Rapid Algorithm for Generating and Selecting Optimal Metro Train Speed Curves Based on Alpha Zero and Expert Experience

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ABSTRACT

According to the current research status of urban rail transit's fully automatic operation (FAO), the train driving speed curves are usually obtained through simulation and calculation. The train driving speed curves obtained by this method not only have low efficiency but also are not suitable for complex road conditions. Inspired by AlphaZero, a reinforcement learning algorithm that utilised vast amounts of artificial data to defeat AlphaGo, an AI Go program, this paper investigates and analyses methods for rapidly generating a large number of speed curves and selecting those with superior performance for train operation. Firstly, we use the powerful third-party library in Python as the basis, combined with the idea of AlphaZero, to produce artificial speed curves for metro train driving. Secondly, we set relevant parameters with reference to expert experience to quickly produce massive reasonable artificial speed curves. Thirdly, we analysed relevant indicators such as energy consumption, running time error and passenger comfort to select some speed curves with better comprehensive performance. Finally, through the many observations with different running distances and different speed limits, we found that the speed curves produced and selected by our algorithm are more productive, diverse and conducive to the research of train driving operation than the actual data from traditional manual driving and ATO (automatic train operation) system.

KEYWORDS

rail transit; speed control; data generation; curve optimisation; urban rail transit; train speed.

1. INTRODUCTION

With the rapid development of cloud computing, the Internet of Things and artificial intelligence, society has entered a rapid development segment, which has also significantly contributed to the development of intelligent transportation [1, 2]. Since the 1980s, the demand for metro systems has been increasing in many major cities and metro train driving technology problems often accompany the resulting traffic efficiency problems. Therefore, choosing the right train driving technology can not only improve trains, but also improve the overall efficiency of the metro network, thus increasing its overall economic efficiency. As a high-efficiency and large-capacity large-scale public transportation, urban rail transit can provide a fast, convenient, low-carbon way to travel and greatly alleviate urban traffic congestion and traffic pollution, traffic energy consumption and other related problems [3]. Beijing and Shanghai have formed a large-scale network of urban rail transit systems covering most residential and commercial areas. Many passengers have started to choose the subway travel mode. From the perspective of energy saving, the energy consumption of rail transportation is only 1/3 of that of road transportation for the same number of passengers. Therefore,

urban rail-based metro systems are the most effective solution to relieve traffic pressure. Although many major cities have been improving their subway service levels, the subway system is not improving fast enough to meet the growing demand for passenger transportation, especially in big cities like New York, Beijing and London [4, 5]. So, with such a vast passenger flow, subway trains operation system and efficiency deserve to be studied in depth, especially the intelligent transportation system bred by combining the subway system with today's rapidly developing artificial intelligence technology.

Currently, the leading train driving technologies are divided into assisted and autonomous driving. Assisted driving is also referred to as guided driving. The subway train system provides relevant information directly to the driver and is not involved in the train operation. This method is not only error-prone but also has a significant human factor and is not universal. The automatic driving system, also known as ATO (automatic train operation) system, means that the subway train system has to guide information and can operate the train instead of the train driver, and can be used by the driver to decide exactly what way to drive the train. The advantages of the automatic driving system are improved operational safety, reduced operating costs and increased flexibility in operational organisation. Therefore, it can be seen that fully automated driving train technology is a critical issue in achieving high efficiency, high service level and high security of metro operation.

The aim is to promote sustainable development and reduce environmental pollution. Giving the train a good reference operating speed is a crucial challenge for the realisation of fully automated metro trains. For example, one of the critical factors affecting passenger comfort is the rate of change in train acceleration. The greater the rate of change of acceleration, the more uncomfortable passengers feel; there is also the train's energy consumption, which is also very much related to the reference running speed of the train in driverless operation. On the other hand, there is total train travel time, stopping accuracy and on-time performance, all of which are related to the running speed referenced in the train driving process.

In the past decade, many scholars have optimised and generated the speed of the train operation process. For example, Cheng et al. developed a train speed profile algorithm based on object-oriented programming (OOP) and C++. They validated it using manual calculations by experts from the Taiwan Railway Bureau [6]. Masafumi Miyatake et al. discussed the problem of train speed profile optimisation using dynamic programming (DP), gradient method and sequential quadratic programming (SQP) to minimise the total energy consumption [7].

Jonas Jonaitis obtained the technical speed of the train through its traction mass and related parameters, in order to minimise the unit total energy consumption related to the mass of the train carriage [8]. Thomas Albrecht et al. used speed and train dwell time control to achieve speed optimisation in rail transit systems [9]. Zhao et al. optimised the relevant indicators of trains by establishing a fuzzy multi-objective decision support model for urban rail transit [10]. Chen et al. proposed three TASC algorithms, heuristic online learning algorithm (HOA), gradient-descent-based online learning algorithm (GOA) and RL-based online learning algorithm (RLA), concerning heuristics, gradient descent and reinforcement learning (RL), and used these algorithms to control the train speed and improve the stopping accuracy [11]. Saeed Ahmadi et al. used the variable regenerative energy recovery rate (RERR) between each station to obtain the train's optimal speed profile to improve energy efficiency [12]. Gailienė conducted relevant research on railway line curves, superelevation and uncompensated lateral acceleration to optimise train speed [13]. Cheng et al. proposed an online optimisation algorithm to achieve multi-objective (safety, on-time performance, energy consumption and passenger comfort) control of high-speed trains [14]. Yan et al. used a multi-objective optimisation strategy of genetic algorithm to optimise the train speed operation profile in five aspects: overspeed, stopping accuracy, on-time performance, energy consumption and comfort [15]. Liu et al. proposed an improved genetic algorithm (IGA) based on directed mutation and gene modification to improve the convergence speed and optimisation effect to obtain the highest train speed profile [16]. Svetla et al. optimised the operating speed of the subway by using a subway simulation optimisation combination [17]. Ran et al. minimised energy consumption by considering a combination of schedule optimisation and train speed op-

eration profiles [18]. Li et al. designed a decomposition method based on alternating directional multiplier (ADMM) for train dwell time regulation and speed profile generation design [19]. Huang et al. proposed a new cooperative cruise control strategy to optimise multiple high-speed trains energy consumption and passenger comfort [20].

Although these scholars have conducted extensive research on optimising train speed profiles, previous studies have typically generated a single train speed operation curve based on specific road sections and then integrated energy-saving optimisation methods based on train energy-saving speed, travel time and comfort. This method can only generate a single train speed operation curve, and their work is limited by the actual situation, lacking discussion of other situations. Based on Alpha Zero's progressive ideas and expert experience [21, 22], AlphaZero is an artificial intelligence algorithm developed by DeepMind. It demonstrates remarkable capabilities in complex strategy games such as Go, Chess and Shogi. The algorithm employs a combination of deep neural networks and Monte Carlo Tree Search, continuously optimising strategies through self-play and a wealth of simulation data, thereby achieving performance surpassing human levels.

Inspired by AlphaZero, this paper posits that a large volume of simulated data can be more beneficial than a small amount of real, optimised data in the generation of train speed curves. With this in mind, we draw upon expert experience to set relevant parameters for train operation and leverage powerful Python third-party libraries, such as NumPy and pandas, to develop an algorithm for automatic speed curve generation. This algorithm integrates the concept of human-machine hybrid intelligence and generates train speed curves through large-scale data. While adhering to specified intervals and specific operation times, we have successfully reduced the order of magnitude of the train running curve.

By generating many train speed curves, it can meet the data requirements of subway trains under various operating conditions in fully automatic driving mode, such as energy consumption optimal curve, travel time optimal curve, comfort optimal speed curve, comprehensive weighted speed operation curve. Moreover, suppose there is a change in the speed limit section of the road section or the expected travel time due to the large amount and diversity of the speed curve generated by the algorithm. In that case, corresponding changes can also be made. This will further enhance the efficiency and energy consumption of the subway train system, effectively alleviate traffic congestion and yield substantial social and economic benefits. Compared to traditional data, our research is more advantageous for exploring subway train speed curves, ultimately fostering the evolution of traditional subways towards intelligent transportation.

2. AUTOMATIC GENERATION ALGORITHM OF TRAIN SPEED CURVE

Since the operation of high-speed trains is a multi-objective problem, many performance indicators need to be considered simultaneously, such as running time error, passenger comfort, number of operation switching and energy consumption of high-speed trains [23]. However, previous studies mainly focus on solving the train operation problem by considering only some specific indicators rather than all. For some unpredictable factors, such as weather conditions, line construction or equipment failures, the automatic train speed curve generation algorithm has become an important part of uncrewed trains and even smart transportation [24]. However, the cost of training and retraining these models using machine learning techniques in the past is very high, so this paper proposes an automatic generation algorithm for subway train running speed curves based on Alpha Zero and expert experience. Based on expert experience, we set the parameter range reasonably, and then combine with Alpha Zero's advanced ideas to generate a large number of train running speed curves, multiple self-games and multiple optimisation screenings, and finally obtain a large number of reasonable train speed running curves the optimal solution.

