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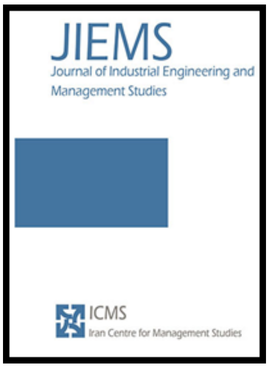

A fuzzy based genetic algorithm for optimizing the pedestrian walking network; case study of Tehran historic district

Sajed Rastbin[1], Mehrdad Gholami Shahbandi[2], Pouya Soudmand[3,*]

Abstract

Fast growth of motorized transportation infrastructures in the cities is a consequence of the urbanization process. Despite the undeniable benefits of the developments, some unwelcome social-environmental damages have been occurred. On top of the list, the movements of the pedestrians and their participation in social activities have dramatically reduced as a result of the vehicles dominancy. Pedestrianization and walking-friendly schemes are the key answer to preserve the valuable element of the urban lifestyle. This need motivated the researchers to study and propose mathematical methods to model the dynamics and behavior of the pedestrians in response to their surroundings. However, most of the models in the literature are suitable for limited small-size area and cannot be applied for a large scale urban zone. In this paper, a fuzzy macroscopic pedestrian assignment model is proposed which is applicable for a large scale network and useful for urban master plans as a decision making framework. In addition, a bi-level mixed integer programming model is presented to optimize the pedestrian walking network via selecting some projects on the network, considering the behavior of the pedestrians. Finally, the problem is solved for a large scale pedestrian network in the city of Tehran. The results show the efficiency of the algorithm where spending half of the maximum possible cost has led to a welfare gain of 82.6 percent. The problem was efficiently solved within 12.5 days which is fairly acceptable for the strategic planning of such a large scale network. The numerical results verify the necessity of the model for urban master plan horizon.

Keywords: pedestrian modeling; bi-level programming; decision making; fuzzy logic; NSGA-II.

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1. Introduction

In the last decades, cities have witnessed huge urbanization programs as a result of the fascinating advances in transportation technologies. This trend has dislodged the pedestrian activities and limited its movements to some restricted areas. This process truly endangers the

* Corresponding author; pouya.soudmand@gmail.com

[1] Department of conservation, Art University of Isfahan, Isfahan, Iran.

[2] School of Civil Engineering, College of Engineering, University of Tehran, Tehran, Iran.

[3] Department of Industrial Engineering and Management Studies, Amirkabir University of Technology, Tehran, Iran.

healthy social life of the citizens and is a destructive element for the valuable characteristics of the cities. To cope with the problem, urban management systems have presented and implemented pedestrian-oriented schemes in order to revival the identity of the cities. Pedestrianization plans play a key role to achieve the necessary goal. These plans consist of several operations from blocking the streets from the entrance of vehicles to the equipping of walkways with pedestrian facilities or enhancing the environmental qualities of the passages. Making a decision from a variety of choices in such a complex system with lots of human variables is a tough one for urban planners. First, they need a tool to analyze the behavior of the pedestrian in their movements, so they can choose an effective plan. Second, they need a decision making framework which is capable of choosing the best alternatives according to the complexity of the system.

To answer the first demand, researchers presented mathematical models to anticipate the dynamics of the pedestrian movements. Most of the proposed models are known as microscopic approaches, suitable for the small crowded places such as stadiums, airports, transportation facilities or multipurpose buildings. These models consider individuals and can predict the movements of the pedestrians in great details. Parisi and Dorso (2005) investigated microscopic dynamics of pedestrian. Abdelghany et al. (2016), Collins et al. (2015), Qu et al. (2014) and Gou et al. (2016) are among those who studied different approaches for microscopic pedestrian modeling. Zhao et al. (2019) applied artificial neural network based modeling for unidirectional and bidirectional pedestrian flow at straight corridors. Sun (2020) proposed a cellular automation model and used kinetic Monte Carlo simulation for bi-direction pedestrian flow with different walk speeds. Vizzari et al. (2020) proposed an agent-based model for plausible wayfinding in pedestrian simulation. Despite the practicality of the models in surrounded places, they are incapable of predicting the dynamics of pedestrians in a large scale problem, due to their computational complexity. Macroscopic approaches are the appropriate surrogates as they can consider numerous pedestrians in bigger places. They bring this advantage in the cost of less accuracy. They consider the pedestrians as a whole and analyze their behavior with the parameters such as the speed and density of a united flow. They are usually based on fluid dynamics rules. Comprehensive reviews on the macroscopic models are given by Karmanova (2013), Twarogowska et al. (2014) and Gupta and Pundir (2015). Although the macroscopic models are a step forward compared to the microscopic approaches, they cannot still anticipate the behavior and distribution of pedestrian in complex network of the walkways in an urban scale. This is the scale of the problem the urban planners encounter, when devising a walking-friendly scheme. Sketch plan models are the first attempts for prediction of pedestrian activities in a large scale zone. Introduced by Pushkarev and Zupan (1971), sketch plan models comprise a group of approaches which are not simulation based like the mentioned models in the above. The model tries to estimate the pedestrian volume using regression analysis and observation counts. The main benefit of the model lies within its simplicity, offering quick estimation of pedestrian volumes. However, they are not applicable in aggregate level and cannot predict the volume of every passage with acceptable accuracy. Configurational models are more sophisticated approaches for dealing with the problem. These models consider the various built environment as the main effective factor in the behavior of the pedestrians. Space syntax (Hillier et al., 1993) is classified in the category of configurational models and has been widely used in urban planning studies. The space syntax approach is based on measuring objective patterns of spatial relationships and linking them to patterns of movement within urban environments. This model considers the topology of the area and analyzes the pedestrian network via graph theory measures (Teklenberg et al., 1993). Visibility Graph Analysis (VGA) is another well-known approach of configurational models, proposed by Turner et al. (2001). The method utilizes same concept as the space syntax, but differs from the latter in the way of modeling the surrounding land use. Moreover, it recognizes the visibility of each node from another one and the number of nodes between the two. In a computational point of view, the VGA has more calculation burden. As a result, it can distinguish a fully loaded passage next to a less crowded one with higher level of accuracy. Nonetheless, configurational models have a fundamental drawback since they do not take into account the existing demand in the network. In the other words, they anticipate the potential of the network in attracting the pedestrians, regardless of the availability of such a demand. More precisely, they also can not consider a specific demand between each pair of the presented graph. Clifton et al. (2004) proposed a method capable of considering any specific demand level of a defined graph of a network, applicable for large scale networks. The method is basically inspired form the conventional four stage modeling of transportation planning. The proposed method has some simplification assumptions and uses a single-class stochastic pedestrian assignment. Clifton et al. (2012, 2013, 2015, 2016(a,b)) investigated about different aspects of the whole structure of the model, mostly on the steps of trip generation, modal split and trip distribution. Hänseler et al. (2017) proposed a network loading model for multi-directional congested pedestrian flows. They modeled the interaction between streams by an anisotropic fundamental diagram. Hoogendoorn et al. (2018) studied pedestrian networks and introduced an analytical derivation of the pedestrian macroscopic fundamental diagram (MFD). They used Simulation-based approach to apply the MFD. Oyama and Hato (2018) presented a link-based route measurement model using a Bayesian approach. They estimated the route choice model on simulation and real GPS data in urban pedestrian networks. Rastbin et al. (2017) investigated the problem focusing on the diversity of pedestrian behaviors and indicated the necessity of a multi-class model. They presented a multi-class pedestrian assignment model suitable for large-scale networks. Regardless of the details, their model is the most appropriate approach with an applicable platform for the problem in the literature.

