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DOI:
10.1109/MITS.2019.2926369

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Document Version
Peer reviewed version

Citation for published version (Harvard):
Zhao, N, Tian, Z, Chen, L, Roberts, C & Hillmansen, S 2021, 'Driving strategy optimization and field test on an urban rail transit system', *IEEE Intelligent Transportation Systems Magazine*, vol. 13, no. 3, pp. 34-44.
https://doi.org/10.1109/MITS.2019.2926369

Link to publication on Research at Birmingham portal

Publisher Rights Statement:
N. Zhao, Z. Tian, L. Chen, C. Roberts and S. Hillmansen, "Driving Strategy Optimization and Field Test on an Urban Rail Transit System," in IEEE Intelligent Transportation Systems Magazine, vol. 13, no. 3, pp. 34-44, Fall 2021, doi: 10.1109/MITS.2019.2926369.

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Driving Strategy Optimization and Field Test on an Urban Rail Transit System

Ning Zhao, Zhongbei Tian, Lei Chen, Clive Roberts, Stuart Hillmansen

***Abstract*—The reduction of train energy consumption is becoming more important due to increasing worldwide environmental concerns. This paper presents a driving strategy optimization study and field test results on an urban rail transit system. A genetic algorithm based optimization method has been developed specifically for this purpose. In order to identify and evaluate the practicability and performance of the optimization results, a field test has been carried out on Guangzhou Metro Line No.7. A driver training study has been developed to help drivers to implement the energy saving features of the optimization. The field test results show that by applying the optimal driver strategy the train traction energy consumption can be significantly reduced within the given journey time constant, proving the developed optimization method is practicable and effective.**

***Index Terms*—Optimization; Railway engineering; Rail transportation; Testing; Vehicle driving;**

I. Introduction

THE urban rail transit system has gained popularity as an efficient and convenient method to transport large numbers of passengers, particularly in large metropolitan areas. However, the rail transit system costs a considerable amount in energy consumption in its daily operation. Due to heightened environmental concerns and rising energy costs, rail operators are facing ever greater pressures to save energy, whilst still maintaining service quality and meeting increasing passenger demand. As one of the main foundations of the rail transit system, the driving strategy plays a key role in the overall energy consumption and managing the driving strategy is a popular way to enhance energy efficiency.

A number of researchers have developed various methods and solutions to model the train operation and optimize the train energy consumption from different theoretical points of view. Howlett applied a Pontryagin principle and proposed a method to find the nature of the optimal strategy and determine the precise optimal strategy [1, 2]. Shuai developed a numerical algorithm to calculate the optimal train trajectory with a fixed journey time and formulated a cooperative train control model to adjust the train running behavior to further reduce the energy consumption [3]. Miyatake proposed a new mathematical formulation in order to calculate the optimal energy-saving operation and implemented three different algorithms to solve the problem [4]. However, due to the complexity of the problem, the numerical algorithms require a significantly large computation time in order to obtain a global optimal solution. Therefore, a number of mathematical methods (e.g. genetic algorithms) have been developed to reduce the computation time with a satisfactory suboptimal solution. Genetic algorithms are very mature and have been applied by many researchers in various fields and the results reveal that they converge to the best solution quickly with less number of generations. Bocharnikov proposed a combined searching method including genetic algorithm and fuzzy logic to calculate the most appropriate train coasting strategy [5, 6]. Chang used a novel approach with a genetic algorithm to calculate the best coasting control strategy [7, 8]. Shigen applied a cooperative train control to achieve prescribed performance tracking [9-11]. Shaofeng implemented a liner programming algorithm to a distance-based train trajectory searching model to calculate the optimal train trajectory [12].

However, most of the previous driving strategy optimization studies are based on computer modelling and simulation. Few of the results have been evaluated using practical data obtained from field tests. In practice, trains may perform differently compared with the simulation due to external disturbances such as driver response delay and system delay. Therefore, it is necessary to carry out field tests in order to evaluate the performance of the optimization algorithm and identify the practicability of implementing the optimal driving strategy in the real world.

This paper firstly introduces a modelling of train kinematics, followed by a description of a genetic algorithm based driving strategy optimization method, which aims to calculate the most appropriate train movement mode sequence for the operation. The paper then presents a driver training study to help the drivers to implement the energy saving features of the optimization. Finally, a field test of the optimal driving strategy on Guangzhou Metro Line No.7 has been presented. The performance of the optimal driving strategy has been evaluated and compared using the practical data obtained from the train on-board information measurement system.

