Passenger Flow Forecast for Low Carbon Urban Transport Based on Bi-Level Programming Model

Yang Tang[1], *Weiwei Liu*[2*], *Saurabh Singh*[3], *Osama Alfarraj*[4], *Amr Tolba*[4]

[1] *Urban and Rural Planning & Design Institute, Zhejiang University, China*
[2] *Department of Transportation Engineering, University of Shanghai for Science and Technology, China*
[3] *Department of Artificial Intelligence & Big Data, Woosong University, South Korea*
[4] *Computer Science Department, King Saud University, Saudi Arabia*
0015405@zju.edu.cn, weiweiliu@usst.edu.cn, singh.saurabh@wsu.ac.kr, oalfarraj@ksu.edu.sa, atolba@ksu.edu.sa

Abstract

In the context of low-carbon city development, this paper further implements a rail transit passenger flow forecasting method to optimize energy consumption by combining the MMA allocation model with a two-tier planning model for carbon emission control. Through this approach, this paper not only fills the gap of rail transportation planning theories and methods compatible with low-carbon city development, but also emphasizes the importance of energy consumption in transportation planning. Based on a two-tier planning model, this paper considers the Starkberg game between multi-modal and multi-type passenger flow forecasting of rail transit and CO_2 emissions of integrated transportation systems. By optimizing the allocation of users in the transportation network from the perspective of both users and planners, while optimizing the CO_2 emissions of the integrated transportation system, the dual optimization of energy consumption and environmental benefits is achieved. The method will also be tested in Shanghai, and this paper will comparatively study three different carbon emission control schemes. By assigning passenger flows to the entire transportation system network in Shanghai based on information from the Fourth Integrated Transport Survey, including passenger flows on each road in the road network, passenger flows on each rail line, and characteristic indicators, this paper provides a reliable data base. This study provides a solid foundation for planning the layout of rail transit in a low-carbon mode and makes a positive contribution to sustainable urban development by optimizing energy consumption.

Keywords: Rail transit, Bi-level programming model, Passenger flow prediction, Low-carbon

1 Introduction

1.1 Background and Motivation

In the last decade, many disasters and increasingly serious energy problems have been caused by global climate change. It makes people begin to examine a series of survival and development tests caused by the unsustainable development model for a long time [1-2].

As the problem of global warming has become more serious, and urban problems such as traffic congestion, pollution and resource shortage have become more prominent, the concept of low-carbon sustainable development has gradually become a consensus [3]. The theme of the Second Global Sustainable Transport Conference emphasizes that low-carbon transport is the key to achieving sustainability [4]. Public transport, which has a higher passenger capacity than cars [5], has been widely recognized as an important mode in the low-carbon transport system.

In the public transport system, for example, due to the dynamic mobility of people, there will be a mismatch between taxi resources and demand, resulting in too many empty cars, long waiting times for passengers and traffic jams [6]. Therefore, rail transport is more popular and can be regarded as one of the most effective transport methods [7]. When passengers from cars, buses and other modes of transport switch to rail transit, carbon emissions are reduced, and the carbon emission reduction effect of rail transit is also verified by quantitative calculations [8-9]. Planning and designing urban rail transit systems based on low-carbon development concepts is one of the keys to achieving low-carbon urban transportation. In the context of low-carbon city development, consideration of energy consumption is equally crucial for planning urban rail transit systems. A reasonable forecast of rail transit passenger flow demand will help to further balance public transportation supply and demand, improve transportation service quality, reduce transportation costs and improve resource utilization by integrating energy efficient technologies and practices. This paper discusses forecasting methods for rail transportation system.

1.2 Literature Review

Linjun Lu [10] established an Optimal Allocation Model of Public Transit Mode Proportion to achieve the lowest CO_2 emissions, it also verified the importance of rail transit for the construction of low-carbon urban transportation. At present, there are few areas of research on the combination of low-carbon city development and rail transit planning.

Traditional demand forecasting methods may only consider factors such as time and travel cost. In recent years, some scholars have paid more attention to the spatial

*Corresponding Author: Weiwei Liu; E-mail: weiweiliu@usst.edu.cn
DOI: 10.53106/160792642023092405005

correlation brought about by the characteristics of fixed rail stations, uniform vehicle speeds and regular schedules in urban rail demand forecasting. The performance was converted into time cost to improve the accuracy of the model [11]. Xu Sun based on the concept of low-carbon, taking travel time, operating cost, energy consumption, pollutant emission and traffic efficiency as the optimal targets, constructing a two-tier model [5]. This method aims at minimizing the total cost of providing bus services. Na Zhang [12] used the traditional four-level model to measure the demand for passenger flow at the city level, obtained the basic target parameters for building a carbon emission reduction model, and applied it in Baoji, China. Under the goal of a low-carbon city, the demand forecasting model of rail transit project adopts the classical four-stage planning model to improve, namely, travel generation forecast, travel distribution forecast and balance distribution under the condition of multiple transport modes and multiple types of integrated networks. At the same time, this paper combines the bi-level programming model to achieve the goal of controlling the total carbon emissions of the transport system.

The Stackelberg game is widely used in the estimation of the origin-destination (OD) matrix of the transportation system, so that the error between the estimated value of the OD matrix and the measured value is minimized, and the travelers can meet the user balance condition [13]. Recently, when studying the bus route planning [14], it is also based on the framework of the Stackelberg game to construct a bi-level programming model to weigh the decisions of the government, service providers, passengers and other stakeholders. Some scholars [15] have also used the same structure as the bi-level programming model to study the best combination of government subsidies and carbon tax policies to promote the reduction of greenhouse gas emissions.

Compared with the traditional planning method, the bi-level planning method has incomparable advantages. The bi-level planning method can analyse two different objectives at the same time in the decision-making process, which makes the multi-value criteria decision-making method closer to the actual situation. What's more, it can clearly express the interaction between the government and the public [16].

Based on the bi-level programming model, this paper describes the Stackelberg game between the multi-mode and multi-type passenger flow prediction of rail transit and the CO_2 emissions of the integrated transport system; that is, considering the perspectives of users and planners, the user allocation in the transport network is optimal and the CO_2 emissions of the integrated transport system are optimal. To make up for the inadequacy of rail transport planning theory and methods in line with the development of low-carbon cities. The research technology roadmap is shown in Figure 1.

