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OPTIMIZING TRAIN SPEED PROFILES TO IMPROVE REGENERATION EFFICIENCY OF TRANSIT OPERATIONS

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ABSTRACT

With reduced environmental impact becoming an increasingly important benefit of the rail transportation mode, continual improvement in efficiency and reduced energy consumption has become a major concern to rail transit operators. For electrified rail transit operations, regenerative braking is one practical way for saving energy because it enables the kinetic energy of a train to be transmitted via the overhead catenary wire or third rail for use by adjacent trains. Although various regeneration technologies have been introduced, work is still needed to improve energy recovery efficiency. This paper focuses on energy recovery efficiency from an operational point of view. In a mass transit system, there are two operating modes for two consecutive trains: the following train either systematically applies the same speed profile as the leading train, or the following train adjusts its speed to a different speed profile according to the position, speed and regeneration potential of the leading train. With operations synchronized to reuse energy, the latter mode achieves better energy recovery efficiency than the former one. Based on the above understanding, the objective of this paper is to develop the optimal speed profile for a following train in order to minimize pantograph voltage fluctuations and improve energy recovery efficiency. Dynamic programming is applied to this problem in order to optimize the speed profile for a set of given infrastructure and train characteristics. Simulation results with Visual C++ demonstrate that the algorithm can provide an optimal operational strategy with better energy performance while satisfying safety constraints and comfort criteria. Based on this work, energy optimization potentials with different headways are discussed in the case study. This research will facilitate development of on-board train control system logic or system energy analysis that will reduce energy consumption and provide rail transit operators with operational cost savings.

INTRODUCTION

Today, as environmental impact and the cost of energy have become a significant concern for public transportation managers, more and more metropolitan areas in the United States have been investing heavily in constructing or extending urban rail transit systems to mitigate traffic congestion and air pollution caused by excessive use of automobiles [1][2].

Urban rail transit (light rail, subway and tramway) has generally been considered more energy efficient than highway vehicles in terms of unit fuel cost and greenhouse gas emissions. Regenerative braking is one of the technologies applied on board electrified rail equipment to achieve this efficiency and lower operating cost. During the braking process, traction motors on the electric locomotive or multiple-unit railcars are converted into generators, and electricity generated from kinetic energy of the train is available for use by auxiliary components on the train, with any excess transmitted back through the catenary to the power grid. This electrical power can be used by other trains in the same power section for propulsion [4]. However, in DC distribution networks, which are common on urban rail transit systems, regenerative energy cannot always be fully absorbed. When there is insufficient power demand from adjacent trains, the excess energy must be dissipated by the resistors on-board the train where electrical power is converted into heat and wasted into the air [5].

The traditional method of transit system energy calculation has been based on the single-train point of view. The total energy cost is regarded as the sum of the traction energy consumed by a single train with a credit for regenerative energy returned to the catenary. In practice, this requires on-board installation of an energy meter. This is common on systems with multiple operators or open access, such as in many European railroad systems, where it provides a convenient method to record energy use when the train is traveling on different infrastructure operators [6]. However, in an urban rail transit system, the infrastructure is owned by a single operator. In addition, with shorter headways, it is more common to have two or more trains in the same power section with frequent energy exchanges among them via the grid. In this case, the true system energy cost cannot be reflected through train-based energy calculation. As a result, substation-based calculation is introduced for rail transit systems to estimate system power consumption. In this method, regenerative energy is no longer generally considered as rewarding unless it is absorbed by other trains.

With the dual objectives of maintaining schedule requirements and optimizing energy efficiency, this paper examines the prospects for recovering and reusing energy from regenerative brakes under transit system operational constraints. Assuming that two consecutive trains are operated in the same power section, analysis of dynamic and electric performance of the following train is conducted in accordance with the given speed profile of the leading train. Dynamic programming is applied to search for an optimal speed profile for the following train in order to obtain the minimum energy cost at the substation level. To demonstrate an application of the optimization framework, energy optimization potentials of transit systems with different headways will be discussed.

PREVIOUS RESEARCH

In 1977, Milroy used a heuristic application of the Pontryagin principle to minimize energy consumption for a single train. Milroy concluded that the optimal driving strategy consisted of a maximum acceleration-coast-brake control sequence. Subsequent studies confirmed the optimality of this control sequence for short journeys, and showed that a speed-hold phase should be included on longer journeys [7].