II. Vehicle Kinematics Modelling

Lomonossoff's Equations are used for the kinematics modelling as the general vehicle motion equations in this study.

This research is jointly funded by the Guangzhou Science and Technology Plan (project ID 201604030061)

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The equations are based on Newton's second law of motion, and subject to the constraints imposed on the train movement [13-15], shown as follows:

$$F_{total} = F_{tr}(v) - R_{mo}(v) - R_{cu}(s) - F_{grad}(s) \quad (1)$$

$$\begin{cases} F_{total} = M_{ef}\,a = M_{ef}\dfrac{dv}{dt} = M_{ef}\dfrac{d^2 s}{dt^2} \\ R_{mo} = A + B|v| + Cv^2 \\ R_{cu} = w_{cu}M_{ef}\,g = \dfrac{AR}{RAD}M_{ef}\,g \\ F_{grad} = w_{gr}M_{ef}\,g = tan(\alpha)M_{ef}\,g \\ M_{ef} = M_{ls}(1+\lambda_w) + M_p \end{cases} \quad (2)$$

where F_{total}, F_{tr}, F_{grad} are the total force, traction force and braking force respectively at the current train speed v; s is the train position; t is the time; g is the gravitational acceleration; a is the train acceleration; R_{mo} is the resistance to motion at the location s, the constants A, B, C being empirical and related to the track and aero-dynamic resistance known as the Davis equation [16]; R_{cu} is the curve resistance; The constant number AR is set at 600 in this study (England and Chinese standard); RAD is the curve radius; F_{grad} is the force due to the gradient; α is the gradient angle; M_{ef} is the effective mass; M_{ls} is the rolling stock mass; M_p is the passenger mass; λ_w is the rotary allowance.

The initial condition and final conditions are imposed as follows:

$$\begin{cases} v_{initial} = 0, s_{initial} = 0 \\ v_{final} = 0, s_{final} = s_t \end{cases} \quad (3)$$

where s_t is the train position at the terminal station.

In this vehicle kinematics model, the time is a dependent variable. Based on Equation (1), the state equation of the train motion and the boundary condition can be further described as follows:

$$\begin{cases} \dot{s} = v \\ F_{total} = u_f \cdot F_{tr}(v) - u_b \cdot F_{br}(v) - R_{mo}(s) \\ \qquad\quad -R_{cu}(s) - F_{grad}(s) \\ v \le v_{\text{limit}}(s) \\ u_f \in [0,1] \\ u_b \in [0,1] \end{cases} \quad (4)$$

where u_f is the control signals for forward traction effort; F_{br} is the braking force; u_b is the control signals for backward braking effort. $v_{limit}(s)$ is the line speed limit at the current position s; the traction or braking effort will equal to zero when the corresponding control signal is set at 0.

Four typical movement modes form a train motion are considered [17], as shown in Fig. 1.

1) In the motoring mode, the forward traction control signal is set at 1. The traction power is then applied to increase the train speed;
2) In the cruising mode, the traction power is used to overcome the motion resistance, the curve resistance and the force due to the gradient. The train is then running at a constant speed;
3) In the coasting mode, both the forward and the backward traction control signal are set at 0. The train motion is then only affected by the resistances and the force due to the gradient. It is considered that the coasting mode should be used as long as possible in order to achieve an energy-effective operation [18, 19];
4) In the braking mode, the backward braking control signal is set at 1. The train then applies necessary braking effort to reduce the speed.

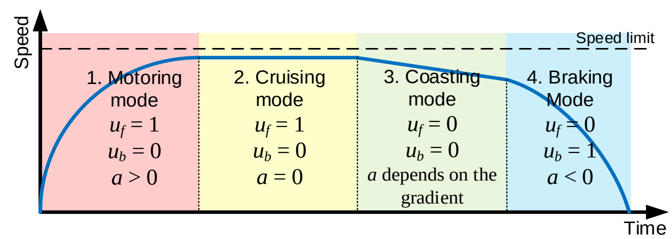

Fig. 1 Four train movement modes.

As shown in Fig. 2, in this study, the route is divided into a number of subsections (grey vertical dash lines) with respect to gradient changes, line speed restriction changes and section length. Applying different movement modes (TM) and maximum cruising speed (CV_{max}) in each section will result in different driving strategies.

