AI-Driven Generative Design: Evolutionary Optimisation of Residential Floor Plans

Zuxing Wu, a1816653

Supervisor: Adel Nikfarjam

Master of Computer Science

June 15, 2025

Contents

1 Introduction

1.1 Aim

Residential floor plan design is a multifaceted and challenging task that necessitates careful consideration of factors such as room dimensions, spatial adjacency, privacy, convenience, and orientation. Conventional approaches to floor plan design are often time-consuming and labour-intensive, frequently resulting in suboptimal outcomes. Evolutionary algorithms have emerged as a promising alternative for optimising floor plans, as they are capable of efficiently exploring the design space and generating high-quality solutions. This project aims to develop an improved method for optimising residential floor plans through the application of evolutionary algorithms, addressing several limitations identified in previous research. The proposed approach utilises a novel and straightforward representation scheme, with the fitness of each floor plan evaluated according to multiple criteria, including privacy, comfort, practicality, and convenience. The findings of this research are expected to advance the field of residential floor plan design and offer valuable insights into the application of evolutionary algorithms to architectural design challenges.

1.2 Motivation

Residential floor plan design constitutes a fundamental component of architectural practice, encompassing the spatial arrangement of rooms, windows, doors, corridors, and ancillary spaces within a dwelling. The configuration of a floor plan profoundly influences the functionality, convenience, comfort, ventilation, and energy efficiency of a residential building. Conventional approaches to floor plan design typically rely on manual drafting or computer-aided design (CAD) tools, processes that are often both time-consuming and labour-intensive. Furthermore, such methods may yield suboptimal outcomes, as they are heavily dependent on the subjective judgment and experience of individual designers.

In contrast, evolutionary algorithms provide a systematic and effective means for optimising floor plans by thoroughly exploring the design space and generating high-quality solutions. These algorithms are inspired by the principles of natural evolution, operating on a population of candidate solutions and utilising mechanisms such as crossover and mutation to iteratively improve design quality across generations. The performance of each candidate solution is rigorously evaluated using fitness functions, which quantitatively assess the extent to which the design satisfies the specified objectives of the floor plan optimisation problem.

2 Literature Review

Previous research has explored the application of evolutionary algorithms to optimise residential floor plans. Brintrup et al. [1] compared three interactive genetic algorithms (i.e., sequential IGA, multi-objective IGA, parallel IGA) on

a multi-objective floor planning task, and found that the multi-objective IGA provides more diverse results and faster convergence for optimising floor plans. They developed interactive evolutionary algorithms that allow designers to incorporate their preferences and constraints into the optimisation process. This method has shown promising results in generating floor plans that meet both functional and aesthetic requirements.

It was found that proportional roulette wheel selection is the best parent selection method for the mating pool, and k-point crossover is the most effective for fitness evolutionary improvement [3]. Combining evolutionary algorithms with greedy-like algorithms can help find near-optimal solutions in Automated Floor Plan Generation (AFPG), though it is a simplified model of multi-objective optimisation by linear composition of the partial evaluation functions [8]. Subramanian et al. [11] used a genetic algorithm with KD tree models in a web application to generate floor plans for even non-expert users.

Wang and Duan [13] tried to optimise floor plan design by focusing on energy consumption and consumer satisfaction, proving that the preferences of different types of consumers differed significantly. Therefore, different evaluation criteria are needed for satisfying different family types [13]. The quality and efficiency of residential floor plan design can be improved by combining Monte Carlo tree search algorithm (MCTS) and particle swarm optimisation (PSO) [14]. The MCTS algorithm takes human experience into consideration so that it can compress the search space and improve the efficiency of the search process [14]. The PSO algorithm can handle continuous variables and is suitable for optimising the size of rooms due to parallel processing [14].

Energy consumption, probable uniformity (PU), and spatial useful daylight illuminance (sUDI) are three objectives that are considered in Chaichi and Andaji Garmaroodi's optimisation process [2] using NSGA-II algorithm, and the results show that the NSGA-II algorithm can provide a set of more sustainable floor plans that requires less computational power and time. Reliable metrics for evaluating the amount of light and the uniformity of light are tested in the optimisation process, and can avoid unwanted convergence because they restrict each other [2].

Shi et al. [9] chose (1+1)-EA (Evolutionary Algorithm) to optimise macro placement by randomly selecting two macros and exchange their coordinate, which only keep one solution and iteratively improves it. Laignel et al. [7] proposes a novel constraint programming-genetic algorithm for automatic apartment layout generation, demonstrating its ability to produce architecturally valid floor plans within a minute by discretizing space into a grid and solving layout assignments under complex constraints.

Zou et al. [16] proposes a memory-based simulated annealing algorithm for fixed-outline floor planning with soft blocks, using a memory pool and geometric auxiliary function to escape local optima and efficiently meet design constraints, showing superior performance on benchmarks. Both Zou [16] and Singha [10] used B*-tree to represent the floor plan, which is a hierarchical structure that allows for efficient storage and manipulation of the floor plan data. Kang and Kim [5] presents a novel method that analyses mobile app logs and Google server

data to identify user behaviour patterns, using a genetic algorithm to generate optimal indoor floor plans that minimise living costs and enhance spatial analysis. Zawidzki and Szklarski [15] developed a multi-objective optimisation framework for single-story house floor plans, balancing functionality, sunlight, view, and noise reduction through gradient-based methods and user-defined preferences, demonstrated via a case study.

Furthermore, the integration of machine learning techniques with evolutionary algorithms has gained attention in recent decades [4]. For example, Wang et al. [12] proposed a hybrid approach that combines a genetic algorithm with a neural network to predict the fitness of candidate solutions. This method significantly reduces the computational cost of evaluating large populations and accelerates the optimisation process.

Overall, the literature indicates that evolutionary algorithms, particularly when combined with other optimisation techniques and machine learning methods, offer a powerful tool for optimising residential floor plans. These approaches not only improve the efficiency and quality of the designs but also provide flexibility in accommodating various design preferences and constraints.

3 Methodology

The methodology of this project involves the application of evolutionary algorithms to optimise residential floor plans. The process will be divided into several key stages: 1. Representation of the floor plan, 2. Solution evaluation, 3. Initialisation of the population, 4. Design of the evolutionary optimisation framework. These stages are described in detail below.

