SmartDrive: Traction Energy Optimization and Applications in Rail Systems

Zhongbei Tian, Ning Zhao, Stuart Hillmansen, Clive Roberts, Trevor Dowens, Colin Kerr

***Abstract*—This paper presents the development of SmartDrive package to achieve the application of energy-efficient driving strategy. The results are from collaboration between Ricardo Rail and the Birmingham Centre for Railway Research and Education (BCRRE). Advanced tram and train trajectory optimization techniques developed by BCRRE as part of the UKTRAM More Energy Efficiency Tram project have now been incorporated in Ricardo's SmartDrive product offering. The train trajectory optimization method, associated driver training and awareness package (SmartDrive) has been developed for use on tram, metro and some heavy rail systems. A simulator was designed that can simulate the movement of railway vehicles and calculate the detailed power system energy consumption with different train trajectories when implemented on a typical AC or DC powered route. The energy evaluation results from the simulator will provide several potential energy-saving solutions for the existing route. An enhanced Brute Force algorithm was developed to achieve the optimization quickly and efficiently. Analysis of the results showed that by implementing an optimal speed trajectory, the energy usage in the network can be significantly reduced. A Driver Practical Training System (DPTS) and the optimized lineside driving control signage, based on the optimized trajectory were developed for testing. This system instructed drivers to maximize coasting in segregated sections of the network and to match optimal speed limits in busier street sections. Field trials and real daily operations in the Edinburgh Tram Line in the UK have shown that energy savings of 10–20% are achievable.**

***Index Terms*—Energy-efficiency, train driving optimization, driver practical training**

NOMENCLATURE

M_e	effective mass of the vehicle [kg]
s	vehicle position along the track [m]
t	time [s]
F	tractive effort [N]
M	vehicle mass [kg]
g	acceleration due to gravity [m/s^2]
α	the angle of the route slope [rad]
R	vehicle resistance [N]
M_t	tare mass of the vehicle [kg]
M_l	payload of the vehicle [kg]
λ_w	rotary allowance
A	Davis equation constant [N]
B	Davis equation linear term constant [N/(m/s)]
C	Davis equation quadratic term constant [N/$(\mathrm{m/s})^2$]
D	experimentally determined constant [Nm]
r	curve radius [m]
E_{tr}	traction energy consumption [kWh]
T	journey time [s]
v_c	cruising speed [km/h]
v_b	braking speed [km/h]
T_d	difference between train running time and scheduled running time [s]
T_{sh}	train scheduled running time [s]
T_{to}	tolerance between train running time and scheduled running time [s]
v_{max}	train maximum speed due to speed limit [km/h]
v_{c_max}	train maximum cruising speed [km/h]
v_{c_min}	train minimum cruising speed [km/h]
v_{b_max}	train maximum braking speed [km/h]
v_{b_min}	train minimum braking speed [km/h]

I. INTRODUCTION

Railway contributes less than 2% of the EU transport sector's total energy consumption even though it has over 8.5% of total traffic in volume [1]. Although the railway system is arguably one of the most efficient forms of land-based transport, how to operate trains more efficiently is still of global importance. To improve sustainability, members of the International Union of Railways and Community of European Railway and Infrastructure Companies agreed to reduce the energy consumption by train operation by 30% and CO_2 emissions by 50% in 2030 [2].

Technologies of railway energy saving have been studied for decades. A comprehensive assessment of energy-saving technologies for rail systems was reviewed in [3, 4]. It is found that railway vehicle operation accounts for 70-90% of the total energy consumption in urban rail systems. Energy-efficient driving, timetable optimization, use of energy storage devices and enhancement of vehicle comfort functions are identified as the most promising energy-saving solutions.

Many heuristic algorithms are developed to design energy-efficient driving styles. A Generic Algorithm (GA) is proposed to optimize the train speed profiles using appropriate coasting control with the consideration of energy consumption, delay punctuation and riding comfort [5]. A GA with fuzzy logic is used to identify the optimal trajectory in

This research is jointly supported by the More Energy Efficient Trams (MEET) project from UKTRAM (444C32), and the Beijing Natural Science Foundation 'The Joint Rail Transit' (No. L171007).

Z. Tian, N. Zhao, S. Hillmansen, C. Roberts are with Department of Electric, Electrical and Systems Engineering, University of Birmingham, Birmingham, U.K. (e-mail: z.tian@bham.ac.uk, n.zhao@bham.ac.uk, s.hillmansen@bham.ac.uk, c.roberts.20@bham.ac.uk).

T. Dowens is with Ricardo Rail, U.K. (trevor.dowens@ricardo.com).

C. Kerr is with Edinburgh Trams, U.K. (colin.kerr@edinburghtrams.com).

[6]. The fitness function consists of energy consumption and running time criteria with various weightings. One heuristic method (GA) and three classical approaches (Golden section search, Fibonacci search and Gradient-based search) are adopted and compared in [7, 8] to identify the necessary coasting points for a metro system. It is found that a heuristic method offers a faster and better solution for multiple coasting points compared with classical searching methods, and multi-coasting points control performs better energy saving in a long interstation section than a single coasting point. Multiple algorithms of searching for optimal single-train trajectory are proposed in [9]. By comparing the simulation results, it is found that Dynamic Programming (DP) performs better than Genetic Algorithms (GA) and Ant Colony Optimization (ACO). The GA performed quite poorly and failed to converge to a good solution in some certain circumstances. The speed profile optimization, which is a complex global optimization problem, is transformed into a simple local optimization problem in [10]. An adjusted algorithm is proposed to search for an optimal coast-brake switching region rather than just one point.

To obtain a fast-response online optimum control system, a mathematical method is developed using a generalized equation of motion [11, 12]. The optimal driving strategies are proved by Pontryagin principle. The maximum principle is used to find a set of optimal controls with the consideration on of track gradients and speed restrictions in [13]. A numerical algorithm is proposed to calculate the optimal speed profiles by distributing the journey time into different sections, which achieves fast optimization [14, 15]. A complete mathematical model of partial train speed trajectory is proposed, and the optimization problem is solved by a mix-integer linear programming algorithm in [16].

With the development of communication, control and computer technologies, Automatic Train Operation (ATO) is playing an increasingly important role in providing safer and more cost-efficient services [17]. An ATO system which tracks the target speed by controlling the traction and braking force is presented in [18]. To avoid the unnecessary switching between traction and braking mode, a method to optimize target speeds based on the ATO control principle is developed in [18]. A multi-objective NSGA-II with fuzzy parameters is applied for the design of ATO speed profiles of a real interstation in Metro de Madrid in [19]. The uncertainties in the traffic operation including the various train load and delays are considered in designing robust and efficient speed profiles in the ATO equipment [20].

Although the theory of energy-efficient driving has been studied for a long time, most previous studies of railway energy-efficient operation are based on simulation and few of the results have been tested and used in practice [21]. Most trains are currently driven by human drivers. The Driver Advisory System (DAS) is used to deliver optimal driving controls to drivers for reducing operating costs, improving energy efficiency and train regulation [22]. DAS is among the latest methods in railway smart operation, which links theoretical optimization techniques with practical operation [23].

