A Method of Generating Energy-efficient Train Timetable Including Charging Strategy for Catenary-free Railways with Battery Trains

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Abstract
Battery train is in development as train which can travel in non-electric section using power supplied from onboard storage system such as lithium-ion battery. However, as this type of train has some problems. First, battery train needs to take charging time when it runs a long distance more than its maximum cruising distance. Second, the energy consumption of battery train depends on the state of charge of the storage system. Needless to say, the energy consumption also depends on running time. Moreover, in catenary-free transportation system, battery train can't give regenerative energy to other trains in acceleration through the catenary. Hence, it's important how much the energy storage system can absorb regenerative energy. In consideration of these characteristics, it can be said that the energy-efficiency of catenary-free transportation system with battery train is in a complicated situation because those factors affect each other. When we design this system efficiently, we have to consider simultaneously "at which station the train should charge the battery", "how fast the train should run", and "how long the train should dwell at each station".

In this research, we propose a method of generating the timetable which is the most energy-saving when a single battery train travels on a route section containing multiple stations. The route section is assumed which distance is longer than the maximum cruising distance and the battery train needs to charge at any station. Although this optimization seems to be defined as a nonlinear programming problem, we use linear approximation to the energy consumption characteristic and ease to solve this problem as a MILP (Mixed Integer Linear Programing). In the end, the proposed methodology and customization analysis are applied on a real case study of the route section of Japan.

Keywords
battery train, lithium-ion battery, energy efficiency, train scheduling, optimization, MILP

1. Introduction

Catenary-free transportation system is tendency and attractive alternative to traditional fuel cars and railways with overhead contact systems. It can realize a beautiful urban landscape by removing catenary and reduce CO2, exhaust gas, and noise of engine. This kind of vehicles is generally powered through the onboard ESS (Energy Storage System) which supply electric energy and absorb regenerative energy. Commonly, regenerative brakes of rail vehicles are used under DC electrification and contribute to enhance the energy-efficiency. Especially, battery train which uses battery as onboard ESS become practical as their capacity increases. When we design a catenary-free transportation system with battery train, an important point is the selection of the ESS based on the cruising distance and its capacity. Although some researches (Ishino et al. 2012) that design optimally the capacity of ESS or charging infrastructures considering route conditions or rapid charge has been conducted, the operation that uses the limited stored energy efficiently has not been focused on. A related work shows that the difference of the SOE (State of Energy) of the ESS effects on the energy consumption of battery train (Noda et al. 2015). One reason of this difference is caused by that the ESS cannot absorb the regenerative energy when SOE is too high. Another reason is voltage drop of ESS. This voltage drop causes a decrease of the traction force and an increase of the energy consumption. The change of SOE is determined by how fast the train run. Hence, the effective strategy of both SOE and running time for the battery train is necessary. The allocation of running time have been studied so far. In this paper, we regard the characteristic of the storage system as constant and investigate the SOE-characteristic of battery train. After that, we present a mathematical programming and propose a method of generating the schedule to minimize the total energy consumption of battery train by allocation of running time, SOE and the location of charging points.

2. Related Work

In the literature, several ways to reduce the energy consumption are proposed and discussed. These ways are classified broadly into two groups. One way proposes the energy-saving train speed profiles (Licheng et al. 2017). Although this study focused on the traditional railway system with the overhead contact system, in the field of catenary-free transportation system, the optimized speed profile for the battery train is also proposed (Noda and Miyatake 2016). Another way optimizes the timetable (Pena-Alcaraz et al. 2012) (Sicre et al. 2010) (Li et al. 2014). They propose the method of generating energy-efficient timetable by adjusting the runtime of trains. There are also some papers which targets the energy-saving of the catenary-free transportation (Ishino et al. 2012). But in these studies, the target of optimization is mainly the speed profiles or the capacity of the energy storage system. It has been rare to optimize the timetable of catenary-free transportation. As it was mentioned before, the earlier study in this field deal with the ordinally train with the overhead contact system. Miyatake, Kuwahara and Nakasa (2012) proposed a comprehensive mathematical formulation as a linear/nonlinear programming for considering energy-saving train scheduling. They use the relation between runtime and energy consumption. It is used for the smooth railway operation, such that absorbs delays and prevent from propagating them, to make a mathematical programming model to optimize the timetable (Andersson et al. (2015)). Furthermore, these solution methods other than linear/nonlinear programming such as Genetic Algorism is also proposed for this kind of problem (Arenas et al. 2015) (Chao et al. 2016).

