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Prioritize Effective Factors of Scheduling in Tehran Metro Station with Fuzzy TOPSIS Model

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Highlights

- Saving money and time, decreasing traffic and pollution are the benefits of using Metro
- The research aims to make the path shorter while maintaining adequate performance accuracy
- An ideal data mining strategy and machine learning fundamentals are provided
- To prioritize the aspects impacting, mathematical data and methodologies are used

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Abstract

Metro is considered one of the fastest and most efficient means of transport within the city in different countries, which reduces traffic and pollution and is more cost-effective and time-efficient. Routing transportation systems is one of the critical parts of determining the route and choosing the optimal route with minimal time and cost for users. Most of the methods that led to optimization in routing in the past, both in the airline and on the ground, are based on smart methods. It should be noted that the discovery of knowledge from the data is also essential to predict the path. Hence, data mining operations will also be considered. This research tries to provide an optimal data mining approach and machine learning principles to predict the route and select the optimal path in metro lines with minimum time, best speed, and minor errors in routing. Identifying the factors influencing the scheduling issue have uncertainty. This study tries to provide an optimal method based on data mining and machine learning principles using Fuzzy Logic and Technique for Order Preference by Similarity to Ideal Solution method to predict the priorities of effective factors in metro scheduling in Tehran and select the optimal route in metro lines with a minimum time, the best speed and the least error in routing. According to the findings, the top priorities have a significant influence on the preferred strategy in the metro plan.

Nomenclature

Indices		MILP	Mixed-integer linear programming
PE	*Prior Enumeration techniques*	MTS	*Modified Tabu Search Algorithm*
MADM	*Multi-Attribute Decision-Making*	*MINLP*	*Mixed-integer nonlinear programming*
MILP	*Mixed integer linear programming*	*TOPSIS*	*Technique for Order Preference by Similarity to Ideal Solution*

1. Introduction

Today, the development of public transportation systems is considered a principled solution for large cities with more than one million people. In addition to the bus, people are also using other systems due to the increasing cost of developing street networks. These systems are designed to achieve different goals, such as increasing travel comfort and safety, reducing air pollution and

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protecting the environment, reducing travel time, and solving traffic problems caused by personal traffic. Metro is one of the public transportation systems with more attention in large cities due to its operating privileges. Since there are various routes on the subway, the movement of passengers should be optimized to reach the destination as quickly as possible. The input of most transportation systems is traffic volume. The total annual traffic volume is divided by 365 [1].

In this project, which identifies the factors of scheduling and prioritizing the effective factors to predict the subway route in Tehran, we try to provide a suitable method in routing with the minimum time and the best accuracy in walking distance between different stations.

2. Literature Review

The classification of a complex network of intra-city passages into groups and systems that have similar characteristics is called the classification of inter-urban passages. The road is a set of passages for motor vehicles, bicycles, and pedestrians. Interstellar roads are called streets. The motorway, which is physically fully segregated along the entire length of the traffic, and is designed so that traffic flows in it without stopping, is called a freeway. In order to provide such conditions on these roads, intersections should be non-level, and the way of entering and leaving the vehicles is fully controlled and based on the correct design. Trails that connect the connection between residential and residential units, connecting them to the street and the player, are local roads. Local passages should not be placed in transit traffic. The traffic volume is the number of vehicles that pass through a certain time in a time unit (hour). The volume of traffic that travels through a specific day during a specific time is called daily traffic volume. The maximum number of vehicles that can be traversed over one hour with a certain quality of traffic from a certain point in the way is possible. A commonly used one-way route that connects two different tugs is called a ramp or shingles [2].

Recently, various methodologies have presented numerous models and algorithms to handle the metro scheduling issue. The coordinate timing method is recommended in [3] to indicate the ratio of short-term metro services to full-time metro services. Researchers showed that the 1:1 scheduling performance pattern outperformed full-time metro scheduling for the OD matrix acquired from a survey, implying a short rotation service. It indicates that it can better fulfill passenger demand than two full-length trips. A short rotation model for optimizing rates, vehicle dimensions, and rotating terminals for quick services and entire subways in subway corridors has been created in [4]. In this work, only a single operational period is considered. At the same time, in [5], the service patterns have been focused on a metro corridor during different periods of operation, taking into account the short rotation strategy and size. Metro variables reduce user and operator costs. In [6], an approach is presented for determining where the rotation terminal for a short rotation service is located and whether a metro is a short rotational service on a real-time two-way metro line. In [7], the placement of short-turn services to handle the scenario of interruption, such as the emergence of a foundation for fast-moving transportation systems, to lower passenger waiting time, is described. In [8], they also investigated a condition with complete obstruction. They offered a linear mixed-numeric linear programming model for calculating the metro program by adopting a short rotation strategy.

Also, to optimize the issue of metro planning with a short rotation strategy in metropolitan rail transportation systems, and in [9], a proper programming model for nonlinear mixing has been implemented to minimize passenger trip expenses and operational costs. In [10], a model aimed at minimizing trains has created passengers' performance by optimizing the spatial distribution of space to optimize and balance the program. Predicting passenger flow and metro levels, [11] discusses different operating patterns with various coordinate program modes and selects a 1-line rotation station in Shanghai, the city's first urban rail line with a short rotation strategy. Passenger and metro flows have been evaluated in [12], utilizing a short rotation approach focusing on a particular line in the urban rail transport network to optimize the metro program by restricting the range of subways and variation of the actual passenger capacity. A multi-faceted model has been created. In [13], the cause of passenger flow imbalance and feasibility analysis of the operational model with a short rotation strategy has been analyzed. It evaluates the metro schedule with the loading factor.

