THE APPLICATION OF PARTICLE SWARM OPTIMIZATION ALGORITHM TO PLAN REDESIGNS OF RESIDENTIAL COMPLEXES. A CASE STUDY IN THE HIGH-RISE APARTMENT COMPLEX IN MASHHAD, IRAN

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Abstract. The special features of some old residential complexes make reconstructing a better option than rebuilding. The complexity of redesign issues, the ability of computers to solve problems, and the capability of evolutionary optimization techniques in architecture make the use of these methods a priority over traditional processes. This paper, while introducing Particle Swarm Optimization (PSO) as one of the swarm intelligence based algorithms, answers the question of how this algorithm can be used to redesign residential complexes. To achieve this, after reviewing the application of PSO algorithms in architectural space planning, the redesign criteria and constraints was divided into four categories; including primary design specifications, contact-related criteria, designer-related criteria and redesign-related constraints. After the quantification process of these criteria, how to implement the algorithm to achieve optimal plans for each of the five plan types available in high-rise apartment complex in Mashhad, Iran, was shown as a case study.

Key words: evolutionary optimization, particle swarm optimization algorithm, redesign, Mashhad's high-rise apartment complex.

1. Introduction

Optimization is a method to search for the best solution in a particular situation. Many optimization problems, both practical and theoretical, are a search for the best configuration of variables to achieve the goals of a problem (Blum and Roli, 2003). When rebuilding residential complexes, the designer encounters a complex set of variables that must be considered in the design process, leading to difficult decision-making. Along with the ability of algorithms to solve complex problems, the use of optimization algorithms, while providing the best or nearest best solution, is an efficient way to avoid removing possibly correct solutions from the design decision cycle.

Evolutionary algorithms, and especially swarm intelligence algorithms, are less developed in architecture than other sciences. There are limited examples of architectural designs based on swarm intelligence and even less examples of it in architectural redesign. Despite the numerous advantages of algorithms in complex designs, in the case of multi-problem combinations, the extensive expansion of search space can be a difficult test for evaluating the algorithms' search capability (Li, 2012).

This research examines how to use PSO algorithms, how to quantify design problems, and how to effectively control the search space dimension as three important subjects in the architectural optimization of redesigning High-rise apartments complex in Mashhad.

1.1. Necessity of redesign

People need healthy and efficient buildings in order to adapt to the natural environment. Buildings will decay throughout their lives and if not properly maintained, will cause problems for the community around them and its health (Jensen and Maslesa, 2015). Buildings also become less efficient over time due to changing user needs. Maintenance, repair and renovation (MR&R) activities can reduce this risk if properly planned and invested in (Grussing and Liu, 2014).

Reconstruction of a building is the process of repairing or replacing existing parts of the building for the purpose of improving their performance by restoring them to an earlier state or adjusting the current one (Ástmarsson *et al.*, 2013); this enables the design and layout of the buildings to be modified to suit current or future user needs. The reconstruction strategy should significantly provide building flexibility to realize functional changes, changes in the systems' capability, and changes in people's lifestyles with existing facilities (Slaughter, 2001). Improving the design of a building through reconstruction should not only be a financial issue, but also a matter of creating added value and better environmental conditions (Jensen and Maslesa, 2015).

The increasing need to reduce fossil fuel usage and greenhouse gas and carbon dioxide emission to avoid serious future climate impacts, increasing energy prices, and focus on sustainability are major reasons for building reconstruction. In addition, due to the high cost of building new complexes in large cities, the scarcity of buildable land in suitable locations and in particular the historical importance of maintaining some Residential complexes and the memory the people have of them, high quality residential complex reconstruction can be a good solution compared to rebuilding them (Alekhin *et al.*, 2018).

1.2. Optimization algorithms

Generally, optimization algorithms are divided into three categories: Deterministic, Heuristic and Metaheuristic algorithms.

When the algorithm's evolutionary process is not accidental and the algorithm starts from and reaches a certain point, the method is called a Deterministic algorithm (Yang and Karamanoglu, 2013).

A Heuristic algorithm gathers system information, tests for random solutions, and decides on generating the next one; therefore, these methods depend on the nature of the problem (Datta *et al.*, 2019). Thus, this algorithm is designed to find a near optimal solution (Hansen *et al.*, 2010).

Metaheuristic algorithms efficiently combine the objective function and the heuristics without depending on the problem's structure (Datta *et al.*, 2019). They are high-level strategies to guide heuristics in search spaces to increase their performance (Blum and Roli, 2003). Three of the main metaheuristic algorithms are described in the following paragraphs.

1.2.1. Evolutionary computation (EC) algorithms

Evolutionary computation methods are a general approach to solving optimization problems; usually using the objective function in an abstract and efficient way considering its mathematical properties and without any deeper insights. These techniques can solve non-convex, nonlinear, and multi-dimensional problems with linear or nonlinear constraints with continuous or discrete variables (Cuevas *et al.*, 2019). This algorithm has many variants, the most common being the genetic algorithm based on the rules of biological evolution (Rodrigues *et al.*, 2013).

1.2.2. Physics-based Algorithms

These algorithms are physics-inspired optimization techniques; such as simulated annealing, external optimization, river formation dynamic, and intelligent water drops algorithms (Datta *et al.*, 2019).

1.2.3. Swarm intelligence (SI) algorithms

The collective intelligence algorithm approach is inspired by humans' scientific understanding of biological, natural, or social systems that at some level of abstraction can be referred to as optimization processes (Cuevas *et al.*, 2019). Collective intelligence is a part of evolutionary calculations that examines the social behavior of natural or artificial decentralized and self-organized systems (Zhang *et al.*, 2015). Such methods are based on the social interactions and behavior of different bird and fish classifications and include various types, such as ant colony optimization (ACO) and Particle Swarm Optimization (PSO) (Dorigo and Stützle, 2019).

1.2.3.1. Particle swarm optimization

Dr. Russell C. Eberhart, an electronics engineer, along with Dr. James Kennedy, a social science psychologist, invented a random optimization method in 1995, which was later named Particle Swarm Optimization. A PSO algorithm is based on a kind of biological system in which the collective behaviors of individuals interact with each other and the environment and form the optimization process. These algorithms, inspired by natural flock and swarm biotic life, use a similar approach to find the optimal solution to the problem in the search space; such as a bird finding its' most suitable place in a flock or as an insect does in a swarm.

Unlike other evolutionary algorithms, the PSO algorithm does not implement the policy of the survival of the fittest. In it, the particles change the situation under the influence of three factors: its own inertia, personal most optimal position and the swarm's most optimal position. There are no selective operations in this algorithm and as a result all particles are preserved during the search process. The position and velocity of each particle in each iteration is updated according to their personal most optimal position and the swarm's most optimal position (Juneja and Nagar, 2016).

Fitness Function: The fitness function is used to determine the performance of a solution that includes several different goals. It determines the quality of one solution over the rest of the population (Liu *et al.*, 2019).

Particle best position is the best amount of the fitness function that each particle has achieved and saved up to this point and is displayed with "pBest". The global best position is the best amount of the fitness function in the evolving particle set and is represented by "gBest".

Velocity: The rate and direction of motion that the variables of each particle should make to approach the particle best position or the global best position and to search for more appropriate solutions, is called the "velocity of the particle". In the classical PSO algorithm, each particle has its own position (x_t) and velocity (v_t), which is initially randomly assigned to it; In each iteration, the position and velocity of the particle, which depends on the extent of the objective function evaluation in the problem, are updated (Li *et al.*, 2018). As shown in Eq. 1, velocity determines the amount and method of how the particle changes to get closer to the optimal result. The influential parameters in defining the velocity of the particle in each step (v_{t+1}) is as follows: 1 - particle inertia (current velocity * inertial weight), 2 - particle difference from pBest * pBest weight, 3-particle difference from gBest * gBest weight (Barrera *et al.*, 2016).

$$v_{t+1} = \omega v_t + r_1 c_1 (pBest - x_t) + r_2 c_2 (gBest - x_t) \quad \mathbf{(1)}$$

According to Fig. 1 implementation of PSO algorithm has the following steps:

1. A number of solutions are randomly generated and considered as the initial particles to start the algorithm. The number of these particles is considered variable depending on the type of project. In research based on the PSO algorithm, no precise recommendations and guidance on particle numbers have been provided; most researchers have used 10 to 50 particles (Sowmya and Mp, 2013). The number of particles can depend on the experience and experiments of the algorithm designer and the problem type. According to Shi and Eberhart, population size rarely has an impact on the performance of the algorithmic approach (Shi and Eberhart, 1998).
2. In each iteration of the algorithm's search, the values of the particle best position and the global best position are estimated. If a better solution is discovered by the algorithm, the appropriate velocity to change (the variables of the) particles is determined according to the above parameters.
3. In each iteration, the particles change according to the velocity set to achieve a better solution.
4. The search is repeated until the appropriate result (the value specified for the fitness function) is obtained.