Based on the earlier study (Miyatake 2012), we make mathematical formulation as a linear/nonlinear programming for the catenary-free transportation system with battery trains to optimize their timetable. However, when we consider the appropriate programming for battery trains, we also need to consider the SOE (State of Energy) of the battery as the second parameter because the energy consumption of battery trains depends on SOE. When the SOE is low, the terminal voltage drops, and the energy consumption increases. Contrarily when the SOE is too high, the energy consumption also increases because the battery can't absorb all regenerative energy. Taking this characteristic into account, it's important for battery trains to keep the SOE within appropriate range. Not only running time, the location of charging spot when stopping at the station is also variable. It is possibility to change the energy consumption to change the charging point because the SOE while running recovers and differs from the same section. As the final goal of this study, we make a mathematical programming to optimize running time, SOE control and charging spot simultaneously for catenary-free transportation with battery train.

3. The Characteristic of the Energy Consumption

Modeling of energy storage and battery train

In this research, we deal with a battery train which uses high power lithium-ion battery as the onboard ESS. Generally, super capacitor is often used as the onboard ESS of battery train. We can make a circuit equation between the current capacity and the terminal voltage for super capacitor. We use the indicator SOC (State of Charge) which represent the current capacity of the battery. However, lithium-ion battery has a nonlinear drooping characteristic between its SOC[%] and its no-load open voltage v[V]. We identify the voltage characteristic of LIM-30H made by GS YUASA Corporation (Seyama et al. 2007) in Fig.1. We approximate this characteristic by the following quadratic equation (1).

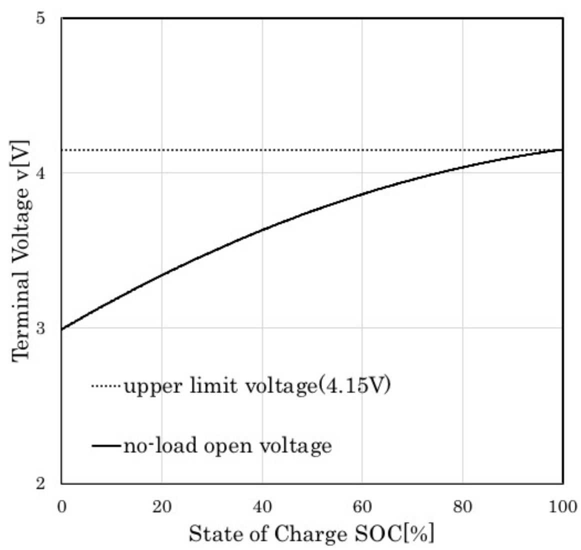

Fig.1 No-load open voltage of LIM-30H made by GS Yuasa Co. (per a cell)
1 unit is composed of 8 cells.

$$\begin{aligned} v &= a_1 SOC^2 + a_2 SOC + a_3 \\ &= f_1(SOC) \end{aligned} \tag{1}$$

Lithium-ion battery is discharged when the battery train accelerates and charged when it uses its regenerative brake. It is necessary to be careful that the battery has the internal resistance. Because of this resistance, the terminal voltage of the battery increases when using the regenerative brake. For example, when the braking train can be regarded as just a current source, it is connected simply with the battery like the circuit of Fig.2. The terminal voltage V[V] is represented by the equation (2).

$$V = v + ri = f_1(SOC) + ri+ \tag{2}$$

Hence, when the SOC is high, a reducing current have to be done because we keep the terminal voltage under the upper limit voltage. This reducing current means that the regenerative energy decreases. We call it "restriction of regenerative power". This restriction effects the total energy consumption of the battery train.