The subway schedule is also important for planning because the number of subways is limited. In [14], a combined optimization approach for metro planning and operational planning issues was developed.

In [15], they created a correct programming model to find an efficient rotation of the railroad on a collection of subways using a branch and pricing method. [16] proposed a model for optimal metro allocation to minimize capacity shortages during busy hours. The optimal solution is more effective than manual planning. In [17], they developed a model that included many features, including metro, inspection, operation route, and operation. The issue of deadlocks is considered in [18], and a model has been proposed to determine the ideal vehicle frequency value and capacities, a combination of caps and short conversion to an integrated fleet management strategy.

Forecasts have been made on subway routes and urban and inter-urban railroads in various aspects and fields. For example, in [19], a business network is provided to predict possible errors during weather instability. A weather forecast has been made to impact railroads, utilizing a weather data set and a rails status data set. In another study, presented in [20], prediction of scheduling contradictions in high-speed railway lines based on fuzzy knowledge has been carried out. The research suggests creating a prediction system for scheduling railway lines for the presence of trains or subways on the rails. In [21], the route selection is provided with operational information in metro networks. This research is divided into two parts. Initially, it discusses the choice of the route optimally. Then it provides a very optimal method.

Other research has also been done in other areas of transportation systems. In [22], regression uses population parameters, vehicle ownership, households, and employees in a family to estimate traffic volumes in one year. [23] provides a multiple regression model using the number of lines, land use, path type, and economic conditions. [24] used the alternating nervous system to estimate 63 locations on the Minnesota Highway Network in the United States. The result of this study is that the approach of using the neural network in later traffic estimation and forecasting methods is that the neural network operates in the same way as other classical methods of estimating traffic volumes when the counting stations are properly classified. And better than them.

[25] addresses the approach of identifying non-return events in urban traffic. The proposed method for identifying and predicting traffic flows is based on nonlinear analysis using the probabilistic neural network. It is planned to carry out operations for forecasting traffic. Three patterns are considered temporal: sustainability, non-consistency, and uniqueness (non-linearity). In [26], in predicting large-accident crashes in real time, their use is based on the analysis of the entropy of the gray-matter relationship and the probabilistic neural network. The main criterion of this study is to show the turbulence in the traffic flow, which is analyzed based on the entropy of the gray-matter relationship and is used to detect and predict the real-time crashes on the road in real-time from the probabilistic neural network.

In [27], a behavioral comparison of route selection has been carried out in subway networks based on a series of criteria, including time, passenger transportation, congestion, road recognition alignment, and metro area demography. The route selection model has been applied to London Underground in London as well as the Santiago metro in Madrid, Spain. A general comparison has been made between travelers' decisions between short routes on these two different metro lines. Also, the short routes to the two metro lines have been compared. It has been generally considered that passengers on the London subway, walking on the subway edge to get a more suitable place to sit further, care to get faster. However, travelers in the Santiago Metro prefer to wait. To reach the subway and get to the destination quickly.

One of the first researches in the doctoral thesis's routing the transportation lines is presented in [28], which presents the problem as a way of finding the least cost between the origin and destination and modeling it. The method presented in [28] was improved in [29] presents a maximum coverage path and the shortest route model with a maximum population. Both models evaluate the options concerning construction costs and social benefits and are modeled in the form of integer programming. In [30], the forbidden search algorithm considered locating a transport line. The objective function of the proposed algorithm is to maximize the population coverage of the path. In [31], a model has been developed in which a vehicle has become commonplace, a competitor of the vehicle. In this study, users assume that transport systems are chosen in a way that minimizes their costs. In [32], the goal is to maximize the population covered by the route. In [33], the concept of travel coverage for the station has been discussed. A solution to the routing problem has been developed using an evolutionary method and a maximum length limit.

A short turning approach for train schedule optimization on an urban rail transit route was presented in [33]. (The case of Beijing subway line 4). Initially, this research created a MINLP model for train schedules. Short-turning and full-length train services are optimized based on the preset headway determined by the passenger demand analysis. To propose appropriate route scheduling in the railway station, the MINLP model is changed into a MILP model based on many transformation features.

