A Coordinated Train Control Algorithm to Improve Regenerative Energy Receptivity in Metro Transit Systems

TRB 15-1318

Accepted for publication in

Transportation Research Record: Journal of the Transportation Research Board

Submitted on March 15th, 2015

Haichuan Tang¹,
Southwest Jiaotong University, Chengdu, China
West Section, High-tech Zone, Chengdu, China 611756
Tel: +1-217-898-3317; Fax: +1-217-333-1924; Email: hctang@illinois.edu

C. Tyler Dick, P.E.
Rail Transportation and Engineering Center - RailTEC
Department of Civil and Environmental Engineering
University of Illinois at Urbana-Champaign
205 N. Mathews Ave., Urbana, IL 61801
Tel: +1-217-300-2166; Fax: +1-217-333-1924; Email: ctdick@illinois.edu

Xiaoyun Feng, PhD
Southwest Jiaotong University, Chengdu, China
West Section, High-tech Zone, Chengdu, China 611756
Tel: +86-288-760-0737; Fax: +86-288-760-0296; Email: fengxy@home.swjtu.edu.cn

5,342 words text (total) + 8 tables/figures x 250 words (each) = 7,342 words

¹ Corresponding Author
ABSTRACT
Current Automatic Train Operation (ATO) algorithms focus mainly on reducing mechanical energy of motion for a single train within an existing timetable. But the reuse of regenerative energy is another factor contributing to energy consumption and conservation in multi-train networks. To improve regenerative energy receptivity and energy savings in a bi-directional metro transit network, this paper formulates a coordinated train control algorithm based on genetic algorithm techniques. The energy saving potential of different station departure time intervals between two opposing trains (synchronization time) is tested. Simulation on the Visual C++ platform demonstrates that the algorithm can provide an optimal train speed profile with better energy performance while satisfying operational constraints. Different synchronization times have different optimization ratios. This research is another step to facilitate development of an ATO control algorithm that considers overall energy consumption. Increased knowledge of the influence of synchronization time at stations on energy consumption in regenerative multi-train networks will also aid design of more energy efficient timetables.

Keywords: Energy Efficient Driving, Coordinated Train Control, Genetic Algorithms, Regenerative Braking
INTRODUCTION
Regenerative braking is a braking mechanism that decelerates the vehicle by converting its kinetic energy into electric energy. It has been widely applied on electric trains, particularly in metro transit systems. Compared with trains with only pneumatic braking, studies show that the use of regenerative braking on metro trains can provide energy savings of 10% to 45% depending on system characteristics (1). In addition to saving energy, regenerative braking also helps mitigate voltage fluctuation when multiple trains accelerate simultaneously during peak hours.

To maximize the use of regenerative braking energy, synchronization of acceleration and braking among multiple trains is a key issue because regenerative energy can only be reused when there are power requirements in the same power section. For instance, if one train accelerates while the other train brakes in the same power section, this acceleration can take advantage of the regenerative braking energy. The total energy cost at substations is consequently reduced. Two alternatives are currently used to improve system regenerative receptivity: the use of an energy efficient timetable and optimization of Automatic Train Operation (ATO) algorithm.

Many researchers have dealt with timetable optimization. In such a problem, dwell time, inter-station running time and service frequency are principal factors for energy efficient timetable design. Some studies adjust dwell time by delaying departure of trains to synchronize acceleration and braking events. Applied control methods include predictive fuzzy control, search technique and heuristics (2-4). Evolutionary methods (such as genetic algorithms) have also been used to investigate the influence of running time on operating cost (5). Service frequency and dwell time are also regarded as influential parameters to be optimized (6). But the application of energy efficient timetables is limited, as service quality is negatively affected as a result.

