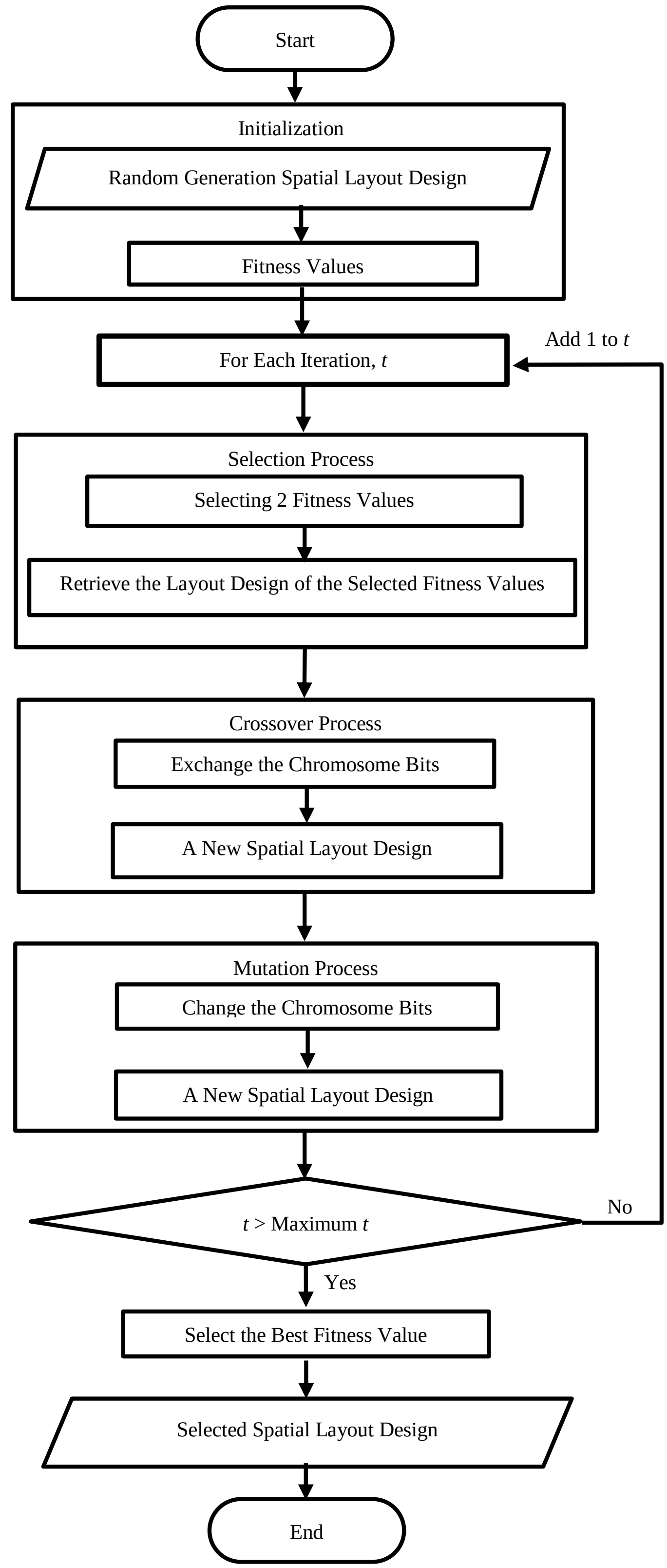


Fig. 2. Adaptation framework on GA in constructing an optimal spatial layout.

Pseudocode 1 GA Based Spatial Layout Construction Optimization

```
Load training samples
begin
Step 1:
    Generate the initial layout population zi, i = 1 ... SN
    Evaluate the fitness (fi) of the population
    Initialize iteration cycle = 1 ... SN
Step 2:
    set cycle to 1
    repeat
        //Selection Phase
        Apply greedy selection for fi of i, i(h1) and i(h2)
        //Crossover Phase
        Exchange the chromosome genes of i(h1) and i(h2)
        //Mutation Phase
        Change the chromosome genes of i(h1) and i(h2)
        Calculate the offspring's fitness fi, h1(fi) and h2(fi)
        Search for least fit individuals, i(g1) and i(g2)
        //New generations
        Replace spatial layout g1 and g2 with h1 and h2
        cycle = cycle + 1
    until cycle = SN
Step 3:
    Memorize the best solutions zi
    Output the best spatial layout found
end
```