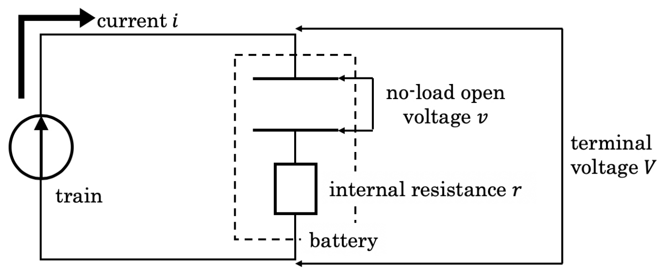

Fig.2 Simple electrical circuit between the train and the ESS (regenerative brake)

Charging infrastructure

When charging battery at the station, the circuit is almost same as the Fig.2. Although lithium-ion battery has high power, it is dangerous with high voltage. Therefore, when we charge lithium-ion battery, we apply CCCV (Constant Current Constant Voltage) control. We have identified the charge characteristic as equation (3) by the charging simulation. In consideration of the situation, we set the charging current at the constant current charging mode $i_c = 90A$.

$$i(t)[\mathrm{A}] = \begin{cases} i_c & (SOC \leq 81.4) \\ i_c \exp\left(-\frac{t-t_0}{\tau}\right) & (SOC > 81.4) \end{cases} \quad (3)$$

We got the current capacity $I(t)$ by integrate current. SOC can be calculated from current capacity easily.

$$I(t)[\mathrm{Ah}] = \int_0^t i(t)dt = \begin{cases} i_c t & (SOC \leq 81.4) \\ i_c t_0 + \tau i_c \left\{1 - \exp\left(-\frac{t-t_0}{\tau}\right)\right\} & (SOC > 81.4) \end{cases} \quad (4)$$

Where, t_0 is the end of time constant current charging mode and τ is time constant which express how fast the current is reduced in constant voltage mode.

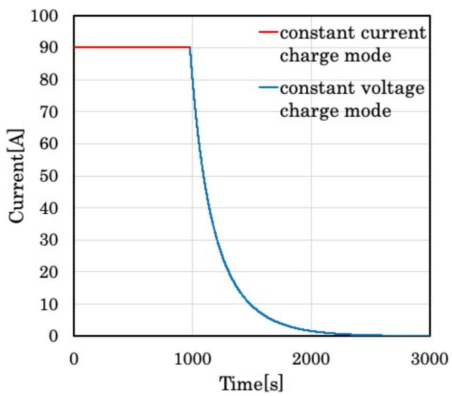

Fig.3 Current characteristic of charging to represent in (3)

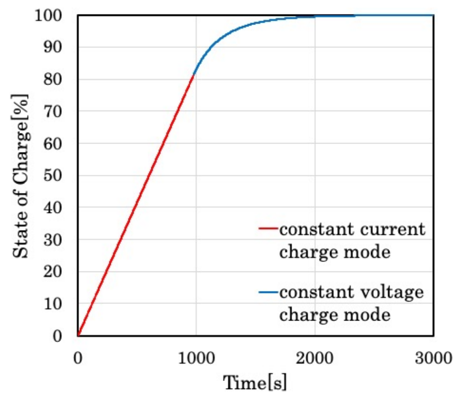

Fig.4 SOC characteristic of charging to represent in (4)

Running Simulation

Now, we conduct the running simulation to investigate how much the energy consumption changes with the SOC and restriction of regenerative power. Table1 shows the status of the battery train which we use in the running simulation.

Table1 Status of battery train

Composition	two-cars
Weight (vehicle)	80.0 ton
Speed control	variable voltage variable frequency
Braking	regenerative brake / mechanical brake
Rated Voltage of the circuit	633.6 V
Capacity of the battery	300 Ah
Numbers of battery units	22 series / 10 parallel
Weight (battery)	4.3 ton
Maximum acceleration (at the rated voltage)	2.0 km/h/s
Maximum deceleration	3.6 km/h/s
Efficiency (acceleration)	90 %
Efficiency (braking)	80 %

The simulation goes following procedure.

