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Multi-objective Optimization Algorithm in Machine Learning for Traffic Planning

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Abstract: Nowadays, urban rail transportation is booming. As a high-capacity transportation mode with strong public service nature, the operational energy consumption, punctuality and travel comfort of urban rail transit are crucial and have high requirements in operation. In order to address the shortcomings of existing transportation planning studies, this paper briefly discusses the project parameters input and project profile for the traffic line optimization system proposed in this paper, based on the discussion of urban rail transit planning and design, multi-objective genetic algorithm optimization and constraints. And the design of the traffic line optimization system is discussed, and finally the proposed multi-objective genetic algorithm optimization is tested experimentally for the optimization of train running time. The experimental data show that the average time of the multi-objective genetic algorithm optimization for five train runs is less than 23.44 s, while the lowest runtime after HE-NSGA-II and MOPSO optimization both reach 112.4 s. Therefore, the proposed multi-objective genetic algorithm optimization for traffic planning has certain superiority.

1. Introduction

Since the 21st century, with the development of urbanization in China, the further concentration of urban population has caused more and more large cities to face the threat of traffic congestion, environmental pollution and other "urban diseases". In this context, urban traffic optimization has become the primary choice for large and medium-sized cities to solve the "urban diseases".

Nowadays, more and more scholars have carried out rich research in transportation planning through various technologies and system tools, and have also achieved certain research results through practical research. Tzanakaki A studied a multi-objective urban traffic signal timing problem. Under the given traffic flow conditions, a scientific configuration parameter is needed, so as to effectively evaluate and construct the traffic capacity and exhaust emission indexes of intersections. Firstly, a multi-objective model of signal timing problem is established based on traffic flow description theory and exhaust emission estimation rules. Secondly, the target model is solved and tested by genetic algorithm. It is found that the Pareto solution set of traffic index obtained by NSGA-III has a large domain [1]. On the basis of big data integration, Phan C fuses the historical train operation data of complex rail transit with the current vehicle data to effectively collect the data during the congestion period. Based on the fusion results of big data dimension and information level, the train time decision is made. Taking the minimum waiting time and the minimum train time as the design objective, a mathematical model of multi-objective scheduling efficiency of complex rail transit system is constructed, and the solution is realized by bacterial foraging optimization calculation. Simulation results show that the provided model effectively improves the efficiency of multi-objective scheduling and driving efficiency of the system [2]. Vidal P provides an optimized NSGA-¢cient method (I-NSGA-Ⅱ) to solve the problem that the elite retention method of NSGA-¢cient leads to a large number of redundant higher-level individuals and the next generation of elite individuals is prone to premature convergence, and applies it to the multi-objective design of traffic signal rearrangement. The experimental results show that I-NSGA-Ⅱ can reduce the delay of vehicles and pedestrians under the premise of keeping the parking rate and queue length basically unchanged. This proves that the proposed algorithm can improve the comprehensive traffic efficiency [3]. Although the existing traffic planning research is very rich, there are still some shortcomings in the application of multi-objective optimization algorithm in traffic planning based on machine learning.

In this paper, based on the discussion of urban rail transportation planning and design, multi-objective genetic algorithm optimization, and constraints, a soft-objective genetic algorithm optimization algorithm is used to design a train operation curve optimization module for line planning of "urban rail transportation operation control simulation platform". The software module was used to conduct experiments to compare the runtime results of five independent runs after the optimization of train curve by multi-objective genetic algorithm optimization (MOGAO) with those of HE-NSGA-II and MOPSO. It can effectively optimize the energy consumption of train operation and ensure the punctuality of train operation.

2. Multi-Objective Optimization Algorithm and Traffic Planning in Machine Learning

2.1. Urban Rail Transit Planning and Design

Its regulation traffic planning and construction needs to integrate the needs of planning department, city managers, rail transit construction department, passengers and other aspects [4].