3.1 Representation of Floor Plans

To represent a concrete representation of the floor plan, we will use a hierarchical structure (shown in Figure 1) to represent the floor plan data. The top-level structure will be a `House` class that contains a boundary and a list of rooms. Each room will be represented by a `Room` class, which includes its dimensions (width and depth), position (x, y coordinates), and lists for doors and windows. The doors and windows will be represented as tuples containing their width, the wall they are located on, and their position on that wall.

To display the floor plan, we used Python's `matplotlib` library to create and save a visual representation of the floor plan. We defined a `save_snapshots` function that takes a layout as one of the parameters, and generates a visual representation of the floor plan. The function iterates through each room in the layout, draws rectangles for the rooms, and adds doors and windows as lines on the walls. The boundary is drawn in black. The resulting image is saved as a PNG file.

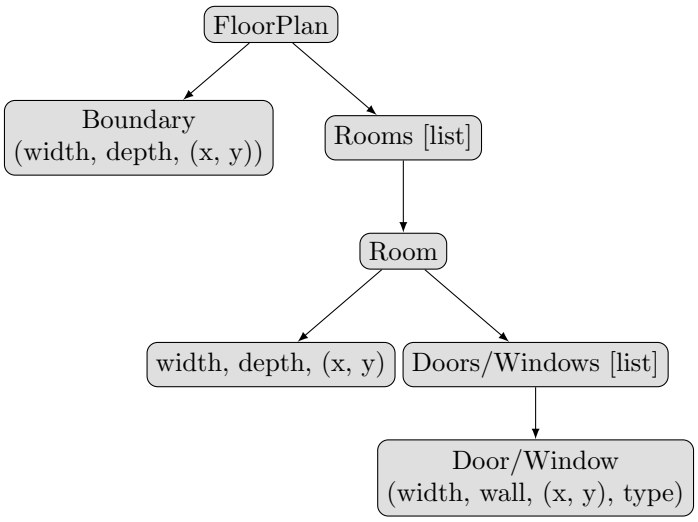


Figure 1: Hierarchical representation of the floor plan data structure.

3.2 Solution Evaluation

Fitness functions will evaluate each floor plan mainly based on these 4 criteria: privacy, comfort, practicality, convenience. We created 24 fitness functions based on Wang and Duan's evaluation indicators [13] along with professional's advice. Our fitness functions are shown in Table 1.

The straight distance between the geometric centres of room m and n is defined as:

$$\text{dis}(m, n) = \sqrt{(x_m - x_n)^2 + (y_m - y_n)^2}$$

but at the late stage of the optimisation process, this distance is calculated through `polygon.distance()` function from the `shapely` library, which is more accurate and convenient than the above formula.

The percentage of area of R to the interior area of the floor plan is defined as:

$$\%\text{ of } R = \left(\frac{\text{Area of } R}{\text{Interior Area of Floor Plan}}\right) \times 100\%$$

The utilisation rate of a house is defined as the percentage of occupied area to the total area of the floor plan:

$$\text{utilisation Rate} = \left(\frac{\text{Occupied Area}}{\text{Total Area}}\right) \times 100\%$$

The overlap rate is defined as the percentage of overlapping area to the total area of the floor plan:

$$\text{overlap Rate} = \left(\frac{\text{Overlapping Area}}{\text{Sum All Rooms Area}}\right) \times 100\%$$

Table 1: List of 24 Fitness Functions (Green means eventually being used)

Function Name	**Description**
dis_MBR_BR	Distance between Main Bedroom and Bedroom
dis_MBR_BA	Distance between Main Bedroom and Bathroom
check_LR_orientation	Living Room orientation check
check_DR_natural_light	Dining Room natural light check
ventilation	Ventilation evaluation
north_facing_area	North-facing area calculation
percentage_hall	Percentage of hall area
percentage_balcony	Percentage of balcony area
utilization_rate	Utilization rate of the floor plan
dis_BR_BA	Distance between Bedroom and Bathroom
dis_BA_LR_door	Distance between Bathroom and Living Room door
check_GAR_side	Garage should be on the same side as the entry
dis_KIC_LR	Distance between Kitchen and Living Room
dis_KIC_DR	Distance between Kitchen and Dining Room
dis_LR_DR	Distance between Living Room and Dining Room
check_no_entry_touch	Entry not touching other closed rooms check
cal_overlap_rate	Overlap rate calculation
diff_public_private	Differentiate private rooms from public rooms
check_KIC_orientation	Kitchen orientation check
dis_LDR_KIC	Distance between Laundry and Kitchen
dis_GAR_KIC	Distance between Garage and Kitchen
dis_MBR_LR	Distance between Main Bedroom and Living Room
dis_MBR_KIC	Distance between Main Bedroom and Kitchen
bigger_MBR	Main Bedroom area > other bedroom area

The differentiation between public and private rooms is based on the classification of rooms into public (e.g., living room, dining room, kitchen, garage and laundry) and private (e.g., bedrooms, bathrooms). The differentiation is evaluated based on the comparison of distance between these rooms and the entry. All public rooms should be close to the entry, while private rooms should be further away. The differentiation is calculated as:

$$\text{diff\_public\_private} = \frac{1}{|P| \cdot |Q|} \sum_{p \in P} \sum_{q \in Q} \mathbb{I}\left(d(\text{entry}, p) < d(\text{entry}, q)\right)$$

where P is the set of public rooms, Q is the set of private rooms, $d(\text{entry}, r)$ denotes the distance from the entry to the centre of room r, and $\mathbb{I}(\cdot)$ is the indicator function that returns 1 if the condition is true and 0 otherwise. This metric measures the proportion of public-private room pairs where the public room is closer to the entry than the private room, thus quantifying the spatial differentiation between public and private spaces.

These proposed methods are implemented in Python. All fitness values are calculated and normalised to a range of 0 to 1, where higher values indicate

better performance. The evaluation process involves calculating the fitness values for each floor plan in the population and selecting the best individuals for particles updating their velocity and position in PSO.