The second requirement for designing an effective plan is a decision making framework. As mentioned before, urban planners are facing a complex system with many variables which are most based on human behavior. They have a set of numerous alternatives as the pedestrianization project. Selecting the optimum projects to obtain a set of predefined objectives is of high difficulty. Hence, they need an intelligent logical tool to help with the selecting process. This aspect was investigated by Rastbin et al. (2017). They stated that the problem is generally equivalent as the Network Design Problem (NDP) in motorized transportation modeling, which is proved to be Non-deterministic Polynomial-time (NP) hard problem with a non-convex solution space. Surveying the solution methods, they presented a multi objective genetic algorithm to solve the problem for large-scale networks. Despite the efficiency of the proposed model, the algorithm cannot consider the uncertainty of the variables of the problem. Dealing with variable as deterministic and crisp values does not properly reflects the uncertainty of variables in the real word, especially those which are directly related to human behavior.

In this paper, an extension to the model proposed by Rastbin et al. (2017) is presented to cope with the uncertainty of the problem nature. We propose a similar bi-level structure for pedestrian network design problem (PNDP) by introducing a novel fuzzy-based macroscopic pedestrian model as the prediction method and an optimization model based on the famous NSGA-II algorithm which can handle new set of decision variables and more objective functions. The main contributions of the paper are summarized as follows:

- Developing a macroscopic multi-class pedestrian equilibrium assignment model for large-scale networks.

- Taking into account the uncertainty of the problem: the linguistic concept of travel time and travel cost is handled via fuzzy logic.
- Proposing a bi-level optimization model for designing the pedestrian networks.
- Developing a genetic-based solution algorithm to the multi objective problem.

First, a comprehensive extension to the model of Rastbin et al. (2017) is presented. The approach is developed to a fuzzy arithmetic multi-class user equilibrium assignment model capable of considering both travel time and environmental qualities in calculating the travel cost. Applying the fuzzy logic in the model accounts for the imprecision and uncertainty of route choice behavior and enhance the accuracy of the model. In the second step, a bi-level mixed integer mathematical model is proposed where the lower level problem (LLP) is the fuzzy pedestrian assignment model (FPAM) and the upper level problem (ULP) is a multi-objective optimization model based on the well-known NSGA-II algorithm. The paper is structured as follows. In the next section, the FPAM is presented. Section 3 describes the upper level problem. Section 4 presents the framework and algorithmic design of the proposed model. In order to evaluate the performance of the method, numerical examples are provided in section 5. Finally, some concluding remarks are given in the last section.

2. LLP: Fuzzy multi-class pedestrian assignment model

As mentioned before, the proposed pedestrian assignment model is an extension to the model of Rastbin et al. (2017). The core model is based on motorized traffic assignment model, originally developed by Clifton et al. (2004). The improvements can be discussed in the three main aspects, as follows:

a) Unlike the motorized modeling where all the users (drivers) are assumed to have same behavior, the diversity of pedestrians is not negligible. Pedestrians with different purpose of travel do not have a same mental function in perceiving the travel cost. A pedestrian on a walk with work purpose tries to find the shortest path to save time, while a pedestrian with the purpose of leisure seeks the route with high environmental quality. As a result, pedestrian are categorized into classes according to their travel purpose, where each group follows a specific intellectual pattern.

b) Instead of a stochastic assignment, a user equilibrium approach is preferred because of more accuracy and compatibility with the real situations. According to the Wardropian law (Wardrop, 1952) the equilibrium is obtained when the travel cost of all used path for a specific OD pair is equal to the minimum cost and equal or less than the cost of unused paths. This condition is equivalent to the Nash equilibrium state in the game theory for a multi-player competitive game (Grange and Munoz, 2009).

c) It is noted that the travel time is a linguistic concept, since the perceived travel cost (PTC) may differ from a pedestrian to another in the same class. Therefore, PTC of a class for a specific route is not a crisp value and lies in a range. The difference in PTC for the pedestrians is related to their age, gender, psychological mood and even the congestion on the network. In this paper, fuzzy arithmetic approach is applied where the travel cost is itself a fuzzy number. The mathematical formulation of FPAM is presented in the following.