(1) Determining the starting and ending points of the line

The starting and finishing points of the lines are first selected by the urban rail transit line planning principles. Due to the construction needs of large cities with multiple centers, rail transit construction is often responsible for the commuting needs of new towns in sub-centers and central urban areas, and its starting and finishing points are mostly suburban new town centers [5]. At the same time, it is necessary to follow the principle of station selection according to the actual traffic demand, and set the starting and finishing points in the areas with concentrated traffic demand and close passenger flow [6].

(2) Line traffic corridor site selection

From the meso level, there is the Yangtze River Delta basin traffic corridor, etc., while the most significant micro level is the intra-city rail transit corridor. Therefore, the construction of transportation corridors is not only conducive to promoting the flow of passengers and goods in the region, but also to strengthen the regional connection and optimize the urban population and spatial structure [7].

(3) Optimize station distribution and station spacing

The last step of rail transit planning is to select the location of rail transit stations within a given transportation corridor and arrange the station spacing reasonably [8]. The site selection consists of two stages: identifying candidate stations and determining the location and connection sequence of stations.

2.2. Multi-Objective Genetic Algorithm Optimization

In this paper, we propose a mathematical model with the objective of minimizing traffic running time [9].

(1) Chromosome encoding, in a train operation period, the schedule of a line consists of the departure times of multiple trains, and the schedule of multiple lines can contain the departure times of each of its lines by a chromosome [10]. One chromosome represents a multi-route timetable, this coding is simple and straightforward for easy understanding and subsequent computation, and the departure time of the timetable is restricted to one time period [11].

(2) Pareto front, which is minimizing the maximum variation in traffic running time. For multi-objective solution problems, it is not possible to solve the optimal solution directly, but only to find the compromise solution, and this compromise solution set is called the Pareto solution set, and the solution set composed of all the non-dominated solutions is called the Pareto frontier [12].

(3) Non-dominated grade, after generating the population, it is necessary to scale for the population for its non-dominated grading, the purpose of grading is to obtain the Pareto optimal solutions of different grades, through the non-dominated grade can obtain the Pareto solutions with higher priority, so the algorithm can converge when searching for the optimal solution [13].

(4) Adaptation function: The adaptation function is used to distinguish the good and bad individuals in the population. In this example is to solve the minimum value of energy consumption, as the optimization objective of the problem [14].

(5) Crossover operator: The crossover operation is to randomly select two individuals from the population and pass the good characteristics of the parent to the offspring by exchanging and combining the two chromosomes. Since the individuals are coded with real numbers, the crossover operation uses the real number crossover method [15].

(6) Variation operator: The purpose of variation is to maintain population diversity. The mutation operation randomly selects an individual from the population and selects a point in the individual to mutate to produce a better individual [16].

2.3. Constraints

(1) For all traffic running time should fall within the standard time period.

$$Estart_{rt}, Fstart_{rt} \in [0,1,2,...M] \tag{1}$$

For all lines r, the difference between the departure time of the tth train and the departure time of the $t-1$th train in the actual case should be satisfied between the defined departure intervals.

$$GS_r^{\min} < Fstart_{rt} - Fstart_{r(x-1)} <= GS_r^{\min} \tag{2}$$

Since the vehicle operation is divided into multiple time slots with M as the unit, taking the first time slot $[0, \ M_1]$ as an example, all the departures of l of the line should be within the time slot.

$$0<=Fstart_{ra}<=M_1 \tag{3}$$

If the transfer passenger of the t train of line r can transfer to the z train of line c, then in the case of $DIFF^{rc}{}_{tzq}=1$, the two trains should satisfy the formula (4).

$$(Fstart_{rt}+Mr_{rq})\in\left[(Fstart_{cz}+Mr_{cq})-DS_q^{\max},(Fstart_{cz}+Mr_{cq})-DS_q^{\min}\right] \tag{4}$$

The changes of the original departure time and the optimized departure time should be within a certain range.

$$0<=\left|Estart_{rt}-Fstart_{rt}\right|<=\eta_r \tag{5}$$

3. Investigation Study of Multi-Objective Optimization Algorithm in Machine Learning for Traffic Planning

3.1. Traffic Planning Project Parameter Input

There are several data and parameters that need to be determined and input to the traffic planning optimization model. In this paper, the input variables and parameters are divided into three categories according to their data characteristics:

(1) GIS-related data, mainly population density data and land use type data. In this paper, the actual population density and land use data of Pudong area can be collected and processed with the help of GIS software.

