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Bilevel Programming Model of Discrete Traffic Network Based on Machine Learning Optimization Hybrid Algorithm

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Abstract: With the rise of living standards, more and more people choose to travel by car, which increases the pressure on the urban traffic network (TN). The TN needs to be re planned and designed. The main goal of the design, organization and management of the TN is to improve the service level and access to the TN. During the planning process, a reasonable and scientific TN model should be developed according to the characteristics of traffic operation in different regions. Therefore, this paper studies and designs the bilevel programming model of discrete TN based on the hybrid algorithm of machine learning and optimization. This paper first describes the construction of the bilevel programming model and the network structure, then designs the hybrid algorithm and sets the weight coefficient, and finally analyzes the sensitivity of the comparison of the average load degree of the road section and the time budget.

1. Introduction

The problem of transport network design in the transport planning process is not only the design of discrete transport networks or the design of continuous transport networks for optimal transport networks, but also the decision on how to increase and improve the traffic access in urban transport networks [1-2]. The design of transport networks is a necessary and important part of planning and managing transport networks [3]. As the design of the transport network has a significant impact on the planning and management of other phases of the transport system, a rational and reliable planning and design of the transport network is required in order to ensure the proper functioning of the transport system, for example [4-5]. In addition, there are complex links between network paths and other subsystems of the city. The search for scientific and comprehensive discrete TN planning models to solve traffic congestion problems has become a popular research, and the creation of a typical and rational TN has important theoretical and practical significance [6-7].

In recent years, discrete transport network two-level planning models have become increasingly important to the development of urban transport systems, and many research scholars have conducted in-depth studies on discrete transport network two-level planning models based on machine learning. For example, Vasaki Ponnusamy et al. constructed an anomalous network traffic detection model through a three-layer parallel network structure and used feature fusion techniques to fuse temporal and spatial features; experimental results showed that the model improved the accuracy of traffic detection with a high sample recognition rate [8]. Dhaya Ramakrishnan et al. proposed the compiler forking technique, and to evaluate the quality of the generated data, we trained several machine learning models to replace the compiler heuristic for loop-related optimisation, and experimental results showed that the trained models performed comparably to the highly tuned compiler heuristic for a few single benchmarks [9]. Machine learning has an important role to play in the development of transportation networks.

With the development of urban economies, many cities are experiencing this problem of traffic congestion, and therefore this paper is based on machine learning for the design of a two-level planning model for discrete TNs. The research structure of this paper is described as follows: the first part of the paper is an overview of the relevant part, which is divided into two parts: the two-layer planning model and the construction of the line network structure; the second part is the model construction part, which constructs the model through both algorithm design and weight coefficients, and the third part is the model analysis part, which mainly includes the average load degree comparison analysis of road sections and the sensitivity analysis of the time budget.

2. Relevant Overview

2.1. Two-tier Planning Models

The problem of transport network design is a huge and complex process that aims to improve the transport network system and make optimal planning decisions as the demand for transport travel continues to grow [10]. The design of transport networks not only requires the cooperation of various government departments and the public, but also involves the interests of government departments, participating enterprises and the beneficiary public. Therefore, the design of a transport network is a comprehensive consideration of the interests of all parties to obtain the optimal decision result. The TN design problem can be seen as a game between the upper and lower levels of decision making. The upper level decisions are usually made by the traffic management and the main purpose is to constrain the behaviour of the lower level users with planning decisions. The decision maker in the lower-level planning model is usually a traveler who is free to choose a path [11-12]. Unlike upper-level decisions, lower-level decisions are not only influenced by their own constraints, but also by the constraining effect of upper-level decisions. In other words, lower-level users are free to make decisions within the constraints that are jointly formed by the upper and lower levels. In general, two-layer planning models are usually used to represent the real-life transport decision-making process in order that it can be more accurately reflected [13]. The upper-level optimisation model depicts the upper-level decision-making process, and the lower-level planning model represents the lower-level decisions, with a one-to-one correspondence between the model and the decisions. The complete mathematical expression is shown below, where the expression for the upper-level model is as described in equation (1) and the expression for the lower-level model is as described in equation (2), where the objective function is G, a is the decision variable and S is the constraint function.