Another alternative to improve regenerative synchronization is to adjust train speed profiles using an optimized ATO algorithm within a pre-defined timetable so that service quality can be maintained. ATO systems are used to generate optimal driving commands for train speed regulation. Traditional ATO algorithms are generally designed to reduce the mechanical energy consumption of single train operation by altering its train speed profile while still satisfying operational constraints. Through the latest train control technologies such as Communications-Based Train Control (CBTC) systems, a train could be aware of the projected speed profiles of other trains in the same power section before leaving its station (7). Accordingly, power flow could be predicted in real-time, allowing for the design of coordinated train control algorithms for ATO systems where acceleration and braking are synchronized with other trains in the same power section. Traditional ATO algorithms can be achieved using analytical methods (8-9) and numerical methods (10-12). Based on these methods, recent research proved the optimality of regenerative receptivity through train speed coordination in single direction operation; gradient method and sequential quadratic programming were introduced (13-15). However, for most urban transit systems, the bi-directional application of coordinated control algorithms should also be studied. Additionally, for this large-scale,
non-linear problem, a global optimization method should be applied to ensure the effectiveness of the solution.

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 operating conditions. Assuming that two opposing trains are operated in the same power section, analysis of the dynamic and electric performance of the later-departing train is conducted in accordance with the prescribed speed profile of the earlier-departing train. To obtain the minimum energy cost at the substation level, genetic algorithms are applied to search for the optimal speed profile for the later-departing train. To demonstrate an application of the optimization framework, energy optimization potentials of transit systems with different synchronization time will be compared.

ARCHITECTURE OF CBTC SYSTEM

The coordinated train control model presented in this paper is based on Communication Based Train Control (CBTC) systems.

Conventional train control systems are not a suitable platform for coordinated driving strategy design due to the limitations of track circuit communication. For example, the precision of train location determination largely depends on the length of the track circuit. Also, only a small quantity of operational information (like speed, signal aspect, etc.) can be transmitted to on board systems through track circuits. Those limitations make it difficult for train control systems to estimate electrical parameters in the network and generate the optimal control strategy.

Unlike track circuit based communication, CBTC is a train control system that improves safety, efficiency and traffic management by making use of bi-directional train-to-wayside data communication. It provides more information for train operation and has been widely applied to light rail, heavy rail and commuter rail systems in many countries. A typical CBTC system architecture is shown in FIGURE 1 (16).

![FIGURE 1 Typical CBTC System](image-url)
In the CBTC architecture, the Automatic Train Supervision (ATS) system fills the role of control center, which is dedicated to train and schedule adherence. For trains in the network, ATO system provides speed regulation and other functions. Automatic Train Protection (ATP) prevents trains from collision or over speed. Train control and status information will be exchanged with other subsystems/trains through the data communication network to ensure the proper functionality of CBTC.

The coordinated train control algorithm proposed by this paper is designed for the ATO module. Due to the lack of operational information from neighboring trains, traditional ATO algorithms regulate train speed profile in order to reduce mechanical energy consumption from a single train’s perspective. However, for CBTC-based ATO subsystems, information on neighboring trains, such as location, speed, and travel direction can be acquired through a data exchange network. This information allows the ATO subsystem to estimate and predict energy consumption and voltage fluctuation based on the operational status of trains in the same power section. By choosing the proper acceleration and braking commands to coordinate its speed profile with other trains’, power peaks can be reduced by absorbing regenerative braking energies.

MODEL DESCRIPTION

Assumptions

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

- A CBTC-based ATO system is used for model analysis.
- The electrical network is based on DC power supply from substations and no inductive resistance is considered.
- Two opposing trains (one eastbound and one westbound) are running in the same power section.
- Speed and position of the earlier-departing train (eastbound) are known.
- Traction energy is provided by power substations at both ends of the power section.
- Resistance in the catenary is evenly distributed.
- Substations are non-reversible. No wayside energy storage devices are included in this problem.

Electrical Network Model

The electrical network model varies according to the current location and status of the two trains within the same power section. As shown in FIGURE 2, two trains \( U_{dc1} \) and \( U_{dc2} \) are running between two substations \( U_{d0} \).
FIGURE 2 Electrical Model When the Eastbound Train (I_{s1}) is in Braking Status and Westbound Train (I_{s2}) is in Traction Status

This model follows the common practice in rapid transit systems where three-phase AC electricity from the general power supply is converted into DC electricity at a substation that feeds train operation via catenary (17-18). In this model, the current conversion at the substation is not considered. Thus, the substation can be described by its external voltage-current characteristics as a Thevenin equivalent voltage source $U_{d0}$. In the model $R_s$ is an equivalent resistor and $I_{u1}$ and $I_{u2}$ are currents from substations at either ends of the power section.