This paper proposes a cheap but effective and applicable approach (SmartDrive) to reduce energy consumption of rail systems. This SmartDrive can be considered as one type of DAS to support human drivers to achieve energy-efficient driving controls. The SmartDrive consists of a train speed trajectory optimization method, associated Driver Practical Training System (DPTS) and awareness package, which are suitable for most rail lines based on human sight driving. The paper is structured as follows: Section II introduces a generic railway traction energy modeling and simulation approach. In Section III, the SmartDrive package is illustrated, which includes the energy-efficient driving controls, analysis the energy flow, optimization algorithms, driver training and practical application. In Section IV, a DPTS and driving control signage are designed and tested on Edinburgh Tram Line.

II. Railway Traction Systems Modeling

A. Energy Flow in Electric Rail Systems

Electric rail vehicles collect electricity from the pantograph for traction and auxiliary systems. Traction energy is the electricity used by traction system for moving the train and overcoming friction and gravitational forces. Fig. 1 shows the typical energy flow through the traction system [24]. During the process of transforming traction energy to kinetic energy, some loss is dissipated. Traction loss is the energy dissipated in on-board electronic convertors and motors as heat. Traction energy subtracted by traction loss becomes mechanical energy exported from motors. The parts of mechanical energy used for overcoming friction and gravitational forces are defined as motion loss and potential loss, respectively. Finally, the train obtains a speed and kinetic energy. If the rail vehicle is implemented with regenerative braking systems, part of the kinetic energy can be regenerated as electricity during braking. The regenerative braking energy can be reused by other rail vehicles, but the usage of regenerative braking energy mainly depends on the receptivity of the traction power network and the timetable [24, 25]. The optimization of regenerative braking energy is not considered in the SmartDrive proposed in this paper.

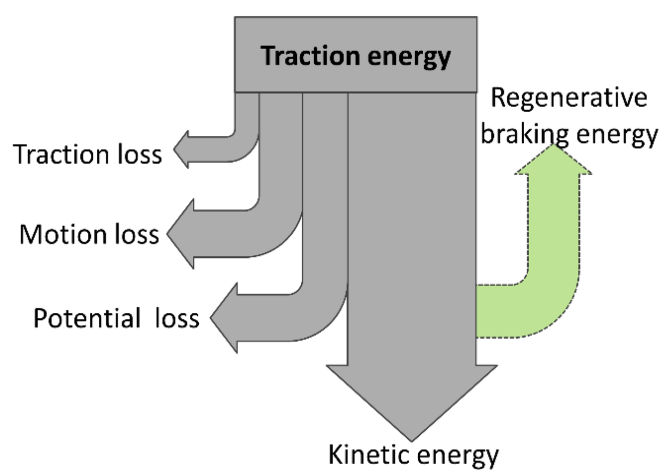


Fig. 1. Typical traction energy flow chart

B. Principles of Train Kinematics

Fig. 2 indicates the forces on a traction vehicle located on an uphill section of track. The tractive effort (F) applied to a vehicle is used for moving the train against the friction forces (R) and gravitational forces ($Mg\sin(\alpha)$) in moving the mass of the train uphill [26]. When the vehicle is braking, a braking effort is applied to the vehicle, rather than the tractive effort. The direction of the braking effort is opposite to the train movement direction.

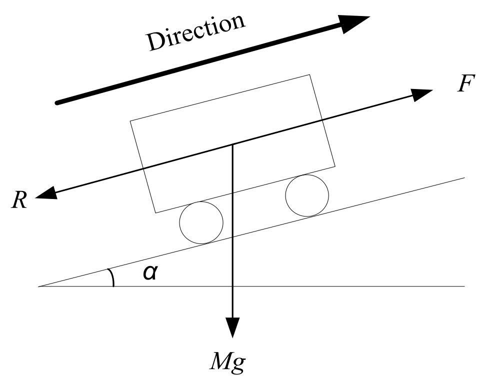


Fig. 2. Forces on a tractive vehicle

The train movement can be determined by standard Newtonian equations of motion. In the longitudinal direction, the motion of the vehicle is governed by the tractive effort, the gradient and the vehicle resistance [27], known as Lomonossoff's equation in (1). F is positive when the train is motoring and becomes negative when the train is braking.

$$M_e \frac{\mathrm{d}^2 s}{\mathrm{d}t^2} = F - Mg\sin(\alpha) - R \tag{1}$$

The vehicle mass is the sum of the tare mass and payload in (2). When a train is accelerated linearly, the rotating parts are also accelerated in a rotational sense. The rotational effect of wheels and motors should be added into the linear train motion by increasing the effective train mass. This rotational inertia effect is called 'rotary allowance' and it is expressed as a fraction of the tare weight of the train (λ_w). The effective mass can be calculated by (3). The value of the rotary allowance varies from 5% to 15%, which is less for a heavy body with a small number of motored axles and more for a light body with all axles motored [28].

$$M = M_t + M_l \tag{2}$$

$$M_e = M_t \times (1 + \lambda_w) + M_l \tag{3}$$

The train moves in the opposite direction to friction and aerodynamic drag. Train resistance consists of rolling resistance and track curvature resistance, as shown in equation (4). The rolling resistance is related to the train mass, shape and aerodynamic characteristics, which is known as Davis Equation. The Davis constant coefficients A, B and C are usually determined by run-down experiments [29]. The curve resistance has a limited effect when the train is running at a speed less than 200 km/h. In most cases, the curve drag can be assumed to be negligible [30].

$$R = A + B\frac{\mathrm{d}s}{\mathrm{d}t} + C\left(\frac{\mathrm{d}s}{\mathrm{d}t}\right)^2 + \frac{D}{r} \tag{4}$$

C. Train Motion Simulator

Train movement is modelled based on the vehicle characteristic and route data. The vehicle characteristic includes vehicle mass, tractive effort parameters and Davis constants. The route data includes gradient, speed limits and station positions along the route. Fig. 3 describes the structure of the motion simulator. The driving strategies are treated as dynamic inputs to the train motion simulator, which typically includes motoring, cruising, coasting and braking. The simulator outputs the train speed profile based on the driving styles and fixed inputs. According to the traction energy results, the driving strategies could be optimized for traction energy savings.

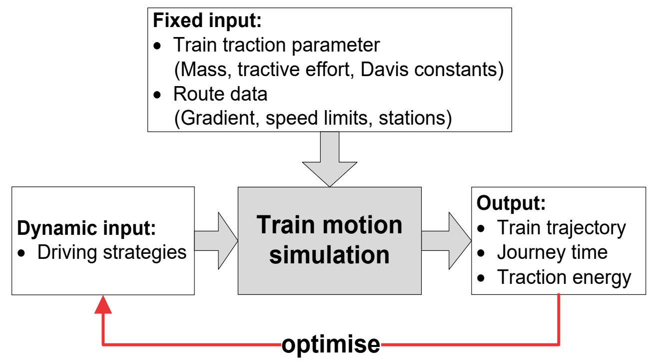


Fig. 3. Structure of train motion simulation

III. SMARTDRIVE FORMULATION

A. SmartDrive Process Map

The process map in Fig. 4 represents the various stages concerned with SmartDrive from initial data gathering and vehicle simulation to post implementation monitoring. Driver Practical Training System (DPTS) is initially developed based on the modeling and optimization of the route. By performance monitoring during the field tests, the data sources are amended. DPTS is improved according to practical measurements. Finally, the benefits to energy saving, driver experience, passengers and rolling stock can be achieved.