2.1 N-segment running curve

The running of a train along a route is affected by many forces, including traction, train resistance, braking force, car force, etc., which are largely caused by train characteristics and line geometry [25]. Therefore, this paper assumes that the train runs under ideal conditions, such as no air resistance, car force, etc., and

proposes an N-segment train speed operation mode, as shown in *Figure 1*. The red dotted line in the figure is the division line of the train running stage, and the solid line is the generated train running speed curve.
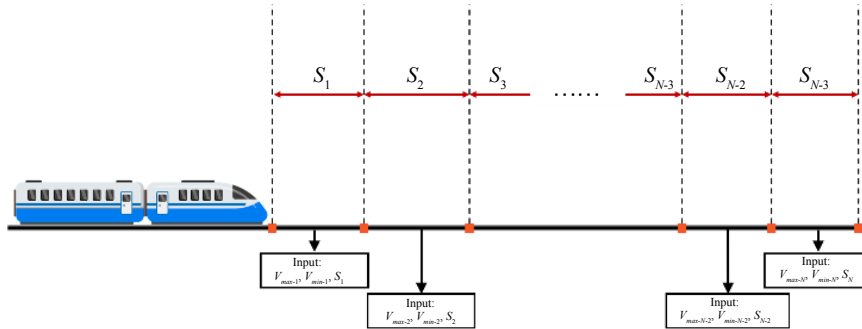

Figure 1 – N-stage running diagram of train

First, according to the road conditions, such as weather, slope, track strength, etc., the curve is divided into *N* sections, and the speed limit interval is set reasonably based on expert experience, and each speed limit interval is defined as a section generated in the train speed running curve algorithm, that is, the interval $S_1, S_2, ..., S_n$, and each speed limit interval S_i corresponds to the expert planning speed limit lower limit V_{min-i} and the expert planning speed limit upper limit V_{max-i}, respectively. Under the constraint of speed, a large number of reasonable train speed running curves are generated, as shown in *Figure 2*.
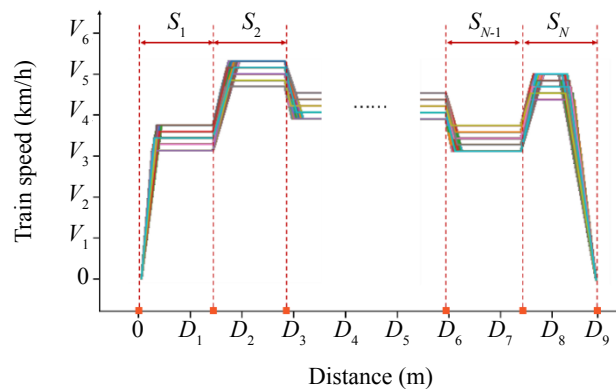

Figure 2 – Schematic diagram of N-segment curve

When a large number of reasonable train speed running curves are generated, and the rail train runs along the target curve, no matter how complex and changeable the road conditions are, one of the generated N-segment curves of reasonable train speed running can always find a suitable one. In the case of unmanned driving, it can ensure safety, energy saving, comfort, accurate parking, punctuality and many other performance indicators of the train. Therefore, it is very important to generate a large number of target speed curves for the operation of urban rail trains. Therefore, this paper proposes an algorithm for generating and selecting a large number of artificial speed curves for subway trains based on Alpha Zero and expert experience.

The expert experience assumed in this paper involves experts providing reliability prediction values for certain train parameters, specifically in the following forms. (1) The reliability prediction value of the train in section *N*, with the planned interval S_i and the planned speed limit V_i; (2) the predicted value of reliability acceleration is provided according to S_i; and V_i; (3) the acceptable time error of the reliability expectation value is given according to the city metro t_0 and the distance error limit S_0. Notably, when α_i, S_i, V_i cannot be satisfied t_0, S_i, this expert experience will not pass the credibility assessment of this algorithm, and the reliability estimate given by this expert experience for the subway train will not be considered, the specific process is shown in *Figure 3*.

First, enter the planning interval S_i and the planning speed limit V_i, considering expert knowledge, to navigate sections 1 through *N* of the driving curve. Subsequently, the algorithm will generate a large num-
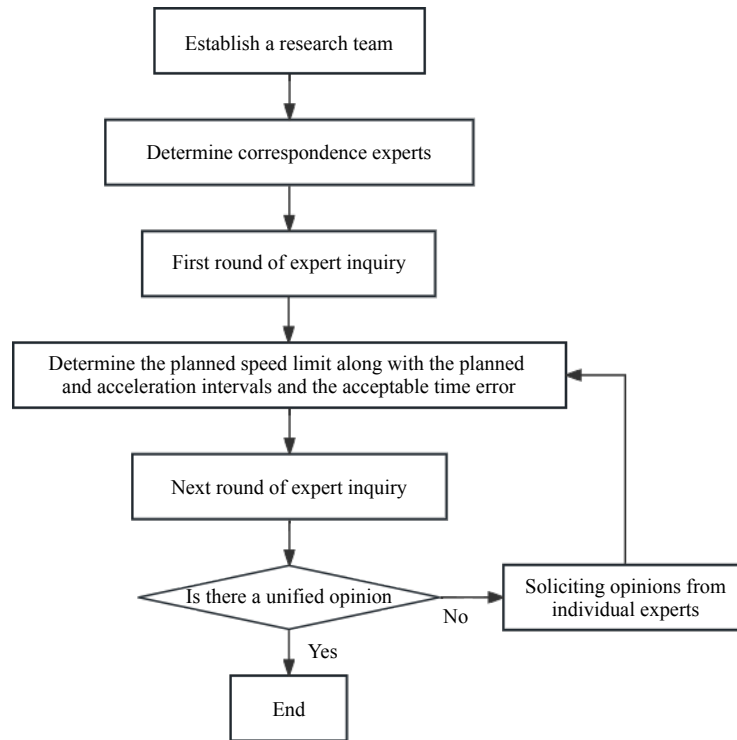
Figure 3 – Expert experience process

ber of acceleration α_i or deceleration β_i, running time T_i, and uniform running time T_{con-i} of each curve. At $i = N$, the algorithm will determine the train's estimated slowing distance S_{re} and observe the train's travel distance S to reach S_{re}, eventually bringing the driving speed down to 0. To summarize, the algorithm flow for generating the train's driving speed curve is shown in *Figure 4*.
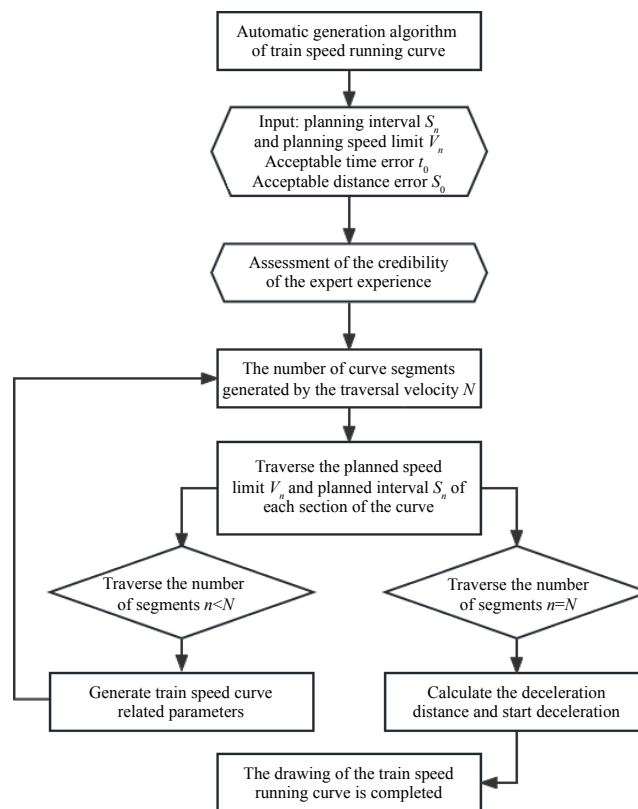

Figure 4 – Flowchart of the algorithm for automatic generation of train speed curve

The pseudo-code is as follows:

Generating and selecting optimal metro train speed curves algorithm

Input: planning district S_i, planning speed limit V_i, acceleration α_i, acceptable time error t_0 and distance error limits S_0, where $i \in N$ and N is the number of segments of the train speed running curve.