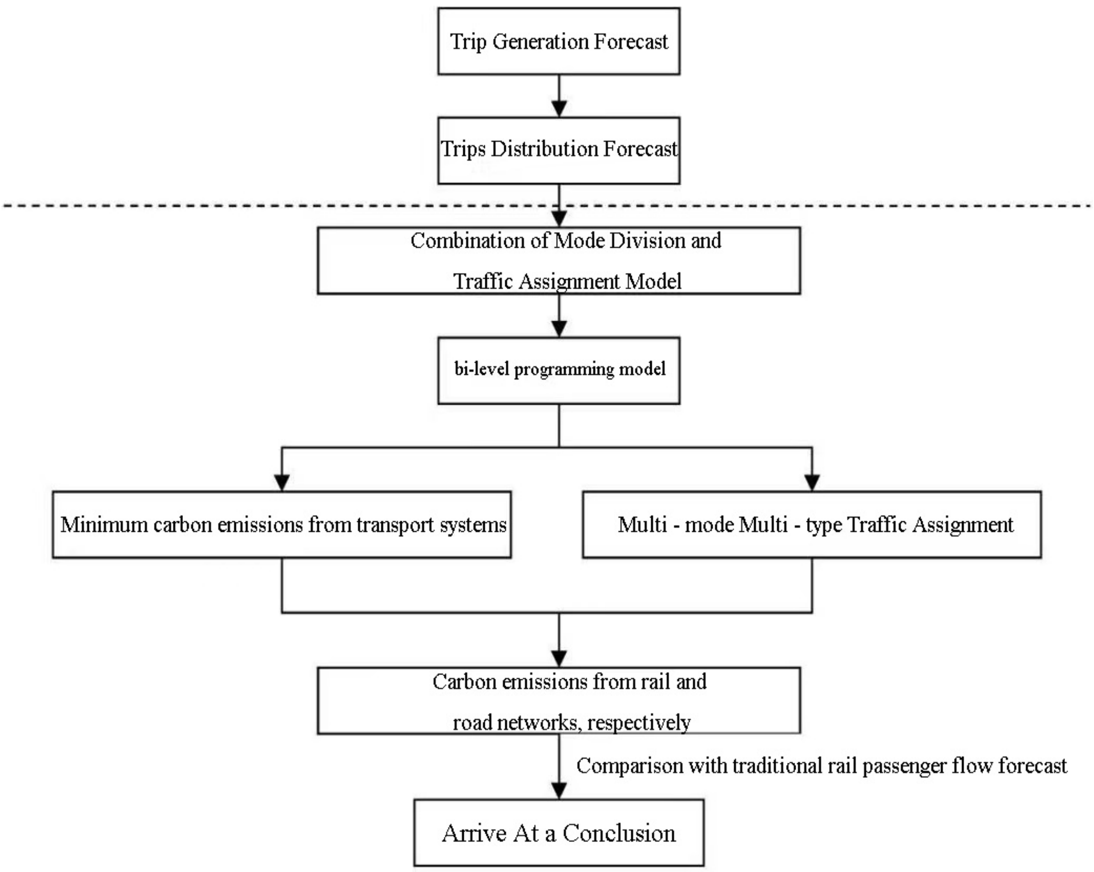


Figure 1. Technical route of rail transit demand forecasting

2 The Bi-Level Programming Model for Minimum Carbon Emissions Under the Low-Carbon City Goal

2.1 Lower Model

In the construction of the lower-level model, the traveler's choice behaviour, including travel mode choice, route choice and parking facility choice, is considered so that the traveler's route choice satisfies the user equilibrium (UE) condition. In considering the traveler's choice behaviour, the traditional "four-stage" forecasting method is combined with the traffic assignment model, and the multi-mode and multi-type traffic assignment method (MMA) is adopted to better serve the planning decision maker. The plan is the basis.

2.1.1 Establishment of Comprehensive Travel Impedance Function VDF for Rail Transit Passengers

The overall travel impedance of the route includes many factors, such as quantitative factors such as fare, mileage and time, as well as qualitative factors such as convenience and comfort of crowding, passenger preference and passenger familiarity with the network [17].

In urban transport, the exact mileage is a very vague concept for most passengers, but the time spent on the journey can be accurately perceived. [19] The survey shows that more than 60% of passengers consider "the shortest time" as the most important factor when choosing a rail journey [20]. In addition, passengers' demands for comfort and convenience are increasing. Assuming that the total travel time of the route is not very different, the number of changes, comfort and congestion also have a great influence on the passenger's choice of rail transit route. An important factor in route choice. At this stage, the operation of the urban rail transit system basically adopts a seamless transfer mode between lines, i.e. once the passenger has determined the origin and destination of the trip, the fare is determined at the same time. There is no additional charge for changing lines. This eliminates the influence of the fare on the overall impedance of the route. Factors such as passenger preference and the degree of passenger familiarity with the Internet have little influence on passenger choice of route and are difficult to quantify, so they are not considered at this stage.

(1) Comprehensive travel impedance function of urban rail transit passengers considering travel time, congestion and other factors

(A) Travel time

The journey time impedance has two parts: the journey time impedance on the line segment and the journey time impedance at the node. In urban rail, the segment time impedance is represented by the running time of the train on the segment; the node time impedance is the sum of the time spent by passengers at the station. For arrival and departure stations, the junction time impedance is the waiting time at the starting point; for passing stations, the junction time impedance is the stopping time of the train; and for the transfer station, the junction time impedance is made up of the transfer journey time and the transfer waiting time.

a. Interval running time

Interval running time, that is, the interval length divided by the average train speed, assuming that $\mathrm{t_a}$ represents the train's running time in the a-th interval, then

$$\mathrm{t_a} = L_\mathrm{a} / v_\mathrm{a} . \tag{1}$$

In the formula, L_a——the length of section a;

v_a—— The average running speed of trains in section a.

b. Waiting time

Assuming that passengers arrive at the station at random and that the service is reliable, the simplest way to calculate the average waiting time is to assume that it is half the headway. This is a reasonable assumption for services with short headway.

$$t_n^w = H_n / 2. \tag{2}$$

H_n——The average departure interval of trains passing through station n.

c. Stop time

The average stopping time of the trains taken by passengers at the station is usually determined as a fixed value based on the number of people getting on and off the train at the station, namely

$$t_n^t = c. \tag{3}$$

t_n^t ——The average stopping time of trains taken by passengers at station n.

d. Transfer time

The transfer time is composed of two parts: the walking time and the waiting time for the transfer.

The walking time for the transfer at the station is expressed by heart, equal to the transfer distance divided by the passenger's average pace, that is

$$t_n^b = l_n^b / v_n^b . \tag{4}$$

l_n^b ——The length of the transfer channel for passengers to transfer at station n;

v_n^b ——The average pace of passengers at station n.