B. Energy-efficient Driving Controls

With fixed train and route parameters, the train speed trajectory is produced by driving controls. The coasting control has been proved to be an energy-efficient operation by the Pontryagin maximum principle [11, 12]. In the study of energy-efficient driving controls, it is proved that maximum tractive and braking power should be applied when the train is motoring and braking for the best energy savings [13, 31]. The partial tractive power operation is only used when the train is cruising. As for a long and complex inter-station distance route (with multiple speed limits and gradients), multiple cruising and coasting controls may achieve better energy-efficiency compared with single cruising and coasting controls. However, with the typical characteristics of tram systems, the distance to the next station is generally short. While multi-coasting commands are possible, in practice single cruising and coasting controls have been shown to achieve good energy efficiency and more practical for implementation [7].

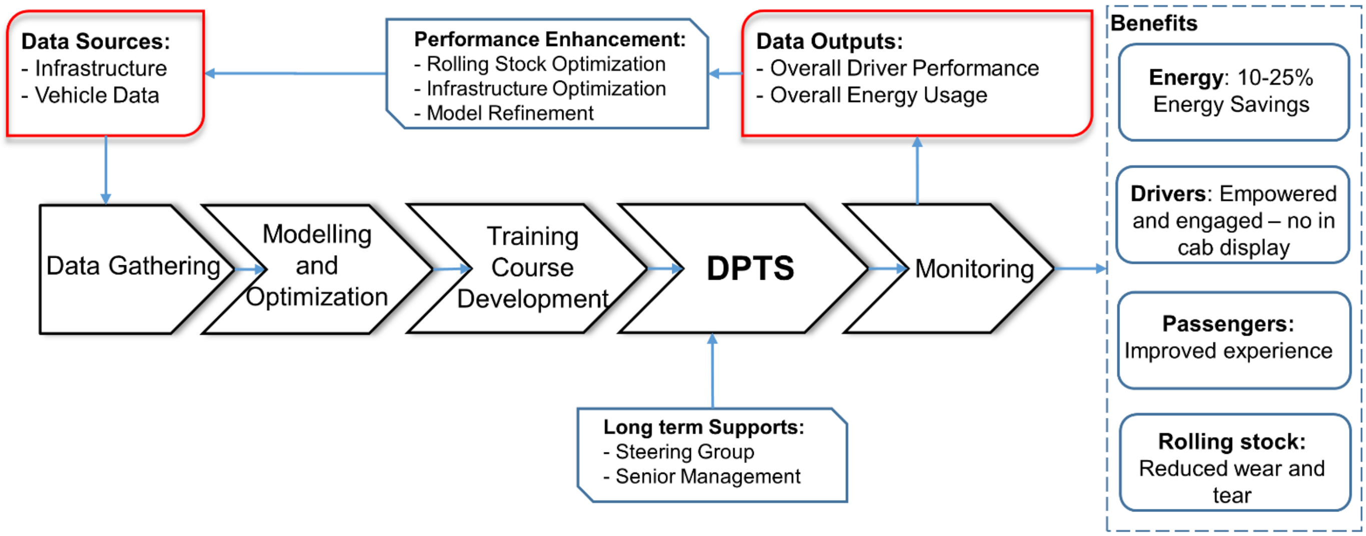


Fig. 4. The process map of SmartDrive

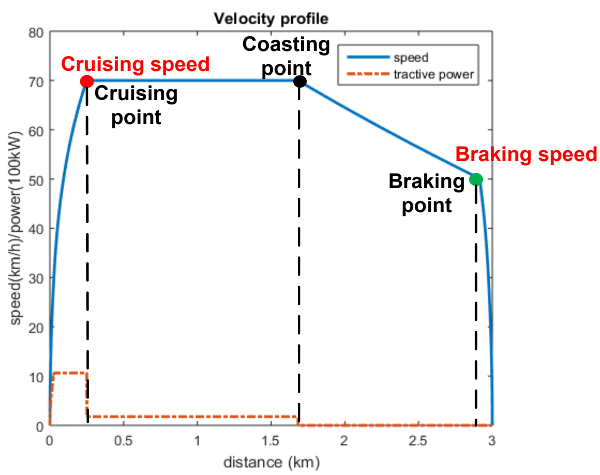


Fig. 5. A sample of speed trajectory with smart driving controls

A sample of a speed trajectory with smart driving controls is shown in Fig. 5. The maximum acceleration is applied in motoring. Cruising mode is achieved at a speed (70 km/h), which is followed by coasting at a preselected point (Coasting point) at 1.8 km. When the speed reduces to the desired braking speed (50 km/h), maximum braking is applied until the next station. The tractive power curve in Fig. 5 shows that when the train is motoring, the tractive power increases to the maximum tractive power. Partial tractive power is applied when the train is cruising. No tractive power is used during coasting and braking.

The speed trajectory can be formulated by the train motion simulator when the cruising speed and braking speed are confirmed, and then the location of cruising, coasting and braking points can be computed. Therefore, the tractive energy consumption can be expressed by a function of cruising speed and braking speed in (5), where f_1 defines the relationship between the two speed factors and the traction energy consumption calculated using the simulator.

$$E_{tr} = f_1(v_c, v_b) \tag{5}$$

The train running time is expressed in (6), where f_2 represents the simulation process to calculate the train running time.

$$T = f_2(v_c, v_b) \tag{6}$$

Train energy consumption can be traded off against running time. In theory, energy consumption is relatively reduced when running time increases. Fig. 6 illustrates this formulation graphically. Each point in Fig. 6 represents the energy consumption against running time resulted by a random driving control. The best driving operations with the lowest energy consumption for each second are shown in red, which constitute the bottom line of the driving results.