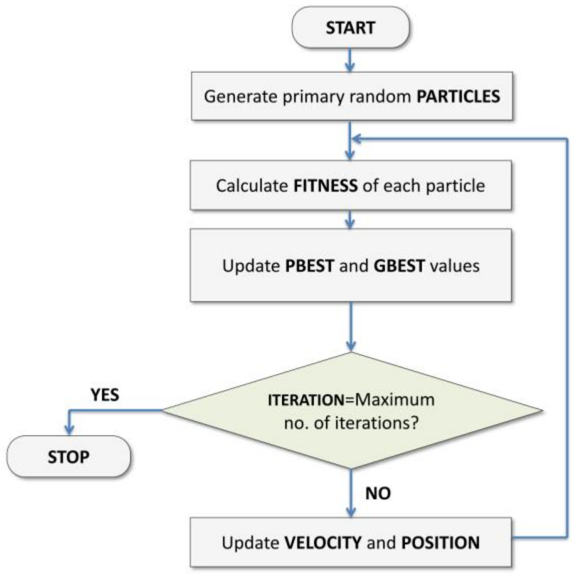

Fig. 1. Flowchart of PSO algorithm.

1.3. Optimization in residential complexes redesign

The subject of redesign and reconstruction, especially in residential complexes with large numbers of residents, usually face a diverse set of contacts views, constraints due to the former structure of the complex, the designer's view as the final decision maker, and different rules. Reconstruction of a building usually responds to several of the building’s challenges at a time, and the complexity of these challenges often requires interdisciplinary expertise (Jensen and Maslesa, 2015). Therefore, due to the large number of variables, it is either impossible or extremely difficult to achieve near optimal conditions using traditional design methods to address these issues; as what humans have in creativity, they lose in repetitive work and are prone to error. Unlike humans, machines are capable of performing repetitive tasks without fatigue and error; but the goal is not to replace the architects’ innovation with computer efficiency, but to use this tool for repetitive tasks in complex applications (Rodrigues *et al.*, 2013).

Given the importance of residential complexes’ residents' satisfaction with their living space and a large number of users being harmed in the event of a design error, the use of evolutionary optimization techniques, that can cover many variables on different scales -from the complex’s site plan design to the details, in space design has many benefits.

Advances in design computing tools in conjunction with artificial intelligence have led to the possibility of computers fully interacting with the design process. Nowadays, due to the wide range of variables affecting the design, the computer is used as a generating tool that investigates the search space for a high-performance solution to the problem, while no possible solutions are eliminated in the design process. In this method, the computer automatically generates and evaluates possible options and gives the designer the optimal or near-optimal solutions (Caldas and Norford, 2002). Metaheuristic optimization algorithms have the potential to give the user a deeper insight while designing spaces and to lead to a creative design by maintaining a balanced amount of convergence and divergence (Dino and Üçoluk, 2017).

2. Literature review of PSO Algorithm application in designing or redesigning architectural plans

The use of evolutionary computing for space plan designing in architecture began in the 1990s and has gained popularity in recent years (Dutta and Sarthak, 2011). However, due to the large number of these studies, different researches have been reviewing and categorizing these studies for different purposes at different times since the year 2000, as can be seen in Table 1.

As Zhang's study in 2015 points out, the number of publications per year regarding PSO is higher than the other seven swarm intelligence based algorithms; this indicates that this algorithm is the most common algorithm in this group and the basis of many changes in swarm intelligence algorithms (Cichock *et al.*, 2017). The PSO algorithm is mainly used in eight fields; electrical and electronic engineering, automation control systems, communication theory, operations research, mechanical engineering, fuel and energy, medicine, chemistry and biology (Zhang *et al.*, 2015). It has also been used in energy research and some cases of building structures since around 2004.

Table 1. Distribution of questionnaires among blocks and plan types in high-rise apartment complex.

publication Year	Author(s)	research purposes
2000	Liggett	• It is one of the first studies to investigate the approach of using evolutionary computation algorithms for the problem of architectural space plan design (Liggett, 2000).
2004	Homayouni	• This reserch outlined the different computational approaches adopted for space layout planning (Homayouni, 2007).
2009	Gen and Lin	• They explored the application of evolutionary computation methods in the design of architectural plans (Gen and Lin, 2009).
2011	Dutta and Sarthak	• Reserchers explored the use of evolutionary computing algorithms in architectural space plan design. • they presented different results such as the great use of genetic algorithms and the non-commercialization of past researchers. • In their view, evolutionary approaches with improved models can be effectively applied to optimize the spatial plans in future architecture (Rodrigues *et al*., 2013).
2013	Rodrigues *et al*.	• They proposed six different approaches based on the type of space alignment problem. • These approaches include Area assignment, Area partitioning, Space allocation, Hierarchical construction, Conceptual exploration, and Design adaptation (Rodrigues et al., 2013).
2015	Calixto and Celani	• Reserchers concluded that the development of evolutionary computing in recent years hasn't had a significant impact on the development of space planning issues in architecture. • They stated taht new algorithms are needed to optimize processing time in order to increase the number of elements in space layouts (Calixto and Celani, 2015).
2018	Du *et al*.	• They investigated Automatic Generation of Architectural Space Layouts with Energy Performance Optimization (Du *et al*., 2018).

Despite the efficiency of this algorithm for planning in dynamic and complex space environments (Nandanwar *et al*., 2016) and despite the high speed and quality of solutions to the design problem, review of the studies done in these years shows that shows that Although research on how to use evolutionary computation algorithms in the design of spatial architectural planning has been carried out, none of the reviewed researches on architectural design, particularly those on spatial plan design, have used swarm intelligence based algorithms as the base algorithm for optimization.

In previous research, despite the use of evolutionary computing algorithms in plan design, no sample was found for plan redesign. The subject of plan redesign, in terms of paying more attention to the audience and limitations such as static spaces and the impact of columns, is different from the subject of design. This study investigates and applies the Particle Swarm Optimization Algorithm in the redesign of the spatial architectural planning of a residential complex as a case study.

3. Research questions

Being nearly half a century old has made the complex incompatible with the current residential needs of the residents, and the deterioration of materials and installations has created an inappropriate visual effect in addition to functional problems. At the scale of the complex, the high population of the residents, the low socializability of the complex, and unused spaces have caused inefficiency and resident dissatisfaction. Thus, on the one hand, the valuable architectural features of the complex create a sense of identity and belonging to the inhabitants, and on the other hand, the spatial inefficiency that is not taken seriously due to the high cost of rebuilding and constraints on residential complexes reconstruction is causing discontent among residents. Observing the complex's residential spaces shows that many residents have made interventions such as changing the dimensions, positions, space usages and adding or removing some spaces in their residential special plan. Therefore, among different optimization applications in architecture, spatial plan optimization of the residential units of High-rise apartment complex in Mashhad was considered. Therefore, the main question of this research is how to apply the PSO algorithm in redesigning architectural spatial systems, in particular in the Mashhad's High-rise apartment complex.

In order to answer this question, it is necessary to determine: 1. What are the criteria and limitations of space system optimization when redesigning residential complexes? 2. What is the process of quantification of these criteria? 3. How is the algorithm implemented to achieve optimal plans?

4. Research method

4.1. Introduction of research area

Mashhad City is considered Iran's second metropolitan, the world's second religious metropolitan and the largest population centre of Eastern Iran. The city is the capital of Khorasan Razawi province and has a population of 2,772,287. The city is located at 36.20º North latitude and 59.35º East longitude, in the Valley of Kashaf River. The city has 13 urban districts, 30,000 hectares in total. As one of the oldest and historical regions of the Great Khorasan Province and Old Toos, Metropolitan Mashhad has historical-political, economic-administrative and cultural-intellectual centrality and religious function. It bears the title of the second religious city of the Islamic world and the second national metropolitan in terms of population (Zanganeh *et al.*, 2013; Mirkatouli *et al.*, 2018). Mashhad city's high rise building had thrived before the revolution and in the early 1970s with residential apartments including construction of Highrise apartment complex or 550 units and 600 appurtenances apartments (Ajza Shokouhi *et al.*, 2018).