Therefore, the transfer time of passengers at station n can be expressed as

$$t_n^h = t_n^b + t_n^w . \tag{5}$$

(B) Crowding effect

Congestion of the service will reduce the attractiveness of the route to passengers and at the same time reduce the attractiveness of public transport in the mode split model. It is necessary to consider the use of the congestion factor in demand modelling and evaluation to set an appropriate time standard. The congestion factor reflects the additional discomfort and inconvenience to passengers. Under normal circumstances, the congestion factor is a continuous function of the ratio of flow to capacity.

The degree of comfort is directly related to the degree of congestion, and the degree of congestion is related to the passenger flow in the section and the capacity of the train. When the number of passengers on the train is less than the number of seats, the additional cost caused by congestion is zero; when the number of passengers is greater than the number of seats, because some passengers must stand or even be overcrowded, the additional cost caused by congestion can be used as follows: Express

$$P_{\mathrm{a}}(x_{\mathrm{a}})=\begin{cases}0, & x_{\mathrm{a}}<z_{\mathrm{a}}\\ \dfrac{x_{\mathrm{a}}-z_{\mathrm{a}}}{z_{\mathrm{a}}}A, & z_{\mathrm{a}}\le x_{\mathrm{a}}\le C_{\mathrm{a}}\\ \dfrac{x_{\mathrm{a}}-z_{\mathrm{a}}}{z_{\mathrm{a}}}A+\dfrac{x_{\mathrm{a}}-C_{\mathrm{a}}}{C_{\mathrm{a}}}B, & x_{\mathrm{a}}>C_{\mathrm{a}}\end{cases}. \tag{6}$$

$$\mathrm{VDF}=\begin{cases}\mathrm{t_a}\cdot\left[1+\left(x_a/c_a\right)\right],\ \alpha=0.15,\beta=4\\ \sum\limits_{\mathrm{n}}(\mathrm{t_n^b}+\mathrm{t_n^w})+\sum\limits_{\mathrm{a}}[1+\mathrm{P_a}(x_{\mathrm{a}})]t_{\mathrm{a}}+\sum\limits_{n}t_n^t\ ,\ VDF_{\min}+U\le \mathrm{y}\end{cases}.$$

In the formula,$P_a(x_a)$, x_a, Z_a and C_a respectively are the comfort-related congestion factor, passenger flow, the number of seats in the train and the maximum number of passengers that the train can accommodate on the section i of the rail transit network; A and B are the correction parameters.

(C) Comprehensive travel impedance threshold

Among all the routes between the same OD pair, some unreasonable routes can be considered not to be chosen by passengers. This unreasonable route includes not only being out of operating hours and transferring more than 3 times, but also including the comprehensive travel impedance. Assuming that the shortest path impedance value between OD is $\mathrm{VDF_{min}}$, set a threshold U, assume that the maximum cost of a connected path between OD is y, and the criterion for judging whether the path is a valid path is:

If $VDF_{\min} + U \le y$, Then the path is not a valid path; otherwise, it is a valid path. The value of U can be determined through passenger travel surveys.

Therefore, the comprehensive travel impedance function of urban rail transit passengers considering factors such as travel time and congestion can be expressed as:

$$VDF=\sum_{\mathrm{n}}(\mathrm{t_n^b}+\mathrm{t_n^w})+\sum_{\mathrm{a}}[1+\mathrm{P_a}(\mathrm{x_a})]t_{\mathrm{a}}+\sum_{n}t_n^t. \tag{7}$$

(1) Establishment of travel impedance function for other traffic passengers

The cost impedance function is:

$$VDF=\mathrm{t_a}\cdot\left[1+\left(x_a/c_a\right)\right]. \tag{8}$$

In the formula, x_a——Traffic on path a;

C_a——Capacity of section a;

(2) Multi-mode and multi-type comprehensive impedance function:

Other means of transportation

Rail transit **(9)**

2.1.2 Lower Model

The lower-level model considers the traveler's choice behavior, including travel mode choice, route choice and parking facility choice. The traveler's path selection satisfies the user equilibrium (UE) condition, that is, between any OD pair, the traveler only uses the alternative path with the smallest generalized cost as:

$$U_{rs}^{m}=\begin{cases}=\mathrm{gc}_{rs}^{m},\mathrm{if}\, f_{rs}^{m}>0\\ >\mathrm{gc}_{rs}^{m},\mathrm{if}\, f_{rs}^{m}=0\end{cases}$$
$$\forall(r,s),m\in\{1,2,3,4,5\}. \tag{10}$$

f_{rs}^{m}——The flow of the m-th traffic mode between O-D point pairs (r, s).

Then, the lower-level model describes the multi-way path selection behavior of network users, namely:

$$\min\sum_{m}\sum_{a\in(\mathrm{r,s})}\int_0^{x_{a,m}}U_{rs,\mathrm{a}}^{m}dx. \tag{11}$$

$$\mathrm{s.t.}\sum_{\mathrm{a}}f_{\mathrm{rs,a}}^{m}=q_{rs}^{m},\ \forall\mathrm{r,s}. \tag{12}$$

$$f_{rs,\mathrm{a}}^{m}\ge 0,\forall r,s,\mathrm{a},m$$
$$Q_{\mathrm{rs}}=\sum_{m\in(1,2,3,4,5)}q_{rs}^{m}. \tag{13}$$

2.2 Upper Model

Traditional urban transport planning and management has not considered the coordinated relationship between the environment and the satisfaction of transport needs, and has ignored the relationship between low-carbon city models and the development of transport systems. In order to achieve sustainable development of the urban transport system, low-carbon city models must be considered in the process of transport planning and management, and low-carbon factors must be introduced into the process of urban transport planning and management, so as to set the goal of meeting transport needs and building low-carbon cities. Planning and management models to reduce and control the carbon emissions of the transport system. Therefore, from the perspective of planners, we hope to minimize the carbon emissions of the urban transportation system and realize a true low-carbon city. Therefore, the top-level planning model, i.e. the decision model of the transport system planner, is obtained - the transport system with the lowest carbon emissions.