In 1988, the predictive fuzzy control method proposed by Mamdani was applied to an Automatic Train Operation (ATO) controller in Japan [8]. After its successful implementation on the Sendai urban subway system, additional research has been conducted to optimize the energy performance of rail transit systems.

The optimal train driving problem has been generally modeled based on motion equations which can be used in continuous control and discrete control. Continuous control can be solved by Pontryagin principle. For the discrete control, Karush–Kuhn–Tucker conditions are widely used to search for optimal switch points to include in the set of train driving commands [9].

With the rapid development of information technology, computers are now capable of solving large-scale optimization problems. As a result, it is now possible to solve more complicated train operational problems such as coordinated control of multiple trains.

In the above problem, headway, dwell time and inter-station running time are three principal factors influencing relative train movement and system power consumption in urban rail transit systems. When the headway becomes shorter, train speed regulation is more likely to be affected by other trains. The gradient method and sequential quadratic programming are proposed for this headway research [10][11]. Some studies deal with dwell time to improve regenerative energy absorption by delaying departure of the following train to synchronize acceleration and braking events. Control methods applied include predictive fuzzy control, search technique and heuristics [12][13][14]. Finally, artificial intelligence (such as genetic algorithms) is proposed to look into the influence of running time on energy [15].

This paper assumes the above factors are fixed for this problem in order to focus on the approach of speed profile optimization to improve system energy consumption and efficiency.

MODEL DESCRIPTION

Assumptions

The model presented in this paper relies on several key assumptions:

- Two trains are running in the same power section.
- Speed and position of the leading train are known.
- Traction energy is provided by power substation at both ends of power section.
- Resistance in the catenary is evenly distributed.
- No wayside energy storage devices are included in this problem. Regenerative energy can only be reused when another train is in traction status.

Electrical Network Model

The electrical network model varies according to the current status of the two trains within the same power section. As shown in **FIGURE 1** and **FIGURE 2**, two trains are running between two substations.

Three-phase AC electricity is generated by a power station for use of the whole transit system. It is then converted into DC electricity at a substation that feeds train operation via catenary. In this model the current conversion at the substation is not considered. Thus, the substation can be described by its external voltage-current characteristics, which is a Thevenin equivalent voltage source. U_{d0} is equivalent voltage source; Rs is equivalent resistor; I_1 and I_3 are currents deriving from substations at either ends of the power section.

Two trains are modeled as ideal current sources that are represented by I_{S1} and I_{S2}. Their actual power during operation varies according to current voltage level. U_{dc1} and U_{dc2} are catenary voltages of the first train and following train respectively. R_1, R_2, R_3 are three catenary equivalent resistors. As the catenary resistance is assumed uniform and constant, their values only depend on the current position of trains within the power section. R_0 is an on-board resistor that is applied during dynamic braking when regenerated electricity cannot be used by other trains.