High-rise apartment complex, as the first high-rise residential complex in Mashhad, being even named as such at the time, was selected as case study. This complex was designed by Dr. Ali Adibi's Consulting Engineering Company, which is an Iranian firm, and was built by two main Iranian civil engineering consulting companies of the time; Navid and Mahsaz (Talebian and Özmen, 2019). with the collaboration of two Italian and French companies as well. The construction of the 1650-unit complex, intended for the university's professors at the time, began in 1973 and stopped in 1979 due to the victory of the Revolution; only one part of the main complex with 550 units was completed and opened after the Revolution. The project was originally constructed out of the city borders. Over time, the city has expanded from the old city center around the Imam Reza Shrine towards the North-East. Therefore, High-rise apartment complex is now located in the new center of the city (Talebian and Özmen, 2019). The blocks of the complex are shaped as three interconnected square rectangular cubes.

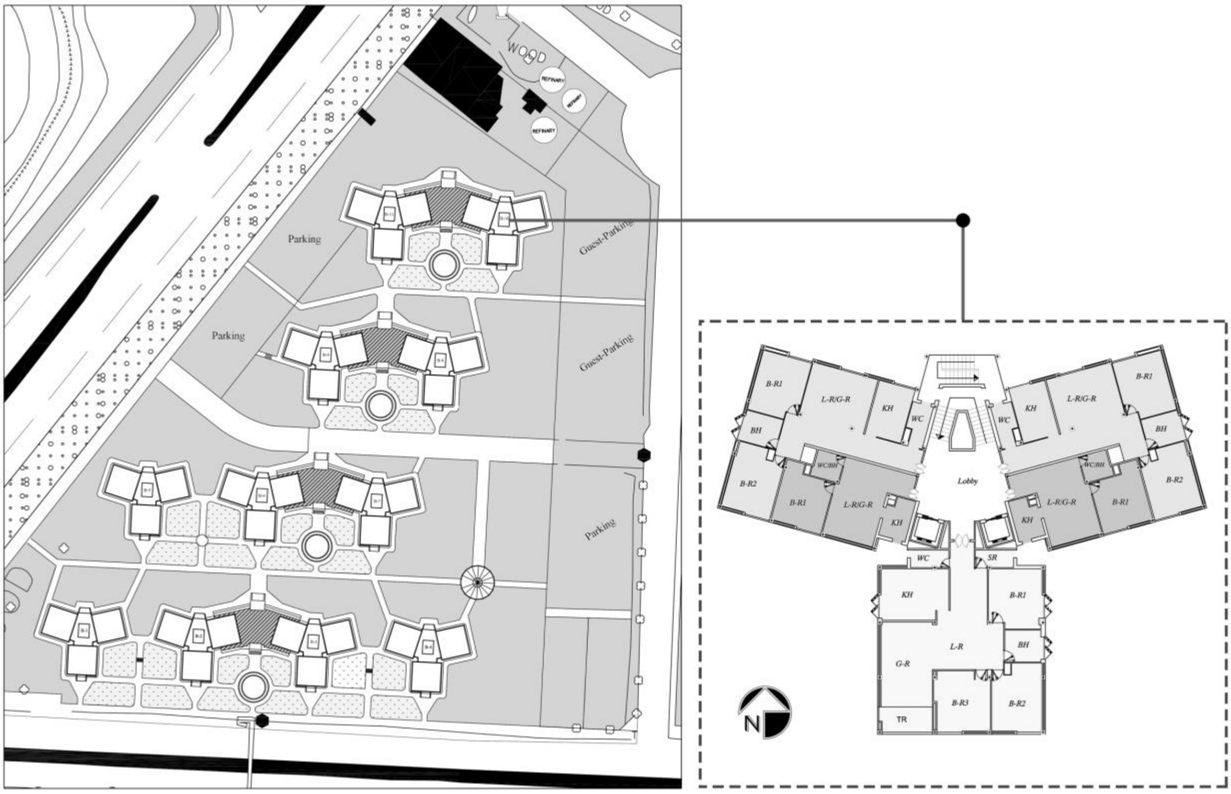

Fig. 2. High-rise apartment complex site plan and current plan of the blocks.

The complex has 11 blocks with each having pilot and 10 residential floors. Each residential floor is 520 m2 and consists of a 3-bedroom apartment, two 2-bedroom apartments and two 1- bedroom apartments (Fig. 2). As such, each block has 50 apartments, which, given the similarity of the blocks to each other, all have one of five plan types. The blocks are oriented to the south, built in four parallel rows with a distance of 20 meters, the distance of two adjacent blocks in each row being about 13 m. The non-residential uses of the complex include commercial, office, religious and green spaces that are on the ground floor and protected from the surrounding environment.

4.1.1. Selecting Mashhad's high-rise apartment complex

Housing is considered as one of the most important needs of human life. It may be asserted that housing problems are globally widespread. However, in developing countries, this problem has become critical because of rapid population and urbanization growth, internal immigrations, lack of sufficient financial resources, problems regarding land supply, construction materials supply, lack of specialized human forces, and most importantly, lack of proper policies and planning concerning land and housing. As one of the developing countries, Iran is not an exception in this regard. Today, housing and its related issues have become a global problem; different countries' planners and policy makers are struggling to solve the problems concerning the issue. Therefore, in metropolitans like Mashhad, as the second population and commercial core of the country and a historical and cultural center on the national and international scale, which has always encountered high population growth rates, settlement and living conditions in urban neighborhoods have been inconsistent with urban sustainable development criteria (Zanganeh *et al.*, 2013). Mass-housing projects are forming the urban morphology of suburbs in metropolises, especially in developing countries, which are struggling with housing shortages (Talebian and Özmen, 2019).

Reconstruction and in some cases redesigning old residential complexes with good construction quality and high resident capacity can be one of the ways to control city expansion and to create new complexes on the outskirts of cities like Mashhad. Among the existing residential complexes in the city, the High-rise residential apartment complex, as the first high-rise residential complex in Mashhad, was selected as the case study.

In terms of the importance of its preservation and reconstruction, the memory the people of Mashhad have of this complex can be stated as one of the reasons for choosing it; as this complex was regarded as one of the symbols of Mashhad for many years due to the architectural features, height and facilities considered for it. The results of a study on four housing complexes in the city of Mashhad have demonstrated the highest level of social participation, place attachment, sense of belonging and feeling of security in the case of the High-rise apartment complex. The complex is now located in the heart of the city and is connected to the city's main axes; residents prefer to live in an old apartment in the wealthy parts of the city rather than move into a newer or bigger house in the suburbs. Plan types ranging from 1 to 3 bedrooms offer the opportunity of moving to smaller or bigger units within the complex, without changing the neighborhood.

However, Iranian houses have changed fast in recent decades. These changes are the result of people's changing lifestyles, communication methods, and needs over time. This is one of the reasons that the High-rise apartment Complex has transformed from a modern complex to an old block of apartments in the center of the city. However, this is not the only transformation, various transformations have occurred during the long life of the complex; namely the social class transformation of the residents, the transformation of the religious beliefs after the Islamic revolution, the urban transformation of the context from the suburbs to the town center, the gardens surrounding the complex transforming into shopping malls, the luxurious character of the complex transforming into an old residential for the elderly, and the physical appearance of the complex changing to an outdated façade (Talebian and Özmen, 2019).

Therefore, despite the need to preserve this complex in terms of its symbolic Features, due to it being the first high-rise building in Mashhad as well as the sense of belonging the residents have towards it, the necessity of redesigning it according to the new needs and lifestyle of the residents is significant. One of the most important areas affected during these changes is the spatial architectural planning.

The focus of this study is to redesign the spatial architectural plan based on the PSO algorithm implementation method. the large number of residential units (550 units) and consequently a variety of plans (5 plan types) in this complex, compared to other residential complexes more than 50 years old in Mashhad, is one of the reasons for choosing this complex to apply the redesign of the optimized plans using the algorithm implemented in this study; since the physical constraints and criteria desired by different residents in each plan type can provide a comprehensive assessment of the methodology implemented for the five different plans simultaneously.

4.1.2. Selecting the statistical population for the distribution of questionnaires

As in clause 4.2.2.3, one of the key criteria for redesigning residential complexes is the criteria and limitations that will result from the review of the contacts' opinions, as end users of the design. The current residents of High-rise apartment complex have been considered the target contacts for the design.