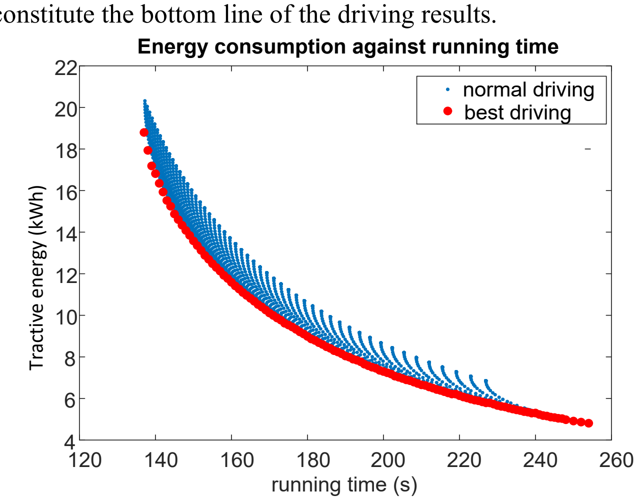


Fig. 6. Results of energy consumption on running time

Traction energy optimization aims to reduce energy consumption within the running time constraints. An example of driving operations with three different driving patterns is shown in Fig. 7. All three operations take the same running time but have different energy consumption costs. From the speed trajectory curves, the first driving cruises at the highest speed (80 km/h) and coasts until it reaches the lowest speed (48 km/h), while the third driving style cruises at the lowest speed (66 km/h) and coasts until it reaches the highest speed (56 km/h). However, the second driving style costs the lowest energy, followed by the first driving style. The tractive energy profile shows the energy consumption during running. As shown in TABLE I, the first driving style with a higher cruising speed leads to higher motion energy loss (5.95 kWh). This is because the high-speed running increases the motion resistance. With the same journey time, a high cruising speed leads to late braking. Thus, the kinetic energy may be reduced, which is 1.91 kWh for the first driving style. As for the third driving style, the motion loss is lower, but the kinetic energy is higher resulting in the highest total tractive energy consumption. Therefore, a balance between cruising speed and braking speed needs to be considered, and the best combination should be found.

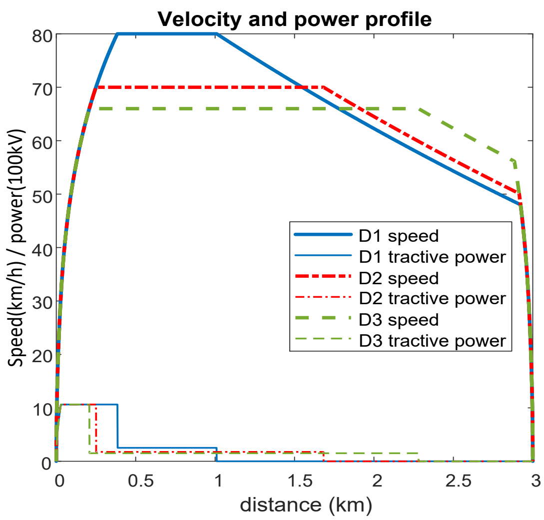


Fig. 7. Speed and power diagram of different driving patterns

TABLE I
PARAMETERS RESULTS OF DIFFERENT DRIVING PATTERNS

Driving pattern	**D1**	**D2**	**D3**
Distance (km)	3	3	3
Journey time (s)	180	180	180
Cruising speed (km/h)	80	70	66
Braking speed (km/h)	48	50	56
Traction energy (kWh)	9.25	8.98	9.46
Traction loss (kWh)	1.39	1.35	1.42
Motion loss (kWh)	5.95	5.55	5.45
Kinetic energy (kWh)	1.91	2.08	2.59

C. Driving Control Optimization

The aim of the train driving optimization is to search the most appropriate driving controls (cruising speed and braking speed) to minimize the train energy consumption, given in (5). The running time is a significant factor on evaluating the performance of energy-efficient driving. The timetable and journey time are regulated by operation companies, based on the passenger demands. The variation of the running time is limited to the regulations. The difference between the actual and scheduled running time is given in (7). For most tram systems, each inter-station running time is allowed within 10 seconds.

$$T_d = |T - T_{sh}| \tag{7}$$

The fitness function with the running time constraints of the optimization is shown in (8).

$$\begin{cases} \min & E_{tr} = f_1(v_c, v_b) \\ s.t. & T_d \le T_{to} \end{cases} \tag{8}$$

A Brute Force (BF) search, also known as exhaustive search, is a straightforward approach to solving problems in the area of computer science by enumerating all the possibilities in the solution domain to find the optimum [32, 33]. As an exact algorithm, BF guarantees to find the optimal solutions if they exist. However, the cost of BF is proportional to the number of candidate solutions, which increases rapidly with the size of the problem. Consequently, it is widely used when the problem size is limited, such as selection sort problems and simple optimization [34]. In order to minimize this weakness, an enhanced BF searching method was developed to address the complexity problem by constraining the solution domain [35, 36].

In order to limit the possibilities in the solution domain, all the cruising and braking speeds are assumed as integers. The enhanced BF algorithm used to solve this optimization is shown in following steps:

- **Step 1: Find the range of the cruising speed within the running time constraints.** The maximum cruising speed is obviously up to the train maximum speed, as shown in (9). The cruising speed range is obtained when coasting mode is not implemented. The running time with minimum cruising speed should fulfil the longest running time constraint. Therefore, v_{c_min} is given by (10).

$$v_{c\_max} = v_{max} \tag{9}$$

$$T_{sh} + T_{to} = f_2(v_{c\_min}) \tag{10}$$

- **Step 2: Find the range of the braking speed within the running time constraints.** The maximum braking speed is obviously up to the train maximum speed, as shown in equation (11). With the same running time, if the cruising speed is higher, the braking speed will become lower, as shown in Fig. 7. Therefore, the minimum braking speed occurs when the cruising speed is the maximum and the running time is the longest. The minimum braking speed can be obtained by (12).

$$v_{b\_max} = v_{max} \tag{11}$$

$$T_{sh} + T_{to} = f_2(v_{c\_max}, v_{b\_min}) \tag{12}$$

- **Step 3: Enumerate all possible solutions in the reduced solution domain.** The traction energy consumption and running time can be calculated by each combination of possible cruising and coasting speed, as in (13).

$$\begin{cases} E_{ij} = f_1(v_{c\_i}, v_{b\_j}) \\ T_{ij} = f_2(v_{c\_i}, v_{b\_j}) \\ v_{c\_min} \le v_{c\_i} \le v_{c\_max} \\ v_{b\_min} \le v_{b\_j} \le v_{b\_max} \end{cases} \tag{13}$$

- **Step 4: Rank the solutions with constraints and find the result.** The solutions will be discarded if the running time constraints are not achieved. Within the constraints, the solution with the lowest energy consumption will be assumed as the result.

D. Driver Practical Training System

The Driver Practical Training System (DPTS) consists of a class training and a field driving training. The class training is used to give drivers a greater understanding of how variations in the control of a rail vehicle affect the amount of energy consumed in a journey allowing, while the field driving training help drivers to put the theory into practice. The University of Birmingham Centre for Rail Research and Education (BCRRE) and Ricardo Rail have started a partnership to use the methodology and simulation software to inform both the development and application of a driver training and education package. This is designed to make drivers more aware of the energy consumption implications of their driving behavior and preferred style, encouraging them to drive in a more energy efficient way by adopting the recommended driving profile. This involves training drivers to drive in a more energy efficient way by raising awareness and changing driving behaviors toward a more efficient style of driving. On a practical basis, drivers will learn to recognize and identify route aspects such as coasting points and cruising speed, whilst maintaining the current timetable and reinforcing safety.