2.1. Mathematical formulation of FPAM

In this paper, it is considered that the overall perceived travel cost is built upon two terms: 1) the travel time as a negative factor which increases the travel cost and 2) environmental qualities which are accounted as positive factor. As the environmental qualities increases, the travel cost decreases as a result of mental satisfactory element. The Pedestrians select their routes according to their perceived travel cost. It is assumed that the source of the differences in various perceived travel costs are embedded in the imprecision and the uncertainty of the travel time part. People have different understandings of their travel time. Fuzzy set theory is known to be a proper tool to deal with this kind of linguistic human Perceptions. Many recent studies have applied fuzzy set and possibility theories to describe the dynamics of pedestrians. Hoogendoorn et al. (2003) utilized fuzzy clustering to describe the characteristics of pedestrian dynamics extracting from video data. Scheunert et al. (2004) applied a fuzzy based method for monitoring and tracking of pedestrians. Zhu et al. (2008) used fuzzy logic for pedestrian evacuation simulations. Ji et al. (2013) proposed a fuzzy logic cell based model to consider and simulate the acceleration and overtaking of pedestrians in a corridor. Nasir et al. (2014) combined fuzzy set theory with genetic algorithm to model the walking path of the pedestrians. Chai et al. (2015) studied dynamics of pedestrians at signalized crossing and proposed a fuzzy cellular automata model to anticipate the pedestrian movements. Chai et al. (2016) investigated the behavior pattern of pedestrians according to their age and gender and presented a fuzzy based observation and evaluation method to analyze the subject. Zhou et al. (2016) suggested a model based on fuzzy logic for simulation of pedestrian dynamics. In this paper, the PTC is considered as the linguistic term and a fuzzy based pedestrian assignment algorithm is presented. It is noted that the PTC of a pedestrian is consisted of his/her travel time and the environmental qualities as the two effective terms in the route choice process. Both the travel time and environmental qualities are considered as fuzzy values. Similar triangular membership functions (MF) are applied for both the travel time and environmental qualities to simplify the computation process. The triangular MF for travel time is consisted of three values: MF center, left limit and right limit. The center denotes the most possible travel time, usually considered equal to the real travel time having the highest perception rate for the pedestrians. The left limit is rationally considered as the travel time when there is no congestion or annoying factor in the passage and the right limit is the most probable perceived travel time occurring during rush hour with the most congestion level in the walking path. Same logic exists for the environmental qualities where the center limit is the exact value of quantified environmental quality and the left and right limits present the minimum and maximum perceived mental profit of environmental quality. Figure 1 shows a sample MF for the travel time and a specified environmental quality. (t^l, q^l), (t^c, q^c) and (t^r, q^r) are the left, center and right limits of the MFs, respectively.

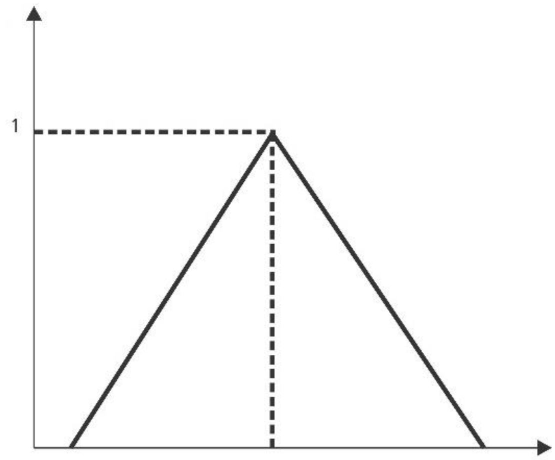

Figure 1. Triangular membership function of travel time and quantified value of environmental qualities

The fuzzy travel time and a fuzzy specified environmental quality of class *m* for link *a* can be shown by three mentioned limits, as follows:

$$\begin{cases} t_a = \left(t_a\left[(1-\alpha_l).v_a\right], t_a(v_a)\ ,\ t_a\left[(1+\alpha_r).v_a\right]\right) \\ q_a = \left((1-\alpha_l).q_a\ , q_a\ ,\ (1+\alpha_r).q_a\ \right) \end{cases} \tag{1}$$

Where t_a and q_a are the travel time and the quantified value of the specified environmental quality in the link *a,* respectively. α_l is the coefficient that determines the left limit of the MF, usually set as free flow time of the pedestrian in the sidewalks in the range of $0 \le \alpha_l \le 1$. α_r is a non-negative coefficient for the right limit, presenting the pedestrians who perceive a travel cost greater than the most possible value. Since solving the user equilibrium pedestrian assignment problem needs finding the shortest paths, it is mandatory to compare the fuzzy numbers to choose the minor one. In this paper, the method of Dubios and Prade (1983) for ranking fuzzy numbers is used. In order to compare two fuzzy numbers, the method utilize four indices, $I = \{I_1, I_2, I_3, I_4\}$, each of which consider a different aspect of the fuzzy numbers. The index I_3 which takes into account the necessity theory and recognizes the number with lower right limit is considered in this paper, because this criterion is the realistic measure and is the most compatible with the behavior of pedestrians. The reader is referred to Dubios and Prade (1983) for more information on the ranking process. Assume *G=(N,A)* to be a graph representing the pedestrian passage network with A as the set of sidewalks and N as the set of the nodes. Consider $I = \{i\}$ as set of OD pairs in the network and $d = \{d_i^m\}$ as the pedestrian demand matrix in which each element is assigned to OD pair *i*. For each OD pair *i*, there exist a set of path K_i and each path is denoted by $k \in K_i$. The multi-class FPAM can be stated by a system of non-linear equations as below:

$$\begin{cases}
\sum_{k\in K_i} f_k^m = d_i^m & \forall i \in I, m \in M & (2) \\
f_k^m.\left[(T_k^{mr} + T_k^{mc}) - (u_i^{mr} + u_i^{mc})\right] = 0 & \forall i \in I, k \in K_i, m \in M & (3) \\
(T_k^{mr} + T_k^{mc}) \ge (u_i^{mr} + u_i^{mc}) & \forall i \in I, k \in K_i, m \in M & (4) \\
f_k^m \ge 0 & \forall k \in K_i, m \in M & (5) \\
v_a^m = \sum_{i\in I}\sum_{k\in K_i} f_k^m.\delta_{ak}^m & \forall a \in A, m \in M & (6) \\
v_a = \sum_{m\in M} v_a^m & \forall i \in I, k \in K_i, m \in M & (7) \\
T_k^m = \left(L\ , C, R\right) & \forall k \in K_i, m \in M & (8) \\
L = \sum_{a\in A} c_a^m\left[(1-\alpha_l).v_a\right].\delta_{ak}^m + \sum_{n\in N} c_n^m.\delta_{nk}^m & \forall i \in I, k \in K_i, m \in M & (9) \\
C = \sum_{a\in A} c_a^m(v_a).\delta_{ak}^m + \sum_{n\in N} c_n^m.\delta_{nk}^m & \forall i \in I, k \in K_i, m \in M & (10) \\
R = \sum_{a\in A} c_a^m\left[(1+\alpha_r).v_a\right].\delta_{ak}^m + \sum_{n\in N} c_n^m.\delta_{nk}^m & \forall i \in I, k \in K_i, m \in M & (11)
\end{cases}$$