[34] proposes a flexible metro train scheduling technique that saves energy costs and passenger wait time. This technique initially developed a nonlinear integer programming model by considering various system limitations such as inventory train constraints, train loading capacity constraints, and train type constraints. Then, complexity analysis and decomposition approaches are described to solve the model. An MTS with PE was created to identify roughly optimum solutions for the specified model. A series of numerical examples were used to validate the efficacy and performance of the suggested methodologies on a simple metro line and the Beijing Metro Yizhuang Line. In [35], collaborative optimization is proposed for metro train scheduling and connections combined with a passenger flow control strategy. The MILP model and Lagrangian relaxation-based heuristic approach are designed to decompose the original problem. The proposed collaboration of this research improved metro line operation efficiency and safety.[36]

3. Proposed Method

This study's urban rail transit route is defined as a double-track rail line, as illustrated in Figure 2. Train operation in one direction is unaffected by train operation in the other. Train service directions are indexed differently. Three depots, A, B, and C, are connected to stations 1, J, and P. The way from station 1 to P is called the up direction, whereas the route from station P to 1 is called the down direction. Area 1 contains the block portion from station J+1 to station P. Area 2 includes the block section from station J+1 to station P. Area 2 designates the block portion between stations 1 and J. Area 2 can accommodate both short-turning and full-length train services. However, Area 1 can only accommodate full-length train services. Short-turning train services, in particular, are characterized as train services that only run-in area 2. The operating period of the urban rail transit line is divided into multiple time intervals based on the passenger traffic flow, which is indexed by k. Also this research introduce i and l to index a train service in the up and down direction with

$i \in S_{service}^{up} = \{1,2, \dots, I_{total}^{up}\}$ and $l \in S_{service}^{down} = \{1,2, \dots, I_{total}^{down}\}$ which I_{total}^{up} and I_{total}^{down} denote the total number of train services for both directions and formulated as Eq (1) and (2).

$$I_{total}^{up} = \sum_{k=1}^{K} I_{up,k} \qquad (1)$$

$$I_{total}^{down} = \sum_{k=1}^{K} I_{down,k} \qquad (2)$$

Where K is the number of time intervals. $I_{up,k}$ and $I_{down,k}$ denote the number of train services during the k'th time interval in the up and down direction, respectively. It is noteworthy that the important priorities for scheduling in the Tehran metro include the existing metro restrictions, the metro load capacity limit, the metro type restrictions, the metro routes, and the metro intersection to change lines and distances.

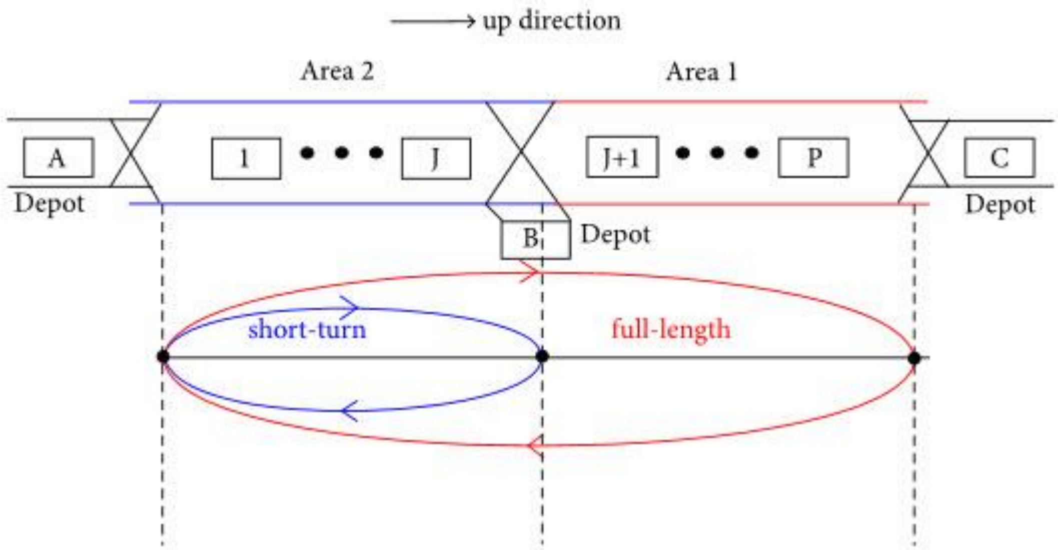

Fig. 1. The design of an urban rail transportation route

There are numerous scenarios for train operations on the urban rail transit route. Figure (2) depicts one possible operation for a short-turning train service in the up direction that departs from Depot A. State 1 shows a quick turnaround train service returning to Depot B. In State 2, a short-turning train service arrives at the destination station, followed by the connecting train service, which returns to Depot A. In State 3, the short-turning train service terminates at station J, and the connecting train service terminates at its target stop, station 1. For full-length train services operating in the urban rail transit line, Figure (2), b part also shows several situations that are similar to Figure (2), apart. Accordingly, there are also 6 situations for the operation of train services in the down direction. Figure (2), b portion depicts numerous circumstances comparable to Figure (2), aside from full-length train services running on the urban rail transit line. As a result, there are six scenarios for the operation of train services in the downward direction.