In order to find the optimal values in the selected criteria, 250 questionnaires were prepared to obtain information about half of the 550 residential units and were given to two trained colleagues to visit the complex. Due to management disallowance and the residents' dissatisfaction with the door-to-door distribution of the questionnaire, they were distributed in the apartment's open spaces and other public spaces. Given the high average age of these individuals and the inability and reluctance to cooperate by some of them, as well a number of units being vacant, after numerous visits at different times of the day and in some cases, with the help of virtual networks, finally 183 questionnaires - equivalent to one third of the population - were collected. To consider all mature age groups, questionnaires were distributed among residents aged from 12 to 81. Table 2 shows the distribution of questionnaires among blocks and units. Considered Parameters in the questionnaire, in addition to questions based on residential and demographic characteristics, included 4 categories of preferences related to the area of each unit's spaces, spaces' proximity, the daylighting of units' spaces and the listing of new spaces in each unit. After entering the collected data into IBM SPSS Statistics: Version 22 software and preparing a Data Document with 105 variables (questions) and 183 rows (number of questionnaires), the statistical data related to these four categories were prepared for each of the five plan types in the complex and analyzed separately for each type using the weighted average of the answers given to the response options, finally determining the criteria influencing the design from the viewpoint of the contacts.

Table 2. Distribution of questionnaires among blocks and plan types in high-rise apartment complex.

Plan type	**Block number**											**Total**
	1	2	3	4	5	6	7	8	9	10	11	
Eastern 2-bedroom	4	3	6	4	3	7	4	4	4	2	3	44
Eastern 1-bedroom	3	3	4	4	5	3	2	3	2	5	4	38
Western 2-bedroom	2	2	1	6	6	5	3	7	2	5	3	42
Western 1-bedroom	3	4	5	2	4	3	5	2	5	2	2	37
3-bedroom	3	3	2	1	1	1	3	1	1	3	3	22
Total	15	15	18	17	19	19	17	17	14	17	15	183

4.2. How to apply PSO algorithm in plan redesign

According to Karlen in his book "Space Planning Basics", architectural space planning includes the following activities (Karlen, 2009):

5. *Input data*: user requirements, basic data (mechanical, electrical and communication related services), contextual data (architectural, historical and social) and various standards.
6. *Data preprocessing*: Summary of useful and quantified factors including square meters, equipment size, communication points and etc.

7. Researching the unknown: gathering case study information on different matters
8. *Data analysis*: discovering various relationships including: working interrelationships, public and private zoning, special acoustic needs, etc.
9. *Interpreting and Charting Data* (Dutta and Sarthak, 2011).

Consistent with this classification, the application of PSO algorithm in plan redesign can be described in three general steps:

1. Determining the problem's goals, criteria, and effective limitations.
2. Quantifying the criteria and constraints.
3. Determining the fitness function and implementation of the algorithm.

4.2.1. Determining the problem's goals, criteria and the effective limitations

Bryan Lawson presented client opinions, user needs, Legislator requirements, and designer approach as the four main generators of a design problem and explained that each limitation helps define the problem (Lawson, 1980).

In this study, considering the issue of the redesigning being done specifically and the absence of an individual or organization as an employer, the "employer comments" are eliminated from Lawson's four proposed categories. Since when redesigning we are faced with restrictions due to the previous structure of the design, that do not exist in the design subject, to define the spatial architectural planning problem more precisely, a category named Redesign Criteria and Restrictions was added to this categorization and the redesign criteria and constraints were classified into four parts to find the best combination (Fig. 3).

1. *Primary Criteria and Limitations*: This category includes the main inputs of the problem as externally applied restrictions to the design, such as the legal requirements of land ownership territories or the architectural requirements relating to the legislative instruments. Due to the fact that some of these requirements are fixed in the redesign problem and others being included in the designers criteria (such as observing the minimum area of some spaces), In this study, each owner's occupied area and the list of spaces defined for each unit are considered as the primary constraints in the problem definition.
2. *Designer's Criteria and Limitations*: A set of criteria are constraints that are applied by the designer, based on their expertise or in accordance to design standards, as a problem input to the algorithm so that the algorithm can achieve the speed and quality required for finding the best solutions.
3. *Contact (client and users) criteria and Limitations*: This group is the criteria that the designer uses to correctly understand the design problem; by receiving the needs of the user or the client's views, who are usually not familiar with architectural design methods and merely convey their opinions, and applying them to the algorithm. Following these criteria will have a significant role in the satisfaction of these groups with the final design. In the case study, these criteria, given the search for a common answer for each plan type, are determined based on the views of all the complex's residents as users of the designed space by using the results of the questionnaires distributed among them. According to the designer, the steps presented in this method can be implemented in the same way with different audiences, at different scales of the complex's blocks, similar levels in different blocks, or even single units. Obviously, the results vary with the

change of audience in each implementation of the algorithm.

4. *Redesign Criteria and Limitations*: The previous structure of the plan in the redesign process poses limitations for the designer. The most important of these factors are the former structure (column positions) of the building and the location of the installation spaces, which due to the impossible or costly structural changes, these redesign restrictions are considered in the problem definition as column positions and non-movable spaces variables.

4.2.2. Quantification of criteria

There are many complexities in trying to optimize architectural problems with evolutionary algorithms, when the designer tries to optimize the design problems with the help of algorithms, he encounters some inherent complexities in architectural designs, and has to convert specific problems to combination or numerical ones to be identifiable by the algorithm (Li, 2012). Therefore, each of the micro-subjects in Section 4.2.1 requires quantification to be usable in the algorithm. The redesign criteria of the plan are converted into quantities as follows:

4.2.2.1. Primary criteria and limitations

4.2.2.1.1. Boundary of the building unit

Eq. 2 Determines the boundary of the unit ($Boundary_i$) means determining the length and width of the rectangle enclosing the spaces. The overall range of planes inside this rectangle can be rectangular or a combination of several rectangles. As illustrated in Fig. 4, due to the Various shapes of the 5 plan types studied, the whole of each plan is enclosed in a rectangle and remaining spaces -as spaces with fixed size and location- are considered in the plan to achieve the main boundary of the building unit; finally, to simplify the equations, a rectangular is introduced to the algorithm as the total space for particle production.

$$Boundary_i = \{X_i, Y_i, Width_i, Height_i\} \qquad (2)$$

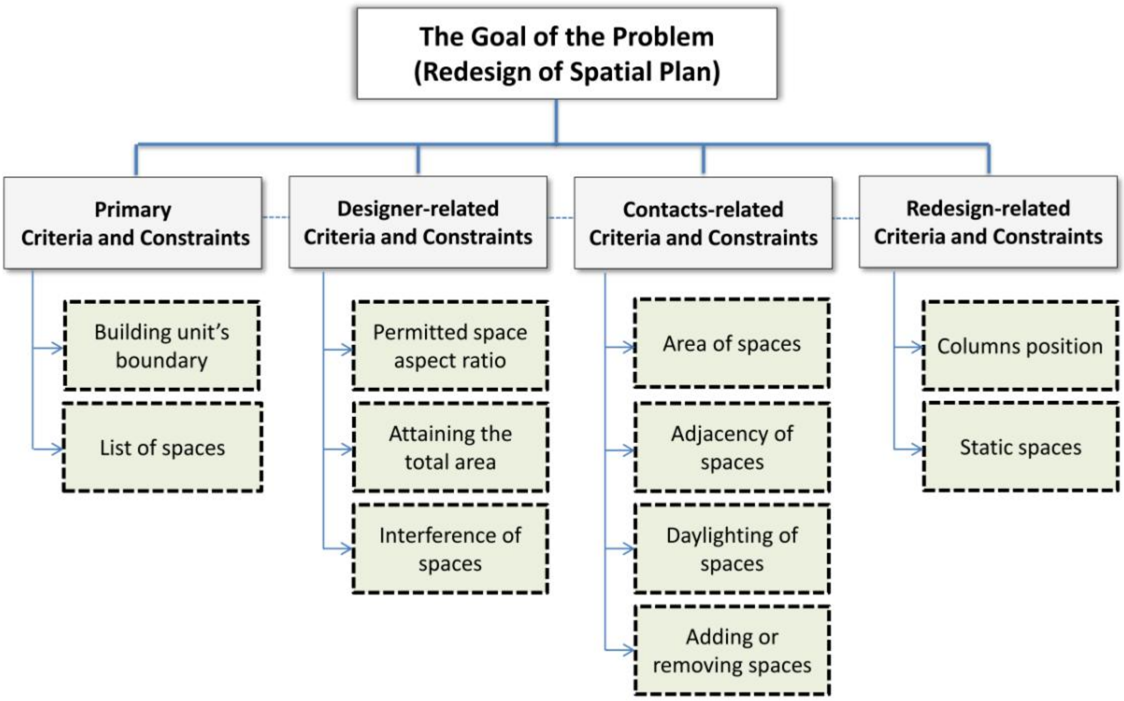

Fig. 3. Problem goals, criteria, and limitations affecting plan redesign.