where $M = \{m\}$ is the set of pedestrian classes and f_k^m is the flow of class *m* on the path *k*. T_k^m and u_i^m are the travel cost of the class *m* in the path $k \in K_i$ and minimum travel cost of the class *m* for the OD pair i, respectively. v_a^m and c_a^m represent the pedestrian volume and the travel cost of class *m* on the link (directed-sidewalk) *a*, in that order. c_n^m is the travel cost of the class *m* in the node *n*. δ_{ak}^{m} is an indicator with the value of 1 if the arc *a* is located in the path *k* of the class *m*, and 0 otherwise. Similarly, δ_{nk}^{m} is an equivalent term for the node *n*. Equation (2) satisfies the demand conservation constraint. Equations (3) and (4) stand for the Wardrop principle and equation (5) shows the non-negativity of pedestrian flows. Equation (6) defines the volume of links as a cumulative term of path flows. Equation (7) determines the total volume of the link as the sum of volumes of different passing modes. Equation (8) defines the travel cost as a fuzzy number with a center value and left and right bounds. Equations (9-11) calculate these deterministic values to generate the fuzzy number.

In this paper, the pedestrians are divided into two classes with different traveling purposes: work and leisure. The pedestrian of each class walk through the network with their own perception of the travel cost. This distinction appears in the form of the function c_a^m, as shown below:

$$c_a^m = \beta^m . \bar{t}_a(v_a) - \gamma^m . \overline{Q}_a \tag{12}$$

where $\bar{t}_a$ and $\overline{Q}_a$ are the normalized walking time and normalized integrated environmental quality of the sidewalk *a*, respectively. β^m and γ^m are two weighted coefficients which determine the importance of each term of the equation (8) in the travel cost on each link for the class *m*. In a comparison point of view, the value of γ^m for leisure purpose trips is higher than the travels with the purpose of work, and opposite results exists for the coefficient β^m .The travel time of the arc *a*, t_a, is derived from the fundamental diagrams of the pedestrian flow theory. Moreover, the travel cost of class *m* in the node *n*, c_n^m, is calculated as follows:

$$c_n^m = \beta^m . d_n^{mk} - \gamma^m . \overline{Q}_n \tag{13}$$

where d_n^{mk} is a normalized constant delay time for the mode m in the path k at the node n, and $\overline{Q}_n$ is the fuzzy normalized integrated environmental quality for the node *n*, respectively. The details of the travel cost formulation and calculation is provided in Rastbin et al. (2017) and is omitted here for brevity.

The equations 2-8 can be transferred into an optimization problem, so that many optimization methods can be used to solve the problem. The equivalent problem, first proposed by Beckman (1956) for motorized modeling, is stated below:

$$\min Z(v) = \sum_{a \in A} \int_0^{v_a} \left[c_a^m(w) + c_a^m((1+\alpha_r)w) \right] dw \qquad \forall m \in M \tag{14}$$

$$s.t. \quad \sum_{k \in K_i} f_k^m = d_i^m \qquad \forall i \in I, m \in M \tag{15}$$

$$v_a^m = \sum_{i \in I} \sum_{k \in K_i} f_k^m . \delta_{ak}^m \qquad \forall a \in A, m \in M \tag{16}$$

$$v_a = \sum_{m \in M} v_a^m \qquad \forall i \in I, k \in K_i, m \in M \tag{17}$$

$$f_k^m \geq 0 \qquad \forall k \in K_i, m \in M \tag{18}$$

The objective function of equation (14) is the equivalent of the Beckman (1956) model for pedestrian flows. Equation (15) presents the flow consistency principle. Equations (16-17) are same as equations (6-7). Equation (18) dictates the non-negativity of path flows. It is noted that the travel cost in the nodes, c_n^m, is independent from the pedestrian volumes in the sidewalks. Consequently, it is omitted in the objective function of equation (14).

The method presented by Ortuzar and Willumsen (1990) utilized with a path-based complementary assignment algorithm is used to solve the FPAM. In the single class assignment algorithm, the problem is solved by decomposing the problem into single OD pairs, each as a sub-problem. Every sub-problem is solved using gradient projection method in the space of path flows. Then, the equilibrium is obtained by solving the sup-problems in an iterative process. The multi class is also solved by an iterative algorithm, similar to method of Rastbin et al. (2017). The algorithm successively solves the equilibrium condition for each class. The method is described in the following steps:

Step 0: Initialization: input the network and demand data. Define $M = \{1,2\}$ where class #1 indicated work category and class #2 represents leisure.

Step 1: Set i=1, j=2 and $\{v_a^1 = v_a^2 = 0 | \forall a \in A\}$

Step 2: solve the FPAM for class #*i*, considering v_a^j as fixed volumes on the network and obtain the equilibrium volumes of v_a^i.

Step 3: if the stopping criterion is met, go to step 4; otherwise switch the value of *i* and *j* and go to step 2.

Step 4: output the equilibrium flows of $\{v_a^1, v_a^2 | \forall a \in A\}$

Different kinds of stopping criterion has been studied in the literature, most common measure are listed below:

I) CPU running time: In order to solve the problem in an acceptable time, the limit on CPU running time can be used as the stopping criterion. However, this measure may lead to inaccurate solutions.

II) Maximum number of iterations: This criterion is somehow similar to the CPU running time, with the same benefit and loss.

III) Numerical convergence measures: these criteria can be classified into two main groups:

III-a) measuring the improvement in two successive iterations: these criteria stop the process if the difference (enhancement) in two successive iterations falls below a certain value. Theoretically, the algorithm is terminated when it cannot result in an effective improvement to the solution, meaning the method has converged. Although these criteria are conceptually superior to the mentioned limits, they still do not guarantee a pleasant solution.