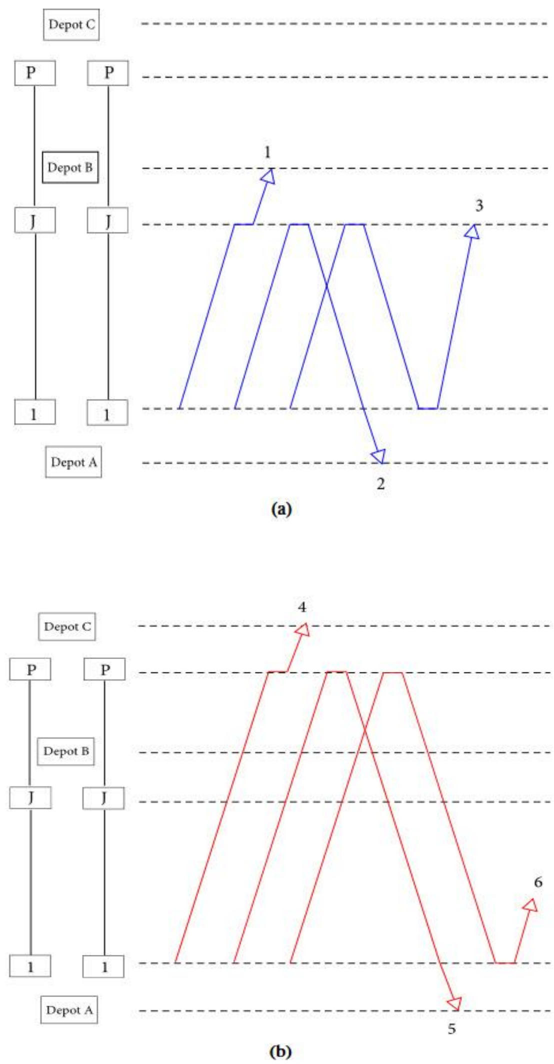

Fig. 2. Conceivable scenarios for railway service operations

The train schedule optimization problem's major decision factors are:

- ✓ Train service departure and arrival times in both the origin and destination stations.
- ✓ Train service types, such as whether a train service is a short turning one or a full-length one
- ✓ Connection affinity among train services in the up and down trends.

Constraints should include departure and arrival times for each train service, train orders for train services, headways for areas 1 and 2, and a train circulation plan. Because the running times and dwell periods are constants that the headway at the interstation should be identical to the headway at the origin station, this study solely addresses the headways at the origin and destination stations.

It is estimated that 5 train services will be provided, with varied passenger needs in areas 1 and 2, where the values are in the 360s and 180s, respectively. Passengers in area 2 want to board a train with a headway of 180 seconds, but passengers in area 1 only require a headway of 360 seconds. Two patterns may be formed with a single frequency for a train operating pattern without a short turning strategy. Pattern 1 is designed to meet the passenger demand in Area 1, with a departure time of 360 seconds. It can result in a 180s x 5 increase in headway, as shown by the headway difference in area 2. Pattern 2 focuses on passenger demand in area 2, and the departure time headway is 180s. It has the same effect as Pattern 1. Nevertheless, the passenger demand for both locations may be met when the short-turning train services depart between two consecutive full-length train services (3).

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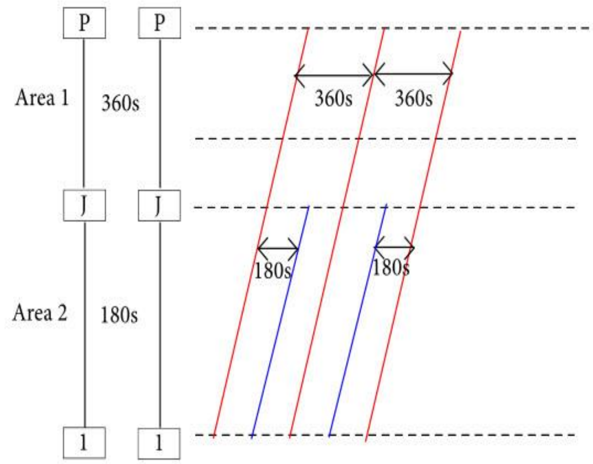

Fig. 3. Both passenger needs in zones 1 and 2 can be met.

So far, the most important factors influencing the scheduling of Tehran's two subway lines have been considered. Now it is necessary to model it with a combined Fuzzy TOPSIS approach. In this approach, n input data is assumed to be in cluster m, and the clusters have a regular one-dimensional or two-dimensional arrangement. The weight vector for each cluster is a sample vector of input patterns linked to that cluster. Suppose the data in a class has the characteristics shown in Table (1) with the specification. In that case, the values of these attributes in each class are shown in Table (2).

Table 1 an example of an information about a data contained in one of the classes

Features Properties	**Feature 1**	**Feature 2**	**Feature 3**	**Feature 4**
Type	Regular	Regular	numerical	numerical
Mean	-	-	0.1	0.4
Value Domain	$\{v_{1,1}, \ldots, v_{1,N}\}$	$\{v_{2,1}, \ldots, v_{2,M}\}$		
Value with maximum iteration	$v_{1,1}$	$v_{2,4}$	-	-

Table 2. the values of the attributes of each class.

Feature 1	Feature 2	Feature 3	Feature 4
$v_{1,1}$	$v_{2,4}$	0.1	0.4

In addition to the definition for replacement with a simple competition, another definition of classifying is proposed to be consistent with the condition of the combination of data, the definition of the appropriate distance criterion. If two data are $X = \{x_1, x_2, \ldots, x_N\}$ and $Y = \{y_1, y_2, \ldots y_N\}$, the distance criterion defined for these two data, which is an extension of the Euclidean relation, is given by Eq (3) is defined.

$$d(X,Y) = \alpha \,.\, distance\big(num(X), num(Y)\big) + \beta . diff\big(cat(X), cat(Y)\big) \tag{3}$$