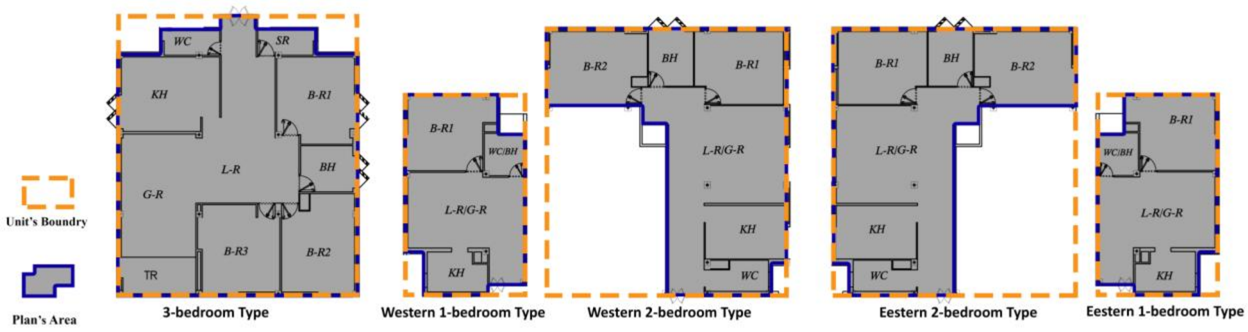

Fig. 4. Determination of building unit's boundary in the 5 plan types.

4.2.2.1.2. List of spaces

In the discussion of input data, except for approaches inspired by biological morphology principles, each space is treated as a rectangular (Rodrigues *et al.*, 2013). if the production of convex spaces (such as the L-shape) is needed, two rectangles can be assigned to a space with definite adjacency as the condition.

As shown in Eq. 3, each space ($Space_i$) can be defined and implemented as arrays with 4 variables: latitude and longitude and length and width in the algorithm. A set of these arrays at the building unit's general boundary can be a solution to the problem of defining plan characteristics at the site.

$$Space_i = \{X_i, Y_i, Width_i, Height_i\} \tag{3}$$

The list of spaces in each of the five plan types of the case study varies according to their area and consists of 3 categories of 3, 2 and 1-bedroom plans that differ in some other spaces besides the number of bedrooms as well.

4.2.2.2. Designer criteria and limitations

4.2.2.2.1. Permitted aspect ratio of spaces

In determining the aspect ratio of spaces (Asp_i), each designer, based on their expertise and design standards, considers a range of a to 1/a (min Asp_i, max Asp_i) as the permitted range of the aspect ratio that allows the length and width or orientation of spaces to be changed in the plan. Fines for the algorithm are penalized if any space violates this range. The amount of penalties applied will bring the solution closer to the permissible aspect ratio. How to quantify the aspect ratio along with the Permitted Area of Spaces is described in Section 4.2.2.3.1.

4.2.2.2.2. Attaining the total area

In order to cover the unit boundary and to attain the total area, the difference of the total area of the building unit's boundary ($S_{Boundry}$) should be evaluated with the sum of various spaces' area ($S_{Space(i)}$) in Eq. 4 and the degree of sensitivity to the full coverage of the boundaries by the designer should be specified. This value ($\Delta s_{allowed}$) can be set to zero. As seen in Eq. 5, area differences ($\Delta S_{Difference}$) with the permitted area specifies the amount of total area difference (ΔS_{Total}) in the fitness function. In some cases, it can be set to slightly more than zero to ignore some differences and ultimately find more solutions.

$$\Delta S_{Difference} = \left| S_{Boundry} - \sum_{i=1}^{n} S_{Space(i)} \right| \tag{4}$$

$$\Delta S_{Total} = \left| \Delta S_{Difference} - \Delta S_{Allowed} \right| \tag{5}$$

4.2.2.2.3. Interference rates of spaces

The amount of space interference ($Interference_{(i,j)}$) is assigning a portion of the entire building unit's boundary to two spaces, which is measurable in single particle spaces in each iteration. This value should be set to zero or close to zero depending on the designer. Interfering with the condition of attaining the precise building unit area causes distance between the spaces. The sum of the interfaces between spaces defines the total interference parameter ($Interference_{Total}$) in the fitness function. In Eq. 6 and Eq. 7, the interference of two spaces and the total interference calculation of the particle in each iteration of the implemented algorithm are mentioned.

$$\mathrm{Interference}_{(i,j)} = \max\left(0, \begin{pmatrix} \min(\mathrm{right}_i, \mathrm{right}_j) - \\ \max(\mathrm{Left}_i, \mathrm{Left}_j) \end{pmatrix}\right) * \max(0, (\min(\mathrm{Bottom}_i, \mathrm{Bottom}_j)) - \max(\mathrm{Top}_i, \mathrm{Top}_j)) \quad (6)$$

$$Interference_{Total} = \sum_{i=1}^{n} \sum_{j=i+1}^{n} Interference_{(i,j)} \quad (7)$$

4.2.2.3. Contacts (client and users) criteria and limitations

4.2.2.3.1. Permitted area of spaces

To further the contact understands about required space areas, a separate set of questions was compiled for each space based on comparisons with the current areas. For example, Table 3 shows the question results for the kitchen space. To determine the contact's desired area (S_c) for $Space_{(i)}$ with the current area of S_i, to find the total coefficient of area variation v_i, the data in Table 4 are analyzed according to Eq. 8 and Eq. 9. α defined by the designer, determines the rate of change compared to the original area.

$$v_i = \sum_{j=-2}^{2} j * n_j / n_{Total} \quad (8)$$

$$S_c = S_i + (v_i * (\alpha * S_i)) \quad (9)$$

To avoid reducing the algorithm's efficiency and limitation of the search space, the exact space areas are not specified and introduced to the algorithm as permitted minimum and maximum values ($\max S_c, \min S_c$) in Eq. 10 and Eq. 11. As in the sample from a western 1-bedroom unit in the case study (Table 5), the areas for each space are determined by analyzing the questionnaire results and adhering to the standards considered by the designer. β is the value of variation coefficient relative to the specified area to determine the minimum and maximum permissible area for each space in accordance with the designer's opinion; such that the minimum and maximum space area is between 0 and the total building unit area.

$$\min\ S_c = \max(S_c - \beta * S_c, 0) \quad (10)$$

$$\max\ S_c = \min(S_c + \beta * S_c, S_{Total}) \quad (11)$$

The area of each space (S_a) can change in different iterations of the implemented algorithm. The penalty amount or area interval and space aspect ratio differences ($\Delta SRange_i$) are estimated according to Eq. 13 and as shown in Eq. 12, the sum of these penalties in different spaces specifies the total area difference ($\Delta SRange_{Total}$) in the fitness function. γ_1 And γ_2 are the amounts of penalties applied in each of the specified area states.

4.2.2.3.2. Adjacency of spaces

In the problem of solving architectural plan relationships, the best method for modeling and coding the different states of space placement is to use graph theory and the adjacency matrix (Golabchi *et al.*, 2012).

In order to determine the proper adjacency matrix from the residents' point of view, they were asked a number of rating questions with a five score scale on the adjacency of each two spaces (Table 6), and their results were determined by the separation of the type of unit analyzed and each units' spaces' adjacency coefficients according to Eq. 14 and Table 7 on a scale of -2 to +2.

$$M_{(i,j)} = round\left(\sum_{m=-2}^{2} m * n_m / n_{Total}\right) \quad \textbf{(14)}$$

The designer applies coefficients -3 and +3 according to existing standards to the proximity of some spaces, which in the process of applying the algorithm is considered as non-adjacency or definitive adjacency.

After determining the adjacency coefficient $M_{(i,j)}$ for each two spaces in a unit, an adjacency matrix is formed for the spaces of that unit type (Table 8).

Table 3. Sample data of the target contact's preference for the kitchen area.

Plan type	The area of our kitchen in my opinion					**Total**
	Very low	Low	Suitable	High	Very High	
Eastern 2-bedroom	1	8	32	3	0	44
Eastern 1-bedroom	13	16	6	3	0	38
Western 2-bedroom	2	16	21	2	0	41
Western 1-bedroom	20	8	5	4	0	37
3-bedroom	0	2	16	4	0	22
Total	36	50	80	16	0	182

Table 4. Model developed for the numerical calculations of permitted dimensions.