III-b) criterion with certain accuracy: These measurements demand a certain level of accuracy for the solution and imply the repetition of the process until the condition is satisfied, regardless of the running time. Neglecting the computational effort, these criteria output the best level of accuracy in comparison to the others. Relative Gap (RG) is of the same category and has been widely used for solving the conventional motorized traffic assignment problem. In this paper, the measure of RG is used as the stopping criterion. The iterations go on until both class reach a desired value of the RG. The RG for the class m can be calculated as below:

$$RG^m = \frac{\sum_{i \in I} \sum_{k \in K_i} f_k^m . T_k^m - \sum_{i \in I} d_i^m . u_i^m}{\sum_{i \in I} d_i^m . u_i^m} \tag{19}$$

The RG is a measurement of the accuracy of the assignment solution. If the equilibrium of the network is absolutely satisfied, the value of the measure is equal to zero, indicating the optimal solution to the problem. As the accuracy of the solution decreases, the value of the measure increases. Considering the complexity of the problem, it is numerically and practically impossible to reach the exact solution for large-scale networks. Hence a small value of the RG is considered to guarantee the quality of the solution.

3. ULP: Multi-objective optimization model

The ULP of the proposed bi-level model is an extension to the multi-objective optimization model proposed by Rastbin et al. (2017). In this paper, new set of variables are introduced which are more consistent with the actions taken in the real world. Moreover, more precise objective functions are considered and optimized in the process. The optimization model is the core of the decision making procedure to decide the best plans in the network. These plans are made up from a set of considered projects on the network. The decision variables are defined on these projects. The action plans can be divided into four main groups, as described below:

1- Widening the sidewalks: the travel time of a pedestrian on a sidewalk is a function of the width of the sidewalk. Widening a crowded passage can reduce the travel time. The corresponding decision variable and its cost in the sidewalk a are dented by i_a and C_a^i, respectively.

2- Improvements of the environmental qualities in the sidewalks: as shown in the equation 9, the environmental qualities have inverse effect on the perceived travel cost. Hence, enhancing the qualities can positively affect the travel cost. Permeability, security, safety, walkability, sociability and sense of richness are the considered environmental qualities. The corresponding decision variable for the quality q and its construction cost in the sidewalk a are dented by j_a^q and C_a^q, respectively.

3- Improvements of the environmental qualities in the nodes: Similar to the sidewalks, the environmental qualities of the nodes can alter the perceived travel cost of the paths. The corresponding decision variable for the quality q and its monetary cost in the node n are dented by K_n^q and C_n^q, respectively.

4- Opening the dead end crossings: There is a serious emphasis for opening the dead end passages in the urban development policies. By doing so, the connectivity of the network is hugely upgraded and some additional benefits will appear in the form of some qualities such as permeability. These projects will change the network itself and are counted to be the most fundamental alterations since they reshape the structure of economic values of the district. The corresponding decision variable and its construction cost are dented by $r \in R$ and C_r, respectively. It is pointed out that all the decision variables except r can be set in a discrete integer space in the interval [0, 10]. The value of zero indicates preserving the current situation and the value of 10 decides the maximum possible improvement for the subject. The decision variable r can be assigned as a binary value of opening or not opening a dead end passage.

5- Motivation of private sector for renovation of the district via considering optimal tax discounts: in order to rebuild an old parcel in the urban areas, one has to pay a tax to receive the legal permission for construction operations. Discount on this tax can motivate the owners to renovate their assets in the district; therefore, an important goal in the urban planning can be achieved.

Another aspect of a healthy urban management system is its long vision diversity in the sense of objectives in every district. Unlike the motorized transportation system where the objectives are the unique for the whole system, the objectives of PNDP may differ in the areas due to the multiplicity of the beneficiary urban managers. This intensifies the problem, since the objectives of each manager in each urban zone is exclusively determined. According to decision variables, the objective functions of the ULP are illustrated as follows:

$$\begin{cases} Max\ Z_{1s}^{qp} = \lambda_s^{qp}.\left(\sum_{m\in M}\sum_{a\in A} v_a^m.q_a + \sum_{m\in M}\sum_{n\in N} v_n^m.q_n \right) & \forall q\in Q, s\in S, p\in P \quad (20) \\ Min\ Z_2 = \sum_{m\in M}\sum_{a\in A} v_a^m.c_a^m + \sum_{m\in M}\sum_{n\in N} v_n^m.c_n^m & (21) \\ Min\ Z_3 = \left(\arg\max\left\{ \frac{v_a}{v_{\max}^a} \middle| \forall a\in A \right\} - \arg\min\left\{ \frac{v_a}{v_{\max}^a} \middle| \forall a\in A \right\} \right) + & \\ \qquad \left(\arg\max\left\{ \frac{v_n}{v_{\max}^n} \middle| \forall n\in N \right\} - \arg\min\left\{ \frac{v_n}{v_{\max}^n} \middle| \forall n\in N \right\} \right) & (22) \\ Max\ Z_4 = F(r) & (23) \\ Max\ Z_5 = \sum_{a\in A}(l_a Ar_a) + \sum_{n\in N}(l_n.Ar_n) & (24) \\ Min\ Z_6 = \sum_{a\in A} C_a^i.i_a + \sum_{a\in A}\sum_{q\in Q} C_a^q.j_a^q + \sum_{n\in N}\sum_{q\in Q} C_n^q.j_n^q + \sum_{r\in R} r.C_r + & \\ + \sum_{a\in A}(l_a.Ar_a.T) + \sum_{n\in N}(l_n.Ar_n.T) & (25) \end{cases}$$

$s.t.$

$$\sum_{a\in A} C_a^i.i_a \le B_w \tag{26}$$

$$\sum_{a\in A} C_a^q.j_a^q + \sum_{n\in N} C_n^q.j_n^q \le B_q \tag{27}$$

$$\sum_{r\in R} r.C_r \le B_c \tag{28}$$

$$\sum_{a\in A}(l_a.Ar_a.T) + \sum_{n\in N}(l_n.Ar_n.T) \le B_l \tag{29}$$

Where Z_{1s}^{qp} is the weighted objective function for of the urban manager $s\in S$ in the district $p\in P$ for maximizing the beneficiary of pedestrian from quality $q\in Q$. The definition of all the objective functions of the ULP is given in the table 1. λ_s^{qp} is the coefficient of importance for the manager *s* in the district *p* in respect to the quality *q*. l_a and l_n are the decision variables for maximizing the renovation in the link *a* and node *n*, respectively. *T* is the monetary tax discounts for the renovation. B_w and B_r are the maximum assigned budget in the urban master plan for widening the sidewalks and developments of the environmental qualities, respectively. B_c and B_l are the maximum assigned budget in the urban master plan for opening the dead end crossings and assigned discounts for renovation of the district, respectively. Equation (26) presents the budget limit for widening the sidewalks. Equation (27) shows the limit of cost for improving the qualities in links and nodes. The assigned budget for opening the dead end crossings are implied in equation (28). Equation (29) preserves the maximum renovation discount budget. It is interesting to note that the ULP has 11 distinctive objective functions, considering 6 different environmental qualities.