A stand-alone DPTS for the field driving training is developed predominately based on static route data and the timetable using the train motion simulation. An example of DPTS screenshot used in the Edinburgh Tram field test is shown in Fig. 8. The DPTS indicates the current driving mode and the next driving mode. To help the driver to conduct next driving mode accurately, the DPTS also displays the countdown timer, target speed and target distance. The DPTS of most inter-station journeys contains four stages, including acceleration, cruising, coasting and braking. Fig. 8(a) shows that the current driving mode is acceleration and the next driving mode is cruising. The target speed and target distance are 70 km/h and 250 m, respectively. The timer informs drivers to switch to the next driving mode after 60 seconds. Similarly, the following slides can instruct drivers to achieve efficient driving controls. The DPTS is only used for training drivers to understand the energy-efficient controls. The driving practice is conducted on empty loading trams.

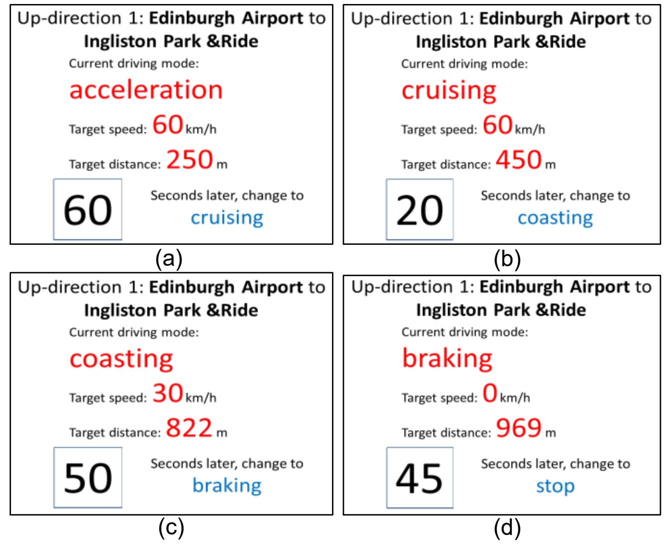


Fig. 8. The DPTS screenshot in Edinburgh Tram field test

E. Coasting Signage

As tram drivers need to pay attention to pedestrians, running vehicles and signals during driving, a DPTS may affect the safety of human driving and is not suitable for daily use. Therefore, a method of using the coasting signage to instruct the driver to achieve energy-efficient driving is proposed. The driver is expected to drive the tram as fast as possible before the coasting signage. Coasting is applied after exceeding the coasting signage. The driver is required to use braking mode as late as possible. There is no acceleration mode after the coasting mode, except for very long routes with various speed limit sections. The optimal coasting location is indicated on the poles along the route, as shown in Fig. 9. The coasting signage provides drivers with advice to achieve energy-efficient operation and sufficient freedom to drive safely according to real-time situation. The application of DPTS and the coasting signage were tested in Edinburgh Tram separately. The results are analyzed in the next section.

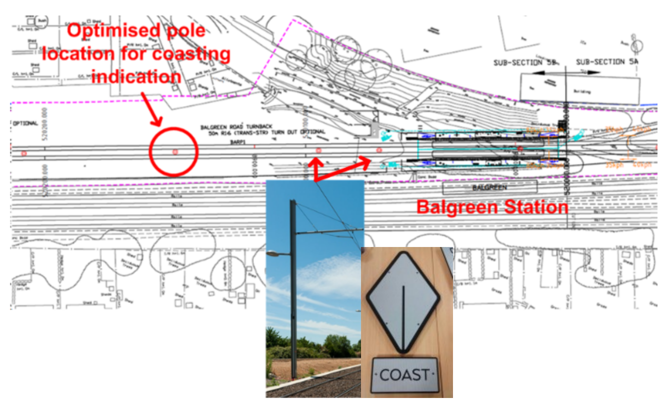


Fig. 9. Optimized pole location for coasting signage

IV. SMARTDRIVE TEST ON EDINBURGH TRAM

A. Vehicle and Line Data

The Edinburgh Tram Line is a suburban tram line connecting Edinburgh Airport to York Place Station (up direction). The line is 13.8 km long with 13 intermediate stations. The line speed limits and height profiles are shown in Fig. 10. The scheduled single journey time is 2620 seconds with 2130 seconds running time and 35 seconds dwell time at each station, as shown in TABLE II. The route from York Place to Murrayfield Stadium is street-running section, where the speed limit is low. The tram runs at an average of around 20 km/h. The route from Murrayfield Stadium to Edinburgh Airport is segregated. The maximum speed of the tram on segregated sections is 70 km/h. However, there are some low speed limit sections along this route due to the sharp curves. The depot is located between Gyle Centre and Gogarburn, the speed limit is lower in this inter-station.

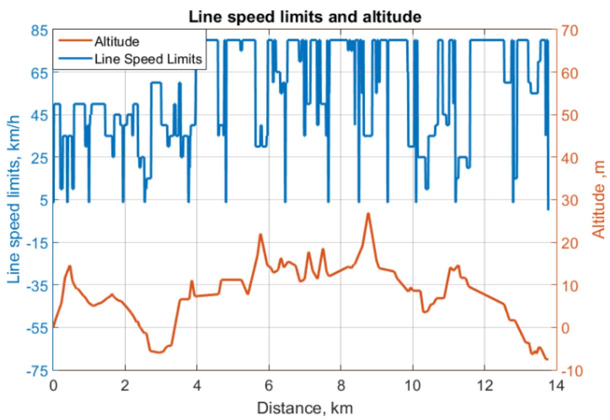


Fig. 10. Edinburgh Tram Line gradient, speed limits and station locations

TABLE II
SCHEDULED TIMETABLE OF EDINBURGH TRAM LINE

No.	Station name	Location [m]	Scheduled journey time, [s]	Dwell time, [s]
1	York Place	0	-	-
2	St Andrew Square	422	140	35
3	Princes Street	1016	150	35
4	West End – Princes Street	1966	180	35
5	Haymarket	2564	120	35
6	Murrayfield Stadium	3789	210	35
7	Balgreen	4827	110	35
8	Saughton	6474	180	35
9	Bankhead	7677	130	35
10	Edinburgh Park Station	8522	90	35
11	Edinburgh Park Central	9315	100	35
12	Gyle Centre	10113	110	35
13	Gogarburn	11222	220	35
14	Ingliston Park & Ride	12819	190	35
15	Edinburgh Airport	13788	200	35
Total		-	2130	490

TABLE III shows the vehicle traction characteristics. The tram is supplied by a DC 750 V overhead line power supply system. The total mass is 287 tones with a standard passenger load (AW2, adding weight with a standard passenger load). The tram is controlled by a human driving system. The maximum service speed and average operation speed are 70 km/h and 35 km/h respectively.