3.3 Population Initialisation

The first step in the evolutionary process is to generate an initial population of residential floor plans. The initialisation process involves generating a set of random rooms and arranging them into a floor plan layout, subject to the following constraints and parameter ranges:

- **House boundary:** width = 15 m, depth = 8 m.
- **Entry:** a line segment at the boundary, `LineString([(0, 4), (0, 5)])`.
- **8 Room types and size ranges:**
  - Garage (`GAR`): width 5–6 m, depth 3–6 m
  - Laundry Room (`LDR`): width 3 m, depth 3 m
  - Dining Room (`DR`): width 3–5 m, depth 3–5 m
  - Living Room (`LR`): width 3–6 m, depth 3–6 m
  - Kitchen (`KIC`): width 3–4 m, depth 3–4 m
  - Main Bedroom (`MBR`): width 3–6 m, depth 3–6 m
  - Bedroom1 (`BR1`): width 3–5 m, depth 3–5 m
  - Bathroom (`BA`): width 2–4 m, depth 2–4 m
- **Window width:** 0.5–1.5 m
- **Door width:** 0.8–1.5 m

The rooms are assigned random sizes within the specified ranges and placed within the house boundary. The initialisation strategy is designed to produce a diverse set of floor plans that serve as a starting point for the evolutionary optimisation process. At the late stage of our research, we only need to randomly generate a single floor plan, which will be mutated and evaluated continuously so as to evolve the floor plan towards an optimal solution.

3.4 Evolutionary Optimisation Framework

The evolutionary optimisation framework initially was based on particle swarm optimisation (PSO) algorithm, which is suitable for optimising the size of rooms due to parallel processing, and Monte Carlo Tree Search (MCTS) algorithm which can handle discrete variables (i.e., room position) [14]. In our implementation, the width and depth are integer values, which means we are using discrete binary particle swarm optimisation (BPSO) algorithm [6, 14]. The topology of this type PSO algorithm is a von Neumann topology [4], where each particle is

connected to its neighbours in a grid-like structure. The PSO algorithm (see Algorithm 1) updates the velocity and position of each particle based on its own best position and the best position of its neighbours. The velocity update equation is given by:

$$v_i(t+1) = w(t) \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_i - x_i(t)) + c_2 \cdot r_2 \cdot (g - x_i(t))$$

where $v_i(t)$ is the velocity of particle i at time t, $w(t)$ is the inertia weight, c_1 and c_2 are the cognitive and social coefficients, respectively, r_1 and r_2 are random numbers uniformly distributed in [0, 1], p_i is the best position of particle i, and g is the global best position among all particles.

Algorithm 1 : PSO-MCTS Hybrid Algorithm

Require: Room size ranges, number of particles N, maximum iterations T, MCTS iterations M
Initialise each particle with random room sizes and zero velocities
Set global best fitness g_{best} to $-\infty$
for $t = 1$ to T **do**
  for each particle i **do**
    Construct room list from particle's sizes
    Use MCTS to generate a layout for these sizes
    Evaluate fitness of the layout
    if fitness > particle's personal best **then**
      Update particle's personal best
    end if
    if fitness > g_{best} **then**
      Update global best layout and fitness
    end if
  end for
  Local search: Swap two random rooms in g_{best} layout, accept if fitness improves
  Record g_{best} fitness in history
  for each particle i **do**
    for each room dimension j **do**
      Update velocity using inertia, cognitive, and social terms
      Update room size within allowed bounds
    end for
  end for
  if t is 0, $T-1$, or divisible by 25 **then**
    Save snapshot of current g_{best} layout
  end if
end for
return Best layout found

However, the MCTS algorithm did not optimise the room position very well, so it was replaced by a simple greedy algorithm called (1+1) Evolutionary Algo-

rithm (EA). The (1+1) EA algorithm (see Algorithm 2) is a simple evolutionary algorithm that maintains a single individual and applies mutation to generate new individuals. The PSO algorithm will be used to optimise the size of rooms, while the (1+1) EA will be used to optimise the room position. The framework will involve the application of genetic operators, such as randomly add or minus a small perturbation to the current room size, swap two random rooms, and so on, to generate new floor plans from the existing population. The optimisation process will be repeated for a specified number of generations or until a termination criterion is met.

Algorithm 2 : (1+1) EA for Mutating Room Positions

Require: Boundary, List of Rooms, Maximum Iterations max_iter

Initialise `placed_rooms` by randomly placing each room at a legal position within the boundary
Set `best_layout` ← layout with `placed_rooms`
Set `best_fitness` ← fitness of `best_layout`
for $j = 1$ to max_iter **do**
  for each room i in `placed_rooms` **do**
    Generate a random number $r \in [0, 1]$
    if $r < 0.05$ **then**
      Randomly select a new legal position for room i
      Create a new layout by moving room i to the new position
      Compute fitness of the new layout
      if new fitness > `best_fitness` **then**
        Update `best_layout` and `best_fitness`
        Update `placed_rooms` with the new position for room i
      end if
    end if
  end for
end for
return `best_layout`, `best_fitness`

Later, the PSO algorithm was replaced by the (1+1) EA as well, so that the room sizes (i.e., width and depth) could be optimised in a similar way to the room position (see Algorithm 3). The (1+1) EA algorithm randomly selects a room in the floor plan and generates a new room size by adding or subtracting a small random perturbation to the current size. The new room size is evaluated using the same fitness functions, and if it results in a better fitness value, it replaces the current best room size. This process continues until all rooms have been assigned their optimal sizes.

Algorithm 3 : (1+1) EA for Mutating Room Sizes

Require: Boundary, Room Size Ranges, Maximum Iterations max_iter

Randomly generate initial room sizes within the specified ranges
Set `best_layout_rooms` $\leftarrow$ initial room sizes
Set `best_fitness` $\leftarrow -\infty$
for $i = 1$ to max_iter **do**
  Copy `best_layout_rooms` to `rooms`
  for each room j in `rooms` **do**
    Generate a random number $r \in [0, 1]$
    if $r < 0.125$ **then**
      Mutate width and depth of room j by adding random integers in $[-3, 3]$, keeping within allowed range
    end if
  end for
  Use `Position_OnePlusOneEA` to optimise positions for current sizes, get `best_layout`, `fitness`
  if `fitness` > `best_fitness` **then**
    Update `best_layout`, `best_fitness`, `best_layout_rooms`
  end if
  Record `best_fitness` in history
end for
return `best_layout`, `best_fitness`

If possible, other optimisation algorithms, such as simulated annealing algorithm or differential evolution, will be explored to further enhance the optimisation process. The final output of the evolutionary optimisation framework will be an optimised residential floor plan with high fitness value that meets the specified design criteria and constraints.