Two trains are modeled as ideal current sources, $I_{s1}$ and $I_{s2}$. Their actual power during operation varies according to current and voltage level. $U_{dc1}$ and $U_{dc2}$ are catenary voltages of the eastbound train and westbound train respectively. Since the catenary resistance is assumed to be uniform, the values of the four catenary equivalent resistors $R_1, R_2, R_3, R_4$ 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.

During operation, when both trains are accelerating, they take energy from substations and the currents $I_{u1}$ and $I_{u2}$ are positive. In this state, the required energy will rise sharply when either train starts to accelerate. The required energy will decrease when the maximum speed is reached and less power is required during a cruise state. When the eastbound train approaches the station ahead, it starts to brake. Regenerative braking is applied and its motor is converted into a generator. Current $I_{s1}$ is transmitted to the overhead wire and is absorbed by the neighboring train in traction status. When the network is not receptive (regenerative energy cannot be fully absorbed), the excess electricity is dissipated by the resistor $R_0$ on-board the eastbound train as in dynamic braking. The diode in the electrical network representation of this train is used to restrict the direction of current during dynamic braking. In practice, dynamic braking is not
encouraged as it wastes energy and also presents a potential risk of overheating and fire. Thus dynamic braking is not considered as rewarding as regenerative braking.

Mathematical Model
This paper aims to find the optimal speed profile for the westbound train according to the prescribed movement of the eastbound train in order to minimize the total energy consumption as measured at the substations.

Model variables are defined as follows:

\( s_1, s_2 \) = Travel distance of eastbound train and westbound train;
\( v_1, v_2 \) = Speed of eastbound train and westbound train;
\( v_{\text{lim}}(s) \) = Speed restriction at position \( s \);
\( P_1, P_2 \) = Electrical power of eastbound train and westbound train;
\( n_{2T} \) = Coefficients of applied tractive effort for westbound train;
\( n_{2B} \) = Coefficients of applied braking effort for westbound train;
\( F_{\text{max}2}(U,v) \) = Maximum tractive effort applied on westbound train for voltage of \( U \), at speed \( v \);
\( B_{\text{max}2}(U,v) \) = Maximum braking effort applied on westbound train for voltage of \( U \), at speed \( v \);
\( R_{\text{adj}}(v) \) = Train resistance;
\( R_G(s) \) = Gradient resistance;
\( R_C(s) \) = Curvature resistance;
\( \Delta r \) = The equivalent resistance of the catenary per unit length;
\( \mu_T \) = Efficiency of driver system in tractive state;
\( \mu_B \) = Efficiency of driver system in braking state;
\( S \) = Required inter-station distance;
\( T \) = Required inter-station running time;
\( \Delta T_{\text{depart}} \) = Synchronization time between two train departures from opposite stations;
\( M \) = Train weight;
\( J \) = Total energy cost at substations.

Note: In the definition of \( F_{\text{max}2} \), \( B_{\text{max}2} \), maximum effort means tractive or braking effort when driver’s handle is at full level. These values are influenced by how much power can be provided by the power section (\( U_{dc} \)). The values also vary with to train speed (\( v \)).

Based on the network description in the previous section, the total energy cost for the power section at the substations can be written as:

\[
\min J = \int_0^T \left( U_{d0} \cdot I_{u1} + U_{d0} \cdot I_{u2} \right) dt
\]
Four types of constraints are mainly considered in this model: infrastructure, motion equations, electrical constraints and operational constraints. Each will be described in the following sections.

**Infrastructure**

Line profile (gradient) and alignment (curvature) are very influential on train performance and energy consumption. These two infrastructure factors are measured at each location by gradient slope and curvature angle respectively. The resulting grade and curvature resistance forces experienced by a train are described in the motion equations in the next section.