According to the IPCC guidelines, two calculation methods are provided for calculating the carbon emissions from transport energy consumption: (1) Calculation based on transportation fuel sales data within the national area and multiplied by the fuel carbon emission coefficient, which is called the “top-down” method; (2) Multiplying the mileage of that mode of transportation by the fuel consumption per km to obtain the total fuel consumption, and then multiplying it by the fuel carbon emission coefficient to calculate the carbon emissions, which is called the “bottom-up” method [18]. The author calculates the carbon emissions of Shanghai residents from transport. Since it is impossible to obtain the exact sales data of transportation fuels, the “bottom-up” improvement method is adopted, By analyzing the energy consumption patterns of different transportation modes and incorporating them into the calculations, a comprehensive assessment of carbon emissions and energy consumption can be achieved. The calculation formula is:

$$Y_m = K_m \cdot F \cdot \mathrm{C} \cdot G \cdot v. \tag{14}$$

In the formula, K_m——Energy consumption per kilometer for different modes of transportation (L/km);

F——Fuel density (kg/L); Diesel density0.835kg/L，Gasoline density0.725kg/L.

C——Emission factor (kg/TJ);

G——Net calorific value (TJ/ kg);

v——Average operating speed of different modes of transportation.

Table 1 to Table 4 lists the values of some parameters.

Table 1. Energy consumption per kilometer of different transportation modes

Public transit	Rail	Taxi	Private car
0.4L/km	0.91kg/km	0.1L/km	0.088L/km
(0#Diesel fuel)	(Standard coal)	(93#Gasoline)	(93#Gasoline)

Table 2. Emission coefficient and net calorific value of different modes of transportation

Emission factor			Net calorific value		
Diesel fuel	Gasoline	Raw coal	Diesel fuel	Gasoline	Raw coal
74100 kg/TJ	69300 kg/TJ	94600 kg/TJ	43×10-6TJ/kg	44.3×10-6TJ/kg	25.8×10-6TJ/kg

Table 3. Operating speed of different modes of transportation

Purpose of travel	Average stroke speed (km/h)
Bike	10
Bus	12
-Taxi	20
Car	18
Rail	35

Table 4. Per capita carbon emissions of different transportation modes

	Rail	Bus	Taxi	Car
Ym	77.736kg	12.771kg	4.451kg	3.526kg
Carbon emissions per capita	51.824g	336.079g	2222.5g	2938.333g

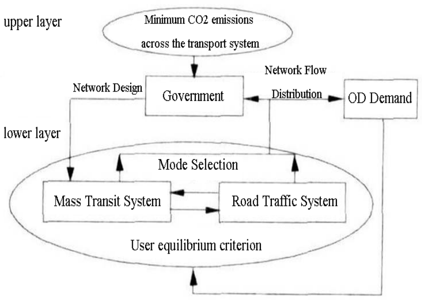
But in practice, managers can take some actions to influence the behavior of travelers, thereby reducing carbon emissions in the entire road network. In this case, the travel time of the road section is not only related to the section flow rate x, but also affected by the manager’s management measures. In this way, the flow delay function becomes $VDF(x_{a,m}, V)$, among them, V is divided into V_1 and V_2, indicating that it is a decision-making variable of the manager. In this section, the entire transportation system is considered. V_1 and V_2 are the simple situations of the maximum speed in the road network and rail network segment defined by the administrator. The upper model can be expressed as

$$\begin{gathered} \min \sum_m \sum_{\mathrm{a}} Y_{a,\mathrm{m}} \cdot x_{a,\mathrm{m}} \\ s.t.\ \ V_1, V_2 \geq 0. \end{gathered} \tag{15}$$

$Y_{a,m}$——The carbon emission per unit time of the m-th transportation mode on section a;

$x_{a,m}$——The flow of the m-th traffic mode on section a.

2.3 Bi-Level Programming Model with the Smallest Carbon Emissions in Urban Transportation Systems



Decision relationship between supply and demand sides

Figure 2. A bi-level plan with the smallest urban traffic carbon emissions

Combining the user's route choice model with the traffic system planner's decision model (Figure 2), the following can be obtained bi-level programming model:

$$\begin{aligned} &\min \sum_{m}\sum_{a} Y_{a,m} \cdot x_{a,m} \\ &s.t.\ \ V_1, V_2 \geq 0. \end{aligned} \qquad \textbf{(16)}$$

Among them, x can be obtained by the following plan s.t.

$$\min \sum_{m} \sum_{a \in (r,s)} \int_0^{x_{a,m}} U_{rs,a}^m dx. \qquad \textbf{(17)}$$

$$\sum_{m}\sum_{\mathrm{a}} f_{\mathrm{rs,a}}^m = q_{rs}^m,\ \forall \mathrm{r,s}. \qquad \textbf{(18)}$$

$$\begin{aligned} &f_{rs,\mathrm{a}}^m \geq 0, \forall r,s,\mathrm{a},m \\ &Q_{\mathrm{rs}} = \sum_{m \in (1,2,3,4,5)} q_{rs}^m. \end{aligned} \qquad \textbf{(19)}$$

2.4 The Solution of Bi-Level Method

Generally speaking, the solution of bi-level programming problems is very complicated. One of the reasons is that because the bi-level programming problem is an NP-hard problem, there is no polynomial solution algorithm, especially for large-scale transportation network optimization problems. The following article will discuss the heuristic algorithm of the model.

In this model, it is assumed that the impedance function (VDF) is strictly increasing. Therefore, for a given traffic demand, when the manager's decision variables are determined, the road flow is unique, that is, $x_{a,m}(V)$ is a continuous function of the traffic demand and the manager's decision variables. When solving the above problems, it is necessary to take into account the subsequent changes in the balance of the road flow due to the manager's decision. Since the balance road flow $x_{a,m}(V)$ is generally a non-linear function and the function form is unknown, the sensitivity analysis method can be used to obtain the derivative relationship of the balance road flow to the manager's decision variables, and the Taylor expansion is used to linearly approximate the non-linear function $x_{a,m}(V)$.

Let V^* be the initial value of the manager's decision-making variables, and $x_{a,m}(V^*)$ be the corresponding balance section flow (which can be found from the underlying problem). but

$$x_{a,m}(V) \approx x_{a,m}(V^*) + \left[\frac{\partial x_{a,m}(V)}{\partial V} \right]_{V=V^*} (V - V^*). \qquad \textbf{(20)}$$

Substituting the above formula into the two-layer objective function, the upper-level problem becomes an ordinary nonlinear optimization problem of manager's decision variables, which can be solved by existing methods. Then, based on the manager's decision-making variables obtained by the upper level, and then solving the lower-level problems, a new road section balance flow can be obtained. Repeating the above ideas, new managers' decision-making variables can be obtained. After repeated calculations, it is expected to converge to the optimal solution of the original bi-level programming model. Specific steps are as follows:

Step 1: Let the maximum speed limit V of the road section take the free flow speed V^0, and set the number of iterations k=0.