Based on the framework in Fig. 2, Pseudocode 1 is developed to show the fundamentals for spatial layout design optimization based on GA, adapted from the algorithms overview by McCall [32]. Based on Pseudocode 1, the GA parameters must be initialized by setting the population size, *SN* to 50. Each individual in the population, z_i is generated with a unique spatial layout design, which includes 300 obstacles. The six obstacles are combined into one large obstacle representing the furniture. Each of the population fitness values f_i will be calculated based on the objective function: 1) overlapping of the elements generated as static obstacles, and 2) distance 1.2 m from doors and walls to meet the standard of interior design.

The number of furniture elements left in the layout after the overlapping process and exist within the layout that has a 1.2 m distance range from doors and walls has been calculated as the total fitness value of the layout. The iteration cycle has been initialized, and in this research, the iteration is set to 100. When entering the iteration cycle, the process will be entering into three phases: 1) selection phase, 2) crossover phase, and 3) mutation phase. A solution acceptance rule is implemented to ensure that the elements do not exceed the allocated space within the layout. Based on this rule, the number of furniture elements must not exceed the initial 300 loaded obstacles, even after 100 iteration cycles. This constraint ensures that the layout remains within the grid limits and complies with interior design standards, particularly by preserving sufficient walking space for pedestrians to access exit points.

B. Selection Process

The selection process in GA determines which individuals from the current population will be the parents to the next generation. This process mimics natural selection in choosing the fittest individuals based on performance or fitness scores. The primary goal is to ensure that high-quality traits are preserved and propagated, thereby improving the overall solution quality over successive generations. Every method available for selection operation has a unique approach to balancing exploration and exploitation within the search space.

1) Roulette Wheel Selection (RWS). The RS method is implemented to find the parents for the further recombination and restoration process of the offspring. This discrimination phase offers selective pressure that applies greedy selection based on the fitness proportionate selection approach as a method in guiding the evolution of spatial layout design. The fitness value fi has been determined from each of the solutions z_i of population i. The roulette slot size probability will be computed based on Eq. (1):

$$p_i = \frac{f_i}{\sum_{i=1}^{SN} f_i} \tag{1}$$

where, the p_i is the probability of each of the fitness values fi from the whole fitness values in the population *i* and *SN* is the maximum number of populations, *i*. The cumulative probability, q_i, for each chromosome is calculated based on Eq. (2):

$$q_i = \sum_{i=1}^{SN} p_i \tag{2}$$

here, p_i is the probability of each of the fitness values, and the cumulative probability has been calculated for each of the population *i* until reaching the maximum number of the population, *SN*. The fixed point of the roulette wheel can be constructed based on the random number generation *r*, where $r \in (0, 1)$. The parents are selected based on the condition; if $r < q_1$, then the first solution, z_1 is chosen as the parent. Otherwise, if $r > q_1$, the algorithm searches for another solution z_i such that $q_{i-1} < r \leq q_i$ and selects it as the parent. The steps have been repeated for two times for each iteration cycle to find the two parents' spatial layout to be recombined and explored for the fittest offspring.

2) Rank Selection (RS). RS method is implemented to identify parents for further recombination and restoration processes in generating offspring. Unlike the RWS method, which relies on fitness proportionate selection, RS imposes selective pressure by ranking individuals based on their fitness and then selecting parents according to their rank, rather than their absolute fitness values. This approach ensures that even individuals with lower fitness have a chance of being selected, thus maintaining diversity within the population.

In RS, each individual solution z_i in the population is assigned a rank r_i, with the fittest individual receiving the highest rank. The selection probability for each individual is then determined based on its rank, not its fitness value. The probability of selecting an individual is calculated using a rank-based probability distribution, where higher-ranked individuals have a greater chance of being selected as parents. This can be represented by Eq. (3):

$$p_i = \frac{2x(SN - r_i + 1)}{SN \times (SN+1)} \quad (3)$$

where, p_i is the probability of selecting the individual with rank r_i, and SN is the maximum number of individuals in the population. This rank-based probability distribution ensures a more uniform selection pressure compared to fitness-proportionate methods to avoid cases where a single individual with a much higher fitness dominates the selection process. The cumulative probability q_i for each individual is calculated based on Eq. (2), as the formula is similar. However, compared to RWS, the p_i is the probability of each of the ranks, and the cumulative probability has been calculated for each of the populations i until reaching the maximum number of the population, SN.