In equation (3), $(distance(num(.))$ is Euclidean distance calculated between two data with numerical properties, the data obtained by the function $num(.)$. In fact, the $num(.)$ Function of a given data only looks at its numerical property and can be represented as Eq (4).

$$num(X) = \{x_i \epsilon feature_{set}(X) | x_i \ is\ numerical\ ; i\ \epsilon [1, |X|\} \tag{4}$$

Also, in (4), a given data's cat (X) function only looks at its characteristic properties. It can be defined as Eq (5).

$$num(X) = \{x_i \epsilon feature_{set}(X) | x_i \ is\ categorial\ ; i\ \epsilon [1, |X|\} \tag{5}$$

As a result, function $diff(X)$ calculates the distance between the attributes of the field and the best path to choose. This calculation is such that the number of characteristic features with different values is counted, and the result is divided by the number of these attributes. In equation 5), the parameters $\alpha, \beta \epsilon [0,1]$ determine the weights of each of the two numerical and group numbers in determining the distance of data. It should be noted that, after separating the features into different classes, action must be taken on how to handle each class. By viewing the types of paths for each group, it is determined which groups and criteria should be included. For this purpose, the classes are correctly predicted.

Another important point about the rules is that the TOPSIS method is not yet mentioned is how they are generated and the calculation of probabilities based on the type of data to be considered, which is discussed below. With respect to each of the data l_k of the set of closest features, a rule is produced in the form of a multi-criteria decision-making algorithm for TOPSIS method. Suppose the properties of l_k are separated into two parts of the decision and the properties. In that case, the whole set of properties can be represented as $I_k = [f_i, \dots f_n, d_i, \dots d_m]$. In this representation, f_i represents features such as the type of connection and d_i represents the decision and accepts 0 or 1. Obviously, for each data, only one decision is made, so from d_i to d_m, only one of them can be 1. All rules are given in the form of Eq (6) for these data.

$$\begin{aligned} &R_1: f_1, \dots, f_{n>} S_i \\ &R_2: f_1, \dots, f_n \rightarrow S_i \\ &. \\ &. \\ &. \\ &R_{2n+1}: f_1, \dots, f_n \rightarrow S_i \\ &i \in [1, m] \end{aligned} \tag{6}$$

As it is clear from equation (6), a decision may be made for a few data. Each law is evaluated by calculating the probability values. The formulas expressed in calculating probabilities are suitable for the data, and numerical data are difficult to obtain here. Based on this method, it is possible to identify new data that is not in the dataset and not proportional to paths and to choose the best route from existing data as paths.

Now that TOPSIS rules and effective priorities in metro scheduling have been identified, due to uncertainty in these two issues, fuzzy logic comes into play, which is a model based on fuzzy TOPSIS to solve the main challenge of identifying and optimizing effective priorities to solve the metro scheduling in Tehran. In the fuzzy TOPSIS algorithm, it is assumed that M is an input, and $S_1, S_2, S_3, \dots, S_n$ are the language variables that have membership functions or N that are used to optimize the M parameter. Each membership function is known based on a language variable. It is assumed that $S_i^{[j]}$, $V_i^{[j]}$, and $P_i^{[j]}$ are the current metro position, metro speed, and i'th the best previous metro location, respectively. $P_{gb}^{[j]}$ is the best global position j'th at time t and a definite iteration round $Iteration_t$. In the fuzzy TOPSIS algorithm, it is assumed that the search behavior is influenced by a neighbor's overcrowding. Specifically, it should be considered to provide the best national position of $P_{gb}^{[S]}$ and the best previous position of metro $P_i^{[s]}$ at the entrance of s'th to evaluate the speed of metro j'th that a structure in the same way. Immigration classification creates a circle that is in the form of an Eq (7).

$$S = \begin{cases} M & if\ j = 1 \\ J-1 & if\ j = 2,3,\dots,M \end{cases} \tag{7}$$

Then, the fuzzy TOPSIS rules section is created based on the Eqs (8) and (9) with an initial manipulation in this research that can perform the maximum optimization in the prioritization operation of the factors affecting metro scheduling.

$$\begin{aligned} V_i^{[j]}(t+1) = k^{[j]}.\Big[w_i^{[j]}.v_i^{[j]}(t) &+ c_1^{[j]}.rand1.\left(P_i^{[j]} - S_i^{[j]}(t)\right) \\ &+ c_2^{[j]}.rand2.\left(P_{gb}^{[s]} - S_i^{[j]}(t)\right)\Big] \end{aligned} \tag{8}$$

$$S_i^{[j]}(t+1) = S_i^{[j]}(t) + V_i^{[j]}(t+1) \tag{9}$$

In these equations, j is the number of metro densities in areas A and B, c_1 and c_2 are the cognitive and social parameters associated with the speed operator, $rand1$ and $rand2$ are random numbers that is evenly distributed [0,1]. Also, super-script $[s]$ displays the circular migration specified in Eq (7). The weight inertia approach as Eq (10) determines the inertial weighting function for metro speed i.

$$w_i = w_{max} - \frac{w_{max} - w_{min}}{iteration_{max}}.iteration \quad (10)$$