Question	How is The current area of $Space_{(i)}$ in your opinion?				
answer	Very High	High	Suitable	Low	Very low
Coefficient of variation ($v_{(i)}$)	-2	-1	0	+1	+2
Selection amount from n_{Total}	n_{-2}	n_{-1}	n_0	n_1	n_2

Table 5. Data analysis table to determine the areas of a western one-bedroom unit's spaces.

	Spaces List	Current Area (S_i)	Coefficient Of variation(v_i)	Contacts Area (S_c)	Minimum Area (min S_c)	Maximum Area (max S_c)
Western 1-bedroom	Kitchen	5.80	1.19	8.56	6.85	10.27
	Living room	22.00	0.13	23.14	18.52	27.76
	Bedroom	16.00	0.29	17.85	14.27	21.42
	Bath	2.30	0.30	2.57	2.05	3.08
	Toilet	2.30	0.30	2.57	2.05	3.08
	Terrace	0	1.72	3.88	0	4.65
	Entrance	3.10	0.35	3.53	2.82	4.23
	Total	**51.50**			**β=0.2**	**α=0.4**

$$\Delta SRange_{Total} = \sum_{i=1}^{n} \Delta SRange_i \quad \textbf{(12)}$$

$$\Delta SRange_i = \begin{cases} (\min\ S_c - S_a) * \gamma_1 & if (S_a < \min\ S_c) \\ (S_a - \max\ S_c) * \gamma_1 & if (S_a > \max\ S_c) \\ (Asp_i - \max\ Asp_i) * \gamma_2 & if (\min\ S_c < S_a < \max\ S_c \wedge Asp_i > \max\ Asp_i) \\ (\min\ Asp_i - Asp_i) * \gamma_2 & if (\min\ S_c < S_a < \max\ S_c \wedge Asp_i < \min\ Asp_i) \\ 0 & if (\min\ S_c < S_a < \max\ S_c \wedge \min\ Asp_i < Asp_i < \max\ Asp_i) \end{cases} \quad \textbf{(13)}$$

Table 6. Data samples of entrance and kitchen adjacency from the contact's point of view.

Plan type	Near adjacency of entrance with kitchen					Total
	Very low	Low	Suitable	High	Very High	
Eastern 2-bedroom	8	3	2	21	7	41
Eastern 1-bedroom	0	2	21	4	10	37
Western 2-bedroom	1	2	3	22	12	40
Western 1-bedroom	3	2	10	15	6	36
3-bedroom	0	4	0	6	12	22
Total	12	13	36	68	47	176

Table 7. Model developed for numerical computation of adjacent spaces.

Question	How much does $Space_{(i)}$ need to be adjacent to $Space_{(i)}$ in your opinion? (1 to 5)				
Answer	1	2	3	4	5
Coefficient of adjacency ($m_{(i,j)}$)	-2	-1	0	+1	+2
Selection amount from n_{Total}	n_{-2}	n_{-1}	n_0	n_1	n_2

Table 9. Kitchen's daylighting data from the questionnaire.

Plan type	The daylighting of our kitchen in my opinion					Total
	Very low	Low	Suitable	High	Very High	
Eastern 2-bedroom	0	6	33	5	0	44
Eastern 1-bedroom	12	5	17	4	0	38
Western 2-bedroom	1	7	30	4	0	42
Western 1-bedroom	22	4	8	3	0	37
3-bedroom	1	6	11	4	0	22
Total	36	28	99	20	0	183

$$\Delta Adjacency_{Total} = \begin{cases} \gamma & \text{if } hasEssential = 0 \\ \sum_{i=1}^{n} \sum_{j=i+1}^{n} adjacency_{(i,j)} * m_{(i,j)} & \text{if } hasEssential = 1 \end{cases} \tag{15}$$

$$hasEssential = \prod_{\{i,j \mid m_{(i,j)}=3\}} adjacency(i,j) \wedge \prod_{\{i,j \mid m_{(i,j)}=-3\}} !adjacency_{(i,j)} \tag{16}$$

Table 8. An example of the adjacent matrix of spaces in a western 1-bedroom unit in the case study.

	Entrance	Kitchen	Living Room	Bed Room	Bed Room	Bed Room	Terrace
Entrance	*						
Kitchen	+1	*					
Living Room	-1	+1	*				
Bed Room	-1	-1	+1	*			
Bath	-1	-1	+1	+3	*		
Tolilet	+1	-1	0	+1	0	*	
Terrace	0	0	-1	-2	-2	-1	*

In order to determine optimal adjacencies, the designer applies permitted ranges to the matrix using the adjacency matrices and introduces them to the algorithm as 3-dimensional arrays. Eq. 15 determines the adjacency difference's penalty amount ($\Delta Adjacency_{Total}$) in the fitness function, the adjacency result ($adjacency(i,j)$) generated by the two space's specified value ($m_{(i,j)}$) is calculated. If the adjacency condition of two spaces that should or shouldn't be adjacent ($m_{(i,j)} = \pm 3$) does not occur in Eq. 16 ($hasEssential = 0$), a heavy penalty (γ) is calculated in the fitness function.

Table 10. Model developed for the numerical calculations of permitted spaces daylighting.

Question	How is the daylighting of $Space_{(i)}$ in your opinion?				
Answer	Very High	High	Suitable	Low	Very low
Coefficient of adjacency ($m_{(i,j)}$)	-2	-1	0	+1	+2
Selection amount from n_{Total}	n_{-2}	n_{-1}	n_0	n_1	n_2

Table 12. The necessary to add a dining area from the contact's perspective.

Plan type	The necessity of existence of dining room in my opinion					**Total**
	Very low	Low	Moderate	High	Very High	
Eastern 2-bedroom	2	3	14	16	9	44
Eastern 1-bedroom	24	4	1	6	3	38
Western 2-bedroom	6	4	6	18	8	42
Western 1-bedroom	10	17	4	4	2	37
3-bedroom	2	5	1	9	5	22
Total	44	33	26	53	27	183

4.2.2.3.3. Daylighting of spaces

Due to the lack of proper understanding of geographical orientations of lighting by the target contacts for it to be accurate for the designer, a number of questions have been asked about the different spaces' lighting quality given their current location (Table 9).

In each plan type, after analyzing the data and calculating the current daylighting coefficient of each space according to the residents' opinion with Eq. 17 and Table 10, the space daylighting matrix was determined according to the designer's experience, existing standards, and the unit side being open or blocked in the overall plan of the residential block.

$$L_i = \sum_{l=-2}^{2} l * n_l / n_{Total} \quad \textbf{(17)}$$

Dealing with the daylighting problem, same as the adjacency topic, is done by defining the daylighting matrix as in Table. 11 and calculating the adjacencies, so that the different fronts of the building unit are considered as rectangles with the length of the building unit and minimal width, and introducing the adjacency of spaces with these fronts to the algorithm. Unifying the methods of dealing with different problems helps to speed up the algorithm and reduce processing time.

Table 12. A sample of the daylighting matrix of spaces in a western 1-bedroom unit in the case study.

	North (west)	(North) east	South (east)	(South) west
	Bloked	Bloked	Bloked	Open
Entrance	0	0	+3	0
Kitchen	-1	-2	-2	+2
Living Room	0	0	-2	+1
Bed Room	-2	-2	-1	+1
Bath	-1	+1	-1	+1
Tolilet	-1	+1	-1	+1
Terrace	0	-3	0	+3

4.2.2.3.4. Adding or removing spaces

Due to the type of problem (plan redesign) and the passage of time since the initial design of the residential units, adding or removing some spaces is needed among the residents. As in Table 12, the surveys targeted the need for these spaces or the segregation of some spaces such as living and dining areas.

Table 13. Developed model for numerical calculations of adding or removing a space.