Similar to RWS, the fixed point of the roulette wheel can be constructed based on the random number generation r, where $r \in (0, 1)$. The parents can be selected by the condition; if $r < q_1$, then the first solution, z_1 has been selected as the parent. However, if $r > q_1$, then the other search has been made on the other individual solution z_1 such that $q_{i-1} < r \leq q_i$. The steps have been repeated for two times for each iteration cycle to find the two parents' spatial layout to be recombined and explored for the fittest offspring.

RS offers a more stable selection process by mitigating the effects of disproportionately high fitness values that can dominate the selection in methods like RWS. This method ensures a balance between exploration and exploitation by allowing less fit individuals a chance to contribute to the next generation, thus enhancing the evolutionary search for optimal spatial layout arrangements.

C. Uniform Crossover

In this research, the uniform crossover has been selected, and the selected parents have been recombined with the crossover phase. Both parents' allele genes have been recombined to construct better spatial layout offspring that are able to produce fit fitness values. The uniform recombination process has examined the genes in the parents separately and recombines each of the genes based on the coin flip method. The flip coin method has randomly made the decision based on 50-50 probabilities [0,1]. If the toss is "0", the gene for both parents has been maintained, whereas if the toss resulted in "1", the gene has been exchanged between the parents. The offspring constructed from the recombination method has been explored to prevent premature convergence to the local optimal solution and diversify the genetic population via the mutation phase approach.

D. Bit Flip Mutation

The mutation phase has amended the offspring solutions to construct new solutions. In this research, the random resetting mutation has been used by selecting each of the obstacles based on the bit flip mutation function, in which the probability of the obstacles' gene selection has been set to a 0.01 mutation rate. Each of the genes of the offspring has been examined, and a random number has been generated to check the mutation rate condition. Based on the rules set, when the random number < 0.01, the mutation has occurred, and the gene bit has been flipped, whereas when the random number >= 0.01, the bit of the offspring has remained the same. The obstacles that are assigned with the random number < 0.01 have been assigned to a randomly chosen gene in the spatial layout grid.

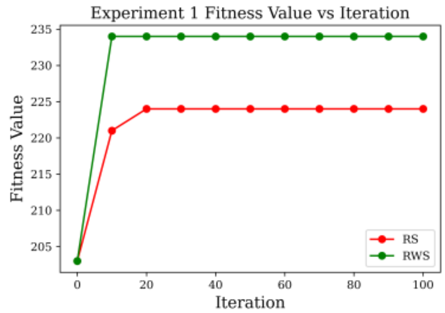
This method is suitable for spatial layout arrangement as the solutions will still provide the 50 large orders of obstacles. The fitness value of the offspring has been determined, and the value has been compared with the fitness values of the current population, f_i. The offspring constructed has been passed to the next iteration cycle as a member of the population and replaces the least fit solutions. The final population i with spatial layout solution z_i after 100 iterations have been compared, and the fittest solution will be selected to represent the selected result for the GA approach in designing an optimal spatial layout.

IV. Results

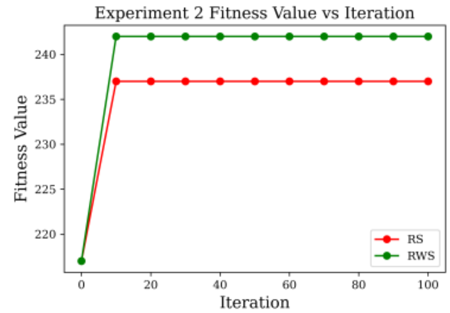
This research compared the Rank Selection (RS) and Roulette Wheel Selection (RWS) methods for constructing GA-based spatial layout arrangements. To ensure unbiased results, ten experiments were conducted, each with 100 iterations. Fig. 3 presents the graphical results of these experiments, illustrating the fitness value for every iteration of each selection method.