Step 2: For a given V^k, solve the underlying problem and get the section flow rate x^k.

Step 3: The sensitivity analysis method is used to calculate the derivative of the balance section flow V^k to the manager's decision variable V^k.

Step 4: Calculate formula $x_{a,m}(V)$ and substitute it into the upper-level objective function to solve the upper-level problem, and obtain a new set of road section speed limit per hour V^{k+1} and total CO_2 p^k.

Step 5: If max $|p^{k+1} - p^k| \leq \varepsilon$ (ε is the preset iteration accuracy), then stop; otherwise, let k=k+1, and go to step 2.

3 Case Analysis

A total of 60,000 households, 60,000 car drivers, and more than 20,000 organisations, enterprises and institutions participated in Shanghai's fourth traffic survey, with more than 230,000 people taking part in the survey. Based on the data from the fourth comprehensive traffic survey in Shanghai, this paper distributes the passenger flow of the entire transportation system network in Shanghai, thereby obtaining the passenger flow of each road in the road network and the passenger flow of the rail line and characteristic indicators.

According to the survey data, it is deduced that by 2020, the passenger flow will be allocated under different carbon emission total control conditions, and then different plans will be compared to draw conclusions.

The calculation formula for the carbon emissions per unit time (hourly) of various modes of transportation is:

$$Y_m = K_m \cdot F \cdot C \cdot G \cdot v. \tag{21}$$

In 2020, three different schemes will be adopted for total carbon emission control:

(1) According to the normal development situation, the UE model is used for passenger flow distribution; and the corresponding passenger flow and carbon dioxide emissions are obtained, as shown in Figure 3 to Figure 4.

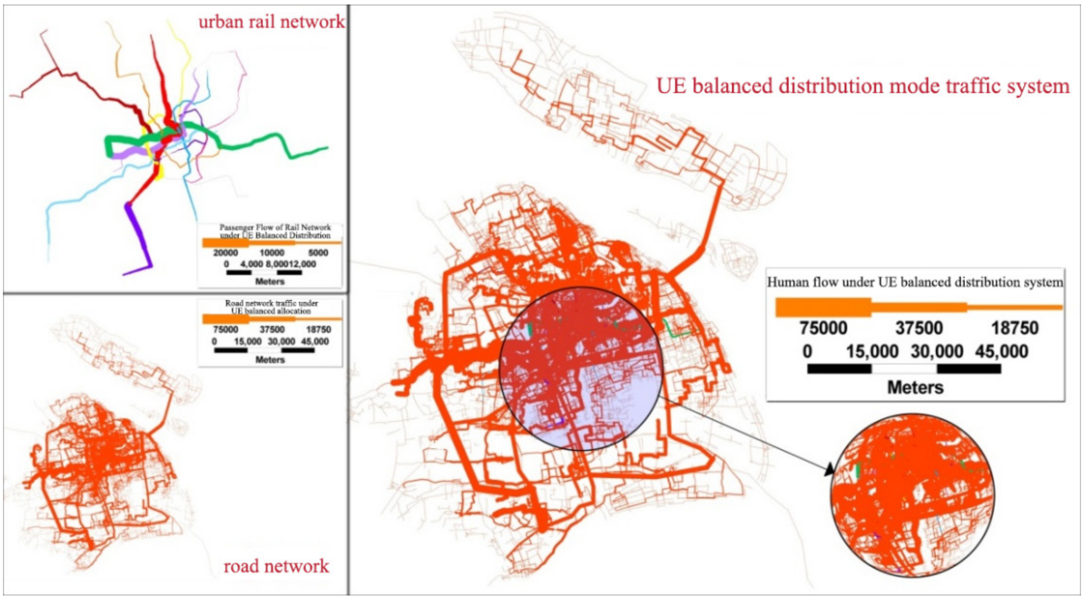


Figure 3. The flow of people (person/h) in the UE balanced allocation mode in 2020

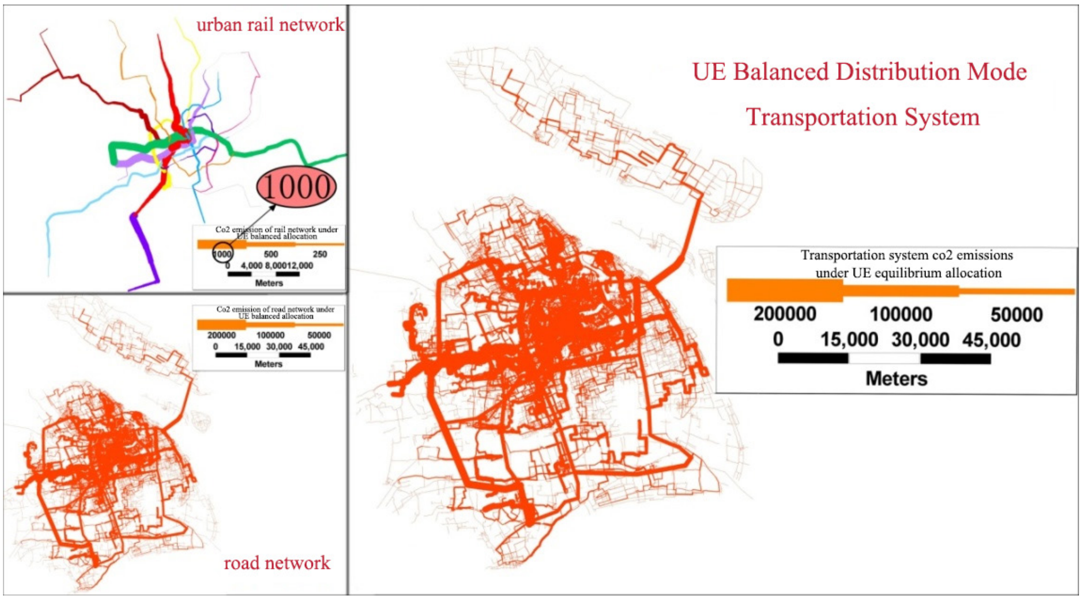


Figure 4. CO_2 emissions in 2020 UE balanced allocation mode (kg/h)

(2) According to the plan, in order to promote the development of a low-carbon model, use the bi-level programming model with the smallest carbon emissions in the transportation system for allocation; and the corresponding passenger flow and carbon dioxide emissions are obtained, as shown in Figure 5 to Figure 6.