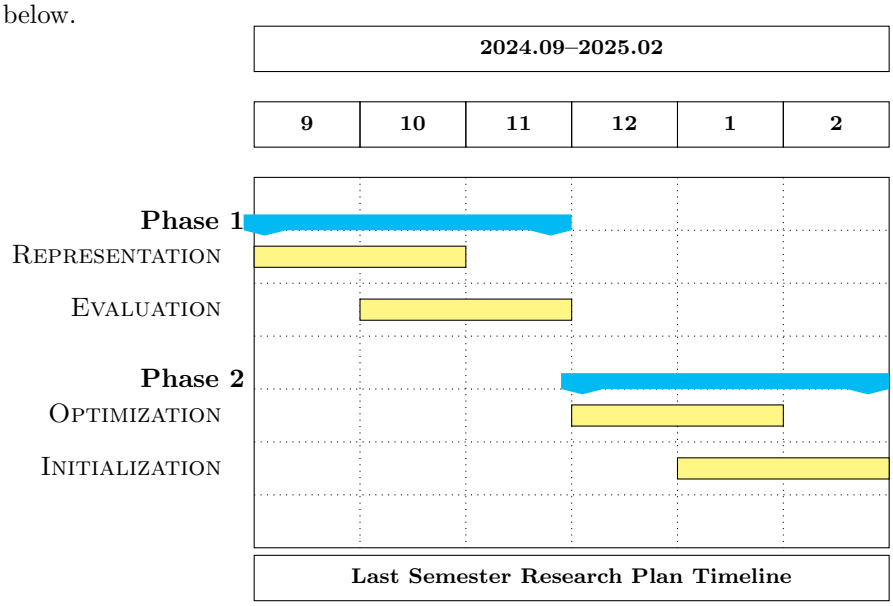
4 Plan vs Progress

4.1 Research Plan

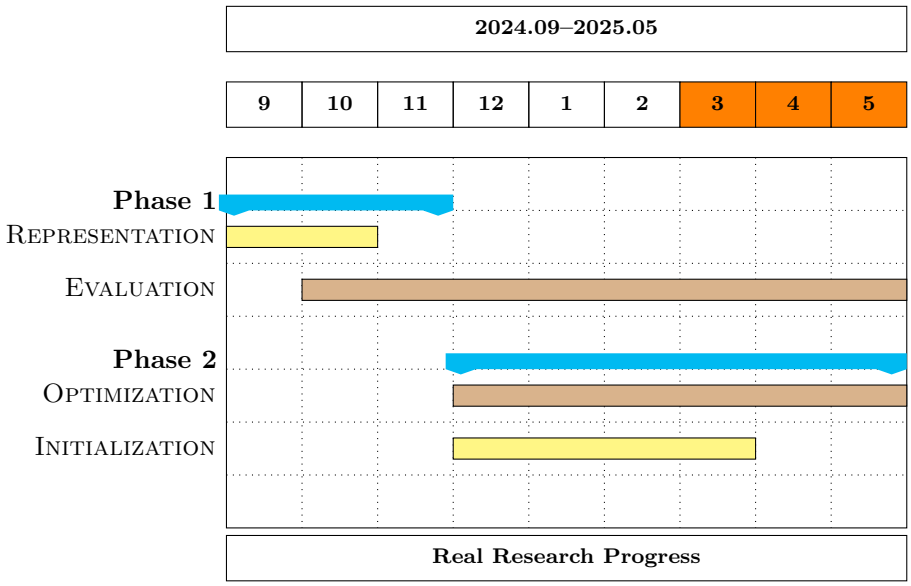
My research plan consists of four main phases through the whole research.

- Phase 1
  1. Solution representation
  2. Solution evaluation
- Phase 2
  1. Population initialisation
  2. Evolutionary optimisation

Each phase involves specific tasks and activities that will be carried out over a period of 6 months (since I did not make a plan for semester 1 of this year). The timeline for the research plan, at that time, is shown in the Gantt chart below.



However, the real research progress did not go as planned. The research plan was adjusted to focus on the solution evaluation and evolutionary optimisation. The solution evaluation is the key to the quality of the generated floor plans, and the evolutionary optimisation is the core of this research. The solution representation is the prerequisite of solution evaluation. The population initialisation can be adjusted according to the progress of the research. The true timeline for the research progress is shown in the Gantt chart below. (Orange means current semester.)



4.2 Progress

It can be seen from the Gantt chart above that the research process has been adjusted to mainly focus on the solution evaluation and evolutionary optimisation.

Last summer holiday, I have completed the solution representation and solution evaluation, respectively using self-defined classes to represent the floor plan and using a set of fitness functions to evaluate each floor plan. All the fitness values are calculated and normalised to a range of 0 to 1.

Fitness functions are designed to evaluate the quality of the generated floor plans based on various criteria, such as privacy, comfort, practicality, and convenience. The evaluation process involves calculating the fitness values for each floor plan in the population and selecting the best individuals for particles updating their velocity and position in PSO.

4.2.1 PSO algorithm + MCTS algorithm

From the start of semester 1 of 2025, I have been working on the evolutionary optimisation process. Initially, I focused on the PSO algorithm, which is suitable for optimising the size of rooms due to parallel processing, and MCTS algorithm, which handles discrete variables (i.e., room position). I had implemented the PSO algorithm (Algorithm 1) and MCTS algorithm (Algorithm 4) in Python, and I tried integrating them into a single framework. The integration process involves combining the two algorithms to create a hybrid optimisation approach that can effectively handle both continuous and discrete variables in the floor plan design process.

Algorithm 4 : Monte Carlo Tree Search (MCTS) for Floor Plan Layout

Require: Boundary, List of Rooms, Number of Iterations N

Initialise root node with empty layout state
for $i = 1$ to N **do**
  Set node ← root, state ← copy of root state
  {`# Selection`}
  while node is fully expanded and not terminal **do**
    node ← child with highest UCB score
    if placing node.action fails **then**
      break (invalid simulation)
    end if
  end while
  {`# Expansion`}
  if node has untried actions **then**
    Randomly select an untried action
    if placing action succeeds **then**
      Add new child node for this action
      node ← new child
    end if
  end if
  {`# Simulation`}
  Copy current state to simulation_state
  while not all rooms placed and attempts < max_attempts **do**
    Randomly select a legal action
    if placing action fails **then**
      break (invalid simulation)
    end if
  end while
  {`# Evaluation`}
  if simulation is valid and all rooms placed **then**
    Compute reward using fitness function
    if reward > best_reward **then**
      Update best_reward and best_state
    end if
  else
    reward ← 0
  end if
  {`# Backpropagation`}
  while node is not None **do**
    node.visits + = 1
    node.value + = reward
    node ← node.parent
  end while
end for
return Layout from best_state or best child of root

4.2.2 MCTS algorithm replaced by (1+1) EA

However, the integration process has proven to be more complex than anticipated, and the MCTS algorithm did not optimise the room position very well. It cannot eliminate overlap even after 2000 iterations (see Figure 2) (bold black line means entry).