Another infrastructure constraint is the maximum allowable speed, generally determined by curvature, turnouts or other operational conditions. Speed restrictions are related to mileposts along the route, and the speed of the westbound train at location $s_2$ must obey these limits:

$$0 \leq v_z(s_2) \leq v_{\text{limit}}(s_2) \quad (2)$$

**Motion Equations**

The motion equation for 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 the traction state, it is experiencing tractive effort, train resistance, grade resistance and curve resistance. When in the regenerative braking state, regenerative effort will be applied instead of tractive effort. The expression is shown below:

$$\frac{ds_2}{dt} = v_2 \quad (3)$$

$$M \cdot \dot{v}_2 = \begin{cases} n_{2T} F_{\text{max}2} (U, v_2) - R_{\text{air}}(v_2) - R_G(s_2) - R_C(s_2) \\ n_{2B} B_{\text{max}2} (U, v_2) - R_{\text{air}}(v_2) - R_G(s_2) - R_C(s_2) \end{cases} \quad (4)$$

Where tractive and braking coefficients $n_{2T}$ and $n_{2B}$ satisfy

$$\begin{cases} n_{2T} \in [0,1] & \text{(Traction)} \\ n_{2B} \in [-1,0] & \text{(Braking)} \end{cases} \quad (5)$$

**Electrical Constraints**

According to Kirchhoff’s circuit law, the DC circuit power networks in this optimal control problem are modeled via equality constraints as:
As the internal resistance of catenary is assumed to be uniform, the equivalent resistances $R_1$, $R_2$, $R_3$, $R_4$ in FIGURE 2 are defined by the positions of trains within the power section:

$$
R_1 = s_1 \cdot \Delta r
$$
$$
R_2 = (S - s_1) \cdot \Delta r
$$
$$
R_3 = (S - s_2) \cdot \Delta r
$$
$$
R_4 = s_2 \cdot \Delta r
$$

Train power is calculated in real-time according to the force coefficient, actual train speed and the catenary voltage. The westbound train power demand during traction and braking are given in equation (8) respectively.

$$
P_2 = \begin{cases} 
\frac{n_{2T} \cdot F_{\text{max}2}(U_{dc2}, v_2) \cdot v_2 \cdot \mu_l}{\mu_g} 
\end{cases}
$$

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. These operational constraints can be described by:

$$
\begin{align*}
&v_{1,2}(0) = 0, \quad v_{1,2}(T) = 0 \\
&s_{1,2}(0) = 0, \quad s_{1,2}(T) = S
\end{align*}
$$

As two running directions have been considered in the same section, departure constraint is also required for operation issues.

$$
t_2(0) - t_1(0) = \Delta T_{\text{depart}}
$$
Equation (10) defines synchronization time, which is the station departure time interval for two opposing trains. This constraint ensures that within the inter-station section, the westbound train leaves the station \( \Delta T_{\text{depart}} \) seconds later than the eastbound train.

**APPLICATION OF ENHANCED GENETIC ALGORITHMS**

Genetic algorithms (GA) is a global search algorithm technique based on the principle of natural selection. It mimics the evolution of biological organisms to achieve optimal solutions with a given objective function in an artificial system.

Compared with other optimization techniques, GA has several advantages for large scale optimization problems. Since this is a large scale, nonlinear problem, GA is proposed to solve the coordinated train control problem to ensure the solution’s effectiveness and efficiency.

**Problem Coding**

In this problem, the control variable is the coefficient of the applied force defined as the percentage of maximum traction/braking force applied by the train. It is discretized in 10-percent increments as 0, ±0.1, ±0.2, ……, ±0.9, ±1. Positive “+” represents traction, while negative “-” represents braking. Coasting is represented by “0”. During train operation, the control variable can be changed according to different infrastructure parameters, such as speed restriction, gradient or curvature. Thus, the solution can be modeled as a sequence of control variables at specific control switching points.

An example of a control switching point is illustrated in FIGURE 3. Control switching points \( s_1 \) to \( s_7 \) are based on infrastructure parameters.

![FIGURE 3 Control Switching Points along the Line](image)

A chromosome is a possible sequence of the control variable (for example: \([n_{21}, n_{22}, n_{23}, n_{24}, n_{25}, n_{26}, n_{27}]\)). Each gene \((n_{2i})\) represents the coefficient of the applied force at corresponding position \( s_i \). The \( n_{2i} \) value can be any discretized number from -1 to +1.