Table 1. Definition of objective functions in the ULP

Objective function	Definition
Z_1^q	Maximizing the beneficial of the pedestrian from each environmental quality
Z_2	Minimizing the total travel cost of the network
Z_3	Minimizing the difference between maximum and minimum flow in the network to create a proportional flow distribution as an indication of just planning
Z_4	Maximizing the economic development as a result of decision variable *r*
Z_5	Maximizing the renovation
Z_6	Minimizing the overall cost of the planning (including the cost of widening the sidewalk, cost of environmental qualities improvement in the network, cost of opening the dead end walkways, cost of the renovation tax discounts)

The ULP of PNDP is a non-convex problem with too many objectives. The methods to solve the optimization problem can be divided into two main categories: exact mathematical methods and metaheuristic algorithms. Since the PNDP is an NP-hard problem, solving the model by exact methods is practically impossible for the medium to large scale problems due to its computational problems. In addition, these methods are usually gradient-based and can be trapped in a local optimum solution in the non-convex space. On the other hand, the metaheuristic algorithm are simple and fast approaches to solve such problems. In this paper, same as Rastbin et al. (2017), the multi-objective metaheuristic proposed by Deb et al. (2000), known as NSGA-II, is applied to solve the ULP. The method is among the most efficient tools to deal with complex optimization problem with too many objectives. The NSGA-II is an extension of the Genetic algorithm for generating Pareto optimal frontier, inspired from the field of evolutionary computation. The algorithm is consisted of two main operators of crossover and mutation and selects the Pareto fronts in each generation according to its crowding distance rule. Here, the stopping criterion of the method is considered as the maximum generations.

4. PNDP: Bi-level model

In this paper, a bi-level mixed-integer programming model is proposed to solve the PNDP. The model is equivalent to a Stackelberg game (1934) where governor plays the role of the leader who decides the condition of the network and pedestrians are followers who behave according to the governors' decision. The model can be envisaged as a decision making tool for urban planners to determine the best projects in the network. It is noted that the model is not completely sufficient for selecting the best solution. It is indeed a remarkable useful assist which can limit the vast solution space to some pre-final alternatives. In fact, the experts should analyze the current situation to define the decision variables for the beginning of the process and also check the output to consider some additional limitations or probably slightly correcting the results. In the other word, human brain cannot foresee all the options in such confusing world, while the proposed model is capable of exploring through the space, including the blind spots. On the contrary, the mathematical model has no knowledge or tangible perception on the final solution, where an expert can analyze the results from a judgmental point of view to resolve its probable errors. These two elements can form a superb combination to tackle to problem. The framework of the model is illustrated in figure 2, with the same structure of the model of Rastbin et al. (2017). As it can be seen in figure 2, the initial population is generated using Monte-Carlo algorithm. Applying the probabilistic technique can enhance the quality of the first generation, reducing the needed population size or generations. The iteratively process can be described by following steps:

Step 0: Generate the initial solutions as the first generation of the genetic algorithm.
Step 1: Assign the demand to the corresponding network of each solution at hand. Determine the equilibrium link flow for each solution.
Step 2: evaluate the objective functions of the problem for each solution based on the assignment results.
Step 3: Apply genetic operators to generate new generation.
Step 4: Evaluate the solution using the FPAM (LLP).
Step 5: Determine new Pareto fronts.
Step 6: If the stopping criterion is met, go to step 7. Otherwise go to Step 3.
Step 7: Output the best solutions (first Pareto front).