(2) The variables related to the rail transit network system. It mainly includes the adjacency matrix of the rail transit network and the travel data within the rail transit system. The table of the raw travel data is shown in Table 1. From the table, it can be found that the starting and ending stations of the trips can be extracted from the data, while the time information and traffic information provided by the TIME and SUM (TIMES) data can be used to count the traffic flow between any two stations in the system during the time period of 17:00-18:30 [17].

Table 1. Sample travel data

Serial number	InboundID	OutboundID	Total (times)	Time	Ticket Type
457	50	58	1	750	38
459	50	58	1	860	38
460	52	58	1	780	5
465	52	58	1	720	5
468	54	60	1	760	3
469	54	60	1	738	3

(3) Parameters required for calculation in the optimization algorithm. The main parameters include station construction cost (LC), rail construction cost (TC), and Pareto algorithm related parameters. In this paper, some of the parameters lack actual data, so they are assumed, as shown in Table 2.

Table 2. Project-related parameters

Parameter items	Parameter Value
Invested Funds	8.5 billion yuan
Station construction costs	54 million yuan
Minimum station spacing	5km
Rail Construction Costs	425 million yuan/km
Average occurrence distance min.	10.2
Population coverage min.	200,000 people
Total number of iterations	300
Population size	100
Crossover Rate	0.6
Variation rate	0.8

3.2. Traffic Planning Project Overview

In this paper, the reliability of the proposed optimization model is tested by using the actual rail transit data in Pudong New Area of Shanghai as a case study. In order to meet the travel needs of tourists, a new rail line is proposed to be built between the two landmarks of Shanghai Pudong New Area, Expo Park (A) and Shanghai Disneyland (B), to meet the huge travel demand between the two places and to improve the performance of the whole rail network. The study area is Pudong New Area, where the rail network consists of 5 rail lines and 67 stations. Assuming a capital investment of RMB 8.5 billion for the whole construction project (which can be determined by the percentage of GDP or the government's construction budget), the goal of optimization is to find the best rail corridor to improve the overall performance of the rail line network [18].

4. Research on the Application of Multi-Objective Optimization Algorithms in Machine Learning for Transportation Planning

4.1. Multi-Objective Optimization Algorithm in Machine Learning for Traffic Line Optimization System Design

In the optimization of urban rail transit planning, we should consider people, vehicles, operating lines and other elements, and study the emergency evacuation of urban rail transit system hub stations, train operation and comprehensive planning. and "network planning". The automatic train operation control system belongs to "line planning", and its main function is centered on train operation. The multi-objective genetic algorithm optimization method is used to study three aspects of operation map adjustment evaluation, train operation curve optimization and train operation curve tracking optimization.