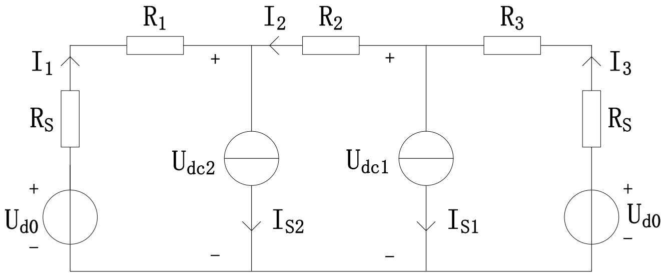

FIGURE 1: ELECTRICAL MODEL WHEN BOTH TRAINS (REPRESENTED BY U_{DC1} AND U_{DC2}) ARE IN TRACTION STATUS

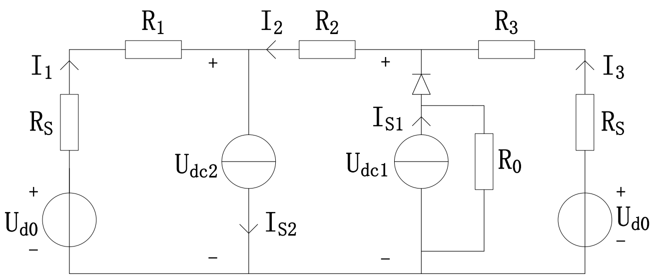

FIGURE 2: ELECTRICAL MODEL WHEN THE LEADING TRAIN (U_{DC1}) IS IN BRAKING STATUS

In **FIGURE 1**, when both trains are in traction status, they take in energy from substations and the current I_1 and I_3 are positive. In this status, the required energy will rise sharply when either train starts to accelerate. This value will drop back when the maximum speed is reached and less power will be required during cruise status. When the leading train approaches the station ahead, it starts to brake. Regenerative braking is applied and its motor is converted in to a generator. Current I_{S1} is transmitted to the overhead wire and is absorbed by the following train while it is in traction status. When the network is not receptive (regenerative energy cannot be fully absorbed), the excess electricity will be dissipated by the resistor R_0 on-board the leading train in dynamic braking. The diode in the leading train is used to restrict the direction of current during dynamic braking. In practice, dynamic braking is not encouraged as it means not only additional weight and costs for on-board resistors, but also a potential risk of overheating and fire. Since the dynamic braking energy is wasted, it is not considered as rewarding as regenerative braking in this problem.

Mathematical Model

This paper aims to find the optimal speed profile for the following train according to the given movement of the leading train in order to minimize the total energy consumption as measured at the substations. In developing the mathematical model, it is important to first establish accurate speed regulation.

Model variables are predefined as follows:

s_1, s_2: the position of leading train and following train;
v_1, v_2: the speed of leading train and following train;
v_{limit}: speed restriction;
U_{dc1}, U_{dc2}: catenary voltage of leading train and following train;
P_1, P_2: electrical power of leading train and following train;
n_1, n_2: coefficients of applied force for leading train and following train;
$F_{max\ 2}$, $B_{max\ 2}$: Maximum tractive effort and braking effort applied on following train;
f_T: maximum tractive effort per unit weight;
f_B: maximum braking effort per unit weight;
r_0: train resistance per unit weight;
r_G: grade resistance per unit weight;
r_C: curve resistance per unit weight;
T: required inter-station running time;
$T_{headway}$: minimum headway between two trains;
S: required inter-station distance;
M: train weight;
J: total energy cost at substations.

Note that in the definition of $F_{max\ 2}$, $B_{max\ 2}$, f_T and f_B, maximum effort means tractive or braking effort when driver's handle is at full power level. These efforts are all influenced by how much power can be provided by the power section (U_{dc}). The values also vary according to different train status (v). The relationship between effort and unit effort is division of train weight M, i.e.: $F_{max\ 2} / M = f_T$; $B_{max\ 2} / M = f_B$.

Based on the network description in the previous section, the objective function can be written as(1):

$$\min J = \int_0^T \left(U_{d0} \cdot I_1 + U_{d0} \cdot I_3\right) dt \qquad (1)$$

Four types of constraints are considered in this model: infrastructure, motion equations, electrical constraints and operational constraints. Each will be described in the following sections.

Infrastructure Considering the line profile (gradient) and alignment (curvature) are the most influential factors for train operation. These two factors are determined by gradient slope and curvature angle respectively. The resulting grade and curvature resistance forces applied on a train will be described in the motion equations. Another infrastructure constraint is the maximum speed restriction generally set by curvature, turnouts or balancing speed on gradients. The speed restriction is related to mileposts along the route, and the speed profile of the following train must obey these limits:

$$0 \le v_2 \le v_{\text{limit}}\left(s_2\right) \qquad (2)$$

Motion Equations The motion equation in this problem is established based on a point-mass model of the train. This is a reasonable assumption given the length of most transit train consists relative to the rate of change of alignment and profile geometry. When the train is in traction status, it is experiencing tractive effort, train resistance, grade resistance and curve resistance; while for train in regenerative braking, regenerative effort will be applied instead of tractive effort. The expression is shown as bellow:

$$\dot{s}_2 = v_2 \tag{3}$$

$$\dot{v}_2 = \begin{cases} n_2 f_T\left(U_{dc2}, v_2\right) - r_0\left(v_2\right) - r_G\left(s_2\right) - r_C\left(s_2\right) \\ n_2 f_B\left(U_{dc2}, v_2\right) - r_0\left(v_2\right) - r_G\left(s_2\right) - r_C\left(s_2\right) \end{cases} \tag{4}$$

Where n_2 satisfies $n_2 \in [-1,1]$; f_T, f_B are obtained based on tractive/braking characteristics of China B-model metro vehicle; r0 yields to Davis Equation; r_G=gsinA with A being the grade of the track and g the gravitational constant; $r_C = cv_2^2/r$ with c being coefficient of friction, r the radius of the track. All the coefficients are defined in the references [16][17].