Output: Train speed running curve data. Curve = $\{l_1, l_2, l_3, \ldots, l_{n-1}, l_n\}$

1. $S_i, V_i, \alpha_i, t_0, S_0 = \emptyset$
// Initialise basic metro train parameters

2. Curve_data = buildbase $(S_i, V_i, \alpha_i, t_0, S_0)$
// Calculate all arrival modes of metro trains

3. Credibility of the expert experience (Curve_data)
    for (k = 1 to n; i++) do
      if ($t_i, S_i > t_0, S_0$) then
        delete l_i
      end
        return Curve_data
// Expert experience reliability assessment

4. for (k = 1; $k \le n$; k++) do
   for (i = 1; $i \le$ N; i++) do
      Each index = Calculate data by sampling at time intervals
// Calculate energy consumption, comfort, stopping accuracy and on-time performance for each subway speed profile

5. Screening optimisation (E_n, C_o, P_t, P_s)

Return Curve = $\{l_1, l_2, l_3, \ldots, l_{n-1}, l_n\}$

2.2 Common operating states

Taking urban subway trains as an example, since the distance between two stations is generally short, between 1 km and 2 km, there are even stations with a distance of about 500 meters, and the road conditions of urban rail transit are good, such as weather, slope, etc. Some unpredictable factors require less train braking or acceleration, so the change of train speed is relatively simple, which can be divided into the following two common types: 3-stage speed operation curve and 4-stage speed operation curve. As shown in *Figures 5 and 6.*
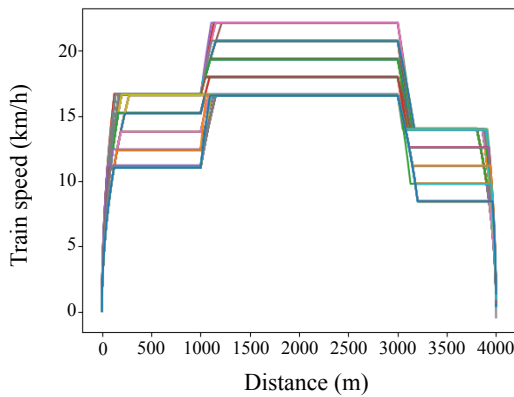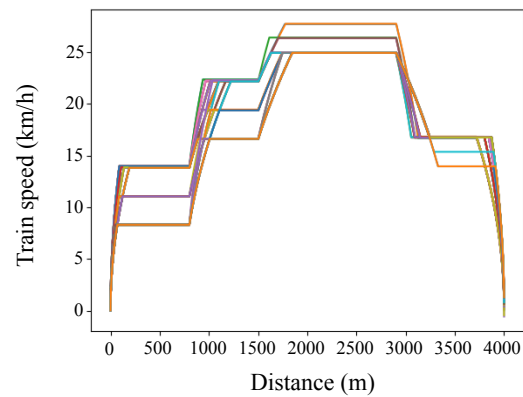

Figure 5 – Three-stage train speed curve
Figure 6 – Four-stage train speed curve

Take the inter-city rail transit high-speed rail as an example. Due to the long distance between two high-speed rail stations, there are usually stations in dozens of kilometres. However, the train will not stop at every station. In most cases, the parking sites are separated by more than 100 kilometres. In addition, the road conditions between the two high-speed rail stations are generally more complicated, and there are many factors to be considered, such as topography, weather, etc. The influence of distance, passenger capacity, slope and signal transmission is greater, so the train is on the inter-city track. The changes in the running speed of traffic are more complex, and this article will not elaborate on them one by one.

To sum up, in the rail transit system, whether it is a subway train with a simple operation in the city or a long-distance high-speed rail train with a complex operation between cities, the train speed generated by

a large number of train running speed curve algorithms proposed in this paper is generated. Therefore, the running curve can always cover its suitable driving method, improve the safety, energy saving, comfort and efficiency of train operation, and get a good application.

3. MODEL BUILDING

The train's movement along the route is governed by the equations of motion and limited by speed. The former, also known as the vehicle dynamics model, is the product of Newton's second law of motion. The latter is to adjust the maximum speed of trains along the line for safety reasons. In addition, the algorithm can set specific operation targets to guide the train's movement, such as speed limit value, speed limit interval and acceleration interval. The following subsections describe the mathematical model for generating the velocity curve.

3.1 Train dynamics analysis

Traditional train dynamics analysis considers trains as single particle force analysis, with a relatively simple structure. In this paper, high-speed trains are considered as a chain of particles of a certain length, where a certain length is the formation length of the train, and force analysis is conducted on the train. This model takes into account the length of the train set and reduces calculation errors. The dynamic model is shown in *Equations 1–5*.

$$W_0 = a + bV + f_w \tag{1}$$

where W_0 is the basic resistance, a and b are empirical constants, V is the current speed of the train and f_w is the air resistance.

$$f_w = \frac{1}{2} c\rho S_w V^2 \tag{2}$$

where c is the empirical constant, ρ is the density of air, S_w is the cross sectional area of the train.

$$W_i = \frac{mg}{1000 L_{train}} i_{slope} L_{slope} \tag{3}$$

where W_i is the slope resistance, L_{train} is the length of the train, i_{slope} the thousandth of the ramp and L_{slope} is the length of the ramp.

$$W_s = 0.00013 L_{tunnel} \tag{4}$$

where W_s is the tunnel resistance, L_{tunnel} is the length of the tunnel.

$$W_r = \frac{D}{R} \tag{5}$$

where W_r is the curve resistance, D is the empirical constant, usually taken as 2,000 and R is the radius of the curve.

3.2 Design of the traction braking zone

In order for trains to travel along a railway line, all speed limits at each location on the line must be obeyed. Therefore, when the train arrives at a specific position, in order to reach the minimum allowable speed V_{min-i} or the maximum allowable speed V_{max-i}, the train needs to speed up or slow down. The author consulted relevant materials and obtained the following relevant data: the average speed of subway trains is 0~40 km/h, and the average acceleration α_i is in the range of 0.6~0.9 m/s^2 in order to consider the comfort of people. Therefore, in order to make a large number of generated train running speed curve data cover the actual situation of the train in reality, the acceleration α_i interval used in this paper is 0.5~1.0 m/s^2. The advantage of this is that a large number of reasonable virtual data are generated. After screening, the optimal solution of the speed curve suitable for the actual train can be obtained. The relationship between the traction acceleration α_i and the planned speed limit interval S_i and the planned speed limit V_i is shown in *Equations 6 and 7*:

$$V_i = V_0 + \alpha_i \cdot t_i \tag{6}$$

$$S_i = \frac{V_i^2 - V_0^2}{2 \cdot \alpha_i} + S_{con-i} \qquad (7)$$

where V_i is the planned speed limit at the current stage, V_0 initial speed of current stage, α_i is the acceleration/deceleration of section I, t_i is the acceleration/deceleration time of section I, s_i is the planned speed limit interval of section I, S_{con-i} is the constant speed driving interval of section I.

The time T_i of the traction braking section can be calculated from the minimum allowable speed V_{min-i} or the maximum allowable speed V_{max-i} of the section, as shown in *Formula 8*:

$$T_i = \frac{V_i - V_0}{\alpha_i} \qquad (8)$$

where T_i is the time of traction braking section, V_i is the planned speed limit at the current stage, V_0 is the initial speed of the current stage, α_i is the acceleration/deceleration of paragraph I.

3.3 Constant speed driving stage

During train operation, when the train speed reaches the specified speed limit, the train keeps running at a constant speed until the running distance is reached and before the next stage. The running time T_{con-i} of the i-th section of constant speed driving can be calculated by the speed limit value V_i of the i-th section of the driving curve, the speed limit value V_{i-1} of the i-th section, and the i-th section acceleration α_i calculated, as shown in *Formula 9*:

$$T_{con-i} = \frac{S_i - \left| \frac{V_i^2 - V_0^2}{2 \cdot \alpha_i} \right|}{V_i} \qquad (9)$$

where T_{con-i} is the constant speed running time of the train in section I, S_i is the planned speed limit interval of section I, V_i is the planned speed limit at the current stage, V_0 is the initial speed of the current stage, α_i is the acceleration/deceleration of paragraph I.

3.4 Deceleration stage

When the travel distance of the train is close to the end point, that is, when $i=N$, the train travels to the last segment in the train speed running curve, that is, the N-th segment, in order to ensure the safety of passengers and improve the quasi-efficiency of the train, is necessary to be calculated in advance. After the predetermined deceleration distance S_{re} is reached, when the travel distance S of the train reaches S_{re}, it starts to decelerate evenly, and finally reduces the running speed to 0. The main calculation formula is shown in *Formulae 10 and 11*:

$$S_{re} = S - \left| \frac{V_N^2}{2 \cdot \alpha_N} \right| \qquad (10)$$

$$T_{re} = \left| \frac{V_N}{\alpha_N} \right| \qquad (11)$$

where S_{re} is the estimated deceleration distance of the train, S is the total distance travelled by the train, V_N is the running speed of section n of the train speed running curve, α_N is the acceleration/deceleration of segment n, T_{re} is the estimated deceleration time of the train.

4. SCREENING ANALYSIS

In real life, because it involves train schedule scheduling, energy consumption control and other issues, we need to arrive at the designated location on time in any given period as much as possible. In this section, the automatic train speed curve generation algorithm described earlier in this paper will be used as an example to generate data. Then, based on this algorithm, the five indicators of passenger comfort, travel time, energy consumption, punctuality and parking accuracy are screened through the calculated data of driving time, acceleration distance, estimated remaining driving distance and estimated remaining driving time. Next, in analysis, data cleaning and data processing, the train speed operation curve that does not conform to the actual situation or is not highly evaluated is eliminated. Finally, the optimal train speed operation curve data set that meets the arrival of each period and has a high service level is obtained.