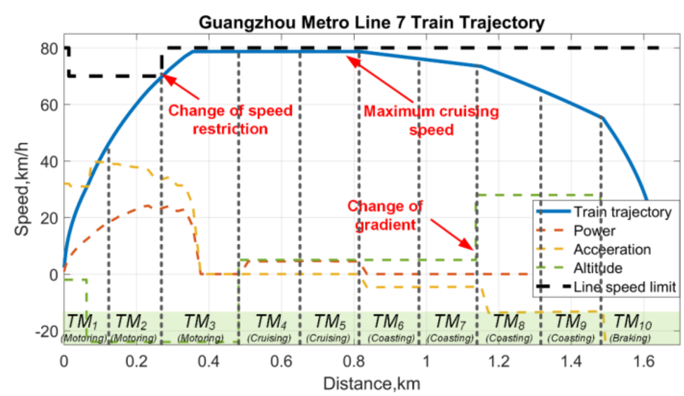

Fig. 2. Driving strategy optimization for an inter-station journey.

III. Driving Strategy Optimization Algorithm

A. *Optimization Objectives*

In this study, the aim of the driving strategy optimization is to search the most appropriate train movement mode sequence (TM) and cruising speed (CV_{max}) to form a train trajectory to minimize train energy consumption (E_t) within a given delay allowance (D_t). f represents for the simulation process to calculate energy consumption (InE) and journey time (InT) for each inter-station operation. The fitness function is shown as follows:

$$\begin{cases} \min \quad M_{fit} = E_{st} \times COS_e\,, \ \ if \ \ D_{st} \le D_{max} \\ \qquad [InT, InE] = f(TM, CV_{max}) \\ \qquad TM = [TM_1, TM_2, \dots, TM_{si}] \end{cases} \quad (5)$$

where M_{fit} is the train traction energy composition that needs to be optimized for a single journey; COS_e is the unit energy cost per kWh; IT is the inter-station journey time; E_{st} and D_{st} are the train energy consumption and delay time respectively; E_{it} is the inter-station energy consumption; s_i is the number of sections; D_{max} is the maximum delay time. In order to minimize the impact of the timetable rescheduling, it is best to set D_{max} at a small number (1 second in this study). E_{sg}, T_{sg} and D_{sg} are the single train energy consumption, journey time and delay time, which can be calculated using the following equations:

$$\begin{cases} T_{st} = \sum_{i=1}^{sn}(InT_i), \quad if\ |InT_i - InT_{shi}| \in [0, InT_r] \\ E_{st} = \sum_{i=1}^{sn}(InE_i) \\ D_{st} = T_{st} - T_{sh} \end{cases} \tag{6}$$

where sn is the number of stations; IT_{sh} is the scheduled inter-station journey time; IT_r is the maximum variation between scheduled journey time and optimal journey time (30 seconds in this study); T_{sh} is the scheduled journey time.

In this optimization, each possible movement mode sequence is assumed as a candidate solution. Depending on the number of sections, the solution domain can be huge. In this study, a genetic algorithm has been applied. It presents a stochastic and iterative process on a generation of individuals.

B. Initialization

Firstly, a number of random individual will be produced, representing the first generation (G). Each individual (S) shows a potential solution to the given problem. The genes in each individual represent the variables of the solution. The number of individuals (*indi_num*) for generation is set at 100 in this study. This stage includes the following steps:

1) Set α =1;
2) If $\alpha \leq$*indi_num*. The algorithm randomly produces an individual S_i=(s_1, s_2,…,s_θ). The individual should meet the constraint requirements shown in Equation (6);
3) Set α=α+1. The algorithm returns to Step 2 and repeats the process until α >*indi_num*.