Electrical Constraints According to Kirchhoff's circuit law, DC circuit power networks are modeled via equality constraints in this optimal control problem as in(5).

$$\begin{bmatrix} U_{dc2} \\ U_{dc1} \\ I_1 \\ I_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & R_{13} & 0 \\ 0 & 1 & 0 & R_{24} \\ R_{31} & R_{32} & 1 & 0 \\ R_{41} & R_{42} & 0 & 1 \end{bmatrix}^{-1} \bullet \begin{bmatrix} U_{d0} \\ U_{d0} \\ I_{S2} \\ I_{S1} \end{bmatrix} \tag{5}$$

As the internal resistance of catenary is assumed uniform and constant, the equivalent resistances R_1, R_2, R_3 in **FIGURE 1** and **FIGURE 2** are defined by the position of the trains within the power segments and are expressed in(6).

$$\begin{aligned} R_1 &= s_2 \cdot \Delta r \\ R_2 &= \left(s_1 - s_2\right) \cdot \Delta r \\ R_3 &= \left(L - s_2\right) \cdot \Delta r \end{aligned} \tag{6}$$

Where the constant Δr is the equivalent resistance of the catenary per unit length (meter).

Train power is another influential factor for energy optimization. Its value will be calculated in real-time according to the force coefficient, actual speed and the catenary voltage. The train power during traction and braking are given in (7) respectively.

$$P_2 = \begin{cases} n_2 \cdot F_{\max 2}\left(v_2, U_{ds2}\right) \cdot v_2 \cdot \mu_t \\ n_2 \cdot B_{\max 2}\left(v_2, U_{ds2}\right) \cdot v_2 / \mu_g \end{cases} \tag{7}$$

Where μ_t and μ_g are the traction and regenerating coefficients respectively.

Operational Constraints Adhering to the operating schedule is essential for urban transit systems. All optimized speed profiles must respect inter-station time and distance requirements. Considering a section between two stations, each train departs from one station and stops at the other. The operational constraints can be described in functions(8).

$$\begin{aligned} v_{1,2}\left(0\right) = 0, \quad & v_{1,2}\left(T\right) = 0 \\ s_{1,2}\left(0\right) = 0, \quad & s_{1,2}\left(T\right) = S \end{aligned} \tag{8}$$

As it is possible to have more than one train running in the same section, minimum headway constraint is also required for safety.

$$t_2\left(s'\right) - t_1\left(s'\right) \geq T_{headway} \quad \forall s' \in \left[0, S\right] \tag{9}$$

Equation (9) ensures for any point in the inter-station section, the following train always arrives $T_{headway}$ seconds later than the leading train.

OPTIMIZATION ALGORITHM

As stated in the previous section, this paper tries to optimize the speed profile of the following train with given running time and distance in order to minimize system power consumption. Dynamic programming is proposed as the solution technique.

Problem Discretization

In order to implement the proposed algorithm, the problem must be discretized prior to further analysis.

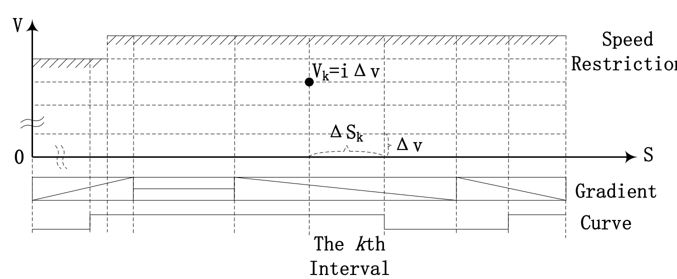

FIGURE 3: PROBLEM DISCRETIZATION

As shown in **FIGURE 3**, the line between two stations is divided into N subsections according to infrastructure parameters. Each subsection length is defined by $\Delta S_k (k = 1, 2 \ldots\ldots N. \sum_{k=1}^{N} \Delta S_k = S)$. For each subsection k, v_k is the train speed at its starting point, and the operating time over this segment is Δt_k. Assuming Δv is the unit speed, any possible train speed v_k must be an integer multiple of Δv within [0, v_{limit_k}], i.e. 0, Δv, $2\Delta v$,...,v_{limit_k}, Where, v_{limit_k} is the speed restriction at the *k*th subsection. In order to have a more precise calculation, the length of subsections could be decreased.