Based on the overall result in Fig. 3, both RS and RWS show the characteristic of GA algorithm results with premature convergence. These results align with the study's focus on optimizing spatial layout arrangements and space utilization, which are critical for applications like autonomous urban planning, facility layout design, and interior design. Given the emphasis on high space utilization and non-complex arrangements for emergency assistance, the selection of GA operators is crucial, especially in scenarios with limited spatial layout size.

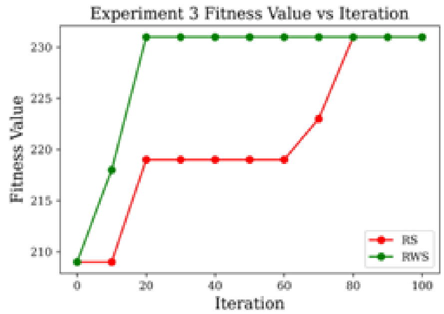
Based on the observation, the highest fitness value for both selection methods shows different values throughout the ten experiments. Based on the graphs in Fig. 3, RS outperformed RWS in 20% of the experiments by optimizing the population fitness value, especially in Experiment 6 and 10. In Experiment 6, RS achieved a fitness value of 230.0 by iteration 40, whereas RWS plateaued at a maximum fitness value of 226.0, beginning as early as iteration 10. Similarly, in Experiment 10, RS reached a fitness value of 236.0 by iteration 40, while RWS plateaued at 232.0 from iteration 50 onwards. These results highlight the potential of RS for achieving faster convergence in certain scenarios.