C. Evaluation

After the initialization stage, each generated solution needs to be evaluated and ranked through a fitness-based process to identify their capability for breeding new individuals. This stage includes the following steps:

1) For each solution, a pair of inter-station journey times (InT) and energy consumption (InE) will be produced using Equation (6). A fitness value (M_{fit}) for each solution will be calculated using Equation (5).
2) The solutions will be ranked by their fitness values using ascending order. The ranked solutions, including TM and VS_{max} will be stored into a matrix $EVAL(S)$.

$$EVAL(S) \leftarrow F(TM, VS_{max}) \tag{7}$$

D. Genetic Operation -Selection-

A genetic operation will be applied to these ranked solutions. Appropriate parent individuals will be chosen to produce new offspring individuals in order to form a new generation (G^{new}). The generic operation includes four phases, namely selection, crossover, mutation and replacement. In the selection phase, the first *top_num* (10 in this study [20]) top ranking individuals in *EVAL(S)* are retained to form the new generation. This phase includes the following steps:

1) Set β=1;
2) If $\beta \leq$*top_num*, then S'_β=$EVAL(S_\beta)$;
3) Set β=β+1. The algorithm returns to Step 2 and repeats the process until β>*top_num*.

E. Genetic Operation -Crossover and Mutation-

The following *cros_num* and *muta_num* ranking individuals will be selected for crossover and mutation respectively. In this study, the numbers are set at 70 and 10 [21, 22]. The crossover phase includes the following steps:

1) Set γ=1;
2) If $\gamma \leq$*cros_num*/2, then two allele genes from two individuals will be selected and exchanged with each other. For instance, assuming two individuals S_η=(s_1, s_m, s_n, s_θ), S_ζ= ($s^\#_1$, $s^\#_m$, $s^\#_n$, $s^\#_\theta$), and genes number m and n are selected, then the new individuals will be generated as S^*_γ =(s_1 , $s^\#_n$, $s^\#_m$, s_θ), $S^*_{\gamma+1}$ =($s^\#_1$, s_n, s_m, $s^\#_\theta$);
3) Set γ=γ+2. The algorithm returns to Step 2 and repeat the process until γ>*cros_num*/2.

The mutation phase includes the following steps:

1) Set δ=1;
2) If $\delta \leq$*muta_num*, then one gene from one individual will be selected and replaced with a random value. For instance, assuming the individual S_o= (s_1, s_p, s_θ) and gene p are selected. Then the new individual will be generated as S''_δ =(s_1, s''_p, s_θ);
3) Set δ=δ+1. The algorithm returns to Step 2 and repeat the process until δ>*muta_num*.

F. Genetic Operation -Replacement-

The replacement will produce *repl_num* (in this study) new individuals to replace the last *repl_num* ranking individuals in $EVAL(S)$. This phase includes the following steps:

1) Set ε=1;
2) If $\varepsilon \leq$*repl_num*, then the algorithm will randomly generate a new solution $S^\wedge\varepsilon$ to replace the existing S_ε;
3) Set ε=ε+1. The algorithm returns to Step 2 and produces another $S^\wedge_\varepsilon$ until ε>*repl_num*.

G. New Generation

After the Genetic Operation, a new generation (G^{new}) has been formed, as shown in Equation (8).

$$\begin{cases} G^{new} = [S'_{\beta}, \dots, S'_{top_{num}}, S^{*}_{\gamma}, \dots, S^{*}_{cros_{num}/2}, S''_{\delta}, \dots, \\ \qquad S''_{muta\_num}, \hat{S}_{\varepsilon}, \dots, \hat{S}_{repl\_num}] \\ pop_{num} = top_{num} + cros_{num}/2 + muta\_num + \\ \qquad repl\_num \end{cases} \tag{8}$$

H. Termination Conditions

The algorithm returns to Stage C (Evaluation) and the generational process is repeated until one of the following terminating conditions are achieved: the number of generations reaches at 100, or the cumulative change in the fitness value is less than 1×10^{-4}, or the manual inspection is done.

I. Algorithm Performance

Fig. 3 demonstrates the procedure by which the fitness function output evolves with the generation using the data shown in Fig. 4 and TABLE 3. It can be found that the searching converges to the optimum in the 40th with the computation time at 542 seconds. The optimal train trajectory is shown in Fig. 7 (e).