Considering the speed profile optimization as a multi-stage decision process, the length of the line is the resource that can be allocated into several subsections. The possible state at the beginning of each subsection corresponds to the train speed at this position. Starting from any speed at this starting point of a given subsection, a decision (force coefficient) must be made so that the train can reach the end of current section by acceleration or deceleration. This decision only depends on the initial state of the leading train at the beginning of each subsection, and is independent of their previous running states. According to the above analysis, the conditions of dynamic programming are satisfied.

Recursive Function

To simplify the solution process, the time constraint is integrated into the objective function. In this case, the dual objectives are to minimize system energy use as well as time deviation from the specified running time. By problem discretization, the objective function(1) can be rewritten as:

$$\min J = \sum_{k=1}^{N}\left(U_{d0}\cdot I_{s1}+U_{d0}\cdot I_{s3}\right)\cdot\Delta t+\lambda\left(t_{total}-T\right) \quad (10)$$

As *J* is total cost of *N* sections, for each section of the line, let g_k be the energy-time cost in the *k*th subsection:

$$g_k\left(\Delta S_k, n_2\right)=\left(U_{d0}\cdot I_{s1}+U_{d0}\cdot I_{s3}\right)+\lambda\Delta t_k \quad (11)$$

According to *Bellman Function* [18], the recursive function of energy-time cost is described as follows:

$$J_k\left(S_k\right)=\begin{cases}\min\left\{g_k(\Delta S_k,n_2)+J_{k+1}\left(S_{k+1}\right)\right\} & \\ & \left(k=1,2,\ldots,N-1\right)\\ 0 & \left(k=N\right)\end{cases} \quad (12)$$

Where J_k is minimum cumulative energy-time cost to move a train from the *k*th subsection to destination (i.e. the *N*th section, $N>k$); decision variable is the force coefficient, which indicates the magnitude of tractive effort or braking force; the initial value of energy-time cost is 0.

Establishment of Recursive Calculation Table

When using the recursive function to calculate energy-time cost from the *N*th section back towards the departure section, speed continuity from v_k to v_{k+1} must be verified. Speed continuity is confirmed on the condition that the train could move from its current state to the next state by a force within the range of available braking or traction characteristics.

TABLE 1: RECURSIVE CALCULATION TABLE

	1	…	k	…	$N+1$
0	$\left(J_{10},t_{10},n_{2,10}\right)$	…	$\left(J_{k0},t_{k0},n_{2,k0}\right)$	…	$(0,0,0)$
Δv	$\left(J_{11},t_{11},n_{2,11}\right)$	…	$\left(J_{k1},t_{k1},n_{2,k1}\right)$	…	——
……	……	…	……	…	——
$i\Delta v$	$\left(J_{1i},t_{1i},n_{2,1i}\right)$	…	$\left(J_{ki},t_{ki},n_{2,ki}\right)$	…	——
……	……	…	……	…	——
$I\Delta v$	$\left(J_{1I},t_{1I},n_{2,1I}\right)$	…	$\left(J_{kI},t_{kI},n_{2,kI}\right)$	…	——

Once speed continuity is verified, the corresponding cost can be recorded in the recursive calculation table, shown in TABLE 1 above. This table is used to record minimum energy-time cost of all states at the beginning of each subsection. It also estimates the arrival time at the next station and the tractive effort/braking force that should be applied at this stage. This table provides control instructions for the train operator at any position on the line. The table unit at state of $i\Delta v$ in *k*th subsection is expressed as $\left(J_{ki}, t_{ki}, n_{2,ki}\right)$.

During recursive calculation, to decide the optimal cost at certain status in the kth section, all the possible status in the (k+1)th section are considered. The objective is to find the minimal sum of inter-section cost (g_k) and the cost stored in the corresponding point in the (k+1)th section (J_{k+1}). This recursive calculation is repeated until it reaches the departure point.

ANALYSIS OF SIMULATION RESULTS

The simulation environment is a Visual C++ platform and the Windows XP operating system. To demonstrate the application of dynamic programming in optimization of system energy use, an actual metro line in Xi'an, China has been selected for simulation.

The case study will be implemented into two steps. In the first step, based on real operational parameters, two consecutive trains running at the same speed profile will be regarded as the base case for comparison. Then with the optimization of the following train speed profile, calculation will be carried out on system energy consumption, voltage fluctuation, time and distance performance respectively. The optimization algorithm will be verified through this process. In the second step, scenarios with different headway are simulated to develop the relationship between optimization ratio and headway.

Simulation parameters are shown in **TABLE 2**.