In order to vigorously develop a low-carbon model in accordance with the plan, use the bi-level programming model with the smallest carbon emissions in the transportation system for allocation; and the corresponding passenger flow and carbon dioxide emissions are obtained, as shown in Figure 7 to Figure 8.

The calculation process and result (Figure 9 and Table 5) are as follows:

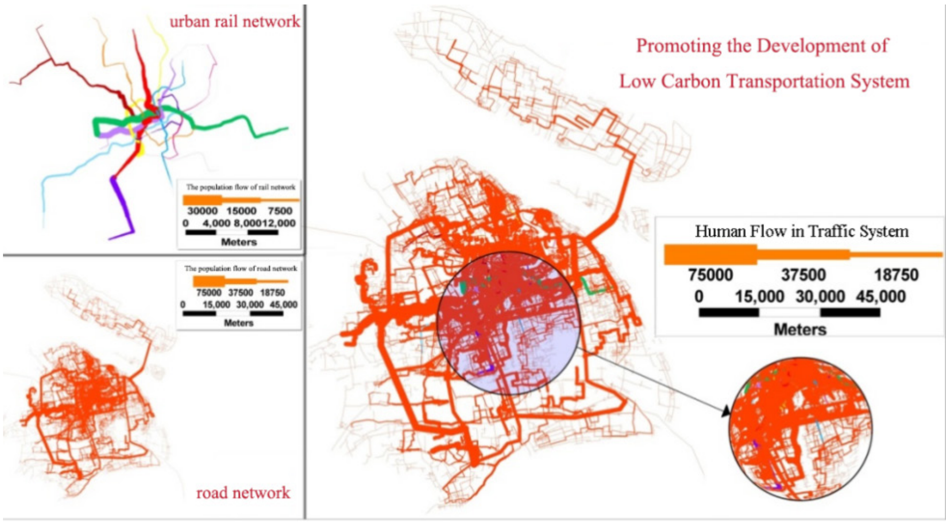


Figure 5. The flow of people (person/h) under the promotion of the development of a low-carbon model in 2020

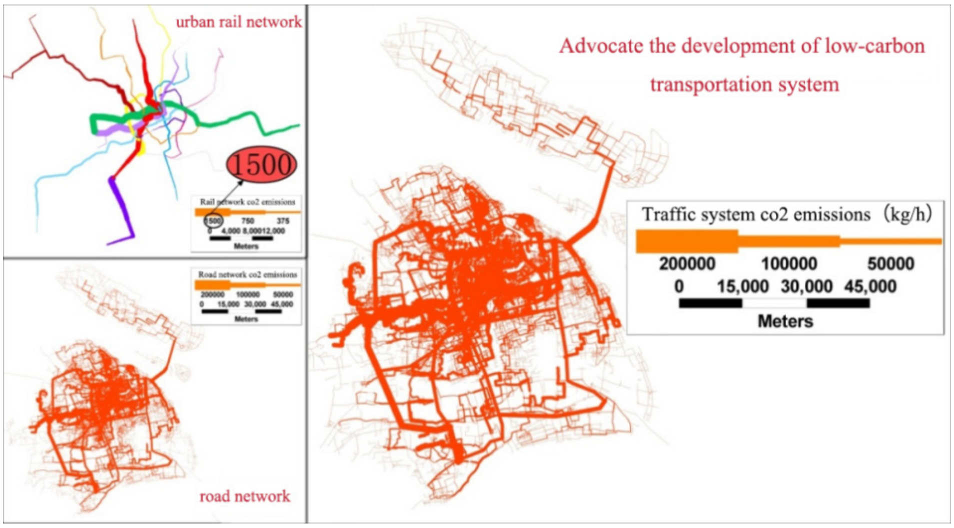


Figure 6. CO_2 emissions under the promotion of low-carbon development in 2020 (kg/h)

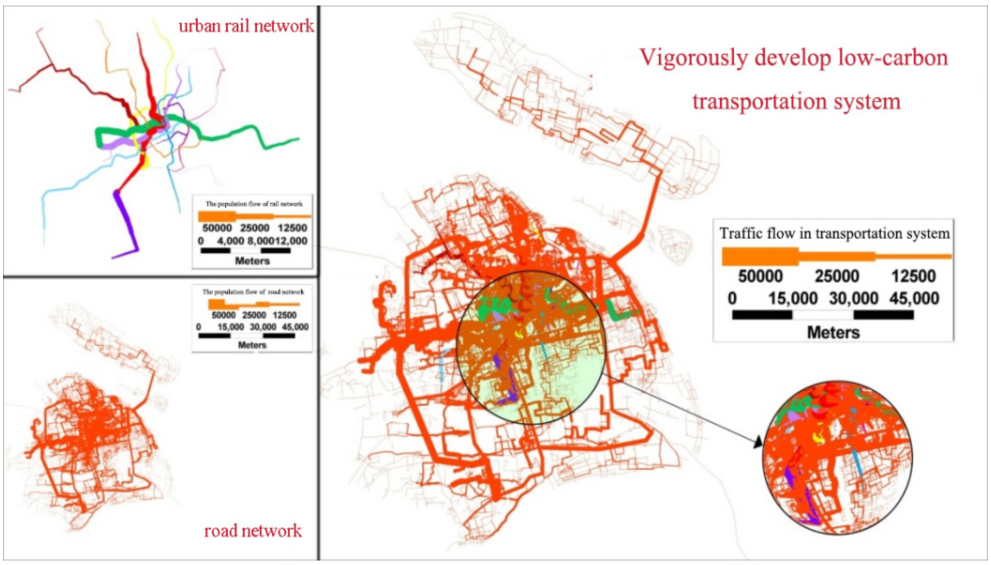


Figure 7. Human flow under the low-carbon model vigorously developed in 2020 (person/h)