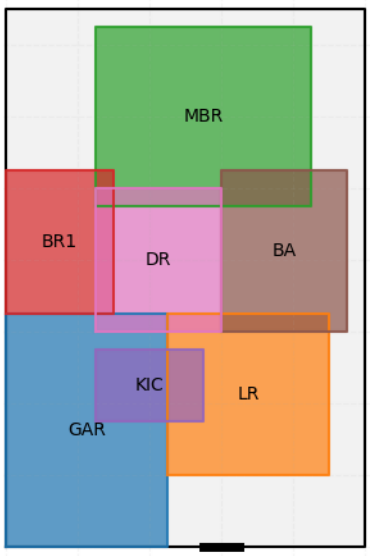


Figure 2: Example of room overlap after 2000 PSO-MCTS iterations. (Bold black line is the entry.)

Therefore, I changed it to a simple greedy algorithm called (1+1) Evolutionary Algorithm, which is a simple evolutionary algorithm that maintains a single individual and applies mutation to generate new individuals. The (1+1) EA algorithm is easier to implement and can be used to optimise the room position (i.e., the (x, y) coordinates) in the floor plan design process. If the new solution has a better fitness value, it replaces the current solution. This process continues until a termination criterion, such as a maximum number of iterations or a satisfactory fitness value, is met. It is a simple yet effective optimisation algorithm that can be used to improve the quality of the generated floor plans, especially in terms of room position.

4.2.3 Swap two random rooms

From this point onwards, swap mutation was adopted to optimise room positions. Swap mutation involves randomly selecting two rooms and exchanging their positions. This operation is simple yet effective, allowing the exploration of a larger design space and the generation of new floor plan solutions. The newly generated floor plan is evaluated using the same fitness functions, and

if it achieves a higher fitness value, it replaces the current best solution. The results (see Figure 3) show this can help reduce the overlap rate and improve the overall quality of the floor plans.

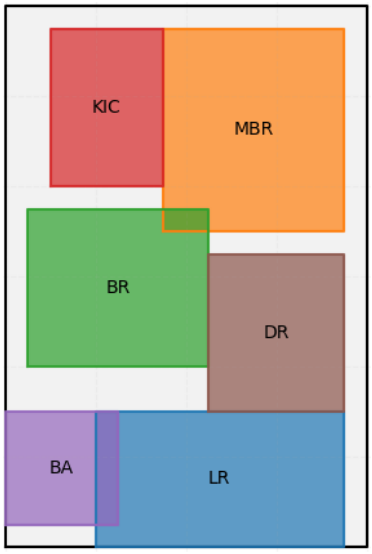


Figure 3: Less room overlap after using swap mutation.

4.2.4 Tune inertia weight

In the PSO algorithm, the inertia weight plays a crucial role in balancing exploration and exploitation. Initially, I implemented a linearly decreasing inertia weight, which reduces the inertia weight from a maximum value to a minimum value over the course of iterations. However, after conducting experiments, I found that a non-linearly decreasing inertia weight performs better in terms of convergence speed and solution quality.

The non-linearly decreasing inertia weight [4] is defined as:

$$w(t) = w_{\max} + (w_{\min} - w_{\max}) \cdot \left(1 - \frac{t}{T}\right)^n$$

where $w(t)$ is the inertia weight at iteration t, $w_{\max}$ and $w_{\min}$ are the maximum and minimum inertia weights, T is the total number of iterations, and t is the current iteration. t is the nonlinear modulation index in the range of [0.9, 1.3].

This non-linear decrease allows the algorithm to explore the search space more effectively in the early stages and focus on exploitation in the later stages. The quadratic term ensures a smoother transition, which helps in avoiding premature convergence and improves the overall performance of the optimisation process.

4.2.5 Prioritized fitness calculation

To improve the performance of the optimisation process, a prioritised fitness calculation strategy has been adopted. This strategy evaluates the fitness of floor plans based on the priority of the criteria, starting with the most important and moving to the less important ones. The prioritised fitness calculation process is outlined as follows:

1. **Define Priorities:** Assign a priority level to each criterion (e.g., privacy, practicality, comfort, convenience). Higher priority criteria are evaluated first. For example, the garage should be on the same side as the entry, and the main bedroom should be larger than other bedrooms. If these criteria are not met, a penalty will be deducted from the final fitness value.

2. **Sequential Evaluation:** Calculate the fitness values for each criterion in the order of their priority. For example, overlap rate is evaluated before utilization rate. This means that if a floor plan fails to meet the zero overlap rate, it will not be evaluated for utilization rate. As can be seen in Figure 4, the floor plan with zero overlap rate is evaluated for utilization rate, while the floor plan with non-zero overlap rate is not evaluated for utilization rate. Later, the privacy criterion is evaluated before the overlap rate optimisation.

3. **Weighted Aggregation:** Combine the rest of fitness values using a weighted sum, where the weights correspond to the significance levels. The overall fitness value is given by:

$$\text{Fitness}_{\text{total}} = \sum_{i=1}^{n} w_i \cdot \text{Fitness}_i$$

   where w_i is the weight for criterion i, and Fitness_i is the fitness value for criterion i.

4. **Early Termination:** If a floor plan fails to meet the minimum threshold for a high-priority criterion, it is discarded without evaluating the lower-priority criteria. This reduces unnecessary computations and speeds up the optimisation process.

This strategy ensures that the optimisation process focuses on the most critical aspects of the floor plan design, improving both efficiency and the quality of the solution generation. It allows for a more efficient evaluation process, since it avoids unnecessary calculations in the early stages.