(i) Maximum acceleration up to the max speed

(ii) Coasting at the point from where the train can stop at the target point using the maximum deceleration

(iii) Maximum deceleration using the regenerative brake as much as possible (If the terminal voltage reached at the upper limit voltage, the current of train should be reduced and the mechanical brake is used which makes the same deceleration as the regenerative brake.)

This operation of speed control is based on the general principle of the energy-saving driving (Licheng et al. 2017). We conducted the running simulation on the typical route changing the Initial SOC of the battery. This route is 3km long and has -3‰ gradient. The result of energy consumption is showed in Fig.5. As showed in Fig.5, the characteristic of the energy consumption draws a downward curve line to the initial SOC. When the SOC is high, a reduction of regenerative power occurs and the total energy consumption increase. Contrary, the traction force of battery train fall when SOC is low. It takes longer time to accelerate to the same max speed than the high SOC. As a result, the energy consumption increases with the low SOC. Needless to say, the energy consumption is inversely proportional to running time. Then, we can plot the characteristic of energy consumption as the two-variable (initial SOC and running time) function in Fig.6. For ease of viewing, the axis of energy consumption is inverted. This function draws downward curve surface in a three-dimensional space. This characteristic is used as a constraint condition in the definition of MILP from the next chapter.

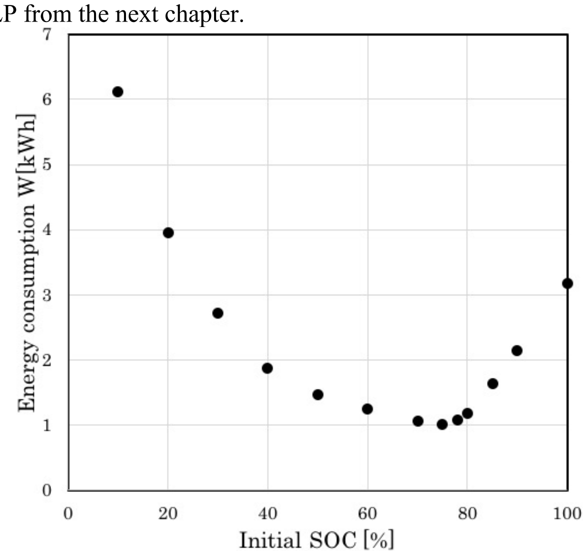

Fig.5 Relevance between Initial SOC and energy consumption

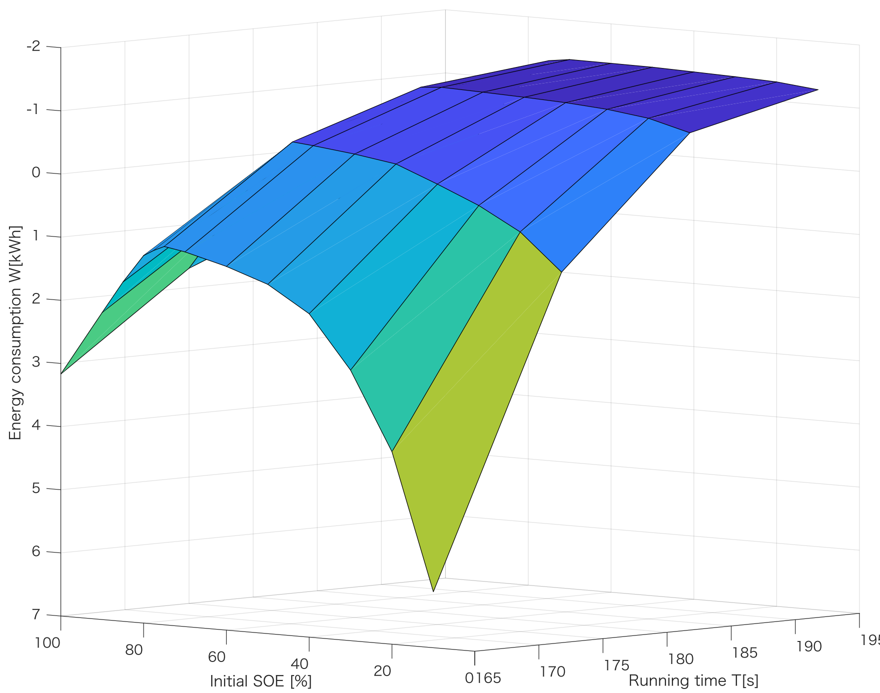

Fig.6 Characteristic of energy consumption among running time and Initial SOC

4. Model to Minimize the Energy Consumption on a Route Section Containing Multiple Stations

As described in chapter 3, we got the characteristic of energy consumption among running time and Initial SOC. The plan which gives an appropriate allocation of running time and SOC of battery train is necessary to enhance energy efficiency for catenary-free transportation system. One well documented method to solve planning problems is to use mathematical programming. Optimization is an often-used method in previous literature to create timetables. In this chapter, we present an optimization model in which allocate running time, control SOC, and also determine the charging point to minimize the energy consumption when a single battery train run a route section containing multiple stations and charging point. This model is originally based on the optimization model for allocating running time presented in a previous research (Miyatake et al. 2012).