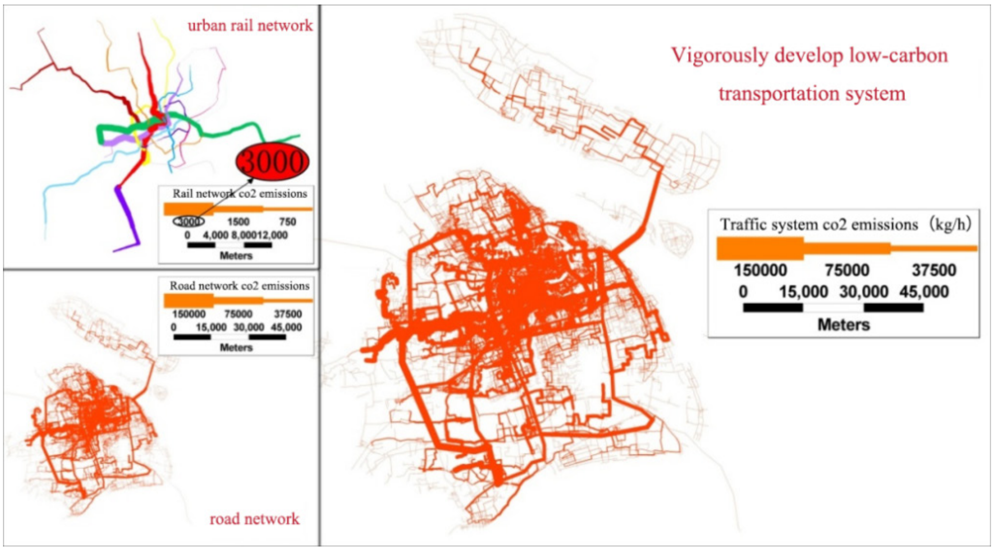


Figure 8. CO_2 emissions under the vigorous development of low-carbon mode in 2020 (kg/h)

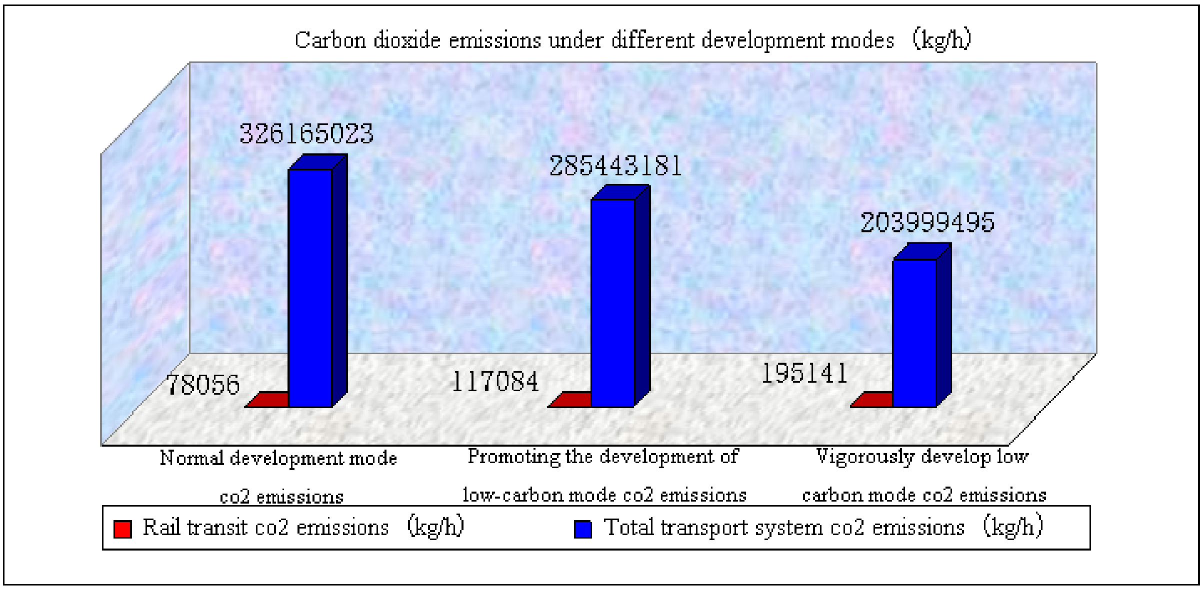


Figure 9. Comparison of CO_2 emissions from different development models

Table 5. Percentage of rail network data under different development modes

Future transportation development model	Normal development model	Promote the development of a low-carbon model	Vigorously develop a low-carbon model
Percentage of people flow in the rail network accounted for in the entire transportation system	1.112%	1.891%	4.304%
The CO2 emissions of the rail network accounted for the percentage of CO2 emissions of the entire transportation system	0.024%	0.041%	0.096%

From the comparison of the above three different development models (Figure 3 to Figure 9), it can be seen that with the change in the transport structure, travelers will choose more rail transit or choose the travel chain based on rail transit in the future. Although the carbon emissions of the rail transit network will increase significantly, because rail transit has incomparably low carbon emissions per capita, assuming that the total travel volume of the whole transport system does not change due to the change in the travel structure, with the increase in the proportion of rail transit in the whole transport network, the CO_2 emissions of the whole transport system have decreased significantly, achieving the goal of low carbon.

4 Conclusion

In this paper, the traditional "four-stage" demand forecasting method is improved by combining the MMA allocation model and the two-stage planning model to control carbon emissions. It minimizes the carbon emission of the transport system and provides a good way for the layout planning of rail transport in the low-carbon mode. The research methods in the field of passenger flow prediction of urban rail transportation under the requirements of low-carbon city development are based, completed and enriched [21-22].

This study also has some shortcomings and limitations. Firstly, the research assumptions are somewhat idealised. In reality, bus signal priority is not very well used at junctions. In addition, some old roads are not segregated between motorised and non-motorised traffic, and the impact of mixed traffic on vehicle operating times and the distribution of traffic flows in the road network needs to be further investigated. The above shortcomings and limitations require further in-depth research and exploration in our future work.

Acknowledgements

This study was sponsored by the National Natural Science Foundation of China (Grant No: 52002244) and by the Researchers Supporting Project Number (RSPD2023R681) King Saud University, Riyadh, Saudi Arabia.

References

[1] Z. Y. Feng, N. Mo, S. J. Dai, Y. Xiao, X. Cheng, Low Carbon Building Design Optimization Based on Intelligent Energy Management System, *Energy Engineering*, Vol. 120, No. 1, pp. 201-219, 2023.

[2] M. Lawrence, Reducing the Environmental Impact of Construction by Using Renewable Materials, *Journal of Renewable Materials*, Vol. 3, No. 3, pp. 163-174, August, 2015.

[3] L. Zhang, The research on low-carbon transport situation and countermeasure in China, *Energy Conservation Technology*, Vol. 31, No. 1, pp. 79-83, January, 2013.

[4] United Nations, Sustainable transport, sustainable development, *Interagency report for second Global Sustainable Transport Conference*, Beijing, China, 2021, pp. 1-120.

[5] X. Sun, H. P. Lu, W. J. Chu, A Low-Carbon-Based Bilevel Optimization Model for Public Transit Network, *Mathematical Problems in Engineering*, Vol. 2013, Article No. 374826, June, 2013.