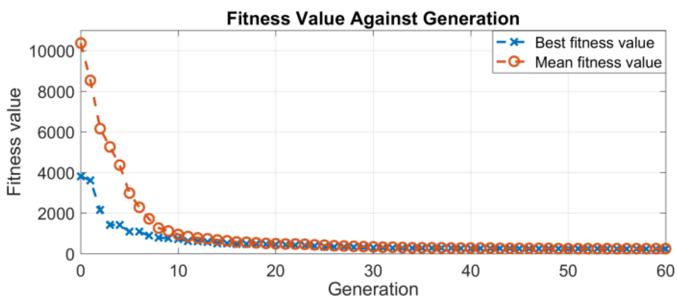

Fig. 3. The mean and minimum outputs at each generation using a GA

Compared with the genetic algorithm, numerical algorithms (e.g. brute force) offer the guarantee of finding the global optimal for a given problem as they enumerate all possible solutions in the solution domain. However, the algorithms become impractical for complex problems as the computation time grows exponentially with the problem size [23, 24]. A brute force algorithm has been developed to solve the same problem for comparison. The results are shown in TABLE 1

TABLE 1
COMPARSION BETWEEN GENETIC ALGORITHM AND BRUTE FORCE

Algorithm	Best fitness value	Computation time, s
Brute force	239.1	320,951
Genetic Algorithm	242.4	542

The genetic algorithm uses iteration methods to guide the search procedure converging. In every generation, each individual acts as a starting point. There are multiple points when the search starts, and multiple directions when the search proceeds. Furthermore, the probability of exploration of the solution domain is very high comparative other algorithms [25]. Therefore, the genetic algorithm is able to achieve much smaller computation time and is able to achieve near-optimal solution more efficiency and accuracy.

IV. Driver Training and Field Test

A. Background

In the previous chapter, an optimal train trajectory has been produced using the genetic algorithm. In order to verify the practicability and performance of the optimization result, a field test was arranged on Guangzhou Metro Line No.7. It is a typical urban rail transit located in the south of Guangzhou City, connecting Guangzhou South Railway Station to Guangzhou University Town with 7 intermediate stations. It is a busy commuter railway line with minimum service interval at 180 seconds and average dwell time at 30 seconds. The scheduled timetable and the line profile are shown in TABLE 2 and Fig. 4. The station speed restriction is 50 km/h.

TABLE 2
SCHEDULED TIMETABLE (EARLY-STAGE)

	Station	Distance between stations, m	Scheduled journey time, seconds
1	Guangzhou South	0	0
2	Shibi	1120	130
3	Xiecun	1908	170
4	Zhongcun	2172	185
5	Hanxichanglong	1642	180
6	Hezhuang	2116	185
7	Guantang	2365	220
8	Nancun	2406	210
9	Daxuecheng South	3778	330
	Total	17507	1610

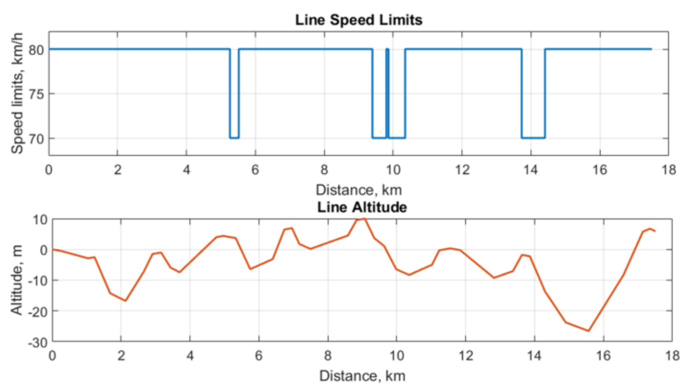

Fig. 4. Guangzhou Metro Line No.7 speed limits and gradient.

TABLE 3 shows the traction characteristics of the vehicle operating on Guangzhou Metro Line No.7. The line is 17 km long and equipped with a 1500 V third-rail power supply network system. The line was put into operation in December 2016 with an early-stage timetable. As a result, the trains are running at a relatively low maximum speed (approximately 65 km/h). After a few month's trial operation, a new timetable will be implemented to speed up the trains and fully function the system. In this case study, the mass of the train is 204 tonnes and the passenger load is considered as 0 tonnes because the train will be empty during the field test.

TABLE 3
TRAIN TRACTION CHARACTERISTICS.

Parameters	Value/Equation
Rolling stock mass, tonnes	204
Passenger mass, tonnes	0 (AW0, for field test)
Train formation	4M2T
Train length, m	118.32
Rotary allowance	0.08
Resistance, N/tonne	$27+0.0042v^2$ (v: km/h)
Power supply	DC 1500V
Maximum traction power, kW	3716.8
Maximum braking power, kW	3911.2
Engine efficiency from electrical power to mechanical power	82%
Maximum operational speed, km/h	80
Maximum Tractive effort, kN	289
Braking effort, kN	352 (constant)
Train control system	Automatic Train Operation (ATO), manually

B. *Driver Training*

The field test was carried out by human drivers because it is impossible to modify the existing ATO system due to company policy and safety concerns. Therefore, a driver training course has been designed to help implement the energy saving features of the optimization to the drivers. The training course presents the concepts of optimization, introduces the benefits of using the optimal driving strategy, and provides training instruction material. All the calculated optimal driving strategies have been converted into the material. The driver is expected to control the train in accordance with the information shown in the document.