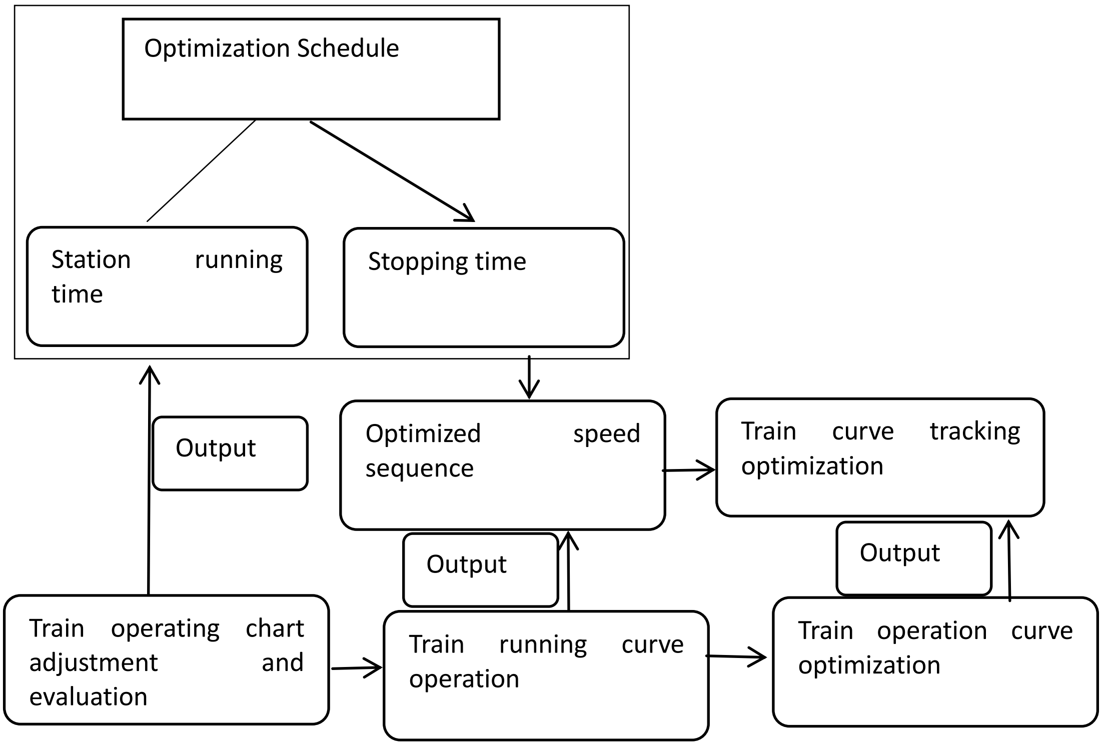

Figure 1. Multi-objective optimization model framework for traffic routes

The interrelationship between the line planning modules is shown in Figure 1. The train operation diagram adjustment and evaluation module is responsible for collecting the initial time data and delay information of interval train operation, optimizing and adjusting the delayed trains, ensuring the robustness of the operation diagram and the efficiency of train operation, and outputting the optimal inter-station operation time and stopping time in the form of an operation diagram. The train running curve optimization module reads the interval running time of a train and optimizes the train running curve based on the fixed time value, and passes the speed sequence with energy saving, punctuality and comfort as the optimization objectives to the train running curve multi-objective genetic optimization algorithm module. Based on the multi-objective genetic optimization algorithm, the module performs precise optimization of the running curve implementation to ensure that the train runs "as planned".

4.2. Application of Multi-Objective Optimization Algorithm in Machine Learning for Traffic Planning

According to the adjusted parameters of the algorithm, the runtime results of the five independent runs of the train curve optimization with MOGAO, HE-NSGA-II and MOPSO are compared experimentally.

Table 3. Algorithm calculated runtime results

Algorithm	MOGAO	HE-NSGA-II	MOPSO
1	35.8	112.4	145.9
2	29.1	139.7	167.4
3	12.8	195.4	158.5
4	22.7	177.2	189.5
5	16.8	188.5	194.7