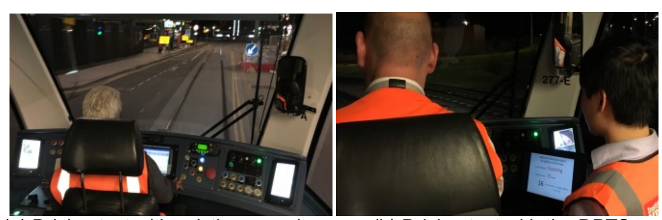
TABLE III
PARAMETERS OF MOTOR EXPERIMENT PLATFORM

Parameters	Value/Equation
Overall tram mass	56.85 ton
Tram length	42.85 m
Rotary allowance	0.07
Resistance	$1.0848+0.007819v+0.0006205v^2$ [N/ton] (v: km/h)
Maximum traction power	904 kW
Maximum operation speed	70 km/h
Maximum tractive effort	105.34 kN
Tram control system	Human driving

B. Driving Test with the DPTS

An energy simulation of Edinburgh Tram Line is developed based on the real parameters. The energy-efficient driving strategy is optimized and a DPTS is produced for drivers on the field test. The field test was carried out at midnight on 14th July 2017 on the Edinburgh tram line. Three members of staff from Edinburgh Tram Company and three researchers from the University of Birmingham participated in the field test. After all service trams had returned to the depot, the test tram departed from the depot and started the test at 23:55.

The participants from the University of Birmingham stayed on the tram with two drivers from Edinburgh Tram Company throughout the test. The tram made three full driving trails. In the first driving, the driver controlled the tram with normal driving experience and timetable. In the second and third runs, the tram driver controlled the tram using a proposed optimal driving strategy from the DPTS. The tram driver is expected to control the tram in accordance with the information given from the DPTS. The photographs of driving without and with the DPTS are shown in Fig. 11.


(a) Driving test with existing experience (b) Driving test with the DPTS
Fig. 11. Photographs on the driving test

The field test results are collected from the vehicle on-board measurement system, including the time, distance, speed and tractive effort. The speed trajectory and traction energy can be calculated based on the instantaneous data. The speed trajectory of three runs in outbound direction is shown in Fig. 12. The speed trajectory of the street-running section is similar. In this part, human drivers have to pay attention to the street signals, pedestrians and vehicles at the same time. Following the instructions from the DPTS is difficult for them. Moreover, due to the low speed limits, the use of coasting is limited. As for the segregated sections, the difference between normal driving and optimal driving is obvious. It can be found that the normal running tram always accelerates at a higher speed, and then performs a gentle braking. However, the optimal running tram usually accelerates at a lower speed and then coasts for a while before a sharp braking. Therefore, compared with the normal running tram, the optimal running tram can complete the journey using the same journey time but with a lower maximum speed.

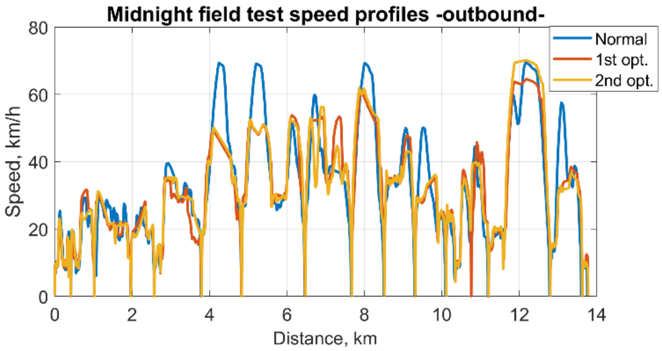


Fig. 12. Tram speed trajectory comparison on outbound direction

Fig. 13 shows the inter-station energy usage comparison between normal running and optimal running. It can be observed that the optimal running tram consumes less energy in most of the inter-station journeys. The energy saving of the first five inter-stations is not significant where the tram is on the street-running section. Most of the inter-station journeys on the segregated section achieve a reduction of energy consumption. However, there are still some inter-station journeys with higher energy consumption. This is due to some unexpected scenarios. For example, the energy consumption of the 2nd optimal running on the 12th inter-station is higher than the normal running. There was a fox on the rail track at that time. The driver decelerated the tram before applying coasting control to save the fox. To arrive at the next station on time, the driver had to re-accelerate the tram to a higher speed than normal. Thus, the energy consumption on this section was increased. The driving disturbed by a fox won't be normal during daytime operation.

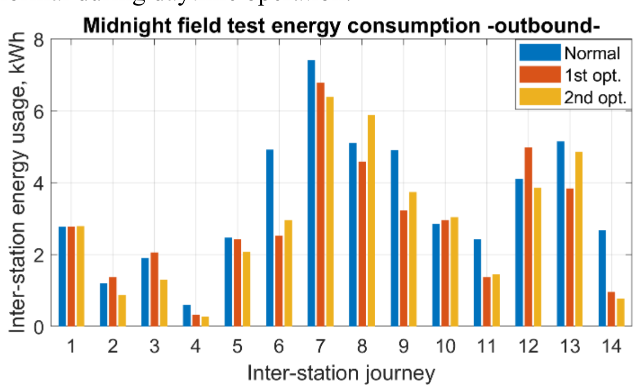


Fig. 13. Energy consumption of each inter-station on outbound direction

The journey time and energy results for the whole cycle are shown in TABLE IV. The optimal driving journey time is shorter than the normal driving. The 1st optimal driving is the first time for the driver to use the DPTS. Compared with the energy consumption of normal driving (103.67 kWh), the energy consumption is reduced by 12.9% to 90.28 kWh. The 2nd optimal driving achieves better performance, where the energy is reduced by 15.8%. The amount of energy saving is related to the coasting time. In the normal driving, the driver used the coasting control for 588 s, while in the optimal driving, the driver used the coasting control for 1334 and 1395 s.

TABLE IV
JOURNEY TIME AND ENERGY CONSUMPTION

Driving style	Running time [s]	Coasting time [s]	Energy [kWh]	Energy saving
Normal	4381	588	103.67	-
1st opt.	4045	1344	90.28	12.9%
2nd opt.	4064	1395	87.25	15.8%

C. Driving Test with Coasting Signage

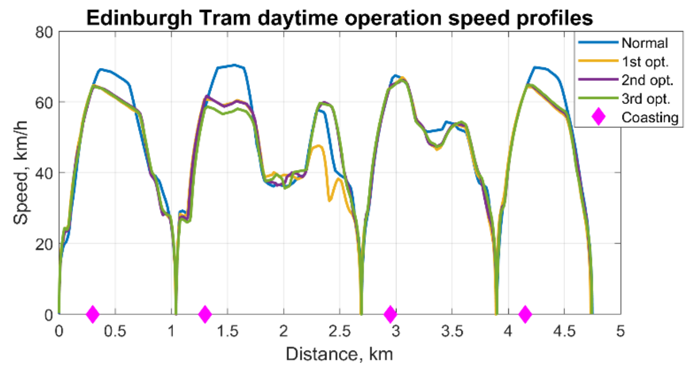


Fig. 14. Tram speed trajectory comparison

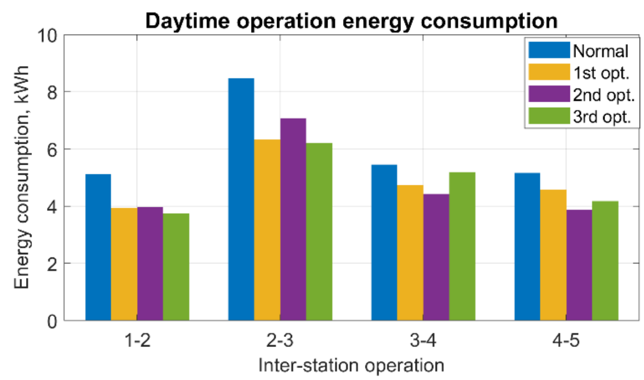


Fig. 15. Energy consumption of each inter-station

TABLE V
JOURNEY TIME AND ENERGY CONSUMPTION

Driving style	Running time [s]	Coasting time [s]	Energy [kWh]	Energy saving
Normal	856	99	47.8	-
1st opt.	864	250	38.4	19.7%
2nd opt.	860	265	38.2	20.1%
3rd opt.	875	259	38.2	20.2%

Another driving training with the DPTS was conducted in Edinburgh Tram. After that, the coasting signage was installed on four inter-stations in the segregated section, which is between Murrayfield Stadium and Edinburgh Park Station as highlighted in TABLE II. Some drivers started to practice energy-efficient driving with the coasting signage during the midnight field test. The latest field test was conducted in the daytime on 20th March 2018. The driving results during the daytime operation are collected and analyzed.