According to the parameters, original and optimal cases are simulated with 60-second headways between two trains. Speed profiles are shown in **FIGURE 7**(b) (Annex). In both cases, the leading train keeps nearly the same speed pattern. In the optimal case, the following train first accelerates until 12m/s, then, as the leading train starts to brake, the following train adjusts its speed according to the regenerative energy available on the electrical network. Maximum tractive effort is applied to obtain full acceleration when the leading train brakes at maximum deceleration. In this manner, regenerative energy will be reused for acceleration and less energy is required from the power station.

TABLE 2 SIMULATION PARAMETERS

Parameters	Value
Number of Trains	2
Minimum headway(s)	60
Inter-station running time(s)	115
Inter-station Distance(m)	1,517
Maximum Speed(m/s)	22

According to the distance and time performance results given in **TABLE 3**, operational constraints are satisfied in the optimal case.

TABLE 3 SIMULATION RESULTS FOR TIME AND DISTANCE

	Given Parameters	Simulation Result	Deviation
Distance(m)	1,517	1,517.28	0.018%
Time(s)	115	114.9	0.087%

By regulating the speed of the following train according to the braking state of the leading train, total energy consumption is reduced. As shown in TABLE 4, the power system can reduce energy consumption by 1.66% through optimization. This ratio is small because in this case, when the following train departs, it is still relatively far from the regenerative braking point. It has to accelerate mostly on non-regenerated power from the substations in order to satisfy running time constraints. The energy benefit is lower as a result. As will be demonstrated later, this ratio will rise as headway is increased.

TABLE 4 SIMULATION RESULT FOR ENERGY CONSUMPTION

	Original Case	Optimal Case	Optimal Ratio
Total Energy Consumption (10^7 J)	15.168	14.916	1.66%

Another benefit of speed coordination is a reduction in voltage fluctuation. This is of benefit to the operator as voltage fluctuations will do harm to power equipment. When a train accelerates, it requires energy from a substation, and the catenary voltage of the train will drop significantly as a result. However, when part of the traction energy required by the train can be fed from another train in regenerative braking, less energy is required from the power station, and the voltage only drops slightly. The voltage performance is illustrated in **FIGURE 4** for comparison.

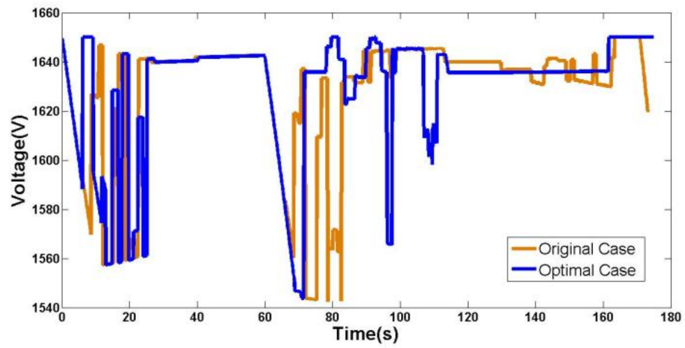

FIGURE 4: VOLTAGE FLUCTUATION COMPARISON BETWEEN THE ORIGINAL BASE CASE AND OPTIMIZED CASE WITH ADJUSTED TRAILING TRAIN SPEED PROFILE

With this model and algorithm, scenarios of different headways can be studied in order to find a relationship between energy consumption and headway. Speed profiles of five scenarios are illustrated in **FIGURE 7a-e** (Annex).

FIGURE 5 shows the energy consumption according to different headways for the original case and the optimized case. When the headway is short under a time constraint, the longer the following train cruises, the more time is lost, and the following train has to accelerate longer to compensate for this time loss, offsetting the benefits from reuse of regenerative energy. The total optimization ratio is lower at shorter headways as shown in **FIGURE 6**.

As the headway increases, the position of the following train during acceleration is closer to the regenerative braking point of the leading train, and it is easier for the following train to postpone its traction state without compromising the time constraint. As more regenerative energy is able to be absorbed, the benefits of optimization increase as illustrated by the vertical distance between the two lines plotted in **FIGURE 5**. However, at some particular headways (90s in this example), the leading train uses regenerative braking at the exact departure time of the following train and the regenerative energy can be easily absorbed by simply applying maximum acceleration. Since further speed profile optimization cannot improve on this scenario facilitated by coincidental timing of maximum acceleration and braking alone, the original and optimized energy consumption results converge at this point.