$$\min G(a,b), subject: S(a,b) \le 0 \tag{1}$$

$$\min g(a,b), subject: s(a,b) \le 0 \tag{2}$$

2.2. Line Network Structure Construction

The L-space approach refers to the construction of an L-space network, which is based on an actual geospatial network with major road intersections as nodes and traffic lines as edges [14-15]. In contrast to the L-space approach, the P-space approach considers traffic lines as nodes of the network and urban areas as edges. In both methods, the L-space method can assign weights based on the characteristics of road sections, while the P-space method constructs an undirected and weightless network [16]. In this paper, the L-space method is used to construct the corresponding complex network. The nodes in an urban TN are the major road intersections and the edges are the traffic routes of each traffic mode. In this way, the network consisting of edges followed by points becomes the basic structure of the urban TN [17]. At the same time, in establishing the topology, there are the following conditions: node 1 in the urban TN can reach node 2 through the line, while node 2 can also reach node 1 through the same line, which means that the urban TN established is abstractly regarded as an undirected network; if there are two lines for the same traffic mode, the process of establishing the topology is simplified to one, while in the process of selecting the individual traffic line network process, temporarily disregard the traffic volume that each traffic mode can carry, as well as the vehicle travel time, which means that the urban TN is abstracted as a non-weighted network [18]. On the basis of the above assumptions, the urban TN model is constructed.

3. Model Construction

3.1. Algorithm Design

This study is based on the idea of solving genetic algorithm and Frank-Wolfe algorithm and combines the actual characteristics of the model to design a hybrid algorithm of genetic algorithm nested in Frank-Wolfe algorithm for solving. In order to simplify the complexity of the two-layer programming model, a scenario-based approach is used to characterise the stochastic demand, which leads to a robust network design solution. The approach has some realistic basis, as most travel activities have scenario properties. With the development of intelligent transport systems, data monitored on a daily basis can also be used for scenario setting. The approach of using scenarios requires a balance between the number of scenarios and the accuracy of the solution. Too few scenes and the solution accuracy is not sufficient: while too many scenes and the solution process takes a lot of computational time. Based on the above considerations, typical demand scenarios can be used as realised values for stochastic demands and applied to the solution of robust TN design problems. Based on the above analysis, the scenario-based hybrid algorithmic two-level planning optimisation model is designed on the basis of solving the two-level planning model. It is worth noting that the initial probability vector needs to be determined using the optimised hybrid algorithm for traffic assignment in all demand scenarios and taking the expected value as the value coefficient in the model. Of course, the subsequent evaluation of each feasible solution is also carried out across all demand scenarios. The algorithmic framework for solving the two-layer programming optimisation model is shown in Figure 1.

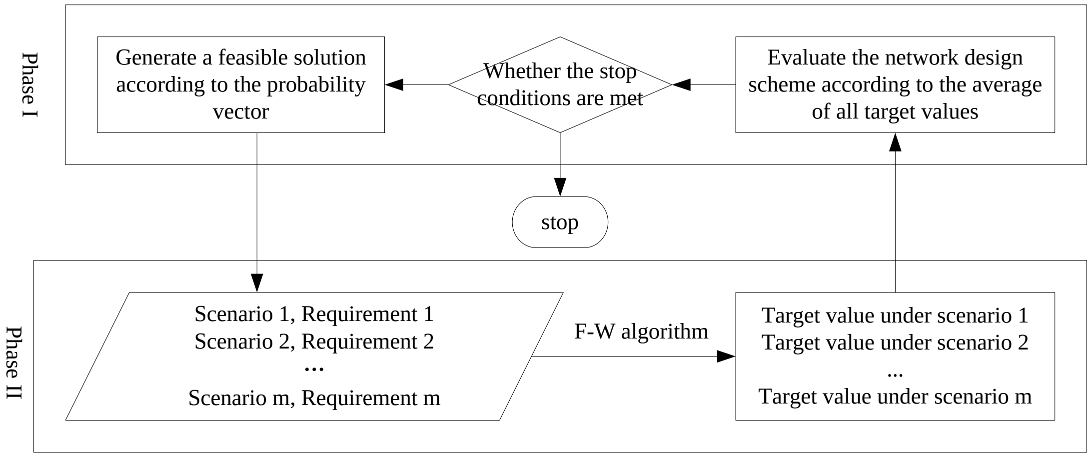

Figure 1. Algorithm framework

3.2. Weighting Factors

The investment cost profile required for the optimal construction of the transport network design with different weight combinations was analysed and the results obtained are described in Figure 2.