As the number of control switching points is pre-determined, the length of chromosome is fixed.

**Fitness Function**
The objective of this algorithm is to minimize system electrical energy consumption with the restriction of travel time and distance. However, GA is formulated to find a maximum value during the search process, as fitness values are always positive. In addition, as a multi-criterion optimization, a proper combination form needs to be determined to satisfy operational constraints. Several modifications have been made to the traditional GA to deal with the above issues.

Therefore, the fitness function has been formulated in equation (11) to deal with the above issues.

\[
f = \frac{1}{\left( \sum (U_{d0} \cdot \Delta I_1 + U_{d0} \cdot \Delta I_3) + w_s \cdot |s_2(T) - S| + w_v \cdot |v_2(T) - 0| \right)}
\]  

(11)

The first term is the minimization objective for network energy consumption. The following two terms ensure the punctuality and stop accuracy for the train arriving at the next station, where \( w_s \) and \( w_v \) are weights for travel distance and speed respectively. These last two terms have higher weights to ensure operational requirements are satisfied first.

The reversed formulation ensures the minimum energy consumption can be achieved when the maximum fitness value is found by the GA.

**Combinational Selection**

Selection is the process used to choose a group of chromosomes from a population for later breeding based on their fitness values. Individuals with higher fitness values are more likely to be chosen to produce the next generation. Two main selection strategies are applied: roulette wheel selection and rank selection.

Roulette wheel selection is a fitness-proportionate selection method and is commonly used due to its efficiency in best individual selection. The probability of a chromosome being selected is proportional to its fitness. However, since this method can quickly eliminate the lower fitted individuals, the solution may inadvertently converge to a local optimum point.

To avoid this possibility, rank selection is used for population selection in the early stages. Instead of using fitness value, rank selection assigns ranking numbers (from 1 to \( N \)) to each chromosome. The worst has 1 and the best has \( N \). The selection probability is then established according to this ranking number. In this way, less-fitted chromosomes have more chances to survive.

The combination of these two methods ensures a variety of species in the early evolution stage and that multiple good solutions will emerge for breeding. As the evolution proceeds, by using roulette wheel selection, better-fitted individuals have greater chances of selection. Therefore, the later evolution process will be accelerated.

**Adaptive Crossover**
Crossover is the process to taking more than one parent chromosome and producing offspring by exchanging part of their gene information. Crossover has two key parameters: crossover probability and crossover operator. The former decides how likely an individual is to be chosen for crossover operation, while the latter decides how parents exchange information.

To ensure the efficiency of evolution, adaptive probability has been applied for crossover probability. According to adaptive probability, higher fitness individuals have lower probability for crossover. This means their good genetic information is preserved for the next generation. On the contrary, less fitted solutions have a higher crossover rate and are more likely to be recombined in an effort to improve them. Adaptive probability $P_c$ is defined as

$$
P_c = \begin{cases} 
P_{c_{\max}} - (f' - f_{\text{avg}}) \cdot (P_{c_{\max}} - P_{c_{\min}}) & f' > f_{\text{avg}} \\
P_{c_{\max}} & f' \leq f_{\text{avg}} 
\end{cases} \quad (12)
$$

In the above equation, $P_{c_{\max}}$ and $P_{c_{\min}}$ are the upper bound and lower bound for crossover probability. $f_{\text{avg}}$ is the average fitness value of the population. $f_{\text{max}}$ is the maximum fitness value of the population. $f'$ is the fitness value of a given chromosome.

For crossover operator, traditional two-point crossover is chosen. Everything between the two points is swapped between the parent chromosomes, rendering two child chromosomes.

**Adaptive Mutation**

Mutation prevents the search from being trapped into a local optimum point by introducing new genes to the selected chromosome. The adaptive method is again used to decide the mutation probability for each chromosome. Similar to the crossover parameter, the actual mutation probability varies according to the fitness of the chromosome.

**Proposed Algorithm Procedure**

The proposed algorithm procedure is shown in FIGURE 4. In this procedure, a reference value will be calculated first. The reference value is the fitness value when both trains use the same single-train-based ATO control algorithm in opposite directions. It is used as the threshold for the two selection methods in the main search loop later on.