4.1 Driving time indicator

Journey time serves as a crucial metric for evaluating the efficiency of train operations. Decreasing travel time can reduce passenger waiting periods and train operating costs, thereby enhancing the overall efficiency of urban rail transit systems. We selected journey time as a metric with the aim of minimising it through the optimisation of the train speed profile, thereby improving the efficiency and punctuality of train operations. The travel time is mainly affected by the running speed of the train and is an important indicator for passengers when they take the train. In order to improve the service level of rail transit and ensure the satisfaction of passengers with the travel time of the train, we need to calculate the travel time in the data set. The mathematical model for calculating the travel time can be obtained from *Equations 8, 9 and 11*, as shown in *Equation 12*:

$$T_a = \sum_{1}^{N} (T_i + T_{con\text{-}i}) + T_{re} \tag{12}$$

where T_i is the time of the traction braking section. $T_{con\text{-}i}$ is the constant speed running time of the i-th section of the train. T_{re} is the estimated deceleration time of the train. α_i is the acceleration/deceleration of the i-th section.

4.2 Energy consumption index

Energy consumption is a pivotal metric for assessing the environmental impact of train operations. Lowering the energy consumption of trains can decrease environmental pollution and carbon emissions, aligning with the principles of sustainable transportation. We selected energy consumption as a metric with the intent of reducing it through the optimisation of the train speed profile, then we can achieve a positive contribution to the environment. Energy consumption is the total energy consumed to overcome resistance during operation. The consumption can be divided into three parts: traction energy consumption, auxiliary energy consumption and regenerative braking energy consumption [26]. As the train travels on the curve, it encounters additional resistance from the curve. This curve resistance is related to factors such as curve radius, train speed and track curvature [27]. Therefore, obtaining accurate results with general mathematical methods is difficult. Therefore, the train speed running curve proposed in this paper does not consider curve resistance, tunnel resistance, ramp resistance, etc., for the time being, based on ideal conditions. However, parameter definitions can be added to the algorithm in combination with the actual situation in the follow-up research to make the generated train speed curve more accurate and close to reality. The specific calculation model of energy consumption is as *Formula 13:*

$$E_n = \sum_{i=1}^{n} (mv_{i+1}^2 - mv_i^2)/2 \tag{13}$$

where m is the mass of the train. V_i is the speed of the i-th node of the train.

4.3 Comfort index

Comfort is a critical metric for evaluating passenger experience and satisfaction. Enhancing train comfort can boost passenger loyalty and the appeal of the metro system, thereby attracting more passengers to utilise public transportation. We selected comfort as a metric with the goal of optimising the train speed profile to improve passenger experience and elevate passenger satisfaction. Among them, comfort is mainly affected by train acceleration and acceleration changes [28]. To ensure passenger comfort, the acceleration range is controlled between 0.5 m/s² and 1.5 m/s². The specific calculation model of comfort is as shown in *Formula 14*:

$$C_o = \Delta|a| = \sum_{i=1}^{n} |a_{i+1} - a_i| \tag{14}$$

where a_i is the acceleration of the i-th node of the train, $\Delta|a|$ is the change rate of acceleration.

4.4 Punctuality indicators

Punctuality is a crucial metric for evaluating the reliability and timeliness of train operations. Enhancing train punctuality can bolster the stability and reliability of transportation, thereby increasing passengers'

trust and willingness to use public transportation systems. We selected punctuality as a metric with the aim of improving it through the optimisation of the train speed profile, thereby providing more reliable transportation services. The punctuality of subway trains is expressed as the deviation between the actual running time and the ideal specified running time. The smaller the deviation is, the higher the actual value of punctuality is, so it can be used to evaluate the punctuality of the train. The specific calculation model of punctuality is as *Formula 15*:

$$P_T = 1 - \frac{|T - T'|}{t_0} \qquad (15)$$

where T is the ideal specified running time of the train, T' is the actual running time of the train, t_0 is an acceptable time error limit.

4.5 Parking accuracy index

Stopping accuracy is a key metric for assessing train stopping operations. Enhancing the stopping accuracy of trains can reduce platform congestion, decrease passenger boarding and alighting time, and improve the operational efficiency of train stations. We selected stopping accuracy as a metric with the intent of optimising the train speed profile to achieve more precise stopping operations, thereby improving the service quality and efficiency of train stations. The accuracy of subway train parking is expressed as the deviation between the actual parking position and the ideal specified parking position. The smaller the deviation, the higher the accuracy. Therefore, it can be used to evaluate the accuracy of train parking. The specific calculation model of parking accuracy is as shown in *Equation 16*:

$$P_S = 1 - \frac{|S - S'|}{s_0} \qquad (16)$$

where S is the ideal specified parking distance of the train, and S' is the actual parking distance of the train, S_0 is the acceptable stopping distance error limit.

5. CASE STUDIES

According to the above, this paper uses short distance, medium distance and long distance to generate the total distance S in the algorithm, and then performs a large number of 3-stage, 4-stage and 5-stage train speed running curves for it respectively (namely N=3,4,5) to verify the effectiveness of our algorithm in optimising the speed curve.

In order to ensure that the algorithm generates a reasonable dataset, we refer to the majority of subway driving conditions and actual subway operation conditions and refer to expert opinions to uniformly input relevant subway train parameters when generating speed profiles. This helps ensure that the generated speed profiles are realistic and can meet operational requirements in various scenarios. Data were collected using a virtual time-series transponder, which was employed to gather data every 0.1 seconds for iterative results. This allows us to obtain high-precision, high-frequency train operation statuses, and then optimise the train speed in each time interval to ensure the reliability and accuracy of the algorithm.

Table 1 – The basic parameters of the train

Parameter	Unit	Enter
Train weight	t	60
Train height	m	3.890
Train width	m	2.950
Train length	m	25
Minimum acceleration (a_{min})	m/s^2	0.5
Maximum acceleration (a_{max})	m/s^2	1.1
Acceptable time error limit (t_0)	s	10
Acceptable stop distance error limit (S_0)	m	3

5.1 Short-distance train speed curve generation

The short distance of subway trains is usually 500 m–2,500 m, which is the distance between two closer stations. In this paper, the total distance S obtained in short-distance driving is 2,000 m; the short-distance road section is not complicated and does not need to perform multiple shifts. However, to verify the algorithm's effectiveness, 3-stage, 4-stage and 5-stage models are still used to generate many train speed curves. By referring to expert opinions, we also get a reasonable planning speed limit, namely V_{min-i}, V_{max-i}. The basic data required by the algorithm are shown in *Table 2*.

Table 2 – Speed limit table of train sections

N	3-segment speed curve		4-segment speed curve		5-segment speed curve	
	Segment (m)	Speed limit (km/h)	Segment (m)	Speed limit (km/h)	Segment (m)	Speed limit (km/h)
1	0–600	30–50	0–500	30–50	0–400	20–40
2	600–1,400	60–80	500–850	50–60	400–800	50–60
3	1,400–2,000	40–60	850–1,500	60–80	800–1,300	60–70
4	/	/	1,500–2,000	40–60	1,300–1,600	40–50
5	/	/	/	/	1,600–2,000	20–40

By building the train operation model, preliminary generation of train speed operation curve dataset is visualised through the Python programming library, as shown in *Figure 7*.