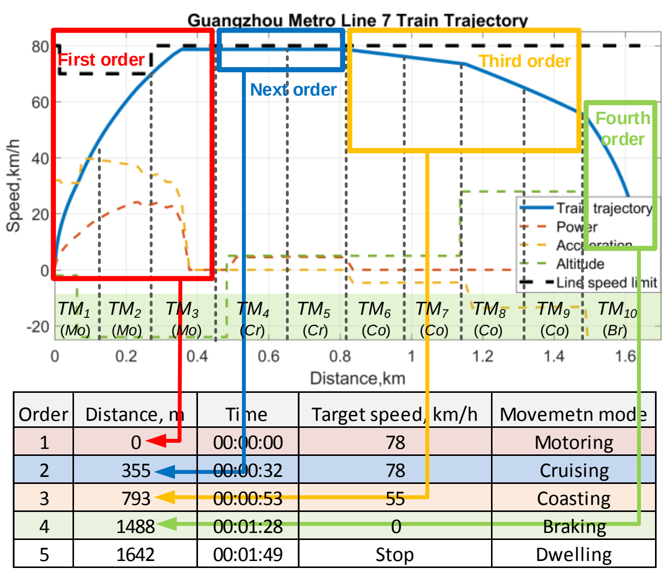

Fig. 5. Converting the optimal driving strategy into a driver training instruction material.

As shown in Fig. 5, the instruction material contains a number of orders in sequence. Each order represents a movement mode for the driver to carry out during the train operation. For instance, in Fig. 5, the train is just departing from the station platform. The first order instructs the driver that the train should accelerate up to a speed of 78 km/h within 32 seconds. Afterwards, the driver is given a second order to control the train cruising at 78 km/h for a further 21 seconds, followed by a coasting order and a braking order until the train stops at the next station.

C. *Field Test*

Four operations were carried out in the field test:

1) The first test represents the existing operation (with the early-stage timetable), where the driver will use his normal strategy to control the train;
2) The second test stands for a fast operation (with a future fast timetable). This driving strategy will be applied after the current trial operation period;
3) In the third and fourth tests, the optimal operation (with the early-stage timetable) will be implemented to evaluate the performance of the optimization results.

The results of the optimal operations will be compared with the other two operations to identify the performance of the driving strategy optimization.

Fig. 6 shows a photo of the field test being carried out on Guangzhou Metro Line No.7 and the designed driver training instruction material. The orders on the material have been divided by the inter-station operations (blue highlighted). Each inter-station operation includes 5 orders, as shown in Fig. 5.

Fig. 6. Designed driver instruction material (left). Field test on Guangzhou Metro Line No.7 (right).

D. *Driving Strategy Comparison*

All the train operation and energy consumption data from the field test are captured by the train on-board information measurement system (TIMS) in real-time. Fig. 7 (a) to Fig. 7 (d) show the field test results of the existing operation, the fast operation, and the two optimal operations respectively. Furthermore, in order to identify the outcome of the driver training, the simulation optimal operation is also presented in Fig. 7 (e), which can be considered as a reference for the optimal operations.

As shown in Fig. 7 (a) and Fig. 7 (b), both the existing operation and the fast operation trains use very little coasting throughout the journey. When the train gets to the top speed, it keeps on cruising until the train reaches the braking points. Compared with the fast operation train, the top speed of the existing operation train is relatively low due to the use of the early-stage timetable, normally between 65 km/h and 70 km/h.