In this case, $iteration_{max}$ is the maximum repetition cycle and $iteration$ is the repetition cycle. The role of the inertial weighting function is crucial for the convergent behavior of the fuzzy TOPSIS algorithm. It is used to control the effect of the previous speed history on the current history. Accordingly, the weighted performance of the inertia regulates a balance between global and local exploration capabilities. In this study, in order to ensure the convergence of the fuzzy TOPSIS algorithm, the contraction coefficient k is confirmed as Eq (11).

$$k = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}} \quad , \quad \varphi = c_1 + c_2 \quad , \quad \varphi > 4 \quad (11)$$

k exists when the contraction criterion controls the system's behavior, and the parameter $\emptyset$ has a series of properties. This system does not differ in the actual amount of search space. It can eventually converge, and it can effectively search different and discrete areas of search space by preventing premature convergence. i 'Th metro positions belong to the j 'th congestion in the n-dimensional search space with the minimum and maximum positions expressed by vectors are limited, which is in the form of Eq (12).

$$[S_i^{[j],min}, S_i^{[j]max}] , \quad (j = 1,2, \dots, M) \quad , \quad (i = 1,2, \dots, N) \quad (12)$$

The speed of the i 'th metro belonging to the j 'th density in the next search space is calculated by Eq (13).

$$[-V_i^{[j],max}, V_i^{[j],max}] , \quad (j = 1,2, \dots, M) \quad , \quad (i = 1,2, \dots, N) \quad (13)$$

Where the velocity vector is composed of maximum terms such as Eq (14).

$$V_{i,lg}^{[j],max} = \frac{S_{i,lg}^{[j],max} - S_{i,lg}^{[j],min}}{Nr} \quad , \quad , \quad \binom{j}{= 1,2, \dots, M} \quad , \quad (i = 1,2, \dots, N) \quad , \quad (lg = 1,2, \dots, n) \quad (14)$$

Here, Nr is the number of searches for subways. It is an important parameter in the fuzzy TOPSIS algorithm. A small Nr facilitates global exploration (search for new areas). At the same time, many tend to facilitate local exploration (accurate adjustment of the current search area). The right amount of Nr usually balances global and local exploration capabilities, thus reducing the number of repetitions needed to find the optimal solution.

The M density problem is employed in the situation of multi-criteria functions. Each congestion applies to each target performance. The implementation of the fuzzy TOPSIS algorithm assumes that each of the densities of M in one of the densities of $M_{Operator}$ that are in a subway line is evaluated. After modeling and optimizing the timing factors, the TOPSIS method enters the fuzzy logic section to select the most optimal answers. Once solutions based on the estimated set are found, it is necessary to display one of them for the final evaluation and optimization output. From the decision maker's point of view, a posterior approach is used to select a solution from all optimum options. It needs a high-level decision-making procedure that selects the best answer from a restricted collection of optimal solutions employing all i. Relevant MADM attributes are frequently employed in the posterior evaluation of optimum solutions to pick the best one. The problem of deciding between standard choices is generally referred to as decision-making on many features, which is a practical approach to rank or pick an alternative to a finite set of other possibilities owing to various features; it is typically contradictory. The chosen attribute provides the maximum level of pleasure for all relevant qualities, and the term "attribute" is employed as a target, criteria, or cost. Many methods have been developed to select the best compromise solution for multiple attribute problems or criteria. The concept of TOPSIS has been used to find the best compromise solution in this research in the fuzzy section. Because the viable, practical design should be close to the ideal solution but distant from the negative ideal solution, the TOPSIS approach was developed. It has become a typical strategy for making multi-objective decisions with few possibilities. It is assumed that $R = \{R_{ij} | i = 1,2, \dots, n ; j = 1,2, \dots, m\}$ and n and m are the number of optimal solutions and the number of targets, respectively. In this relation, $n \times m$ is the decision matrix, and R_{ij} is the efficiency ratio of X_j (optimal solution) according to the property A_i (the value of the objective function). To determine the weight of targets by measuring entropy, the decision matrix requires normalization for each $A_i$target as Eq (15).

$$p_{ij} = \frac{R_{ij}}{\sum_{p=1}^{n} R_{pj}} \quad (15)$$

As a result, a normal decision matrix represents the relative performance of the alternatives obtained as Eq (16).

$$p = \begin{bmatrix} p_{11} & \cdots & p_{1m} \\ \cdots & \cdots & \cdots \\ p_{n1} & \cdots & p_{nm} \end{bmatrix} \quad (16)$$

The amount of decision information available in equation (16) and emitted is characteristic of A_j $(j = 1,2, \dots, m)$ and, therefore, can be measured by the value of entropy, which is related to Eq (17).

$$e_j = \frac{-1}{ln\, n} \sum_{i=1}^{n} p_{ij}\, ln\, (p_{ij}) \quad (17)$$

The degree of convergence or d_j is the mean of the inherent information in each property of A_j $(j = 1,2, \dots, m)$ is calculated as Eq (18).

$$d_j = 1 - e_j \quad (18)$$

The normalized value of the target weight v_{ij} is also calculated as Eq (19).

$$v_{ij} = w_i p_{ij} \tag{19}$$

After determining the performance ranking of the alternative options and the target weight of the features, the next step is to collect them to produce a total performance index for each option. This collection process is based on the ideal positive solution, i.e., A^+, and the negative ideal solution, A^-, which are calculated by two Eqs (20) and (21), respectively.