a) Three-segment train speed curve

b) Four-segment train speed curve

c) Five-segment train speed curve
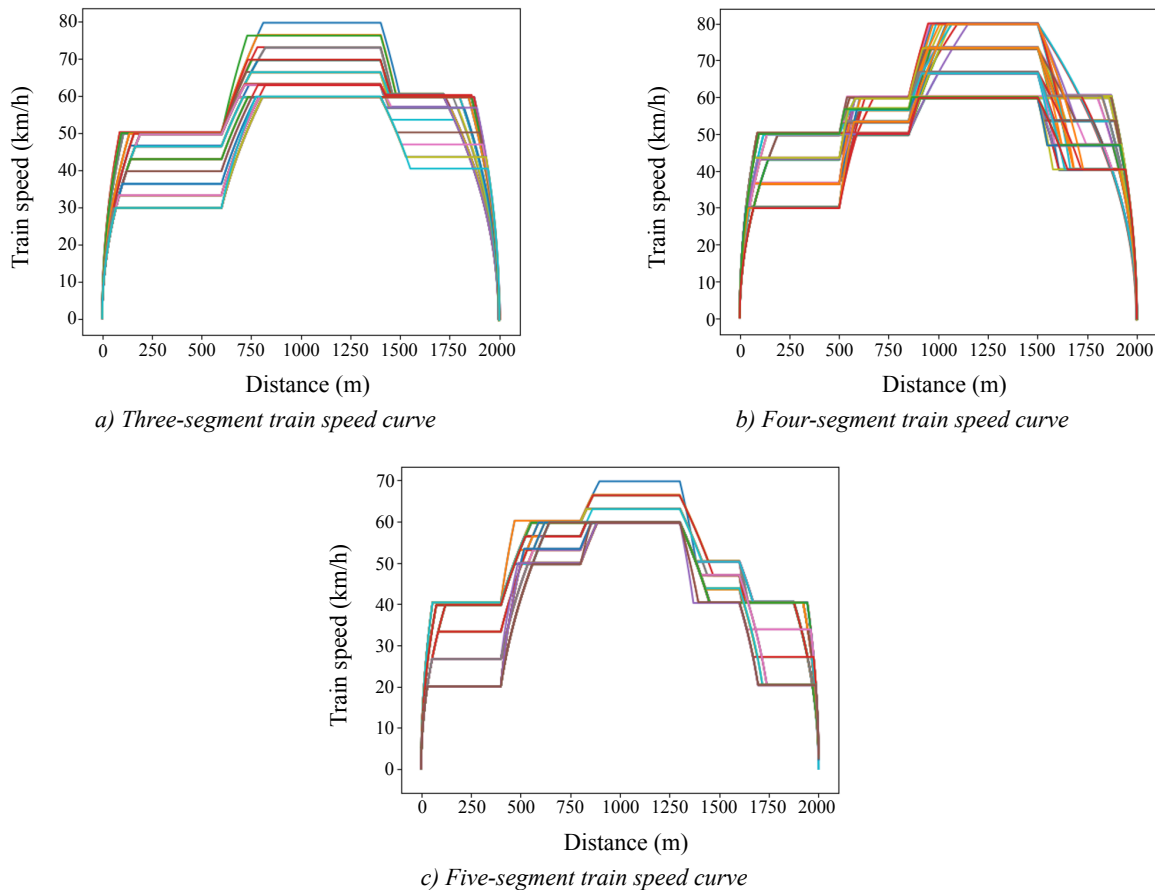
Figure 7 – Speed operation curve of short distance trains

Implemented through Python programming and exported as a CSV file, in these train running curve data, the shortest travel time of the 3-stage type is 120.0 s, the longest travel time is 200.5 s, the shortest travel time of the 4-stage type is 120.5 s, and the longest travel time is 194.3 s, the shortest travel time of

the 5-segment type is 145.1 s, and the longest travel time is 241.9 s. The time distribution diagrams of the travel time are shown in *Figure 8*.

a) Three-segment curve travel time distribution

b) Four-segment curve travel time distribution

c) Five-segment curve travel time distribution
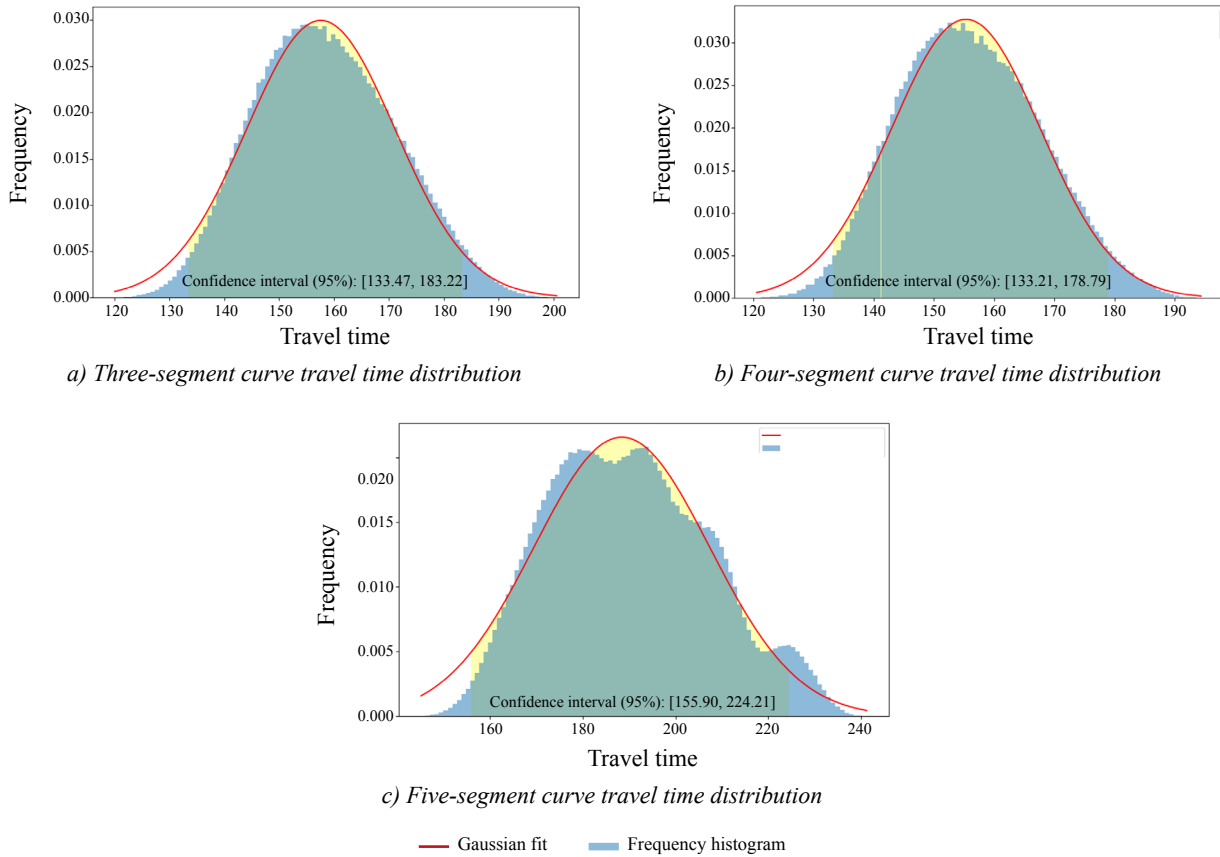
— Gaussian fit   ▬ Frequency histogram

Figure 8 – Short distance travel time frequency

According to the train speed running curve data set generated above, the algorithm designed by us is used to screen the train travel time, energy consumption, comfort, average parking accuracy and average on-time rate. Finally, three filtered data sets are obtained. The optimisation of data sets before and after filtering is shown in *Table 3*.

Table 3 – Statistics of train data after screening

Parameter	Three-segment speed curve		Four-segment speed curve		Five-segment speed curve	
	Before screening	After screening	Before screening	After screening	Before screening	After screening
E_n (kJ)	41,731	31,596	41,734	30,838	46,361	39,332
C_O (m/s^2)	3.2	2.4	4.1	2.9	4.8	3.3
P_S (%)	56.6	99.1	54.5	99.2	58.7	99.1
P_T (%)	63.9	92.8	58.7	93.7	66.6	93.2

Through the comparative analysis of the above data, under ideal conditions, the average energy consumption of the three-segment curve obtained by the screening optimisation algorithm is reduced by 24.3%, the average comfort level is improved by 25%, the average parking accuracy is improved by 42.5% and the average on-time rate is improved, 28.9%. The average energy consumption of the four-segment curve is reduced by 26.1%, the average comfort level is improved by 29.2%, the average parking accuracy is improved by 44.7% and the average punctuality rate is improved by 35.0%. The average energy consumption of the five-segment curve is reduced by 15.1%, the average comfort level is improved by 31.25%, the average parking accuracy is improved by 40.3% and the average punctuality rate is improved by 93.2%. It can be seen that this curve screening optimisation algorithm can make the train achieve better performance.

5.2   Medium t-distance train speed curve generation

The example in 5.1 states that the distance between two subway stations is 500–2,500 m. However, 500–2,500 m certainly cannot cover the distance between two subway stations in most cities. We also need to consider the city's typography, such as the subway trains built across rivers and rivers, so we also need to consider the generation of medium-distance subway train speed curves. Through expert opinions, we know that generally, the longer distance between two urban subway stations is 2,500–4,000 m, so in the example of the long-distance train speed curve generation, we set S as 3,500 m. By referring to expert opinions, we get a reasonable planning speed limit, namely V_{min-i}, V_{max-i}. The basic data required by the algorithm are shown in *Table 4*.