Introduction State of Energy:
As an indicator of the state of the ESS, we used SOC which is the value of current capacity as a percentage. It is because that current capacity is generally used to express the voltage characteristic. From here, to make ease the relationship between the state of the ESS and

energy consumption, we use SOE (State of Energy) which is the value of energy capacity as a percentage instead of SOC. Energy capacity is simply calculated from current capacity to multiple the terminal voltage of the battery.

Definition as a Mathematical Programming
In the model we assume the route model shown in Fig.7. The number of stations is N. Variables are divided into two groups. Each station has variables in the first group. SOE_k represents how much energy is remained in the battery at station k. p_k is the binary. It shows that whether the battery train charge at the station or not. D_k is dwell time at each station. In this programming, D_k is not variable but given value. The second group of variables is about each section between stations. There is energy consumption W_k and running time T_k. It seemingly unnatural to set W_k to variables because we illustrate energy consumption depends on running time and SOE. The reason of this will be explained later.

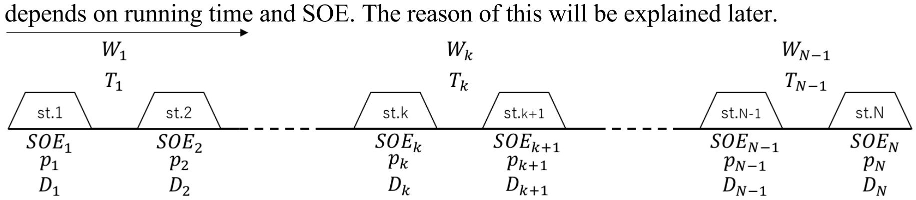

Fig.7 Route model and variables

Parameters:

N	= number of stations
T	= sum of running time of each station
M	= maximum number of the sum of charging points.
D_k	= dwell time at the station k
SOE_{min}^k	= minimum value of SOE at station k.
SOE_{max}^k	= maximum value of SOE at station k.
T_{min}^k	= minimum value of running time at station k.
T_{max}^k	= maximum value of running time at station k.

Variables:

SOE_k	= SOE at station k
p_k	= indicates if the battery train charge at station k (=1) or not (=0)
W_k	= energy consumed between station k and station $k+1$
T_k	= running time between station k and station $k+1$

Objective function:
The objective function (5) is the sum of the energy consumption at each station and the margin of SOE between the starting station and the terminal station. To add this margin to the objective function, the energy for using charging can be considered.