$$A^+ = (max(v_{i1}), max(v_{i2}), \dots max(v_{im})) = (v_1^+, v_2^+, \dots, v_m^+) \tag{20}$$

$$A^- = min(v_{i1}), min(v_{i2}), \dots, min(v_{im})) = (v_1^-, v_2^-, \dots, v_m^-) \tag{21}$$

The distance between the options can be measured with a n-dimensional Euclidean distance. The separation of each option from the ideal solution is as described in Eq (22).

$$d_j^+ = \{\sum_{i=1}^{m} \left(v_{ji} - v_i^+\right)^2\}^{\frac{1}{2}} \quad , \quad j = 1,2,\dots,n \tag{22}$$

Similarly, each alternative is separated from the negative answer as given in Eq (23).

$$d_j^- = \{\sum_{i=1}^{m} \left(v_{ji} - v_i^+\right)^2\}^{\frac{1}{2}} \quad , \quad j = 1,2,\dots,n \tag{23}$$

The relative proximity to the ideal solution to replace X_j is calculated as Eq (24) with respect to A^+.

$$C_j = \frac{d_j^-}{d_j^+ + d_j^-} \quad , \quad j = 1,2,\dots,n \tag{24}$$

When $d_j^- \geq 0$ and $d_j^+ \geq 0$ are large, it is clear that $C_j \in [0,1]$. To do this, the TOPSIS model selects an alternative with a maximum C_j in descending order to select an optimal function. It is clear that the alternative to X_j should be close to A^+ relative to A^- as the C_j approach.

4. Simulation and Results

The data are generally 48565 rows and 11 columns. The data is from line 1 and subway 2 of Tehran, which is for a month. In this dataset, features such as time traffic, the traffic volume of passengers in a specific station, the number of metro lines in the line, the distance between stations, and the presence or absence of another line in a line to the other lines are considered. On each line, 21 stations are assumed. We also assume the speed of the subway is between 100 and 250. The number of lines connected to the subway lines is 5 lines. The program's output window is generally shown in Figure (4).

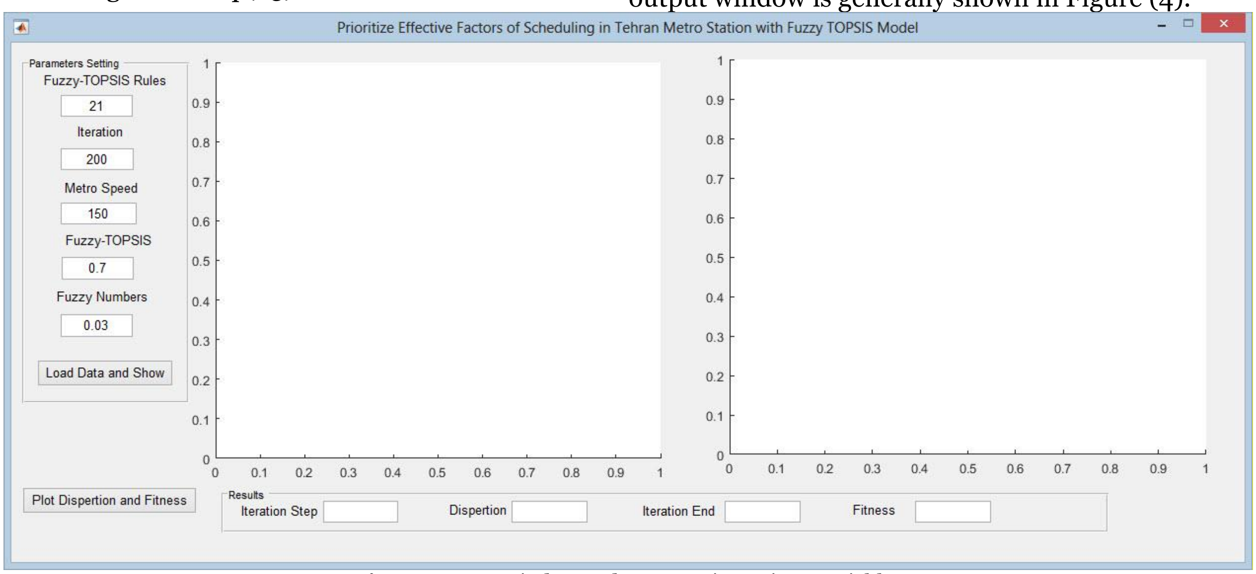

Fig. 4. Output Window and Parametric Settings Variables

Once the parameters have been set, the run is performed. At run time, the left window in Figure (4) displays the number of stations along with the lines showing the subway paths at the station. With the initial settings shown in Figure (4), it is clear that the implementation is performed, as can be seen in Figure (5), where the station's position is located.

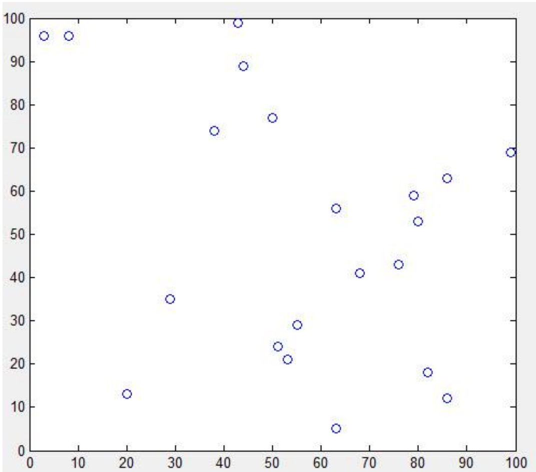

Fig. 5. Number of stations and their deployment

After applying the fuzzy TOPSIS approach and identifying decision rules and criteria, Figure (6) identifies the factors affecting scheduling to predict optimal metro routing between lines and stations.