Table 4 – Speed limit table of train sections

N	3-segment speed curve		4-segment speed curve		5-segment speed curve	
	Segment (m)	Speed limit (km/h)	Segment (m)	Speed limit (km/h)	Segment (m)	Speed limit (km/h)
1	0–1,000	30–50	0–500	50–60	0–600	35–60
2	1,000–2,500	60–100	500–1,500	80–100	600–1,200	60–80
3	2,500–3,500	20–40	1,500–2,800	60–70	1,200–2,200	80–100
4	/	/	2,800–3,500	40–60	2,200–2,900	60–80
5	/	/	/		2,900–3,500	30–40

By building the train operation model, the train speed operation curve data sets are initially generated in a centralised manner, including 823,543 data, 800,000 data, and 746,496 data, and are visualised through the Python programming library, as shown in *Figure 9*.

a) Three-segment train speed curve

b) Four-segment train speed curve

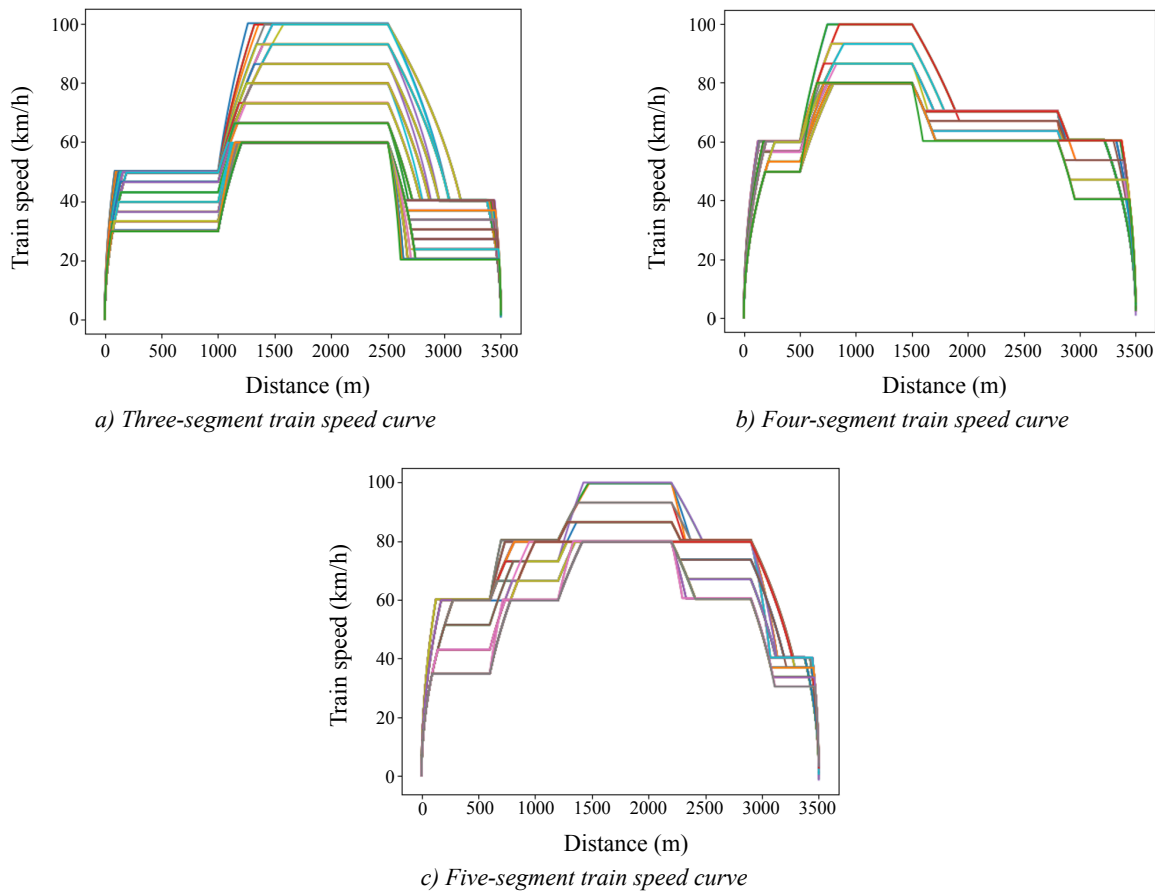*c) Five-segment train speed curve*

Figure 9 – Speed operation curve of medium distance trains

Implemented through Python programming and exported as a CSV file, in these train running curve data, the shortest travel time of the 3-stage type is 210.8 s, the longest travel time is 393.3 s, the shortest travel time of the 4-stage type is 178.7 s, and the longest travel time is 251.9 s, the shortest travel time of the 5-segment type is 185.4 s, and the longest travel time is 273.7 s. The time distribution diagrams of the travel time are shown in *Figure 10*.

a) Three-segment curve travel time distribution

b) Four-segment curve travel time distribution

c) Five-segment curve travel time distribution

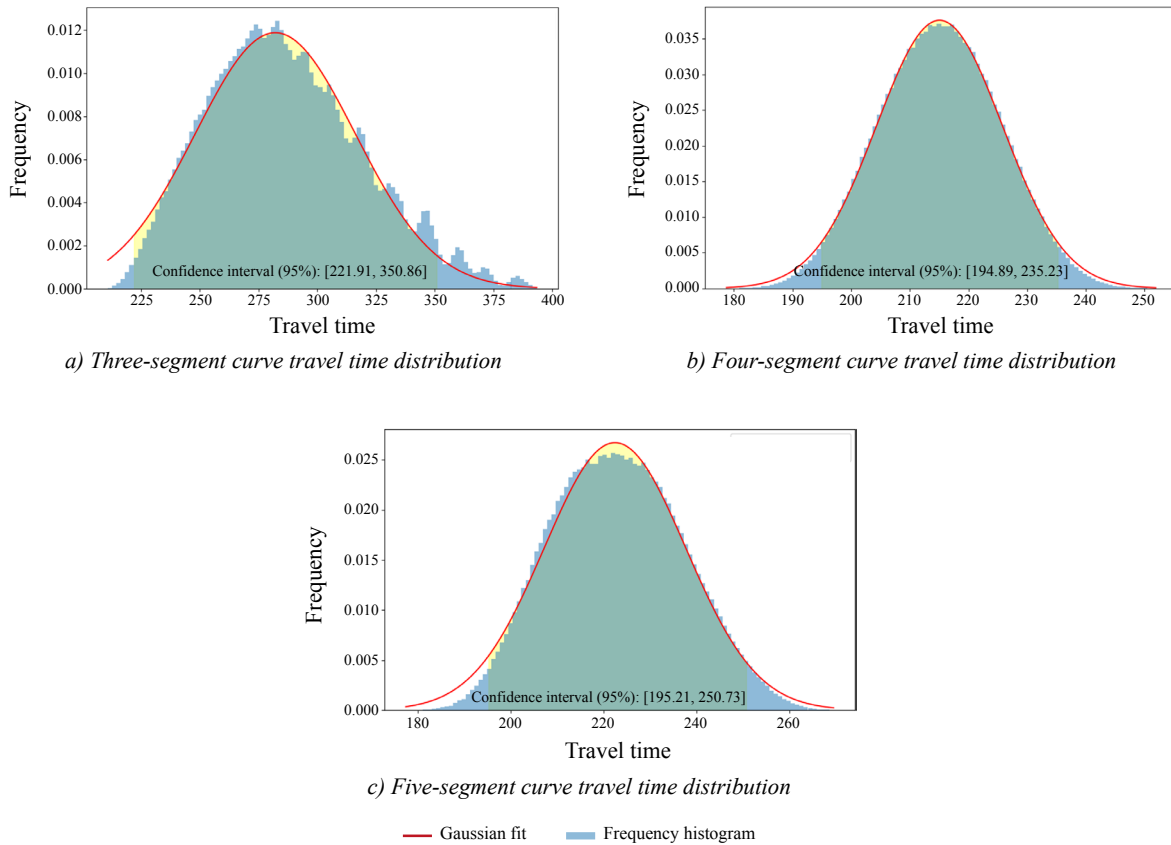Gaussian fit   Frequency histogram

Figure 10 – Medium distance travel time frequency

According to the train speed running curve data set generated above, the algorithm designed by us is used to screen the train travel time, energy consumption, comfort, average parking accuracy and average on-time rate. A three-segment train speed running curve dataset of 0.1 s, from 187–273 s, a four-segment train speed running curve dataset of 0.1 s, from 263–379 s, a five-segment step of 0.1 s. The average travel time, average energy consumption, average comfort level, average parking accuracy and average on-time rate of these three data sets are shown in *Table 5*.

Table 5 – Statistics of train data after screening

parameter	Three-segment speed curve		Four-segment speed curve		Five-segment speed curve	
	Before screening	**After screening**	**Before screening**	**After screening**	**Before screening**	**After screening**
E_n	60,309 kJ	46,774 kJ	60,828 kJ	50,117 kJ	67,663 kJ	58,222 kJ
C_O	3.2 m/s2	4.1 m/s2	4.8 m/s^2	3.2 m/s^2	4.1 m/s^2	4.8 m/s^2
P_S	66.2%	57.3%	65.6%	66.2%	57.3%	65.6%
P_T	69.0%	64.3%	69.4%	69.0%	64.3%	69.4%

Through the comparative analysis of the above data, under ideal conditions, the average energy consumption of the three-segment curve obtained by the screening optimisation algorithm is reduced by 22.4%, the average comfort level is improved by 31.2%, the average parking accuracy is improved by 32.5% and the average on-time rate is improved, 23.9%. The average energy consumption of the four-segment curve

is reduced by 16.8%, the average comfort level is improved by 24.3%, the average parking accuracy is improved by 41.8% and the average punctuality rate is improved by 27.9%. The average energy consumption of the five-segment curve is reduced by 13.9%, the average comfort level is improved by 29.1%, the average parking accuracy is improved by 33.8% and the average punctuality rate is improved by 24.1%. It can be seen that this curve screening optimisation algorithm can make the train achieve better performance.