$$Minimize \sum_{k=1}^{N-1} W_k + c_1(SOC_1 - SOC_N) \tag{5}$$

Constraints:
The following constraints are used in the optimization model to restrict the train running, energy consumption and the SOE at each station. The constraint (8) represents the transition of SOE between stations. The SOE at the station $k+1$ is calculated like that the SOE at the

station k minus the energy consumption between station k and station $k+1$, and plus the charging energy at the station k. If the battery train charge at the station k ($p_k = 1$), SOE recovers in proportion to dwell time D_k. It is meaningless to charge at the starting station and the terminal station. Hence, the binary variable p at these two stations should be zero by the constraint (11).

$$\sum_{k=1}^{N-1} T_k = T \tag{6}$$

$$\sum_{k=1}^{N-1} p_k \leq M \tag{7}$$

$$SOE_{k+1} = SOE_k - c_2 W_k + c_3 p_{k+1} D_{k+1} \tag{8}$$

$$SOE_{min}^k \leq SOE_k \leq SOE_{max}^k \tag{9}$$

$$T_{min}^k \leq T_k \leq T_{max}^k \tag{10}$$

$$p_1 = p_N = 0 \tag{11}$$

Constraints (characteristic of energy consumption)

As the constraints, we use the characteristic of energy consumption among running time and Initial SOC got in chapter 3. We suppose the characteristic is two-variable function which determine W_k from T_k and SOE_k. But it is difficult to express this function as a explicit function. Therefore, we include the relationship among the W_{k+1}, T_{k+1} and SOE_k as the implicit function to constraints.

$$f(W_k, T_k, SOE_k) = 0 \tag{12}$$

This is the reason why we deal with W_k as the variable. The function is different by each section. We firstly conduct running simulations in the all section in the route model in the same way in chapter 3. After that, characteristics of energy consumption at each section draw downward curved surfaces like Fig.4. As shown in Fig.7, the controversial point is that this characteristic is nonlinear and cannot be included in the MILP. If we use this characteristic as it is to make a nonlinear programming, there is a possibility that the calculation time to obtain the optimum solution is too huge with respect to the scale of the problem. Therefore, in this paper, we use a method of dividing energy consumption characteristics defined on the space as curved surfaces into fine lattice shapes and approximating it as a polyhedron composed of minute triangles, thereby creating a linear condition.

Linear approximation is done in the following way. First, we discretize continuous and smooth curved surfaces $W(T_k, SOE_k)$ by m samples in the T-axis direction and n samples in the SOE-axis direction. In this way, linear approximation is performed by complementing between the grid points of $m \times n$ created on the surface with a plane. As shown in Fig.6, (13) is the equation of the plane which is created by selecting three adjacent points in the lattice points.

$$a_1 T_k + a_2 SOE_k + a_3 W_k = 1 \tag{13}$$

When we choose any lattice point $(T_k, SOE_k, W(T_k, SOE_k))$, we can make 2 planes (14) and (15). Note that $W_{i,j} = W(T_i, SOE_j)$

$$① \cdots \begin{pmatrix} T_i & ISOE_{j,} & W_{i,j} \\ T_i & ISOE_{j+1,} & W_{i,j+1} \\ T_{i+1} & ISOE_{j+1,} & W_{i+1,j+1} \end{pmatrix} \begin{pmatrix} a_{11} \\ a_{21} \\ a_{31} \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \tag{14}$$

$$② \cdots \begin{pmatrix} T_i & ISOE_{j,} & W_{i,j} \\ T_{i+1} & ISOE_{j,} & W_{i,j+1} \\ T_{i+1} & ISOE_{j+1,} & W_{i+1,j+1} \end{pmatrix} \begin{pmatrix} a_{12} \\ a_{22} \\ a_{32} \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \quad (15)$$