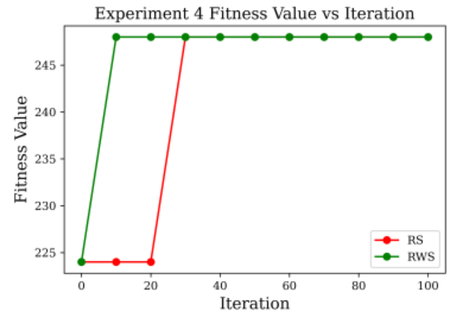
(a) Experiment 1



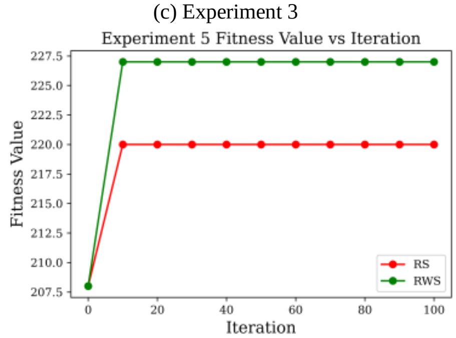
(b) Experiment 2



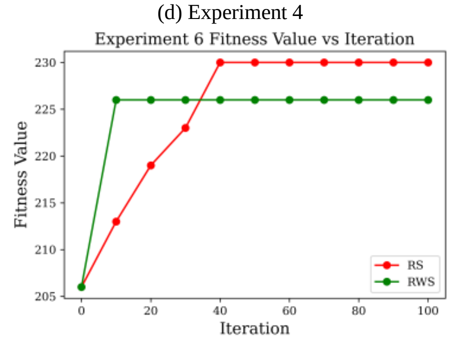
(c) Experiment 3



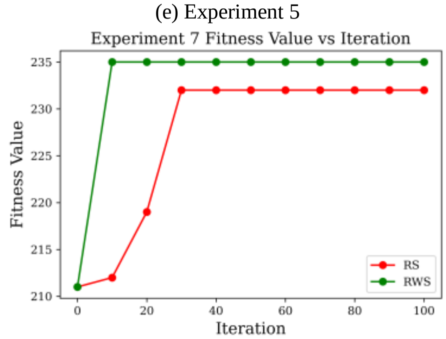
(d) Experiment 4



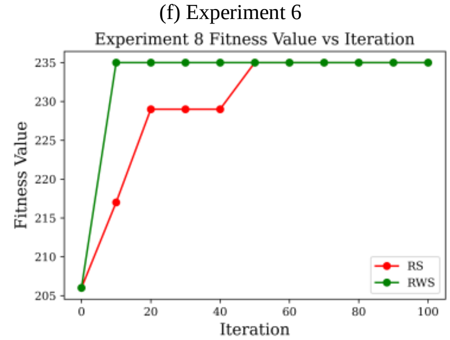
(e) Experiment 5



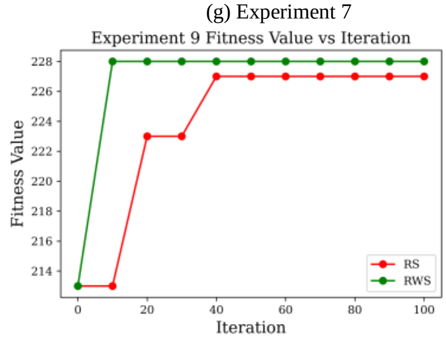
(f) Experiment 6



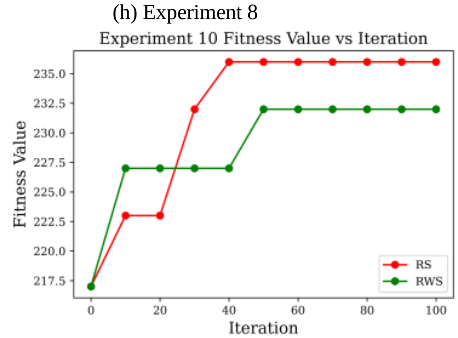
(g) Experiment 7



(h) Experiment 8



(i) Experiment 9



(j) Experiment 10.

Fig. 3. Graph comparison of Rank Selection (RS) and Roulette Wheel Selection (RWS) fitness value of over 100 iterations.

In 30% of the experiments, both RS and RWS exhibited comparable performance, achieving similar fitness values at different iterations. Based on the observations, the maximum fitness value for Experiment 3 reached 231.0 at iteration 80 using RS but was achieved earlier by RWS at iteration 20. The maximum fitness for Experiment 4 reached 249.0 at iteration 30 by RS but achieved earlier by RWS at iteration 10. In addition, the maximum fitness value for Experiment 8 reached 235.0 at iteration 50 by RS while RWS reached it earlier at iteration 10. These results indicate an overlapping convergence behavior, likely due to the limitation of layout size in accommodating all layout elements.

Furthermore, in 50% of the experiments, the RWS selection method outperformed the RS in terms of final fitness value. RWS shows better optimization compared to RS due to the offspring selection strategy that is based on the relative fitness of individuals. This proportional selection approach groups individuals by fitness level, increasing the likelihood that higher-fitness individuals are selected as parents, thereby generating stronger offspring. Compared to RWS, the selection in RS is also able to generate higher fitness values. However, due to the selection of the top 2 highest-fitness parents in RS caused the offspring generated to be too fit and unable to replace the lowest value of population members. Hence, resulting in the slow convergence speed compared to RWS. Although RWS is generally associated with slower convergence, its use of a solution acceptance rule (i.e., constraints related to layout capacity) allows it to increase fitness values earlier in the experiment, often resulting in the highest fitness value by iteration 100. Additionally, the RS selection method is computationally expensive due to the population sorting based on the fitness value compared to the RWS selection method. Fig. 4 shows the graph comparison between the processing time (milliseconds) in every experiment for the RS and RWS-based GA approach spatial layout design arrangement.

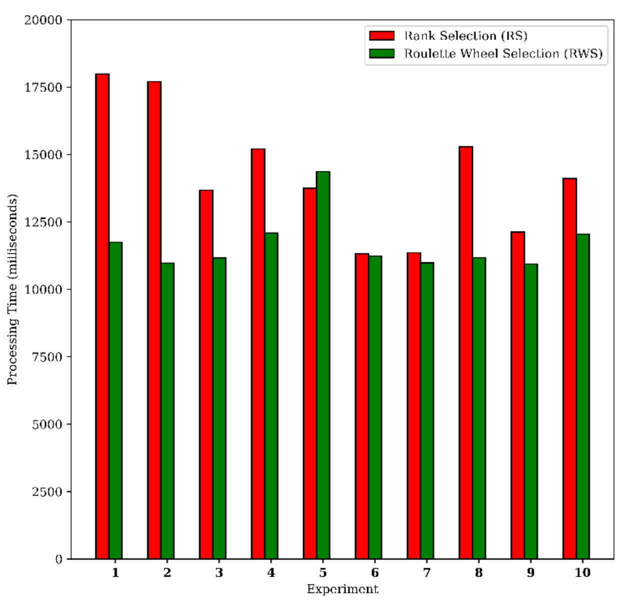


Fig. 4. Graph comparison between the processing time of Rank Selection (RS) and Roulette Wheel Selection (RWS) for 10 experiments.