5.3 Long-distance train speed curve generation

In the above two examples, the distance between two stations in the urban subway is pointed out. Still, to improve traffic efficiency during subway operation, there is also a mode of cross-station operation, generally a longer distance. The generation and verification of this long-distance train speed curve are not only because of the distance between the two subway stations but also because if we research high-speed rail in the future, the long-distance travel of high-speed rail can also be verified through our algorithm. Therefore, through expert experience, we know that the running distance of this mode is generally maintained between 3,000–5,000 m, so we set the distance S as 5,000 m in the large-scale generation of long-distance train speed curves and get a reasonable planning speed limit, namely V_{min-i}, V_{max-i}. The basic data required by the algorithm are shown in *Table 6*.

Table 6 – Speed limit table of train sections

N	3-segment speed curve		4-segment speed curve		5-segment speed curve	
	Segment (m)	Speed limit (km/h)	Segment (m)	Speed limit (km/h)	Segment (m)	Speed limit (km/h)
1	0-1,500	60-80	0-1,300	30-50	0-1,000	30-50
2	1,500-3,500	80-110	1,300-3,000	60-80	1,000-1,800	50-60
3	3,500-5,000	60-70	3,000-4,000	80-90	1,800-3,500	80-100
4	/	/	4,000-5,000	40-60	3,500-4,300	60-80
5	/	/	/	/	4,300-5,000	30-40

By building the train operation model, the train speed operation curve data sets are initially generated in a centralised manner, including 823,543 data, 800,000 data, and 746,496 data, and are visualised through the Python programming library, as shown in *Figure 11*.

Implemented through Python programming and exported as a CSV file, in these train running curve data, the shortest travel time of the 3-stage type is 215.9 s, the longest travel time is 311.6 s, the shortest travel time of the 4-stage type is 273.3 s, and the longest travel time is 412.2 s, the shortest travel time of the 5-segment type is 280.5 s, and the longest travel time is 402.6 s. The time distribution diagrams of the travel time are shown in *Figure 12*.

According to the train speed running curve data set generated above, the algorithm designed by us is used to screen the train travel time, energy consumption, comfort, average parking accuracy and average on-time rate. A three-segment train speed running curve dataset of 0.1 s, from 187–273 s, a four-segment train speed running curve dataset of 0.1 s, from 263–379 s, a five-segment step of 0.1 s. The average travel time, average energy consumption, average comfort level, average parking accuracy and average on-time rate of these three data sets are shown in *Table 7*.

Table 7 – Statistics of train data after screening

Parameter	Three-segment speed curve		Four-segment speed curve		Five-segment speed curve	
	Before screening	After screening	Before screening	After screening	Before screening	After screening
E_n	63,131 kJ	53,804 kJ	65,118 kJ	57,131 kJ	67,203 kJ	58,057 kJ
C_O	3.2 m/s^2	2.5 m/s^2	4.1 m/s^2	2.8 m/s^2	4.8 m/s^2	3.3 m/s^2
P_S	57.2%	98.5%	56.4%	98.6%	62.9%	99.1%
P_T	61.9%	91.4%	66.4%	92.9%	68.2%	93.6%

a) Three-segment train speed curve

b) Four-segment train speed curve

c) Five-segment train speed curve
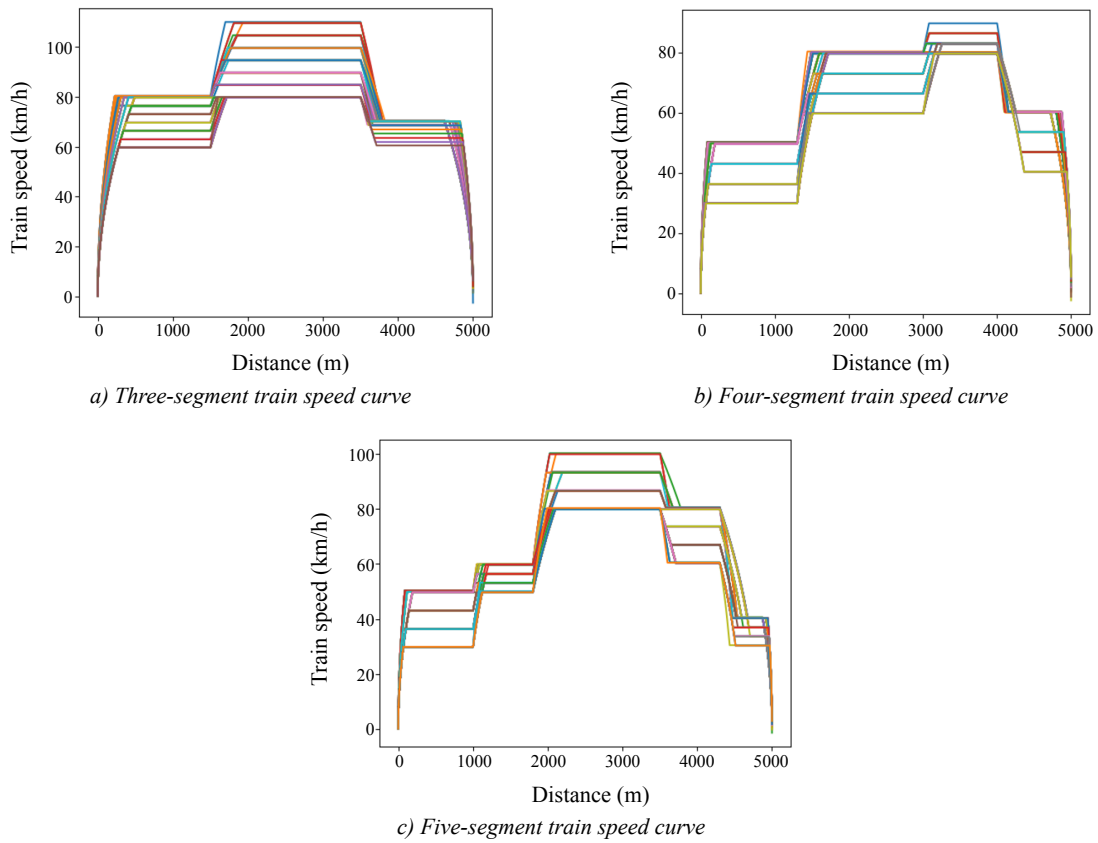
Figure 11 – Speed operation curve of long-distance trains

a) Three-segment curve travel time distribution

b) Four-segment curve travel time distribution

c) Five-segment curve travel time distribution
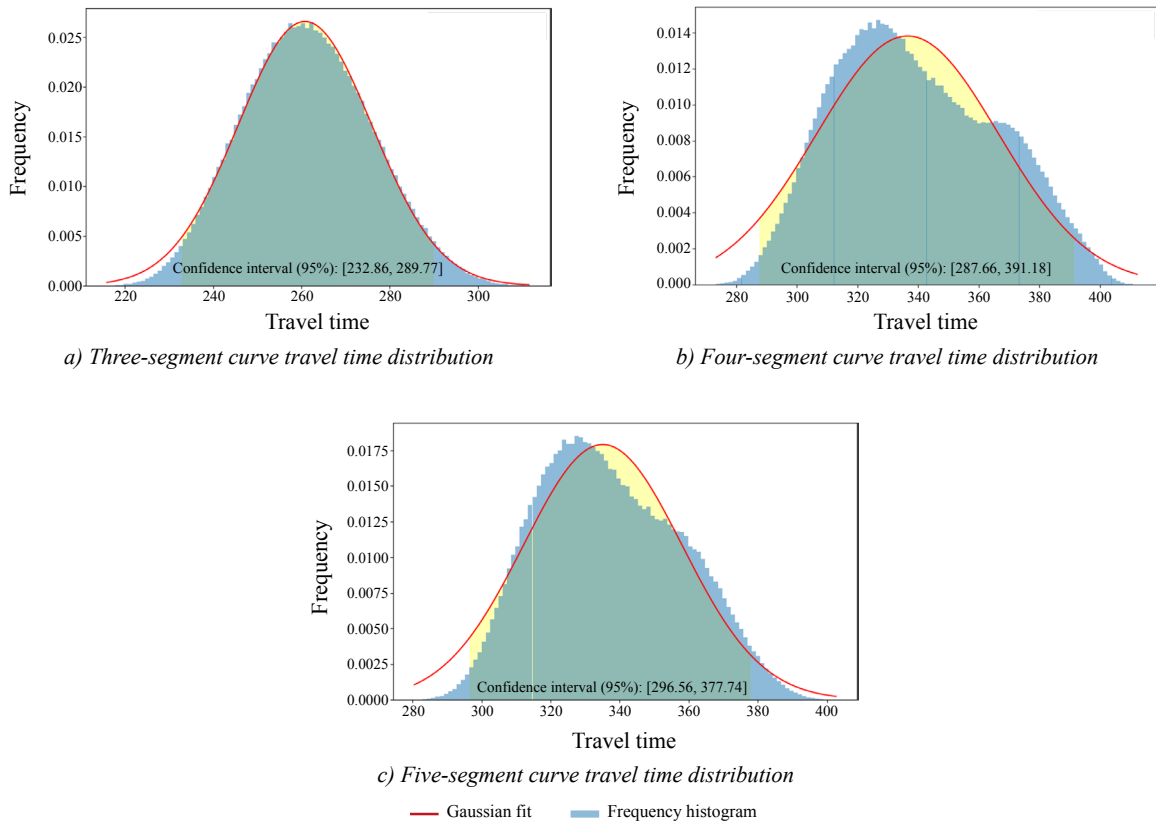
— Gaussian fit   ▬ Frequency histogram