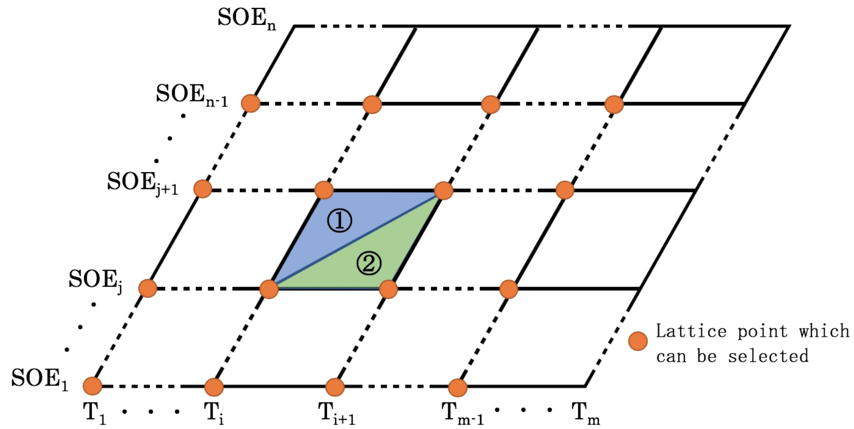

Fig.8 Polyhedron approximation of curved surface

In this way, $(m-1) \times (n-1)$ grids points are selected. Linear Constraints made by this approximation are added to equation (8). Furthermore, to regard the characteristic as a polyhedron, there is no problem to replace the equation (12) to the inequality (16).

$$f(W_k, T_k, SOE_k) \leq 0 \quad (16)$$

Even in this way, if energy consumption is minimized inevitably it gives the same result as the equation constraint, so there is no problem as inequality constraint. By doing this, we can get even more advantage. It is not necessary to define the domain of the approximated plane with respect to the convex constraint, it is possible to prevent the constraint expression from becoming complicated.

Coefficients:
Coefficients c_1, c_2, c_3 has each physical meaning and should be set properly. Mainly, these coefficients convert units between some values (e.g. SOE and W).

5. Case Study

A numerical experiment is performed for real-world case with data from the Japanese suburban line, see Fig.9. The model line is that cannot run without the train battery charging at a station. The total length of the line is 90km assuming an actual local line. We intend to optimize running time and make an energy-efficient timetable for battery train using MILP defined in chapter 4.

5.1 Default timetable

Firstly, we conducted running simulation to determine the default running time at each section and make the default timetable. For initial running time is that the battery train runs this section with a maximum speed 90km/h. Speed profile is determined by the general energy-efficient theory shown in the chapter 3. However, there are some section where the train stop at the front of the next station. In this case, traveling with maintaining the maximum speed is inserted before the battery train decelerate as shown in Fig.10. Moreover, dwell time at each station is set with reference to the actual operation. Dwell time at each station is shown in Table2. The blue line in Fig.11 shows the default timetable. As the feature of the default timetable, there is a comparatively long dwell time at the station H. This is because this route section has only a single track and station H is equipped for two-way transportation.

Secondly, we investigate the characteristic of energy consumption by running simulation. We set the maximum speed 120km/h and minimum running time with this maximum speed. The simulation is performed while changing running time to 10 second increments. Maximum running time is set so that the difference from the default running time is equal to the difference between the minimum running time and the default running time. For example, if the default running time is 200 second and the minimum running time is 170 second, the maximum running time should be 230 second.