[6] D. Cao, K. Zeng, J. Wang, P. K. Sharma, X. M. Ma, Y. H. Liu, S. Y. Zou, BERT-based Deep Spatial-Temporal Network for Taxi Demand Prediction, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 7, pp. 9442-9454, July, 2022.

[7] S. Lin, X. K. Wei, Exploration of low-carbon transport policies, *International Conference on Information Management, Innovation Management and Industrial Engineering*, Sanya, China, 2012, pp. 252-255.

[8] F. Chen, X. P. Shen, Z. J. Wang, Y. Yang, An Evaluation of the Low-Carbon Effects of Urban Rail Based on Mode Shifts, *Sustainability*, Vol. 9, No. 3, Article No. 401, March, 2017.

[9] L. L. Zhang, R. Y. Long, W. B. Li, J. Wei, Potential for reducing carbon emissions from urban traffic based on the carbon emission satisfaction: Case study in Shanghai, *Journal of Transport Geography*, Vol. 85, Article No. 102733, May, 2020.

[10] L. J. Lu, C. Wang, W. P. Deng, X. Bing, An Optimal Allocation Model of Public Transit Mode Proportion for the Low-Carbon Transportation, *Mathematical Problems in Engineering*, Vol. 2015, Article No. 390606, March, 2015.

[11] Q. C. Tang, M. N. Yang, Y. Yang, ST-LSTM: A Deep Learning Approach Combined Spatio-Temporal Features for Short-Term Forecast in Rail Transit, *Journal of Advanced Transportation*, Vol. 2019, pp. 1-8, February, 2019.

[12] N. Zhang, Z. J. Wang, F. Chen, J. N. Song, J. P. Wang, Y. Li, Low-Carbon Impact of Urban Rail Transit Based on Passenger Demand Forecast in Baoji, *Energies*, Vol. 13, No. 4, Article No. 782, February, 2020.

[13] H. Yang, Y. Iida, T. Sasaki, The equilibrium-based origin-destination matrix estimation problem, *Transportation Research Part B: Methodological*, Vol. 28, No. 1, pp. 23-33, February, 1994.

[14] X. Y. Liu, J. Yu, X. G. Yang, W. J. Tan, Multiperspective Bus Route Planning in a Stackelberg Game Framework, *Journal of Advanced Transportation*, Vol. 2020, pp. 1-16, November, 2020.

[15] E. Martelli, M. Freschini, M. Zatti, Optimization of renewable energy subsidy and carbon tax for multi energy systems using bilevel programming, *Applied Energy*, Vol. 267, Article No. 115089, June, 2020.

[16] Y. F. Song, Z. Y. Gao, A Bilevel Programming Model and Solution Algorithm for the Continuous Equilibrium Network Design Problem, *Journal of Highway and Transportation Research and Development*, Vol. 16, No. 1, pp. 40-43, March, 1999.

[17] N. H. Pang, *Study on Coordination Theory and Method of Train Operation on Urban Mass Transit Network*, Ph. D. Thesis, Beijing Jiaotong University, Beijing, China, 2011.

[18] IPCC, *IPCC guidelines for national greenhouse gas inventories*, 2006. http: //www. ipcc-nggip. iges. or. Jp/ Public/gl/invs1. html.

[19] W. Liu, Y. Tang, F. Yang, C. Zhang, D. Cao, G. J. Kim, Internet of things based solutions for transport network vulnerability assessment in intelligent transportation systems, *CMC-Computers Materials & Continua*, Vol. 65, No. 3, pp. 2511-2527, September, 2020.

[20] W. Liu, Y. Tang, F. Yang, Y. Dou, J. Wang, A multi-objective decision-making approach for the optimal location of electric vehicle charging facilities, *CMC-Computers Materials & Continua*, Vol. 60, No. 2, pp. 813-834, 2019.

[21] W. W. Liu, J. Wang, Evaluation of coupling coordination degree between urban rail transit and land use, *International Journal of Communication Systems*, Vol. 34, No. 2, Article No. e4015, January, 2021.

[22] W. W. Liu, C. N. Zhang, H. Sun, J. M. Zhang, G. J. Kim, Analysis on Parking Sharing Capacity Based on Supply-Demand Relationship, *Journal of Internet Technology*, Vol. 21, No. 5, pp. 1253-1262, September, 2020.

Biographies

Yang Tang is working in Urban-Rural Planning & Design Institute, Zhejiang University. His research interest focus on sustainable transportation and low-carbon city. He has attended or in charge of several National Natural Science Foundation projects and published more than 30 academic papers and book chapters.

Weiwei Liu is working in Business School, University of Shanghai for Science and Technology. He has presided over and participated in a number of National Natural Science Foundation projects, etc. He has published 40 academic papers in international academic journals, of which more than 20 papers have been retrieved in SCI and EI.

Saurabh Singh received the Ph.D. degree from Jeonbuk National University, Jeonju, South Korea, carrying out his research in the field of ubiquitous security. He was a Postdoctoral Researcher with Kunsan National University, South Korea. He currently joined as Assistant Professor in Woosong university, Daejeon South Korea. He also worked as Assistant Professor in Dongguk University, Seoul, South Korea. He has published many SCI/ SCIE journals and conference papers. His research interests include blockchain technology, cloud computing and security, the IoT, deep learning, and cryptography. He received the Best Paper Award from KIPS and CUTE Conference, in 2016.

Osama Alfarraj received the master's and Ph.D. degrees in information and communication technology from Griffith University, in 2008 and 2013, respectively. He is currently Professor of computer sciences with King Saudi University, Riyadh, Saudi Arabia. His current research interests include eSystems (eGov, eHealth, and ecommerce), cloud computing, and big data. He has served as a Consultant and a member of the Saudi National Team for Measuring E-Government, Saudi Arabia, for two years.

Amr Tolba received the M.Sc. and Ph.D. degrees from the Mathematics and Computer Science Department, Faculty of Science, Menoufia University, Egypt, in 2002 and 2006, respectively. He is currently a full professor of computer science at King Saud University (KSU), Saudi Arabia. He has authored/coauthored over 160 scientific papers in top-ranked (ISI) international journals. He has been included in the list of the top 2% of influential researchers globally (prepared by scientists from Stanford University, USA) during the calendar years 2020, 2021 and 2022 respectively. His main research interests include artificial intelligence (AI), the Internet of Things (IoT), data science, and cloud computing.