4.2.6 Change land size and orientation

In the initial version of the code, the land size and orientation were fixed, which limited the flexibility of the design process. To enhance the adaptability of the floor plan generation, I have modified the code to allow for variable land sizes

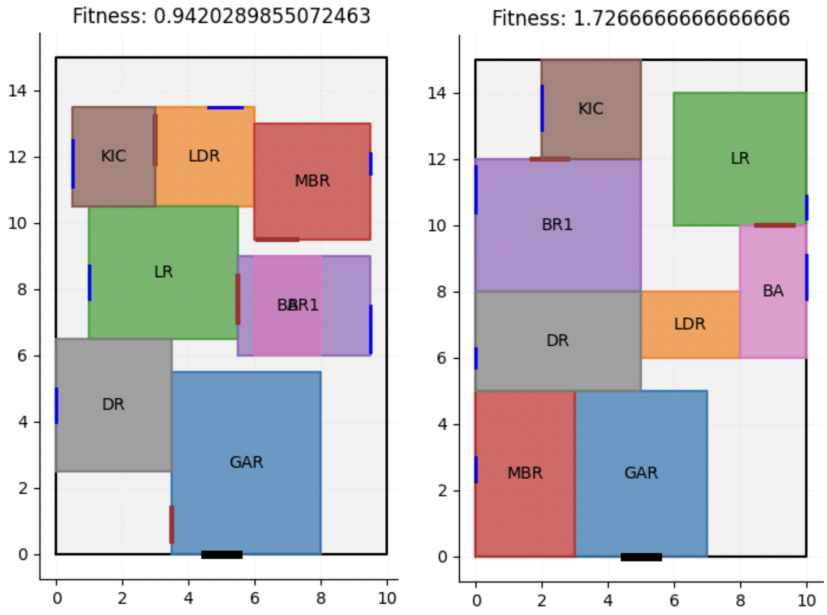


Figure 4: Example of prioritised fitness calculation. The left one is still working on reducing overlap rate. Utilization rate is only calculated for floor plans with zero overlap rate (the right one). (Bold blue lines are windows; bold brown lines are doors)

and orientations. This change enables the optimisation process to spot potential problems and explore a wider range of design possibilities, accommodating different land configurations and orientations. The new approach allows for more diverse and flexible floor plan designs, making it easier to meet the needs and preferences of specific users.

4.2.7 Remove windows and doors

In the previous version of the code, the windows and doors were added to each room immediately after the floor plan was generated no matter whether overlap exists or not. However, this approach led to a significant increase in the complexity of the optimisation process, as the presence of windows and doors added additional constraints to the evaluation. As a result, the optimisation process became slower and less efficient, and the overall quality of the generated floor plans was not satisfactory even after 2000 iterations. To address this issue, I have removed the windows and doors from the early generation process. Instead, the optimisation process will focus on generating the basic layout of the floor plan, including room sizes, positions, and an entry, without any additional features. Once the optimisation process is completed and a satisfactory floor plan has been generated, windows and doors can be added to the floor plan.

This approach simplifies the optimisation process and allows for more efficient exploration of the design space at the early stages.

4.2.8 PSO algorithm replaced by (1+1) EA

After that, we found that the PSO algorithm is not suitable for optimising the size of rooms, because it always gets trapped at a local optimum and can hardly break through it. It also takes a huge amount of time to complete one iteration through all particles. Therefore, I changed it to (1+1) EA too, so that the room size (i.e., width and depth) can be optimised in a similar way to the room position optimisation. The (1+1) EA algorithm will randomly select a room in the floor plan and generate a new room size by adding or deducting a small random perturbation to the current size. The new room size will be evaluated using the fitness functions, and if it results in a better fitness value, it will replace the current best room size. This process continues until all rooms have been assigned their optimal sizes.

4.2.9 Dotted line for open space

In the earlier design phase, the open space in the floor plan was represented by a solid line, which made it difficult to distinguish between open space and closed rooms (e.g., dining room, living room, and kitchen. See Figure 5). To improve the clarity of the design, I have changed the representation of open space to dotted lines. This change allows for a clearer visualisation of the floor plan, making it easier to identify open spaces from other rooms in the house.

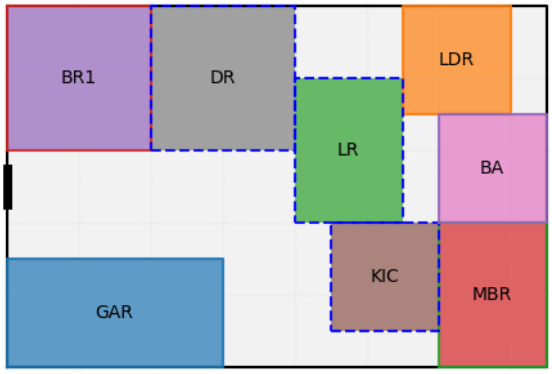


Figure 5: Example of open space surrounded by dotted line.

4.2.10 Tune weights for fitness functions

In the final stages of the optimisation process, I have been tuning the weights of the fitness functions to achieve better results. The weights are used to balance the importance of different criteria in the evaluation process. By adjusting the

weights, I can prioritise certain aspects of the design, such as low overlap or high utilization rate, to achieve better overall results. This tuning process is iterative and may require multiple rounds of testing and evaluation to find the optimal balance for the specific design goals.

4.2.11 Filling Blank Areas

In the final stages of the optimisation process, I have been working on filling blank areas in the floor plan. The goal is to improve the overall layout and utilisation of space by expanding rooms into adjacent blank areas. This process involves heuristically expanding public areas first (Algorithm 5), and then closed rooms (Algorithm 6) to four directions (up, down, left, right) until they reach the boundary of the house or another room (see example result in Figure 6). The expansion is done in a way that maintains the overall structure and flow of the floor plan while maximising the use of available space. This approach helps to create a more efficient and functional layout, making better use of the available area.

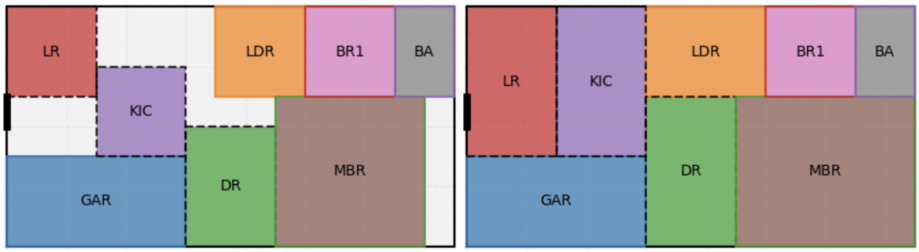


Figure 6: Filling blank areas in the floor plan. The left one is the original final floor plan, and the right one is the floor plan after filling blank areas.