The speed trajectory comparison in the outbound direction is shown in Fig. 14. The normal driving speed trajectory was collected before the coasting signage implemented. The driver normally accelerates to a relatively high speed and then cruised to remain the speed. The coasting signage location is shown in Fig. 14. Driving with the coasting signage, the driver accelerates a relatively low speed and then conducted braking for the first and forth inter-stations in Fig. 14. For the second and third inter-stations, there are two high-speed limit segments which is segregated by a low-speed limit segment in the middle. A coasting signage could be implemented for each high-speed segment. However, the coasting time for the second high-speed segment is very short. To reduce the difficulty of driving manipulation, no coasting signage is implemented after the decreased speed limit in the second and third inter-stations. The driver will follow the speed limits to complete the interstation journey. Because the rest of the journey is short, the driving with one coasting control still shows a good energy-saving performance.

The energy consumption of each inter-station is compared in Fig. 15. Compared with the energy consumption by normal driving, the energy consumption is reduced in each inter-station. However, the energy-saving performance is not the same. The total running time and energy consumption for a cycle by normal and optimal driving is compared in TABLE V. The running time by normal driving is slightly shorter than optimal driving. The coasting time is improved significantly, which is increased from 99 s to around 260 s. Thus, the energy consumption is reduced by around 20%.

V. Conclusion

This paper presents an applicable driving solution for reducing traction energy consumption. The theoretical optimal driving strategies are produced by train simulation using an enhanced Brute Force searching algorithm. To achieve the application of energy-efficient strategies, a DPTS was developed to help drivers practice energy-efficient driving controls in midnight field tests. Compared with the normal driving, driving with the DPTS reduced the traction energy consumption by around 15%, and the total journey time is reduced. To instruct drivers use energy-efficient driving styles, coasting signage was implemented in the segregated sections of Edinburgh Tram. The energy consumption in daytime operation is compared and analyzed. The result indicates that the traction energy of driving with coasting signage is reduced by around 20%. From the field test, it can be concluded that with practice the driver can improve the energy saving performance. This technology is cheap and effective, which can be widely developed and applied in various urban rail lines of sight driving. The Birmingham Centre for Railway Research and Education will collaborate with Ricardo Rail to provide further supports to Edinburgh Tram, including training courses, field tests and daily energy consumption analysis. Based on the success of the traction energy-efficient train driving optimization and its application, the improvement of usage of regenerative braking energy can be further studied. In addition, the field tests of multi-train operation can be conducted in the future.

VI. References

[1] UIC and CER, "Rail Transport and Environment: Facts & Figures," UIC-ETF (Railway Technical Publications) 2015.

[2] UIC and CER, "Moving towards sustainable mobility: A strategy for 2030 and beyond for the european railway sector," UIC Communications Department2012.

[3] A. González-Gil, R. Palacin, P. Batty, and J. P. Powell, "A systems approach to reduce urban rail energy consumption," *Energy Conversion and Management,* vol. 80, no. 0, pp. 509-524, 2014.

[4] X. Yang, X. Li, B. Ning, and T. Tang, "A Survey on Energy-Efficient Train Operation for Urban Rail Transit," *IEEE Transactions on Intelligent Transportation Systems,* vol. 17, no. 1, pp. 2-13, 2016.

[5] C. S. Chang and S. S. Sim, "Optimising train movements through coast control using genetic algorithms," *Electric Power Applications, IEE Proceedings -,* vol. 144, no. 1, pp. 65-73, 1997.

[6] Y. V. Bocharnikov, A. M. Tobias, C. Roberts, S. Hillmansen, and C. J. Goodman, "Optimal driving strategy for traction energy saving on DC suburban railways," *Electric Power Applications, IET,* vol. 1, no. 5, pp. 675-682, 2007.

[7] K. K. Wong and T. K. Ho, "Coast control for mass rapid transit railways with searching methods," *Electric Power Applications, IEE Proceedings -,* vol. 151, no. 3, pp. 365-376, 2004.

[8] K. K. Wong and T. K. Ho, "Coast control of train movement with genetic algorithm," in *Evolutionary Computation, 2003. CEC '03. The 2003 Congress on*, 2003, vol. 2, pp. 1280-1287 Vol.2.

[9] S. Lu, S. Hillmansen, T. K. Ho, and C. Roberts, "Single-Train Trajectory Optimization," *IEEE Transactions on Intelligent Transportation Systems,* vol. 14, no. 2, pp. 743-750, 2013.

[10] J. Yang, L. Jia, S. Lu, Y. Fu, and J. Ge, "Energy-efficient speed profile approximation: An optimal switching region-based approach with adaptive resolution," *Energies,* vol. 9, no. 10, p. 762, 2016.

[11] P. G. Howlett, "The Optimal Control of a Train," (in English), *Annals of Operations Research,* vol. 98, no. 1-4, pp. 65-87, 2000.

[12] P. G. Howlett, P. J. Pudney, and V. Xuan, "Brief paper: Local energy minimization in optimal train control," *Automatica,* vol. 45, no. 11, pp. 2692-2698, 2009.

[13] R. Liu and I. M. Golovitcher, "Energy-efficient operation of rail vehicles," *Transportation Research Part A: Policy and Practice,* vol. 37, no. 10, pp. 917-932, 2003.

[14] S. Su, T. Tang, X. Li, and Z. Gao, "A Subway Train Timetable Optimization Approach Based on Energy-Efficient Operation Strategy," *IEEE Transactions on Intelligent Transportation Systems,* vol. 14, no. 2, pp. 883-893, 2013.

[15] S. Su, T. Tang, and C. Roberts, "A Cooperative Train Control Model for Energy Saving," *IEEE Transactions on Intelligent Transportation Systems,* vol. PP, no. 99, pp. 1-10, 2014.

[16] S. Lu, M. Q. Wang, P. Weston, S. Chen, and J. Yang, "Partial Train Speed Trajectory Optimization Using Mixed-Integer Linear Programming," *IEEE Transactions on Intelligent Transportation Systems,* vol. 17, no. 10, pp. 2911-2920, 2016.