After creating an initial population, the search includes two steps: main search loop and secondary search loop. The main search loop tries to find the best-fitted individuals based on a randomly initialized population. Two selection methods are used to ensure population diversity during the early stage and efficient convergence during the late period. Once the main search loop ends, the best solution will be passed to the secondary search loop. A regular genetic algorithm procedure is then followed to search the neighboring area around the best solution. The final optimal solution will be achieved after the two search loops complete.
CASE STUDY

In this section, we analyze the simulation results obtained. Simulations have been carried out based on the platform developed by Visual C++ installed on a desktop computer with 8 GB of RAM and a 3.2 GHz i3 processor, which allows us to verify the effectiveness of genetic algorithms on coordinated train control.

The chosen bi-directional simulation section is a part of the Xi’an metro line in China. The distance between the two selected stations is 4977 feet, and the scheduled travel time is 115 seconds for both directions. Rated voltage for DC substations is 1650V. Internal resistance on the catenary is 43.45 mΩ/mile. The maximum train acceleration is 2.39 mph/s. Two trains are included in this simulation. The westbound train leaves the station 70 seconds later than the eastbound train.

A population of 60 randomly generated chromosomes with length of 83 genes is used in the genetic algorithm as the initial population. Maximum crossover rate is 0.8, while minimum crossover rate is 0.4. Maximum mutation rate is 0.1, while minimum mutation rate is 0.001.

To demonstrate the optimality of the coordinated control algorithm, the base case for the case study uses initial speed profiles developed for the eastbound and westbound trains with a single-train-based ATO algorithm (2). Therefore, their mechanical energy consumptions are already minimized; however, optimization of regenerative energy receptivity is not taken into account.
The case study is implemented in two steps. In the first step, using the above parameters, the optimized case where the westbound train applies the coordinated control algorithm with a synchronization time of 70 seconds is analyzed and compared to the base case. In the second step, scenarios with different synchronization time are developed to study the relationship between synchronization time and optimization ratio.

The results of the first step of the case study are shown in FIGURE 5. The solid blue line is the speed profile of the eastbound train. The dashed blue line is the speed profile of the westbound train in the base case. The dashed orange line is the speed profile of the westbound train in the optimal case. The three speed profiles are plotted in the same time scale and the westbound train departs 70 seconds later than the eastbound train.

![Speed Profile for Eastbound Train](Speed Profile for Eastbound Train)

![Speed Profile for Westbound Train (Base Case)](Speed Profile for Westbound Train (Base Case))

![Speed Profile for Westbound Train (Optimal Case)](Speed Profile for Westbound Train (Optimal Case))

FIGURE 5 Simulation Results of Speed Profiles

In the base case, the two trains are under the control of the single-train-based ATO algorithm. In the optimal case, the eastbound train is operated with the same original commands. The westbound train deviates from the original profile, adjusting its actual tractive and braking efforts according to the energy available on the catenary and in order to make use of the regenerative energy from the eastbound train. After the eastbound train stops, the westbound train mainly applies coasting and braking during the rest of the journey, avoiding additional energy consumption.

<table>
<thead>
<tr>
<th></th>
<th>System Energy (kW•h)</th>
<th>Time (sec)</th>
<th>Distance (feet)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Case</td>
<td>36.69</td>
<td>115.9</td>
<td>4970.76</td>
</tr>
<tr>
<td>Optimized Case</td>
<td>32.03</td>
<td>115.8</td>
<td>4973.03</td>
</tr>
</tbody>
</table>
As shown by the simulation results in TABLE 1, regulating the speed of the westbound train according to the braking state of the eastbound train reduces total system energy consumption at the substation by 12.7%. The time and distance deviations are only 0.69% and 0.08% respectively from the required 115 seconds and 4977 feet. For a daily, 18-hour operation of a metro transit system, assuming 6 minute headway for 8 hours and 12 minute headway for 12 hours, application of the coordinated driving strategy could save 652.4 kW•h for an inter-station section per day. Furthermore, for a metro line with 15 stations, an annual savings of US$400,000 is estimated due to the reduction in train operating cost.