In this problem, considering the number of non-linear constraints, the application of dynamic programming significantly reduces the difficulty and computing power required to obtain the optimal result. The calculation time of 55.5 seconds in this case is fairly acceptable. However, it will grow exponentially when the problem dimensions become larger. Finally, the dynamic programming algorithm can be applied for real-time control. The online adjustment can still achieve on-time performance, as the time to destination at every point during the operation can be obtained from the Recursive Calculation Table (see **TABLE 1**), but the result may not be energy efficient.

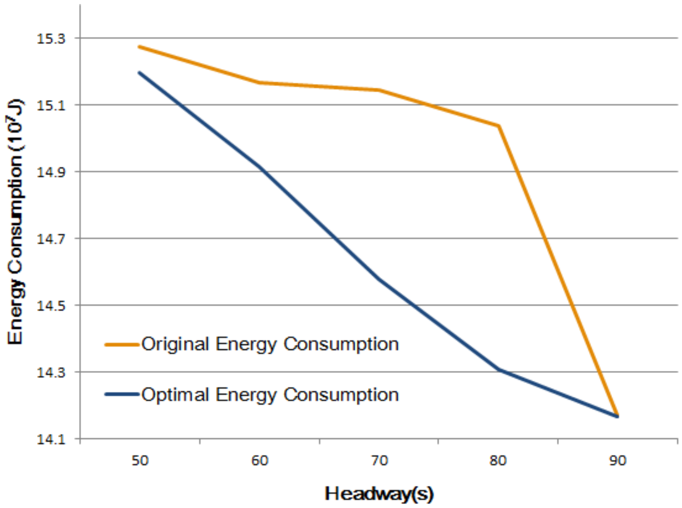

FIGURE 5: ENERGY COMPARISON BETWEEN THE ORIGINAL CASE AND THE CASE WITH AN OPTIMIZED SPEED PROFILE FOR THE TRAILING TRAIN

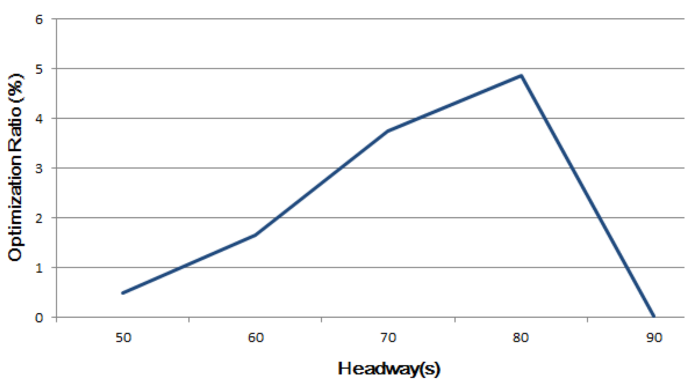

FIGURE 6: OPTIMIZATION RATIO OF ORIGINAL BASE CASE ENERGY CONSUMPTION TO OPTIMIZED ENERGY CONSUMPTION

CONCLUSIONS

In this paper, a model to optimize the energy consumption of two trains operating in the same power section has been established. As the problem is regarded as a multi-stage decision process, dynamic programming can be used to find the optimal speed profile of the following train in order to minimize energy use as measured at the substation. Simulation results show that, respecting the operational constraints, the optimal algorithm can successfully reduce total energy consumption and voltage fluctuation by increasing the use of regenerative braking energy produced by the leading train. Also, the case study shows that different headways correspond to different optimization potentials. The energy reduction potential through optimization could be very low when the headway is either too short or too long; while a point of maximum benefit exists between these extremes where the natural default speed profiles are out-of-synch and little regenerative energy can be reused in the base case.

The algorithm developed in this paper could be applied for optimal train speed profile design and to provide input on the selection of headway for urban rail transit systems.

FUTURE WORK

In busy urban transit system, when the headways become shorter, it is possible to have three or more trains in the same power section. The energy interference and interactions between three trains could potentially be more complicated. It is important to analyze the relationship between energy and operational factors. It would also be more beneficial if speed profiles of all trains in the same section could be optimized simultaneously. Dynamic programming no longer fits this problem. In this case, a new algorithm needs to be developed.