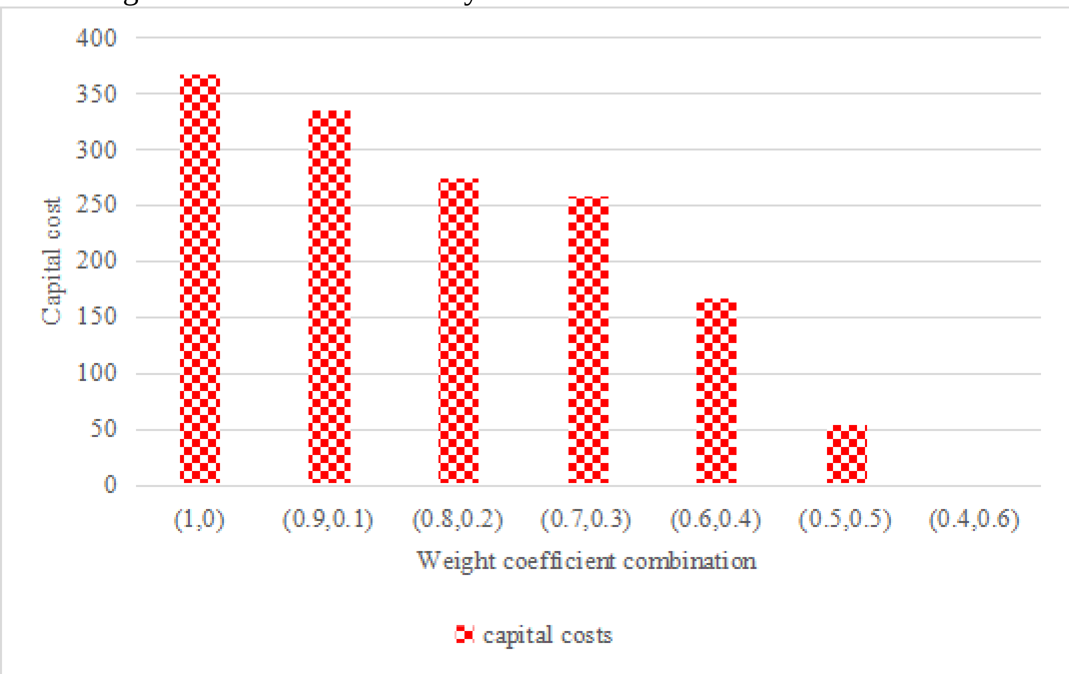

Figure 2. Investment costs for different combinations of weighting factors

As can be seen from Figure 2, since the investment cost in the model is targeted at the minimum value, the investment cost in the figure decreases with the increase of the weighting coefficient corresponding to it. When the weighting coefficient of the investment cost target in the model is 0.6, the investment cost drops to the minimum value of 0, and the original TN is kept unchanged at this time. Combining the investment cost and the saturation of each road section under different weight coefficient combinations, a comprehensive quantitative analysis was carried out on the above four groups of weight coefficient combinations with better TN optimization effects, and the results are shown in Table 1.