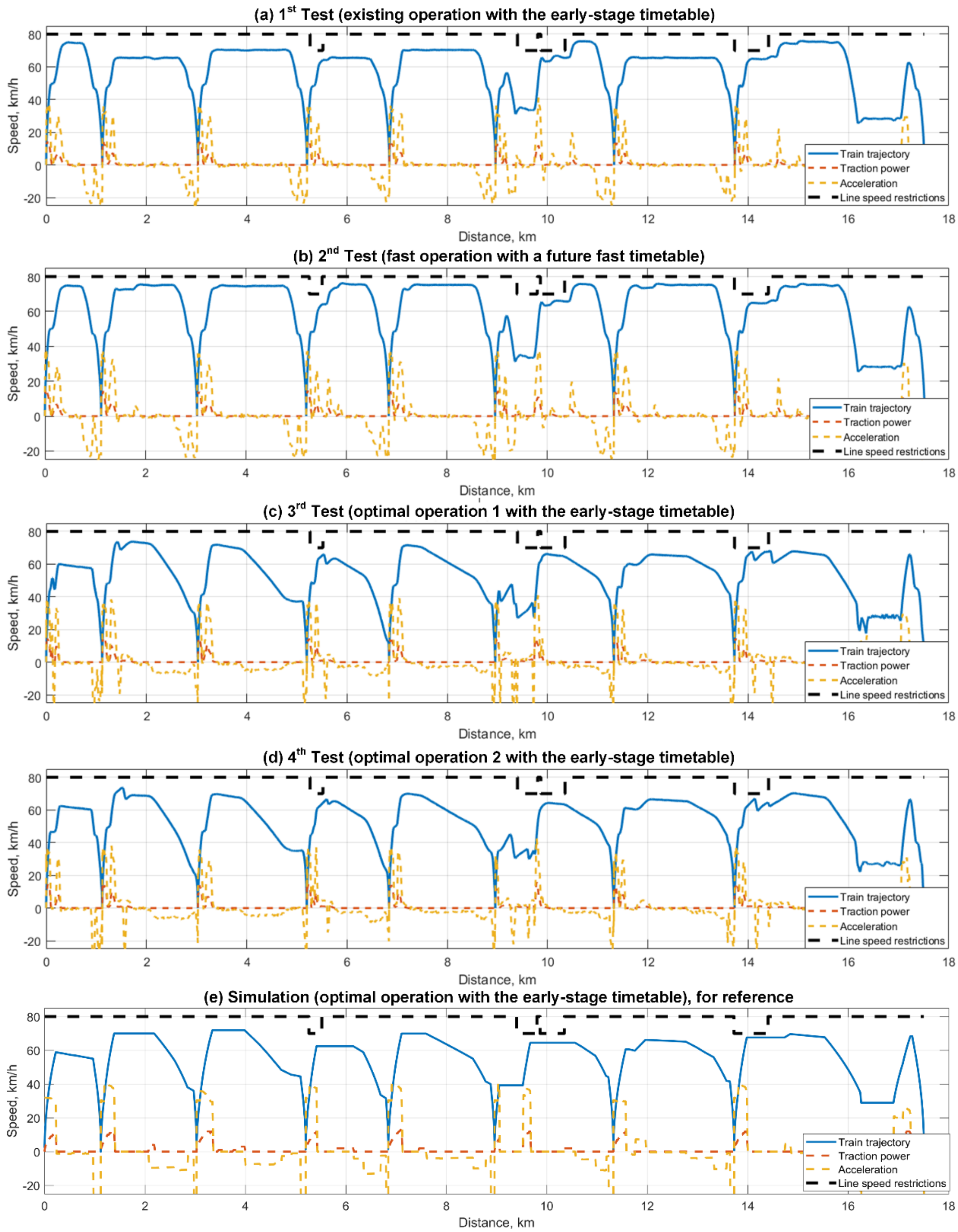

Fig. 7. Driving strategy comparison between different operations (including the simulation optimal operation).

Fig. 7 (c) and Fig. 7 (d) show the results of the two optimal operations. It can be observed that the trains are running more efficiently throughout the journey. After reaching the target speed, the trains perform a long coasting until braking is applied for the station stops. Such a running strategy significantly reduces the energy consumption by up to 21% compared with the existing train operation, while the total journey time difference is less than 1 minute.

Fig. 7 (e) shows the simulation result of the optimal driving strategy. It can be seen that the train trajectory is similar to the actual optimal operations presented in Fig. 7 (c) and Fig. 7 (d) in terms of the maximum running speeds, coasting points and coasting ending speeds. This identifies that the proposed driver training is able to help the drivers improve their driving strategy effectively and thus achieve the design requirements. Furthermore, it also shows that the developed train kinematics model and optimization algorithm are accurate and satisfactory.