Figure 12 – long-distance travel time frequency

Through the comparative analysis of the above data, under ideal conditions, the average energy consumption of the three-segment curve obtained by the screening optimisation algorithm is reduced by 14.8%, the average comfort level is improved by 21.9%, the average parking accuracy is improved by 41.3% and the average on-time rate is improved 29.5%. The average energy consumption of the four-segment curve is reduced by 13.9%, the average comfort level is improved by 31.7%, the average parking accuracy is improved by 42.2% and the average punctuality rate is improved by 26.4%. The average energy consumption of the five-segment curve is reduced by 13.6%, the average comfort level is improved by 31.2%, the average parking accuracy is improved by 36.1% and the average punctuality rate is improved by 25.3%. It can be seen that this curve screening optimisation algorithm can make the train achieve better performance.

5.4 Screening optimisation analysis summary

After screening and analysing the above short, medium and long distance data with algorithms, we can find that the energy consumption after screening will be greatly reduced, and the comfort, parking intensive reading and punctuality rate have been well optimised, as shown in *Figure 13*.

a) Energy consumption optimisation result

c) Parking accuracy optimisation result

b) Comfort optimisation result

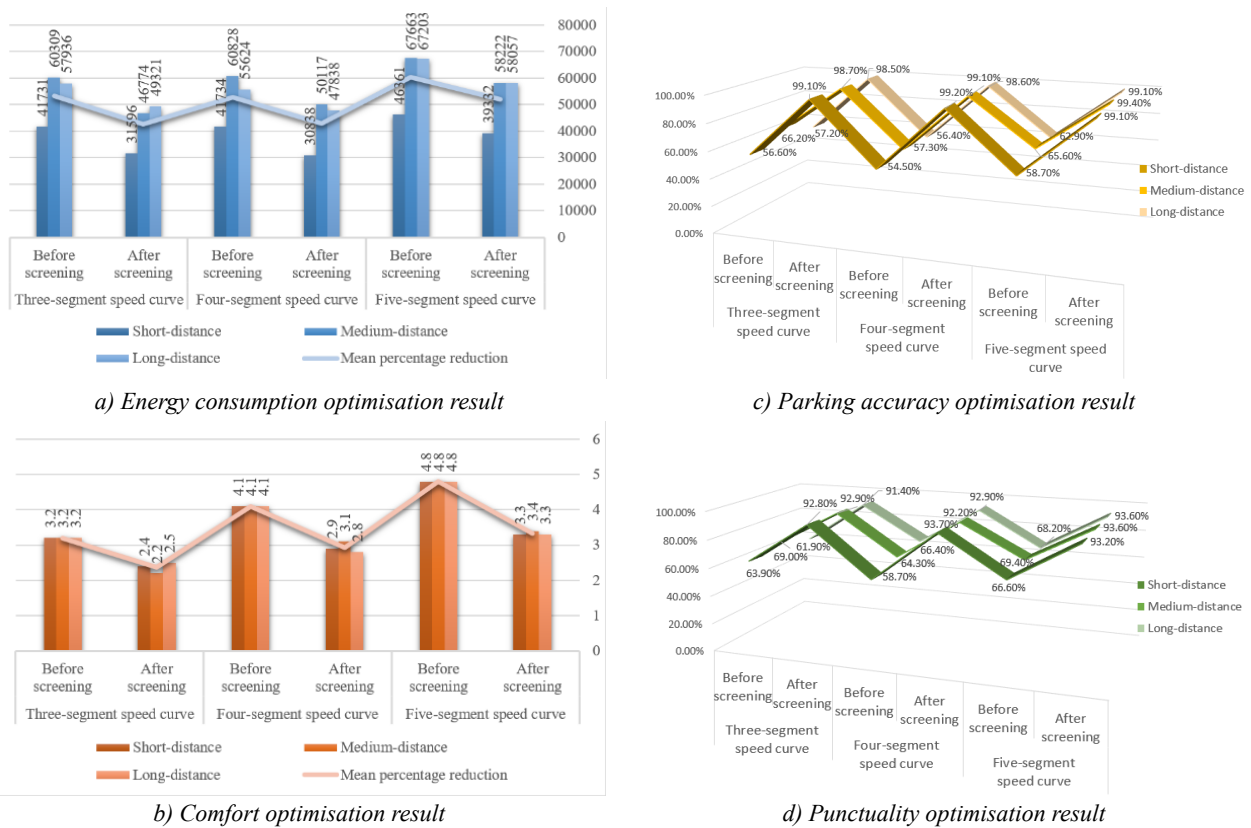*d) Punctuality optimisation result*

Figure 13 – Algorithm optimisation rendering

We can see from the figure that as the number of segments of the train speed driving curve increases, the generated data can still ensure its effectiveness, and the energy consumption, comfort, parking accuracy and punctuality have been greatly improved.

In order to highlight the performance of virtual data generation methods in improving data quantity and diversity, the results were compared with existing methods [29, 30]. The proposed method has achieved significant breakthroughs in speed limitations and road segment diversity, with an average increase of 39% in the number of virtual data. At the same time, we can extract high-performance curves from many virtual driving curves. In addition, the virtual scene and train speed limit required in this method can be adjusted according to actual needs, so it has better flexibility than existing methods.

6. CONCLUSIONS

The research results in this paper have broad implications and potential for future development. Firstly, our algorithm offers an efficient and precise approach for the automatic generation of subway train speed operation curves. This algorithm could be utilised in future subway operations to facilitate the implementation of autonomous driving and intelligent operation of subway trains, thereby enhancing operational safety and stability.

Secondly, a multi-modal selection strategy could be developed in the future to enhance the flexibility and adaptability of subway train operation. By incorporating additional operation modes, such as energy-saving, high-speed, comfort and balanced modes, we can more effectively cater to the demands of train operation under varying circumstances, thereby improving operational efficiency and performance. Furthermore, the integration of real-time data acquisition and analysis technology could allow for dynamic selection of optimal operation modes based on actual conditions, further optimising train operation outcomes.

Additionally, the research results of this paper serve as a significant reference for optimising subway train operations. By analysing and selecting the optimal speed operation curve, we can achieve reductions in train energy consumption, enhance passenger comfort, and improve stop accuracy and punctuality. These optimisation strategies will effectively mitigate traffic congestion and enhance the operational efficiency and service quality of urban rail transit.

In summary, the research results of this paper hold substantial significance not only for metro operation and autonomous driving technology, but also offer valuable insights for the development and optimisation of urban rail transit. Moving forward, we will continue to refine our algorithms and models, broaden the application of multi-modal selection strategies, and persistently enhance the optimisation of train operations, thereby making positive contributions to the sustainable development of modern cities.

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基于Alpha Zero和专家经验的地铁列车大规模人工速度曲线的快速制作和选择算法

摘要：

根据目前城市轨道交通全自动运行的研究现状，列车运行速度曲线通常是通过仿真计算得到的。所获得的速度参考曲线效率低，并且对于不同的情况而言不是通用的。受AlphaZero(一种利用大量人工数据击败人工智能围棋程序AlphaGo的强化学习算法)的启发，本文研究和分析了快速生成大量速度曲线并选择性能优越的速度曲线用于列车运行的方法。首先，我们以Python中强大的第三方库为基础，结合AlphaZero的思想，生成地铁列车行驶的人工速度曲线。其次，我们参考专家经验设置相关参数，以快速生成大量合理的人工速度曲线。再次，通过能耗、运行时间误差和乘客舒适度等相关指标进行分析，选择出一些综合性能较好的速度曲线。最后，通过对不同运行距离和不同限速的多次观测，我们发现，与传统人工驾驶和ATO(自动列车运行)系统的实际数据相比，我们的算法生成和选择的速度曲线更具适用性、多样性，更有利于列车驾驶运行的研究。

关键词：

轨道交通；速度控制；数据生成；曲线优化；城市轨道交通；列车速度。