Another benefit of speed coordination is reduced voltage fluctuation. Frequent voltage fluctuation will harm the on-board and substation electrical equipment, impacting system reliability. When a train accelerates and requires energy from a substation, the catenary voltage of this train will drop significantly. However, when part of the train’s required traction energy can be fed from another train in regenerative braking, less energy is required from the power station, and the voltage drop is decreased. The voltage performance of the case study is illustrated in FIGURE 6.

To further investigate the performance of the coordinated train control algorithm, the energy saving levels at different synchronization times from 10 to 100 seconds have been tested.

FIGURE 7(a) shows the energy consumption for both the base case and the optimized case for different synchronization times. FIGURE 7(b) shows the corresponding ratio of optimized to base energy consumption, termed the “energy optimization ratio”. When both trains apply
single-train-based ATO algorithms as in the base case, system energy consumption decreases as the synchronization time increases. Without optimization, energy consumption can be reduced by 18% by increasing synchronization time from 10 seconds to 100 seconds. Through optimization and introducing regenerative energy recovery into the ATO algorithm, further reductions can be achieved for a given synchronization time. The benefit of optimization is relatively small when the synchronization time is near 10 seconds or 100 seconds, while the optimization ratio reaches its peak (12.7%) at 70 seconds.

As shown in FIGURE 5, when the westbound train leaves the station 70 seconds after the departure of the eastbound train, the westbound train will start coasting at 100.1 seconds, waiting for regenerative energy to become available on catenary for further acceleration. The longer the westbound train coasts, the more time is lost. To satisfy running time constraints the westbound train must accelerate longer to a higher speed to compensate for this time loss, offsetting some benefits from reuse of regenerative energy. As the synchronization time increases, the position of the westbound train during acceleration is closer to the regenerative braking point of the eastbound train, and it is easier for the westbound train to postpone acceleration 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 7(a). However, at some particular synchronization time (100 seconds in this example), the eastbound train uses regenerative braking at the exact departure time of the westbound train and the regenerative energy can be easily absorbed by simply applying maximum acceleration under the default speed profile. Since further speed profile optimization cannot improve on this scenario facilitated by coincidental timing of maximum acceleration and braking, the base and optimized energy consumption results converge at this point.

FIGURE 7 Energy Evolutions at Different Synchronization Times
CONCLUSION

In this paper, a mathematical energy consumption model of bi-directional trains running in the same power section has been established based on train operation and electrical theories. Genetic algorithms have been applied to generate an optimal speed profile for the second train to minimize energy consumption at the power substations. Improvements like dual search loops and adaptive probability are introduced to the GA formulation to ensure the efficiency and effectiveness of the algorithm.

Although the energy savings from regenerative braking is estimated to be between 10% to 45% (1), it usually cannot be reached due to various factors. Based on current system regenerative receptivity level, simulation results show that the coordinated train control algorithm can save up to 12.7% additional regenerative energy, enabling the system to receive more benefit from regenerative braking.

Investigation also shows that the optimization ratio by coordinated train control algorithm differs according to different synchronization time pre-defined by the timetable. Different synchronization times may have different optimization ratios.

The method proposed in this paper can be used for multi-train-based ATO control algorithm design in DC traction power systems (valid for both overhead catenary and third rail systems). The study of optimization ratio for different synchronization times can be used to aid the design of energy-efficient timetables.

FUTURE WORK

The next step for model improvement is to consider more inter-station sections for optimization. When a power substation covers more than one inter-station section, regenerative braking trains in one section can provide energy for accelerating trains in another section, giving more possibilities to improve regenerative energy receptivity and to reduce power fluctuation. However, due to different electrical structure and power loss during transmission, the ATO control algorithm and corresponding optimization ratio may be different. Future study will allow the model to be improved to better represent the actual conditions of metro transit systems and be applicable to a wider range of scenarios.

ACKNOWLEDGMENTS

The authors would like to thank Southwest Jiaotong University, Chengdu China for train performance simulation software and simulation data. The primary author thanks the Rail Transportation and Engineering Center (RailTEC) at the University of Illinois at Urbana-Champaign for advice and support as a visiting scholar and thanks China Scholarship Council’s financial support for this research.
REFERENCES