Algorithm 5 : Expand Public Rooms to Fill Blank Areas

Require: House layout with all rooms placed
Define public room types: Kitchen, Living Room, Dining Room
for each room in house **do**
  if room is a public room **then**
    for each direction in [left, right, up, down] **do**
      while room can be expanded by 1 unit in this direction without overlap and still within boundary **do**
        Expand room by 1 unit in this direction
      end while
    end for
  end if
end for

Algorithm 6 : Expand Other Rooms to Fill Blank Areas

Require: House layout with all rooms placed

Define public room types: Kitchen, Living Room, Dining Room
for each room in house **do**
  if room is **not** a public room **then**
    for each direction in [left, right, up, down] **do**
      while room can be expanded by 1 unit in this direction without overlap and still within boundary **do**
        Expand room by 1 unit in this direction
      end while
    end for
  end if
end for

4.2.12 Add windows and doors

After filling the blank areas, I added a post-processing step to place windows and doors in each room. Windows and doors are added according to design criteria and constraints, such as their width and position relative to the rooms and the house. This step enhances the aesthetics and functionality of the floor plan by providing natural light and ventilation. An example of the final floor plan with windows and doors is shown in Figure 7.

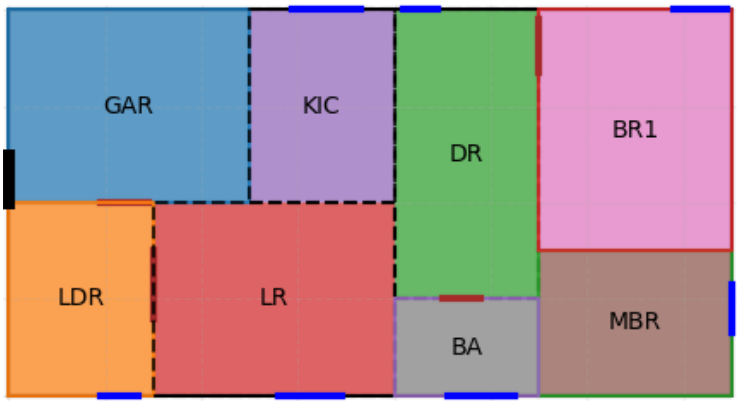


Figure 7: Final floor plan with windows and doors. (Bold blue lines are windows; bold brown lines are doors)

Windows are placed on room sides that face outside, while doors are added to walls between rooms. Both are represented as lines in the floor plan, with properties such as width and position. Importantly, windows and doors are only added after the optimisation process is complete, ensuring they do not interfere with the optimisation of room sizes and positions.

The algorithms for generating windows and doors are shown in Algorithm 7

and Algorithm 8. Window placement is based on exterior-facing walls, and door placement is based on walls between rooms. The width and position of each window and door are randomly determined within allowed ranges, ensuring they fit within the room and meet design constraints.

Algorithm 7 : Generate Windows for Rooms

```
for each room in the house do
    if room is not a garage then
        Initialise empty window list for the room
        Find all sides of the room that face outside
        if there is at least one such side then
            Randomly select one side as the wall for the window
            Randomly determine window width within allowed range and not
            exceed the room size
            Randomly determine window position along the selected wall
            Add window to the room
        end if
    end if
end for
```

Algorithm 8 : Generate Doors for Rooms

```
for each room in the house do
  if room is not kitchen, living room, or dining room then
    Initialise empty door list for the room
    Find all sides of the room that do not face outside and are adjacent to public areas
    if there is at least one such side then
      Randomly select one side as the wall for the door
      Randomly determine door width within allowed range and not exceed the room size
      Randomly determine door position along the selected wall
      Add door to the room
    else
      for each direction do
        if the side does not face outside then
          Add this direction to options
        end if
      end for
      if options is not empty then
        Randomly select one side from options as the wall for the door
        Randomly determine door width and position as above
        Add door to the room
      end if
    end if
  end if
end for
```

5 Experimental Results

5.1 Run same iterations for 3 Algorithm Combinations

To compare the performance of different algorithm combinations, I ran three different algorithms for 30,000 iterations each. The first algorithm is a dual (1+1) EA approach, which uses two (1+1) EAs to optimise room positions and sizes separately. The second algorithm is a PSO-(1+1) EA combination, where PSO optimises room sizes and (1+1) EA optimises room positions. The third algorithm is a PSO-MCTS combination, where PSO optimises room sizes and MCTS optimises room positions.

From the line chart in Figure 8, it can be seen that the fitness value of the floor plan has been improved significantly after about 2000 iterations using PSO-(1+1) EA and dual (1+1) EA, except PSO-MCTS. When running the PSO-MCTS algorithm, the fitness value gets stuck at 2.7, which means it is struggling on reaching an utilisation rate of 0.8. It cannot break through the local optimum even after 30000 iterations.

The PSO-(1+1) EA algorithm attains a fitness value of 16.26 after 30,000

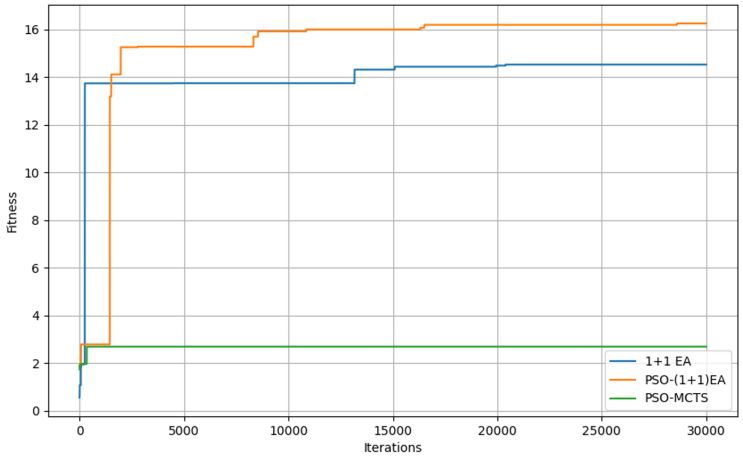


Figure 8: Fitness comparison between 3 Algorithm Combinations.

iterations, whereas the dual (1+1) EA approach surpasses a fitness value of 2.8 in a shorter duration compared to the PSO-based method, and can generate a good-enough floor plan in less than 2000 iterations (Table 2). Consequently, the dual (1+1) EA algorithm is identified as the most effective strategy for floor plan optimisation in this study.

Table 2: Comparison of Execution Time and Best Fitness

Method	**Execution Time**	**Best Fitness**
Dual (1+1) EA	22 min 31 sec	14.53
PSO–(1+1) EA	42 hr 19 min 30 sec	16.26
PSO–MCTS	133 hr 33 min 30 sec	2.7

5.2 Comparison by running same amount of time

To further evaluate the performance and stability of each algorithm, I conducted five independent runs for each of the three algorithm combinations, with each run limited to a maximum execution time of one hour. For each run, the highest fitness value achieved was recorded. The maximum, average, and standard deviation (std) of the best fitness values were then calculated for each algorithm. The results are summarised in Table 3.