Table 1. Comprehensive quantitative analysis of results

Weight coefficient combination	Road section number	Road saturation	capital costs
(1，0)	Section 13	0.2378	367
(0.9，0.1)	Section 13	0.1965	335
(0.8，0.2)	Section 13	0.4378	274
(0.7，0.3)	Section 12，Section 13	0.8721，0.4756	258

From the observation in Table 1, it can be obtained that the saturation of road section 12 is 0.8712 in the two sets of optimization results with weighting coefficients of (0.7, 0.3), which may cause local traffic congestion for a short period of time, but the saturation of this road section has not reached the state of oversaturation and has little impact on the whole TN; the saturation of road section 13 is lower than 0.5 in all four sets of optimization results, of which the saturation of road section 13 is 0.1965 in the two sets of optimization results with weighting coefficients of (0.9, 0.1), the saturation of road section 13 is 0.1965, which will cause a more serious waste of road resources, while in the two sets of optimization results with weighting coefficients of (0.7, 0.3) and (0.6, 0.4), the saturation of road section 13 is 0.4378 and 0.4756 respectively, which is very close to the saturation range expected by the model and is relatively more reasonable; the rest of the TN The saturation of the remaining sections of the TN are all within the reasonable range expected by the model. In summary, with the weighting factors, the TN does not cause prolonged traffic congestion, with road section 13 having a low utilisation of road resources under the (0.9, 0.1) weighting, and road section 16 possibly causing traffic congestion for a short period of time. In terms of investment costs, the combination of weighting factors (0.8, 0.2) requires a higher investment cost than the latter two groups. Therefore, weighing both the saturation optimisation results and the required investment costs, the weighting factor combination (0.7, 0.3) is considered to be superior to the weighting factor combination (0.9, 0.1) to a certain extent, and therefore the weighting factor combination (0.7, 0.3) is chosen in this paper.

4. Model Analysis

4.1. Comparative Analysis of Average Road Section Loadings

The elastic demand scenario is compared with the fixed demand scenario and the impact of different one-way traffic scenarios on the congestion level of the road network is analysed using the average roadway loading index.

Table 2. Comparison of average road section loadings

	After the implementation of one-way traffic		Before the implementation of one-way traffic		Amount of change in load factor(%)	
	$S_{arterial}$	S_{branch}	$S_{arterial}$	S_{branch}	$S_{arterial}$	S_{branch}
Elastic demand	2.43	1.76	2.24	1.88	-19	12
Fixed demand	2.51	1.64	2.42	1.69	-9	5
Change value	-0.08	0.12	-0.18	0.19	-10	7

As shown in Table 2, the average load level on the trunk roads under the flexible demand scenario is 10% lower than the fixed demand scenario, and the average load on the slip roads is 7% higher than the fixed demand scenario. This indicates that the traffic flow is dispersed under the elastic demand scenario by means of one-way traffic restrictions, which direct traffic from the trunk roads to the feeder roads. The two-level planning and optimisation model of the traffic network under the elastic demand scenario takes into account the variation in traffic demand on different road sections and is more in line with realistic traffic road operating conditions. When congestion occurs on the main roads, travellers are guided to choose the slip roads, so that the traffic flow is dispersed and the network is less congested under the flexible demand scenario, which makes the two-layer planning and optimisation model more effective.

4.2. Time Budget Sensitivity Analysis

Because time budget is an important parameter affecting the unreachable flow, the following experiment is used to analyze the change of model solution when time budget changes. Specifically, make the parameter θ Take 1.2, 1.3, 1.4, 1.5, 1.6 and 1.7 respectively, and the corresponding calculation results are shown in Figure 3. The broken line represents the change of the unreachable flow, and the histogram represents the change of the number of roads requiring reversible lanes.