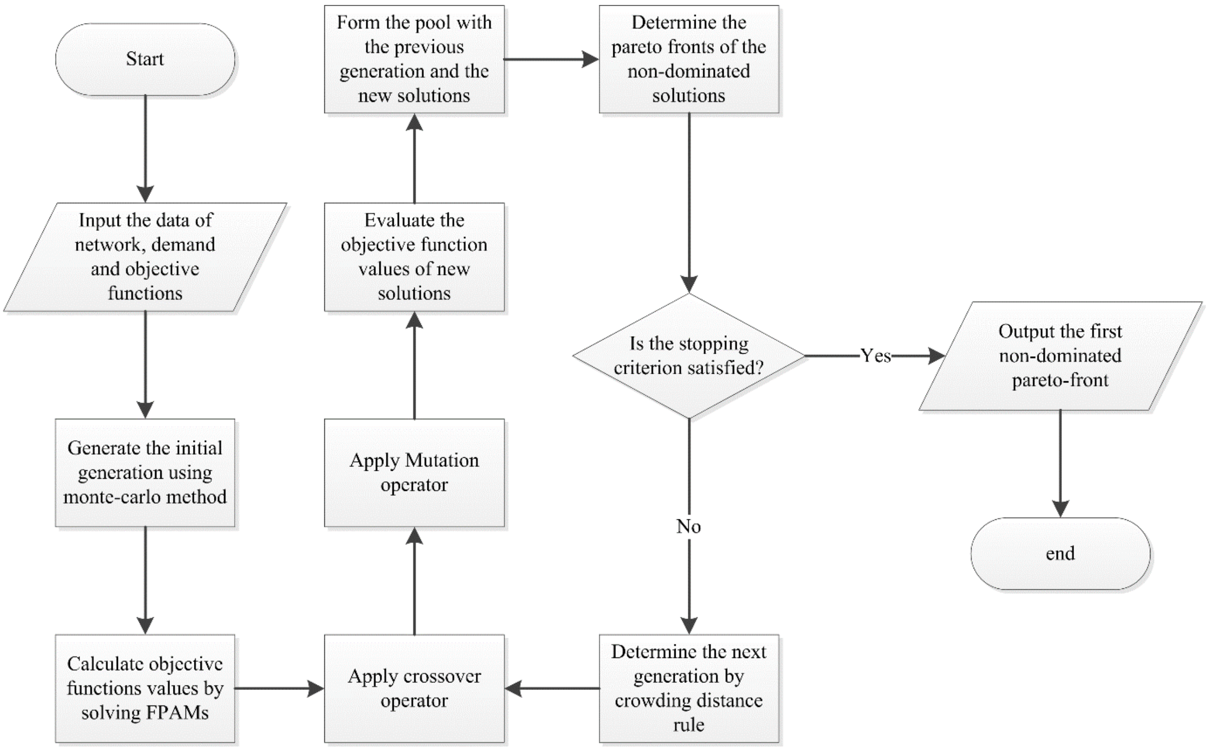

Figure 2. The Proposed genetic based algorithm for solving the PNDP

5. Numerical experiment

In order to assess the performance of the proposed method in a large scale network, the algorithm is applied for a pedestrian network in the historic district of the city of Tehran. The defined pedestrian network has 55 nodes, 98 arcs, 906 OD pair of leisure trips and 922 OD pair of work trips, which indicate a relatively large-scale network. The corresponding defined graph of the network is depicted in the figure 3. Considering all the decision variables in the network, 1.30×10^{862} different state of the network is generally possible. This number reveals the mind-blowing dimensions of the problem. The proposed algorithm is implemented in C# programming language. The FPAMs are solved with the accuracy equal to the RG of 10^{-4}. The results of FPAM model was verified by comparing the obtained equilibrium flows with the observed pedestrian flows in the area. The algorithm was executed on a desktop computer with an Intel 3.90 GHz CPU and 32GB memory. Due to the stochastic nature of the ULP, the algorithm is performed 20 times and the average results are reported. Table 2 shows the settings of the ULP in solving the problem.

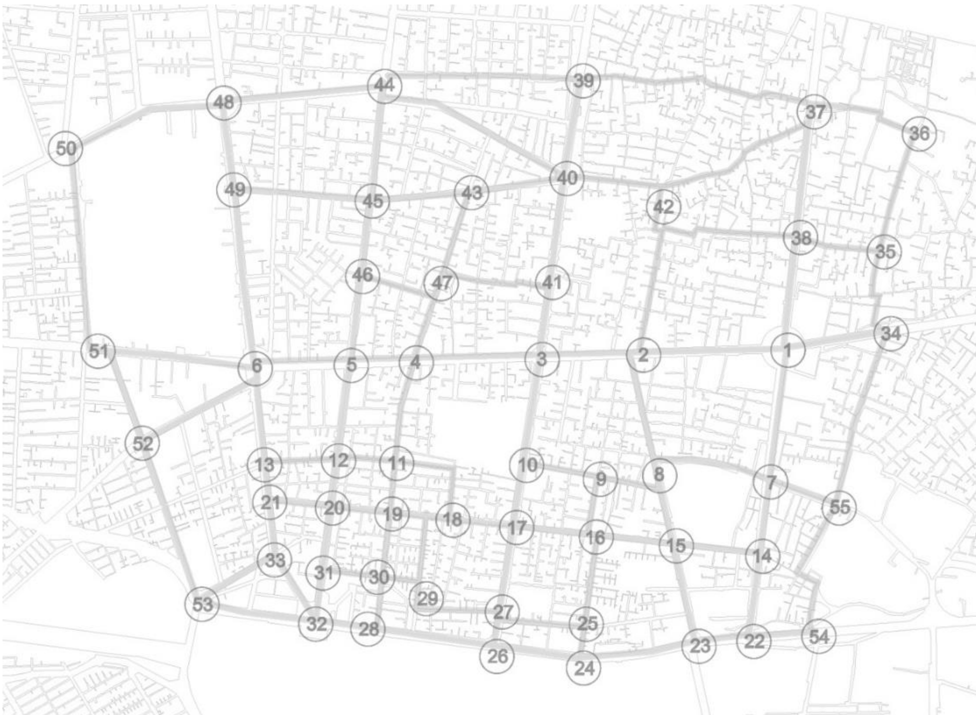

Figure 3. The directed Graph of the considered pedestrian network

Table 2. Settings of the ULP in solving the problem

Subject	Value/rate	Type
Crossover	0.6	multiple cut point
Mutation	0.2	substitution
Population	1000	-
Maximum Generation	3000	-
Pareto frontier	-	Crowding distance
$\frac{B_w}{TC_w}$	0.5	-
$\frac{B_r}{TC_r}$	0.5	-
$\frac{B_c}{TC_c}$	0.5	-
$\frac{B_l}{TC_l}$	0.5	-

where TC_w, TC_r, TC_c and TC_l represent the maximum cost of developing the sidewalks, developing the qualities in the network, opening the dead end crossings and tax discounts, respectively. Applying these constraints, the solution space shrinks to 4.075×10^{739} possible solutions which is still an extraordinary number. The parameters of the algorithm were tuned via a try-and-error process where different set of parameters were applied to solve the model for a test network, presented in Rastbin et al. (2017). The process is similar to an experiment design where the parameters are calibrated by assessing the results of different sets.

Figure 3 illustrates the average objective functions values of the successive generations. As shown in this figure, after 2360 generations, all the objective functions reach a stable condition and converge to the final solution. According to the convergence of the algorithm and properties of the genetic operators, it can be concluded that the validity of solutions are verified. Table 3 reports the results for the found solution as well as the best state for each objective function.

Table 3. Results of the proposed algorithm for considered pedestrian network

Objective function	Best solution value	Pareto average value	Best possible value	Welfare gain (%)
Z_1 (Security)	181,334,059	152,296,439	193,664,630	81.08
Z_1 (Safety)	482,805,449	398,358,143	497,768,050	84.81
Z_1 (walkability)	243,903,353	181,474,428	261,201,297	88.50
Z_1 (sociability)	139,127,029	129,725,801	150,385,765	75.03
Z_1 (sense of richness)	98,600,212	95,304,639	107,616,126	79.02
Z_1 (Permeability)	27,102,917	26,288,221	29,539,167	81.04
Z_2	12,526,396	16,246,970	11,773,426	83.65
Z_3	0.23	0.26	_(***)	_
Z_4	296.18	242.79	337.4	85.98
Z_5	14,807.98	13,681.52	15,963.0	84.30
Z_6	47.86	54.49	0	_

(***) The best value of this objective cannot be calculated without total enumeration, due to its' complexity.