These results show that both (1+1) EA-based methods can achieve significantly higher fitness values than PSO-MCTS within the same time limit. However, the standard deviations for the (1+1) EA-based methods are also larger, indicating greater variability in their performance across different runs. In contrast, PSO-MCTS is much more stable but consistently achieves lower fitness values. This suggests that while the (1+1) EA-based approaches are more effec-

Table 3: Statistical Comparison of Algorithm Performance (5 runs, 1 hour per run)

Method	**Max Fitness**	**Average Fitness**	**Std**
Dual (1+1) EA	16.5113	13.2129	5.6406
PSO-(1+1) EA	19.0984	15.4169	6.3322
PSO-MCTS	1.9400	1.9209	0.0112

tive at finding high-quality solutions, their results may be less consistent from run to run.

5.3 Same amount of iterations & One more bedroom

To further evaluate the robustness of three algorithm combinations, I ran each algorithm for up to 1 hour each and recorded the best fitness value achieved.

6 Conclusion

In this thesis, I have presented the progress of my research on optimising residential floor plans using evolutionary algorithms. The research focuses on the representation of floor plans, evaluation of solutions, and the application of evolutionary optimisation techniques. The initial plan was to use a combination of PSO and MCTS algorithms, but due to the limitations of the MCTS algorithm in optimising room positions, I switched to a (1+1) EA approach. The optimisation process has shown promising results, with significant improvements in fitness values after 2000 iterations. The final results indicate that the dual (1+1) EA algorithm is the most effective strategy for floor plan optimisation, achieving a fitness value of 14.53 in 23 minutes. The research has demonstrated the potential of evolutionary algorithms in generating high-quality residential floor plans that meet various design criteria and constraints.

7 Future Work

Future work will focus on further enhancing the optimisation process by exploring additional evolutionary algorithms to improve the quality of the generated floor plans and develop a robust framework for real-world applications.

Planned improvements include:

- Explicitly representing corridors in the floor plan to ensure better connectivity and circulation.
- Incorporating corridors, doors, and windows into the evaluation process, so their placement and properties are considered in the fitness calculation.
- Applying other algorithms, such as simulated annealing and differential evolution, to further explore the solution space and escape local optima.

8 Plagiarism Declaration

I hereby declare that this submission is my own work and to the best of my knowledge, it contains no material previously published or written by another person, except where due to acknowledgement is made. Furthermore, I believe that it contains no material which has been accepted for the award of other degree or diploma in any university or other tertiary institutions.

9 References

[1] A. M. Brintrup, H. Takagi, and J. Ramsden. Evaluation of sequential, multi-objective, and parallel interactive genetic algorithms for multi-objective floor plan optimisation. In F. Rothlauf, J. Branke, S. Cagnoni, E. Costa, C. Cotta, R. Drechsler, E. Lutton, P. Machado, J. H. Moore, J. Romero, G. D. Smith, G. Squillero, and H. Takagi, editors, *Applications of Evolutionary Computing*, pages 586–598, Berlin, Heidelberg, 2006. Springer Berlin Heidelberg.

[2] B. Chaichi and A. Andaji Garmaroodi. Multi-objective optimization of a residential zone by proposing appropriate comfort factors using none dominated sorting genetic algorithm. *Journal of Building Engineering*, 86:108842, 2024.

[3] A. de Almeida, B. Taborda, F. Santos, K. Kwiecinski, and S. Eloy. A genetic algorithm application for automatic layout design of modular residential homes. In *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 002774–002778, 2016.

[4] E. H. Houssein, A. G. Gad, K. Hussain, and P. N. Suganthan. Major advances in particle swarm optimization: Theory, analysis, and application. *Swarm and evolutionary computation*, 63:100868–, 2021.

[5] S. Kang and S. K. Kim. Floor plan optimization for indoor environment based on multimodal data. *The Journal of supercomputing*, 78(2):2724–2743, 2022.

[6] J. Kennedy and R. Eberhart. A discrete binary version of the particle swarm algorithm. In *1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation*, volume 5, pages 4104–4108 vol.5. IEEE, 1997.

[7] G. Laignel, N. Pozin, X. Geffrier, L. Delevaux, F. Brun, and B. Dolla. Floor plan generation through a mixed constraint programming-genetic optimization approach. *Automation in construction*, 123:103491–, 2021.

[8] M. Nisztuk and P. B. Myszkowski. Hybrid evolutionary algorithm applied to automated floor plan generation. *International Journal of Architectural Computing*, 17(3):260–283, 2019.

[9] Y. Shi, K. Xue, L. Song, and C. Qian. Macro placement by wire-mask-guided black-box optimization. In *Proceedings of the 37th International Conference on Neural Information Processing Systems*, NIPS '23, Red Hook, NY, USA, 2023. Curran Associates Inc.

[10] T. Singha, H. Dutta, and M. De. Optimization of floor-planning using genetic algorithm. *Procedia technology*, 4:825–829, 2012.

[11] R. Subramanian, T. DheenaDayalan, T. Badhrirajan, C. Dhinakaran, C. Devakirubai, and R. R. Sudharsan. An automated house plan generator leveraging genetic algorithms. In *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, pages 1–6, 2021.

[12] L. Wang. A hybrid genetic algorithm–neural network strategy for simulation optimization. *Applied Mathematics and Computation*, 170(2):1329–1343, 2005.

[13] T.-K. Wang and W. Duan. Generative design of floor plans of multi-unit residential buildings based on consumer satisfaction and energy performance. *Developments in the Built Environment*, 16:100238, 2023.

[14] S. Yan and N. Liu. Computational design of residential units' floor layout: A heuristic algorithm. *Journal of Building Engineering*, 96:110546, 2024.

[15] M. Zawidzki and J. Szklarski. Multi-objective optimization of the floor plan of a single story family house considering position and orientation. *Advances in engineering software (1992)*, 141:102766–, 2020.

[16] D. Zou, G.-G. Wang, A. K. Sangaiah, and X. Kong. A memory-based simulated annealing algorithm and a new auxiliary function for the fixed-outline floorplanning with soft blocks. *Journal of ambient intelligence and humanized computing*, 15(2):1613–1624, 2024.

A Appendix

A.1 Code

Our code is available on GitHub: https://github.com/ZuxingGit/EvolutionaryOptimisation/blob/main/code/3_optimization/run_pso_mcts.py