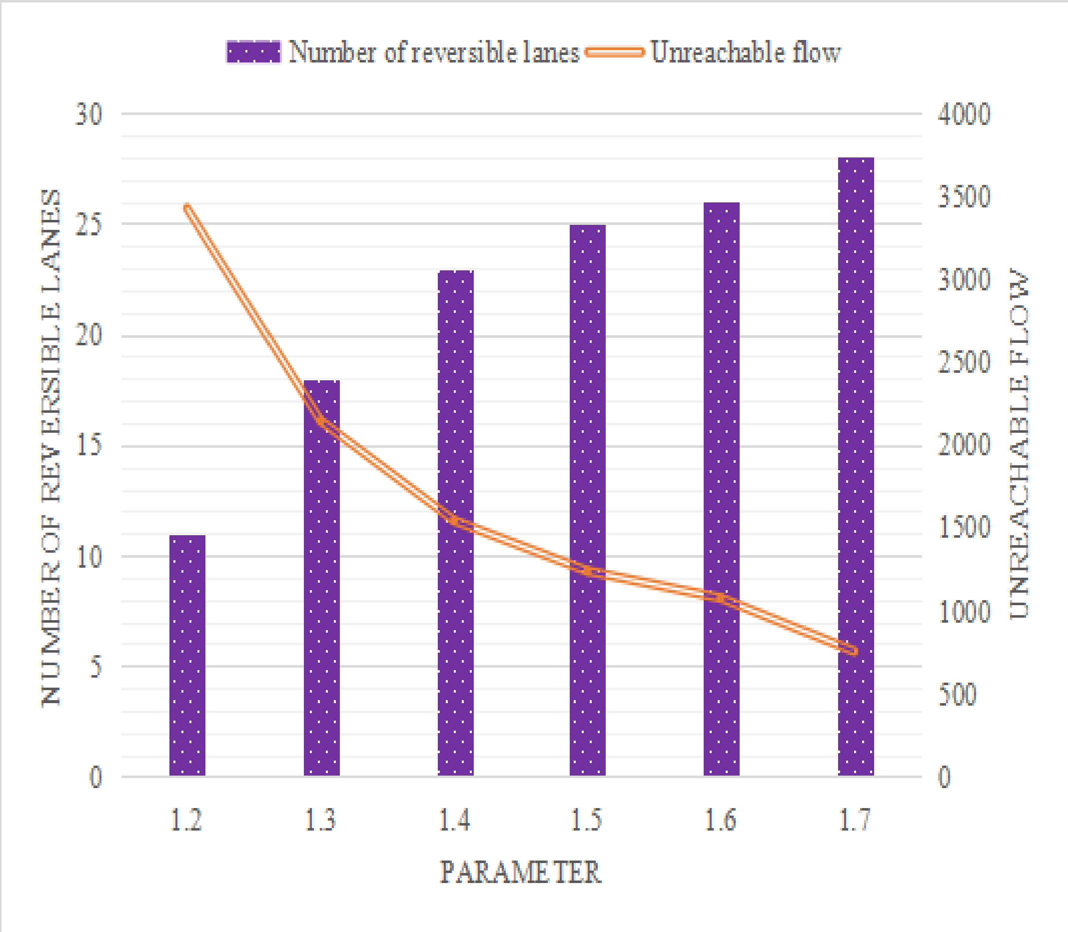

Figure 3. The number of unreachable flow and reversible lane under parameter change

It can be seen from Figure 3 that the unreachable flow varies with the parameter θ But the decrease is smaller and smaller on the whole. This is because when the travel time budget is more and more adequate, the actual number of people traveling increases. It can be seen from the histogram in Figure 3 that when θ= At 1.2, 11 roads in the whole network need to be set with reversible lanes, while when θ= At 1.7:00, this figure rose to 28. This is because when the travel time budget is reduced, the number of people actually traveling is reduced, and the road network structure does not need to be adjusted excessively. The bi level programming optimization model established in the text can identify the key sections where reversible lanes need to be set. In fact, except for individual road sections, the optimal solutions under different conditions are similar, at least the direction of setting reversible lanes is almost the same. In this sense, the optimal solution of the model is not very sensitive to the daily changes of parameters. It should be noted that the traditional method needs to allocate all the demands to the road network, so it is impossible to measure the network's unreachable flow and the coupling between supply and demand. However, the method proposed in this paper can reflect the above problems, and can measure the interaction between reversible lane setting and time budget.

5. Conclusion

With the development of information technology, machine learning is applied in more and more fields. Therefore, this paper studies the bilevel programming model of discrete TN based on the hybrid algorithm of machine learning and optimization. Through research, the following conclusions are drawn: after weighing the saturation optimization results and the required investment costs, the weight coefficient combination of this paper is (0.7, 0.3). Low congestion in the transport network under the flexible demand scenario. The bi level programming optimization model established in the text can identify the key road sections where reversible lanes need to be set and can reflect the interaction between reversible lane setting and time budget. There are many places to be improved in this paper, but there are also innovations.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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