[17] J. Yin, T. Tang, L. Yang, J. Xun, Y. Huang, and Z. Gao, "Research and development of automatic train operation for railway transportation systems: A survey," *Transportation Research Part C: Emerging Technologies,* vol. 85, pp. 548-572, 2017.

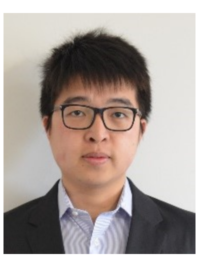
[18] S. Su, T. Tao, L. chen, and B. Liu, "Energy-efficient train control in urban rail transit systems," *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit,* 2014.

[19] W. Carvajal-Carreño, A. P. Cucala, and A. Fernández-Cardador, "Optimal design of energy-efficient ATO CBTC driving for metro lines based on NSGA-II with fuzzy parameters," *Engineering Applications of Artificial Intelligence,* vol. 36, pp. 164-177, 2014.

[20] A. Fernández-Rodríguez, A. Fernández-Cardador, A. P. Cucala, M. Domínguez, and T. Gonsalves, "Design of Robust and Energy-Efficient ATO Speed Profiles of Metropolitan Lines Considering Train Load Variations and Delays," *IEEE Transactions on Intelligent Transportation Systems,* vol. 16, no. 4, pp. 2061-2071, 2015.

[21] N. Zhao, L. Chen, Z. B. Tian, C. Roberts, S. Hillmansen, and J. D. Lv, "Field test of train trajectory optimisation on a metro line," *IET Intelligent Transport Systems,* vol. 11, no. 5, pp. 273-281, Jun 2017.

[22] RSSB, "GB Operational Concept Standalone Driver Advisory System (S-DAS)," *The Rail Safety and Standard Board,* 2012.
[23] Z. Hainan, S. Xubin, C. Lei, G. Shigen, and D. Hairong, "Analysis and design of Driver Advisory System (DAS) for energy-efficient train operation with real-time information," in *2016 IEEE International Conference on Intelligent Rail Transportation (ICIRT)*, 2016, pp. 99-104.
[24] Z. Tian, P. Weston, N. Zhao, S. Hillmansen, C. Roberts, and L. Chen, "System energy optimisation strategies for metros with regeneration," *Transportation Research Part C: Emerging Technologies,* vol. 75, pp. 120-135, 2017.
[25] Z. Tian *et al.*, "Energy evaluation of the power network of a DC railway system with regenerating trains," *IET Electrical Systems in Transportation,* vol. 6, no. 2, pp. 41-49, 2016.
[26] R. J. Hill, "Electric railway traction. I. Electric traction and DC traction motor drives," *Power Engineering Journal,* vol. 8, no. 1, pp. 47-56, 1994.
[27] S. Hillmansen, "Electric railway traction systems and techniques for energy saving," in *IET Professional Development Course on Electric Traction Systems*, 2012, pp. 19-23.
[28] C. J. Goodman, "Overview of electric railway systems and the calculation of train performance," in *Electric Traction Systems, 2010 IET Professional Development Course on*, 2010, pp. 1-24.
[29] B. P. Rochard and F. Schmid, "A review of methods to measure and calculate train resistances," *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit,* vol. 214, no. 4, pp. 185-199, 2000.
[30] M. Chymera and C. J. Goodman, "Overview of electric railway systems and the calculation of train performance," in *Electric Traction Systems (2012), IET Professional Development Course on*, 2012, pp. 1-18.
[31] S. Su, T. Tang, X. Li, and Z. Gao, "A Subway Train Timetable Optimization Approach Based on Energy-Efficient Operation Strategy," *Intelligent Transportation Systems, IEEE Transactions on,* vol. 14, no. 2, pp. 883-893, 2013.
[32] A. Levitin and S. Mukherjee, *Introduction to the design & analysis of algorithms*. Addison-Wesley Reading, 2003.
[33] C. Paar and J. Pelzl, *Understanding cryptography: a textbook for students and practitioners*. Springer Science & Business Media, 2009.
[34] D. E. Knuth, *The art of computer programming: sorting and searching*. Pearson Education, 1998.
[35] H. M. Faheem, "Accelerating motif finding problem using grid computing with enhanced Brute Force," in *2010 The 12th International Conference on Advanced Communication Technology (ICACT)*, 2010, vol. 1, pp. 197-202.
[36] N. Zhao, C. Roberts, and S. Hillmansen, "The application of an enhanced Brute Force Algorithm to minimise energy costs and train delays for differing railway train control systems," *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit,* vol. 228, no. 2, pp. 158-168, 2014.



Zhongbei Tian received the B.Eng in Huazhong University of Science and Technology, Wuhan, China, in 2013. He received the B.Eng. and PhD degree in Electrical and Electronic Engineering from the University of Birmingham, Birmingham, U.K., in 2013 and 2017. He is currently a Research Fellow at University of Birmingham. His research interests include railway traction system and power network modeling, energy systems optimization, advanced power systems design, analysis of electric railways.

Ning Zhao received M.Sc. and Ph.D. degrees in Electronic, Electrical and Computer Engineering from the University of Birmingham in 2009 and 2013 respectively. He is a research fellow at the University of Birmingham's Centre for Railway Research and Education. His main research area includes railway energy saving, railway system modeling, train trajectory optimization and optimization techniques.

Stuart Hillmansen received his Ph.D. degree from Imperial College, London. He is currently a Senior Lecturer in electrical energy systems with the Department of Electronic, Electrical, and Systems Engineering at the University of Birmingham. He is a member of the Birmingham Centre for Railway Research and Education where he leads the Railway Traction Research Group, whose portfolio of activities is supported by the railway industry and government. His research interests include hybrid traction systems for use in railway vehicles and the modeling and measurement of energy consumption for railway systems.

Clive Roberts received his Ph.D. degree from the University of Birmingham. His Ph.D. dissertation was on condition monitoring of railway infrastructure. He is currently a Professor of Railway Systems with the Department of Electronic, Electrical, and Systems Engineering and Director of Research with the Centre for Railway Research and Education at the University of Birmingham. He has developed a portfolio of research in railway systems engineering, system modeling and simulation, network capacity research, railway fault detection and diagnosis, and data collection and decision support applied to railway traction, signaling, mechanical interactions, and capacity.

Trevor Dowens has over 37 year's practical railway operations management experience including previous responsibility for the safe and reliable operation of a major metro system and train operating company. A proven record of ensuring safe rail operations across the full spectrum of rail systems from tramway, light rail and metro to heavy rail. He leads the operational readiness and operations testing for a number of UK and overseas railways. He has practical understanding of issues surrounding light and heavy rail track sharing projects, also a proven leader of teams and projects.

Colin Kerr leads our Engineering team and is responsible for managing all aspects of tram and infrastructure maintenance contracts. Colin has joined Edinburgh Trams from Thales where he worked on several projects on London Underground. His background in electromagnetic compatibility engineering and safety assurance has meant he has played an invaluable part in the Edinburgh Trams project since 2007. Colin leads the assured delivery of the tram system through to operation service and continues to ensure that the tram network remains compatible with adjacent infrastructures.