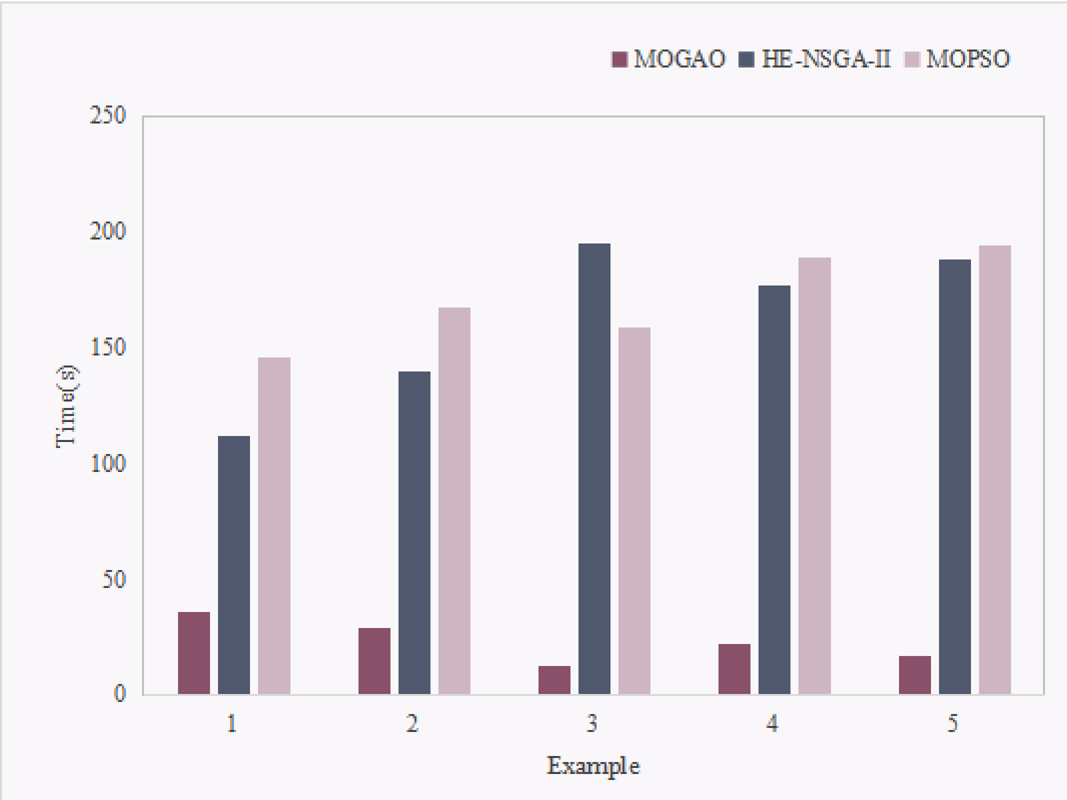

Figure 2. Comparison of the effect of (MOGAO) with HE-NSGA-II and MOPSO algorithms

In Figure 2, the experimental results of the time averaged over five runs of the train by the Multi-Objective Genetic Algorithm Optimization (MOGAO) with HE-NSGA-II and MOPSO are shown. The time of the first run with MOGAO is only 35.8s, while the time of the first run with HE-NSGA-II and MOPSO is 112.4s and 145.9s, respectively. In the third run, the train running time was only 12.8s with MOGAO, while the train running time was 195.4s and 158.5s with HE-NSGA-II and MOPSO, respectively. In the fourth and fifth trains, the train running time using multi-objective genetic algorithm optimization (MOGAO) was below 25s, while the train running time using HE-NSGA-II and MOPSO was between 176s and 195s.

5. Conclusion

In this paper, we study the traffic planning optimization problem oriented to multi-objective optimization algorithm in machine learning. Firstly, the key parts of urban rail transit planning and design are discussed from three aspects: determining the starting and ending points of the line, selecting the location of the line traffic corridor and optimizing the station distribution and station spacing. For the complex constraints in traffic planning optimization, a hybrid coding method and the decoding strategies of arrival and departure line occupancy and arrival time are designed to convert the original constrained optimization problem into an unconstrained optimization problem. A multi-objective genetic algorithm is proposed to optimize the application system in urban rail transportation planning. The effectiveness of multi-objective genetic algorithm optimization is verified through experiments, and the rapid and reasonable adjustment of urban rail transit is realized.

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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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