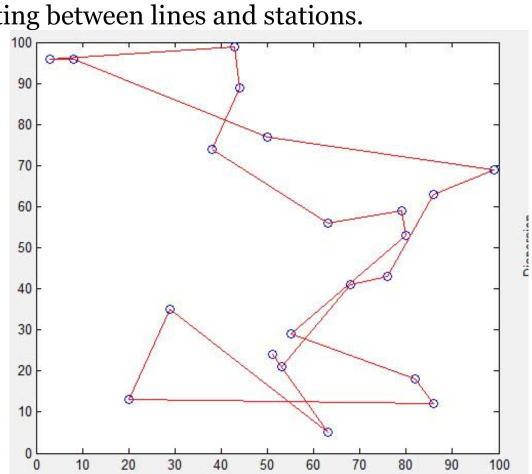

Fig. 6. Metro Routing Between Lines and Stations

When it comes to decision-making algorithms, displaying the output of the dispersion of fit is essential. Figure (7) shows the dispersion diagram at the optimal metro route after scheduling, and Figure (8) shows the fitting diagram at the optimal metro route after scheduling.

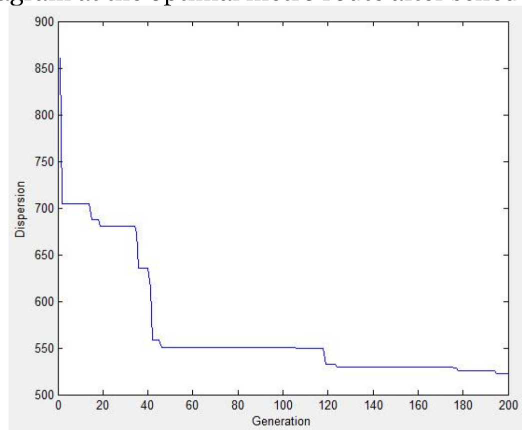

Fig. 7. Dispersion plot in optimal metro route after scheduling

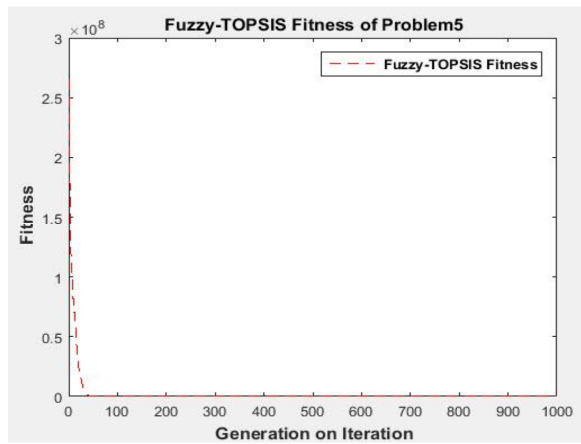

Fig. 8. fitting diagram during metro optimal routing after scheduling

The following is a series of evaluation criteria calculated based on the basic formulas. The evaluation results can be found in Table 3 based on accuracy, sensitivity, mean squared error, peak signal-to-noise ratio, and signal-to-noise ratio.

Table 3. Results of Evaluation

Accuracy (Error Rate %)	Sensitivity (Error Rate %)	MSE	PSNR (dB)	SNR (dB)
6.0606	0.7248	0.2000	55.1205	5.5918

As a result of the table, the accuracy error value is 6.0606%. The proposed approach has 93.9394% correct accuracy in predicting the optimal route for the subway between the lines (21 stations). The sensitivity error rate is also 0.7248%, which is 99.2752% sensitivity.

5. Conclusions

By creating metro lines, less time is spent on road traffic, and due to the metro performance points, it is more important than other transportation systems. Proper routing and location of lines and stations are essential to create a proper metro network. To do this, it is necessary to identify a series of factors affecting the scheduling to have metro lines with minimal traffic. One of the most common methods in line routing is using expert opinions, engineering judgments, and field studies in line with the selected corridors of comprehensive transportation and traffic studies. Another method of routing is the use of mathematical models in which personal opinions are not allowed. The whole routing process is done by mathematical data and methods based on prioritizing the factors affecting the scheduling structure. This study also tries to prioritize the factors influencing the scheduling of the Tehran metro by providing an optimal method to perform the shortest route with the best time and sufficient accuracy in performance. The proposed method uses a fuzzy TOPSIS approach. The results represented that the main priorities, which include existing metro constraints, metro loading capacity constraints, metro type constraints, metro routes, and metro intersections to change lanes and distances, have a high impact on the desired approach in the metro schedule. However, the most important of these, in turn, is the capacity of the metro to load in one direction when reaching the intersections to change the route over long distances. The subway type impacts the fuzzy TOPSIS structure for scheduling the least.

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