Question	How is the necessity of existence of in $Space_{(i)}$ in your opinion?				
Answer	Very low	Low	Moderate	High	Very High
Coefficient of adjacency ($m_{(i,j)}$)	-2	-1	0	+1	+2
Selection amount from n_{Total}	n_{-2}	n_{-1}	n_0	n_1	n_2

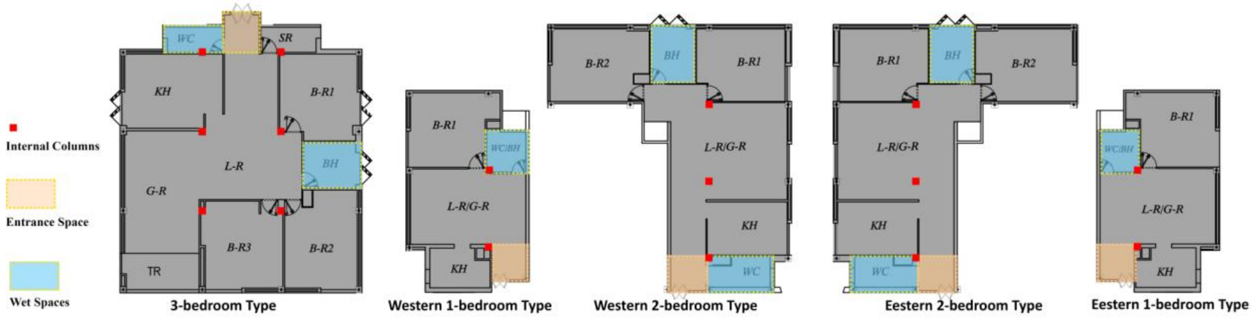

Fig. 5. Location of internal columns and spaces with fixed places in the 5 plan types in the case study

Based on the results of the data analysis and the determined S_i coefficient value in accordance with Table 13 and Eq. 18 for the selected spaces, the designer will either add or subtract a number of spaces including a 4-variable array if needed.

$$S_i = \sum_{s=-2}^{2} s * n_s / n_{Total} \quad (18)$$

Due to each type's area and the tendency to add or remove a space, minimum and maximum space area, permissible aspect ratio, adjacency and appropriate day-lighting were added to the problem data.

4.2.2.4. Redesign criteria and limitations

4.2.2.4.1. The effect of the columns' positions on the layout of the plan

The placement of internal columns in building plans has always been one of the most important challenges in reconstruction and redesign. Due to the problem raised in the case study and the existence of 2 to 6 columns in different units being redesigned, maximum effort has been made to place these columns in the inner walls during the implementation of the algorithm.

To apply the column constraints ($\Delta Columning_{Total}$) in Eq. 19, the interference of all spaces with interior columns is measured. If all columns do not cover the boundaries of at least one space, a heavy penalty (γ) is applied to the fitness function in Eq. 20, otherwise it is 0.

$$\Delta Columning_{Total} = \begin{cases} \gamma & if\ isOnColumn_{Total} = 0 \\ 0 & if\ isOnColumn_{Total} = 1 \end{cases} \quad (19)$$

$$isOnColumn_{Total} = \prod_{\forall j \in \{AllColumns\}} \left(\coprod_{\forall i \in \{AllSpaces\}} isOnColumn_{(i,j)} \right) \quad (20)$$

4.2.2.4.2. Spaces with fixed places

As in Fig. 5, some of the spaces in the current plans, such as the entrance, are unmovable due to the inability to modify the units' relations to the shared spaces (like the lobby). Wet spaces (toilet and bathroom) have also been considered unmovable due to the change in location and not dimensions being economically disadvantageous. To address this problem, the x_i and y_i parameters in Eq. 20, which determine the space's position in the plan, are considered constant, and in all algorithmic steps only the $width_i$ and $height_i$ parameters that are related to space dimensions change.

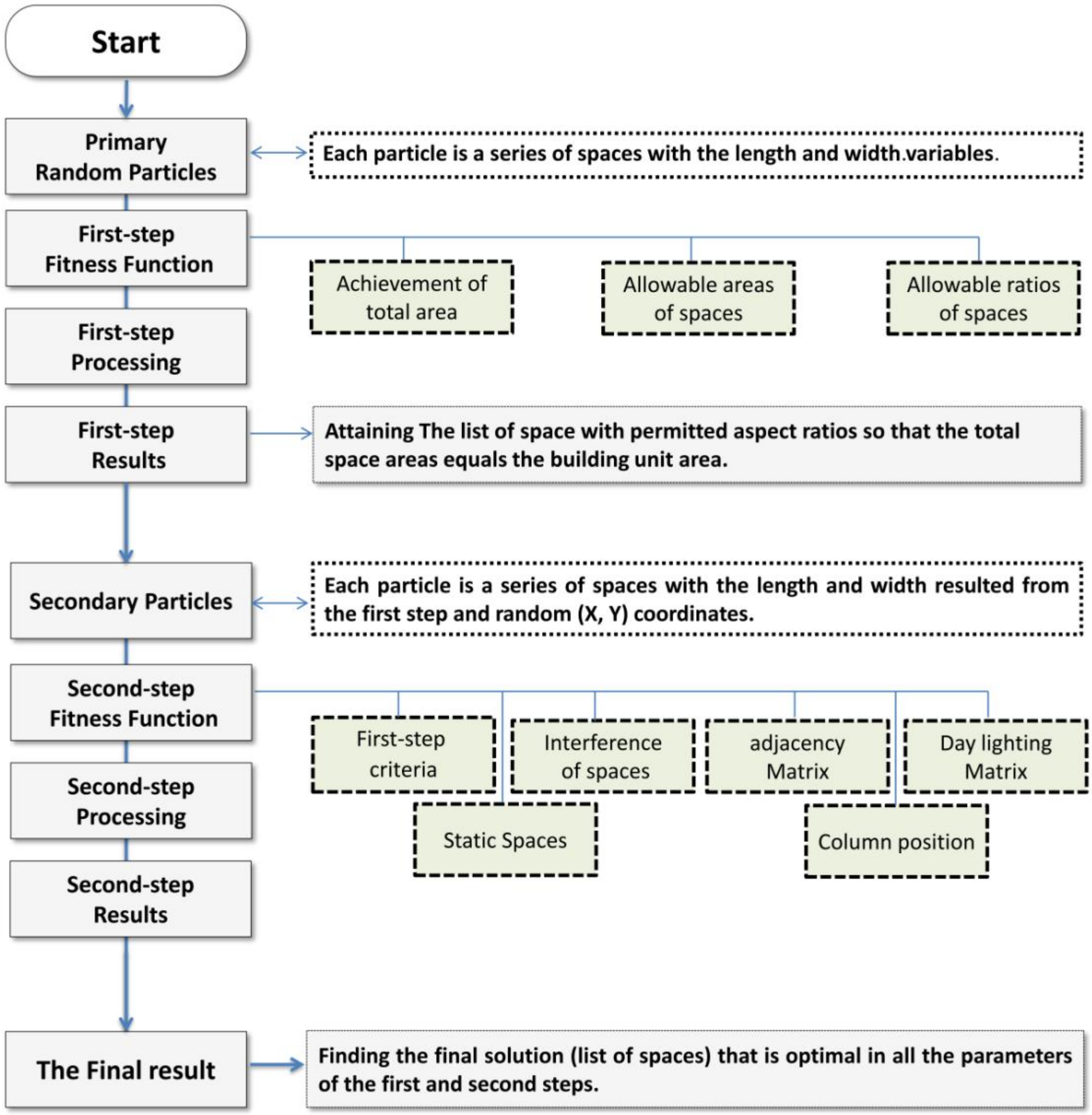

Fig. 6. Flowchart of the implemented algorithm based on PSO algorithm for plan types in the case study.

4.2.3. Implementing the algorithm based on PSO algorithm

In the algorithm implementation, after determining the goals of the problem, the effective criteria and constraints, and the quantification of the criteria, the fitness function is defined and each particle is evaluated by it in each iteration.

To limit the search space of the algorithm for finding the suitable solution and to prevent the curse of dimensionality that results in faster and better quality of solution generation, the algorithm is implemented in two consecutive steps as illustrated in Fig. 6. Dimensional curse is often referred to as a concept where the problem space is so large that finding a suitable solution among the possible options is impossible. This term was first used by Bellman in 1961 to describe a combination of multivariate functions (Beyer *et al.*, 1999).

4.2.3.1. First step

In the problem implemented based on the PSO algorithm, In Eq. 21 each particle refers to a set of spaces with 4 variables of latitude and longitude and length and width of the building unit's boundary, which may be considered as the best solution to the problem.

$$F_2(x) = \Delta S_{Total} + \Delta SRange_{Total} + Interfrence_{Total} + \Delta Adjacency_{Total} + \Delta Lighting_{Total} + \Delta Columning_{Total} \quad (23)$$

$$particle_i = \{space_1, space_2, space_3, \ldots, space_n\} \quad (21)$$

$$F_1(x) = \Delta S_{Total} + \Delta SRange_{Total} \quad (22)$$

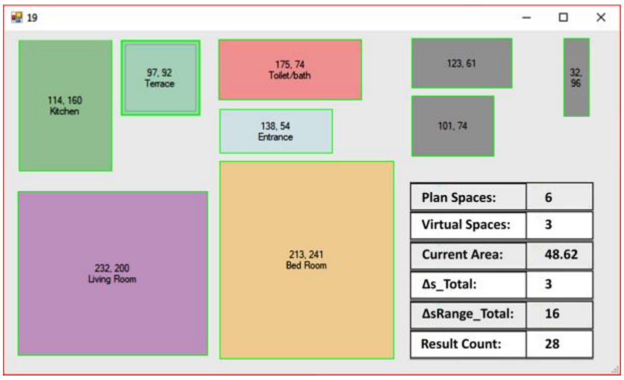

Fig. 7. A sample of the first step solution of the algorithm implementation for a western 1-bedroom plan.