E. Energy Consumption Comparison

Fig. **8** shows the accumulated and inter-station energy consumptions for the four actual field test operations discussed in the previous section. It can be found that due to the implementation of the coasting mode, the optimal operations (yellow line and purple line) achieve significantly smaller accumulated energy usage, which is 17% and 21% lower than the normal operation (blue line) respectively. Furthermore, the optimal operation trains cost less inter-station energy than the other two operations throughout the journey.

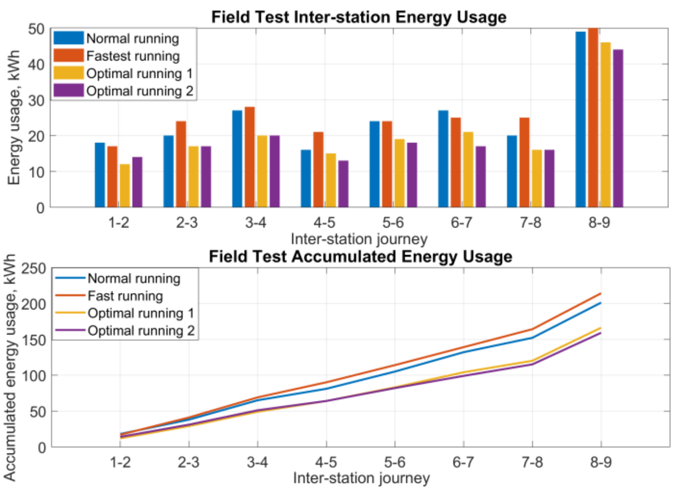

Fig. 8. Energy comparison between different operations.

TABLE 4
RESULTS BETWEEN DIFFERENT OPERATIONS IN THE FIELD TEST

Station	1st test (existing)		2nd test (fast)		3rd test (optimal 1)		4th test (optimal 2)	
	Time (s)	Energy (kWh)	Time (s)	Energy (kWh)	Time (s)	Energy (kWh)	Time (s)	Energy (kWh)
Guangzhou South Station	0	0	0	0	0	0	0	0
Shibi	135	18	119	17	136	12	134	14
Xiecun	184	20	153	24	180	17	182	17
Zhongcun	190	27	172	28	194	20	194	20
Hanxichanglong	186	16	145	21	191	15	186	13
Hezhuang	191	24	163	24	186	19	195	18
Guantang	223	27	208	25	223	21	225	17
Nancun	215	20	174	25	217	16	213	16
Daxuecheng South	300	49	298	50	333	46	322	44
Total	1624	201	1432	214	1660	166 (-17%)	1651	159 (-21%)

TABLE 4 presents a detailed comparison of the journey time and energy usage between the four actual operations. It can be observed that the total journey times of the existing operation train and optimal operation trains are 1624, 1660 and 1651 seconds respectively. Compared with the number in the scheduled timetable (1610 seconds), the differences are smaller than 1 minute, which are in line with the metro operator policy. The fast operation train runs much quicker because it follows a fast timetable. It costs a larger amount of energy compared with the existing operation train, but the journey time is significantly reduced by 12% from 1624 seconds to 1432 seconds.

V. Conclusion

This paper presents a study of driving strategy optimization and the results of a field test on an urban rail transit system. A train kinematics model and a genetic algorithm have been developed specifically for this purpose in order to calculate the optimal driving strategy.

A field test has been carried out in order to evaluate the practicability and performance of the optimization results. Furthermore, a driver training has been delivered to help implement the optimal driving strategy to the drivers. Compared with expensive Driving Advisory Systems, the training course provides a more flexible and balanced cost-benefit method for train operators to gain benefit.

The field test results show that the actual optimal operation trains perform a similar running trajectory to the simulation results. Therefore, it can be proven that the train drivers are able to control the trains in accordance with the optimization results delivered in the driver training course. Furthermore, the comparisons between the optimal operations and the existing operation show that applying the optimal driving strategy is able to significantly reduce the train energy consumption by up to 21% (42 kWh) without affecting the scheduled timetable. There are 304 services each day on Guangzhou Metro Line No.7. Assuming an energy cost of £0.1 per kWh, the annual energy saving could up to 4,660,320 kWh, that is, £466,032 per year. Therefore, it can be concluded that the developed optimal driving strategy is practicable and is able to deliver a significant reduction in energy consumption cost.

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