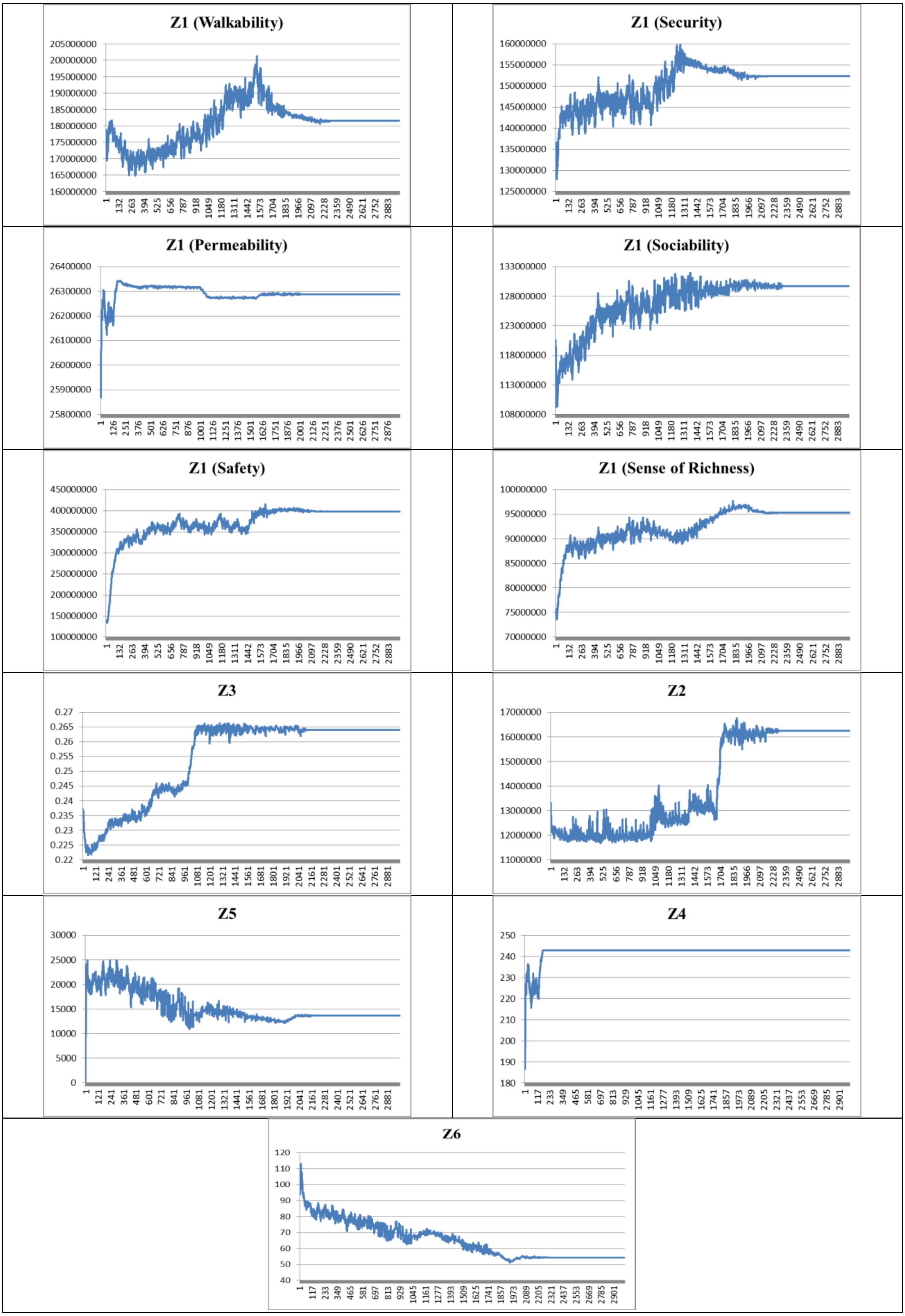

Figure 3. The value of objective functions in successive generations

The welfare gain of the function (i) is calculated as below:

$$Welfare\,Gain(i) = \left| \frac{OFV_i - OFV_i^c}{OFV_i^c - OFV_i^b} \right| \tag{30}$$

where OFV_i is the value of objective function i in the best solution found, OFV_i^c is the value of objective function i in the current situation and OFV_i^b is the best possible value for the function i, ignoring the other objective functions. The average welfare gain of the proposed algorithm is 82.6. It implicitly verifies the performance and the efficiency of the algorithm, since spending half of the maximum possible construction cost has led to a welfare gain of 82.6 percent. It should be noticed that the problem was solved by executing FPAM for 2401000 times. Since solving the FPAM takes 0.45 seconds, the algorithm found the solution after approximately 12.5 days by surveying only a fraction of the solution space.

6. Conclusion

In this paper, the pedestrian network design problem (PNDP) and its aspects are discussed. A fuzzy macroscopic multi-class pedestrian assignment algorithm is proposed which is capable of solving the pedestrian assignment problem for a large scale network of sidewalks. In addition, a bi-level mathematical mixed integer programming model is presented to for solving the PNDP. The ULP of the model is a multi-objective optimization problem and is solved by the well-known NSGA-II algorithm. The LLP is the proposed FPAM which is solved by a novel iterative method based on a path-based assignment algorithm. The model can output the optimum budgeting plan for selecting the projects in public places, while satisfying the financial limits and constraints of the network. Thus, the model can be used by urban planners to design efficient urban master plan. The problem is solved for a relatively large scale pedestrian network for the city of Tehran. Based on the results, the proposed algorithm was able to achieve a remarkable welfare gain of 82.6 percent, while spending less than the half of the maximum construction cost. It is noted that the minimum welfare gain was 75 percent for the objective function of sociability, which proves the capability of proposed algorithm in solving the multi objective problem. The performance of the method satisfies the need for urban planning. Moreover, to the satisfying performance of the algorithm in optimizing the objective function, it narrows the vast solution space to a portion of high quality solutions and solves the problem in a reasonable amount of time, thanks to the efficient operators of the NSGA-II algorithm. The problem was efficiently solved within 12.5 days which is fairly acceptable for the strategic planning of such a large scale network. The results verify the capability of the model and its necessity as a powerful decision making tool in the urban development designs. The outcome are so much promising and encourage further investigation and extension of the proposed models to solve the problem. In the future studies, different optimization algorithms can be implemented in the ULP to enhance the search algorithms. Moreover, considering more classes of pedestrians, according to their non-heterogeneity can increase the accuracy of the process.

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