In this step, the fitness function $F_1(x)$ only examines geometry-related variables in Eq. 22 such as the total building unit area amount (ΔS_{Total}) and the space's aspect ratio and area preservation $(\Delta SRange_{Total})$; not variables related to location. The particles generated at this stage only have length and width, and the task of the algorithm at this stage is to control the length and width of the spaces in each particle. The best solution among all the particles produced in this optimization step is the one that achieves the minimum defined value when placed in the fitness function. This particle is used as the initial data for generating random particles in step two and implementing the algorithm in that step. The length and width of the particles can be modified and improved in the second step to both maintain the required variation and have the algorithm achieve better solutions.

An example of the algorithm results at this step in the western 1-bedroom plan in the case study in Fig. 7.

4.2.3.2. Second step

As indicated in Eq. 23, with the aim that the end result is the best possible solution to all defined criteria and constraints, in the second step, in addition to the criteria affecting the first step, the other criteria and constraints defined in the fitness function $F_2(x)$ are considered. New criteria include estimation of interference $(Interfrence_{Total})$, adjacency $(\Delta Adjacency_{Total})$, appropriate positioning for daylighting $(\Delta Lighting_{Total})$, and also attention to column position $(\Delta Columning_{Total})$. The algorithm's progress in this step, which is based on random particles, depends on the minimum value defined for the fitness function. In this step, the spaces of each particle still have 4 attributes, but the longitude and latitude (location) change as well as the length and width. In the initial particle set, this length and width are equal to the length and width of the preceding step's optimized particle spaces, and is modified in each iteration to achieve the desired result.

A sample of the second step result of the algorithm implementation for a western 1-bedroom plan in the case study is shown in Fig. 8.

4.2.3.3. Algorithm Implementation Platform

Although it is possible to implement basic optimization algorithms in Rhino and Revit softwares with the grasshopper and dynamo plugins that have a strong visual nature, the capability to change the structure of optimization algorithms is available only by adding Scripts to these plugins. Since only a small group of advanced users have the knowledge and experience of advanced programming to use plug-ins, it is not possible to restructure optimization algorithms by a greater community of architects; Nisztuk and Paweł, in a 2018 study with this topic, stated that the solutions for implementing algorithms in research are often lacking in visual interface and are functionally limited. They believe that future tools should be developed based on the specific nature of the design process, and in constant contact with their main users, meaning architects, and focus on the needs of the group (Nisztuk and Paweł, 2018).

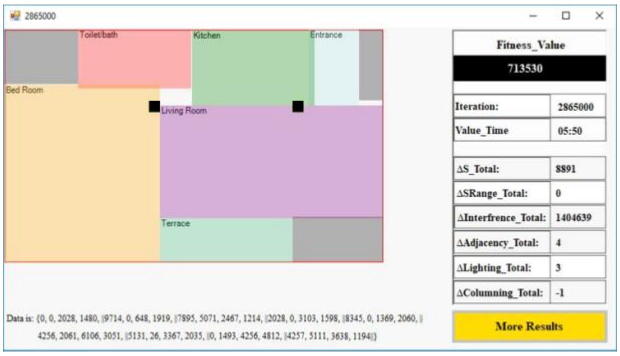

Fig. 8. A sample of the second step solution of the algorithm implementation for a western 1-bedroom plan.

In this research, the algorithm was implemented as an application based on .NET programming framework with graphical user interface (GUI).

Fig. 9 is part of the plan optimization steps for the 3-bedroom plan type in the case study obtained by the algorithm implemented on a PSO basis in the mentioned application.

5. Conclusion

Residential complexes that, over time, have become structurally disordered and unable to meet the needs of their current contacts face many rebuilding constraints, which makes reconstruction a priority over rebuilding. On the other hand, the multifaceted problems in the reconstruction of these residential complexes lead to the inefficiency of traditional design methods. The use of evolutionary optimization algorithms in architecture has increasingly improved today with the development of computers and software. In this research, based on the advantages of using PSO algorithm in architecture, three steps are suggested for applying optimization in redesigning the architectural plans of Mashhad's High-rise apartment's complex using this algorithm. 1- Determination of problem goals, design criteria and constraints in the complex 2- Quantification of the aforementioned criteria and constraints 3- Determination of the algorithm's fitness function and implementing it. The problem's goals are examined in the four general scopes of physical criteria, designer, contact, and redesign criteria and limitations and the Quantification process and the final model was implemented based on the PSO algorithm using a .NET programming framework to further the architects' understanding of the complex's redesign process. Fig. 10 shows the generated plans for each of the 5 plan types available in the case study using the application implemented based on PSO algorithm. Since it is not possible to introduce the criteria to the algorithm without quantifying these concepts for the considered optimization algorithm, in this research many quantitative criteria affecting the plan redesign are quantified for the use of the PSO algorithm.

Also, a number of qualitative criteria, such as adjacency-related topics, themselves affecting issues such as the quiet and privacy of spaces were introduced to the algorithm quantitatively.

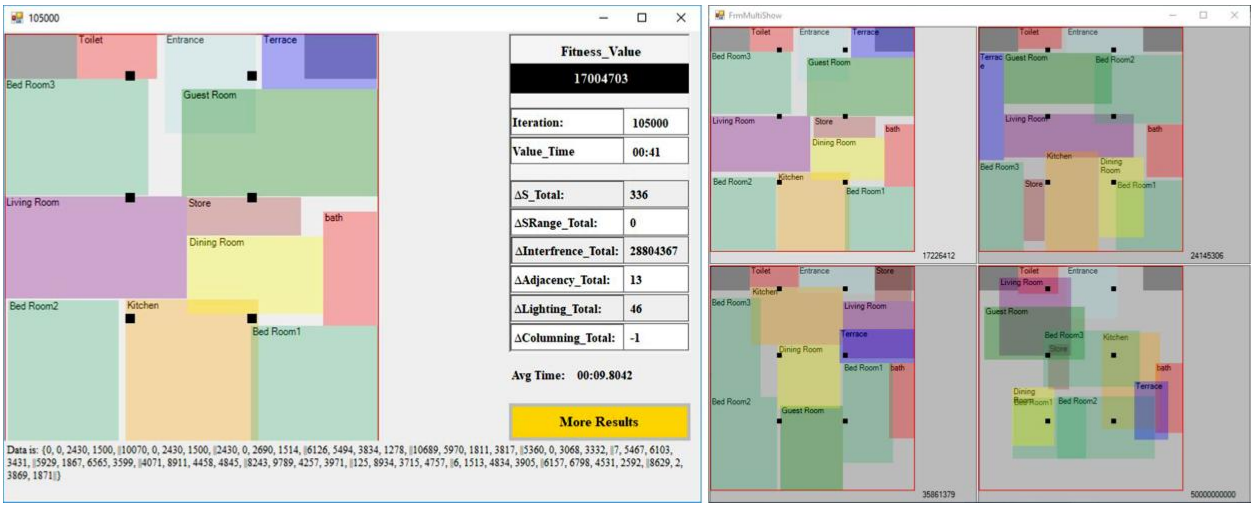

Fig. 9. Graphical user interface of the implemented algorithm.

Fig. 10. Redesigned plans for the 5 plan types available in the case study using PSO algorithm.

Some other con-ceptual criteria have also been addressed while emphasizing the role of the designer as the final decision maker in defining the criteria and selecting the final options.

Quantifying restrictions, especially in conceptual or qualitative criteria such as notions related to aesthetics are one of the important issues in research based on optimization algorithms, Issues related to intermediate and connecting spaces between two different spaces as well as movement circulations include a combination of quantitative and qualitative parameters. Also furniture arrangement spaces and its effect on the overall shape and final plan is one of these combined issues. Due to their extent and complexity, identification, quantification and implement-tation of these criteria can be a suggested field for future research in this area.

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