Based on Fig. 4, the graph of processing time shows that RS consistently takes extra processing time compared to RWS in most experiments, with the exception of Experiment 5 as the 10% outlier, where RS recorded 13752 ms compared to 14369 ms for RWS. This result indicates that RS is generally slower in this context. In Experiments 1, 2, 3, 4, 6, 7, 8, 9, and 10, RWS shows significantly faster processing time, with 90% of the experiments showing the improvement of processing time percentage. Table I summarizes the percentage improvement of RWS over RS.

TABLE I. PROCESSING TIME COMPARISON WITH PERCENTAGE OF RWS IMPROVEMENT COMPARED TO RS

Experiment	RS Time (ms)	RWS Time (ms)	Faster Method	RWS over RS (%)
1	17991	11747	RWS	34.69
2	17708	10974	RWS	38.02
3	13681	11168	RWS	18.37
4	15209	12088	RWS	20.54
5	13752	14369	RS	-4.49
6	11320	11236	RWS	0.74
7	11359	10986	RWS	3.28
8	15292	11178	RWS	26.89
9	12130	10941	RWS	9.80
10	14110	12047	RWS	14.62

Based on Table I, among the 90% of experiments where RWS demonstrated superior performance, the results show the improvement ranging from modest gains, such as 0.74% in Experiment 6, to substantial differences exceeding 38% in Experiment 2. The most significant time reductions were observed in Experiments 1 and 2, where RWS reduced computation time by 34.69% and 38.02%, respectively, compared to RS. This substantial difference in the efficiency of these two methods is potentially due to the computation cost in population sorting based on fitness value that is required in the RS algorithm, which increases the computation complexity. RWS, by contrast, is more computationally efficient and enables faster spatial layout optimization.

Compared to the other experiments, in Experiment 5, RS was slightly faster by 4.49%, which is an exception to the trend observed from the whole experiment. This anomaly suggests that under certain conditions, particularly where early convergence occurs or solution acceptance thresholds align more favorably, RS may offer computational advantages. However, this case appears to be an outlier rather than a consistent pattern. The outlier also reflects the unbiased nature of the experimental setup, which was intentionally designed to allow either method to succeed under appropriate conditions.

Based on Fig. 4 the solution acceptance rule acts as a limiting factor for space utilization optimization, and RWS demonstrates a better balance between the fitness value optimization and processing time that making it a more practical choice for the selection process in the future GA approach for optimizing the autonomous spatial layout arrangement design and space utilization in autonomous urban planning.

V. Conclusion

This study aimed to evaluate the effectiveness of two Genetic Algorithm (GA) selection methods: Rank Selection (RS) and Roulette Wheel Selection (RWS) in optimizing spatial layout arrangements to improve space utilization and emergency responsiveness. Through this research, it was shown that RWS was able to outperform RS by consistently achieving higher fitness values and demonstrating greater computational efficiency. This was due to its proportional selection mechanism, which enhances the likelihood of selecting fitter individuals and accelerates convergence while maintaining layout standards for emergency situations. While RS occasionally showed better performance in specific instances, its approach often led to slower convergence and increased computational demands. The requirement for population sorting based on fitness in RS contributed to its higher computational cost. Overall, RWS proved to be the more effective method for optimizing spatial designs, meeting the study's objective of identifying the most efficient GA operator for enhancing spatial layout arrangements and space utilization in autonomous urban planning. The future research direction of this study is to explore hybrid selection methods in GA that combine the selection mechanisms and features of RS and RWS to further enhance the optimization of spatial layout arrangements in urban planning. Additional studies can be carried out to investigate the application of RWS in different urban planning scenarios to validate its effectiveness in improving space utilization and emergency responsiveness across diverse environments.

Acknowledgment

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