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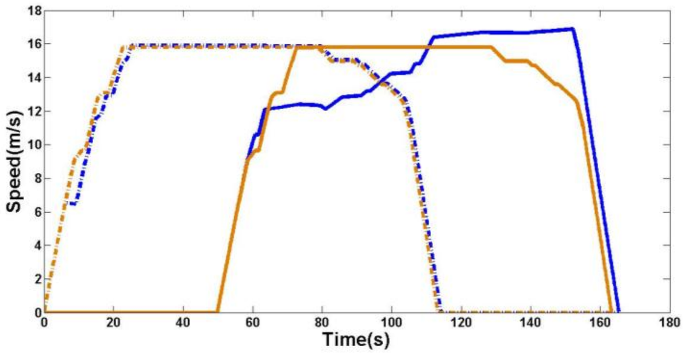
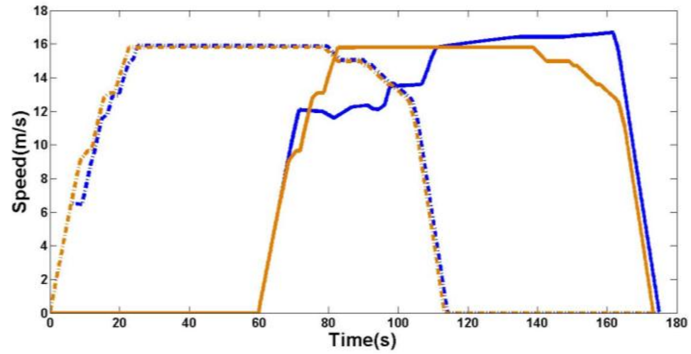
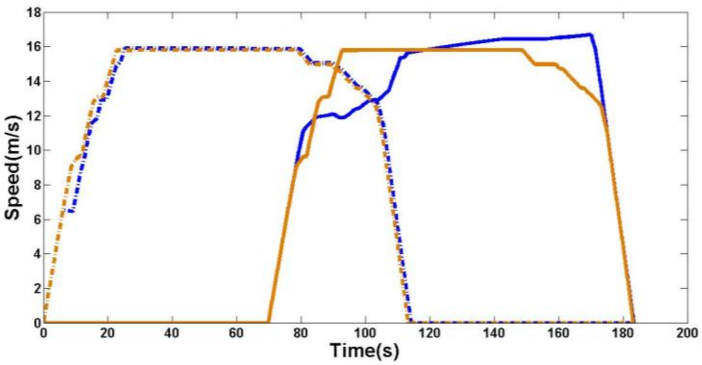
ANNEX



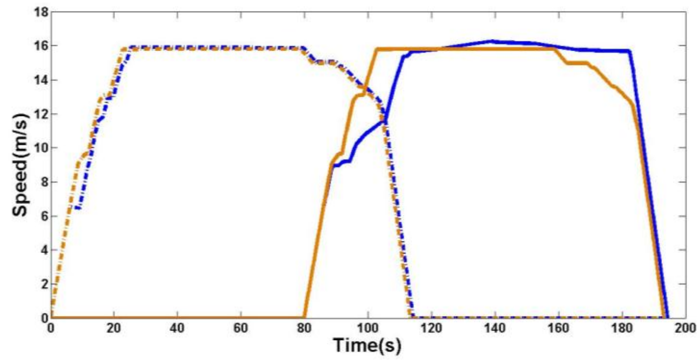
(a) Headway = 50s



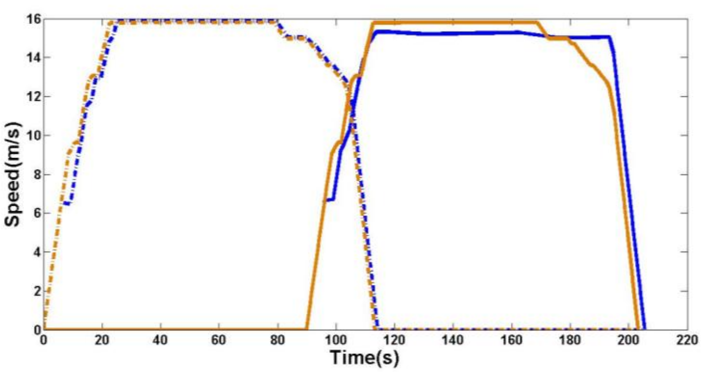
(b) Headway = 60s

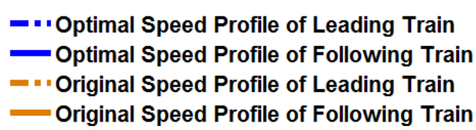


(c) Headway = 70s



(d) Headway = 80s





(e) Headway = 90s

FIGURE 7: TRAIN SPEED PROFILES WITH DIFFERENT HEADWAYS