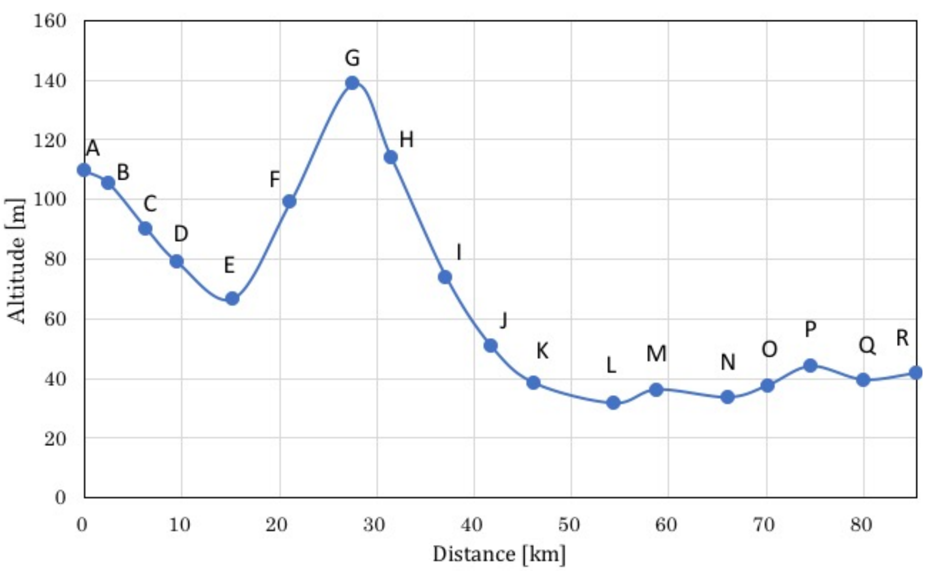

Fig.9 Model of line, the point A, B, C … means the stations

Table2 Dwell time at each station

Station	A	B	C	D	E	F	G	H	I
Dwell time[s]		90	30	50	110	40	40	430	30
	J	K	L	M	N	O	P	Q	R
	30	60	40	40	30	30	80	60	

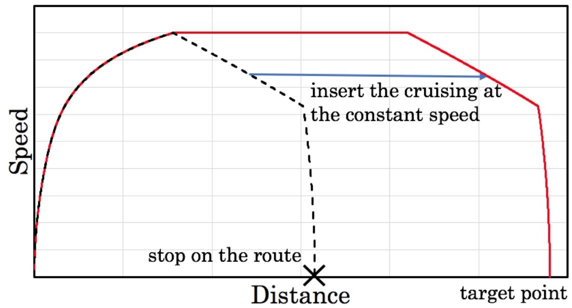

Fig.10 Operation when the train stop at the front of the next station

5.2 Optimization and result

With these conditions, the optimization is defined as a MILP in the way shown in chapter 4. As an additional condition, the upper limit of the number of charging point is set 2. The upper limit of SOE is set 95% and the lower limit 20%. This MILP can be solved by the solver: "intlinprog". This is included in "Optimization Toolbox" of the MATLAB.

The calculation finishes in the several seconds. We show the optimized timetable in Fig.11. Furthermore, according to the allocating running time, second running simulation is conducted to get the speed profile of the battery train and more accurate transition of SOE and energy consumption. We show the speed profile in Fig.12, the transition of SOE in Fig.13 and the transition of the integrated value of the energy consumption in Fig.14.

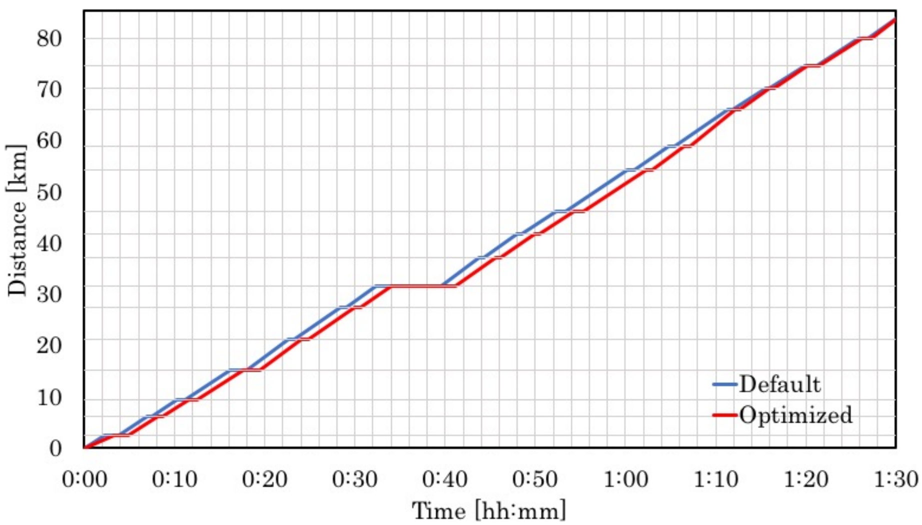

Fig.11 Default and optimized timetable

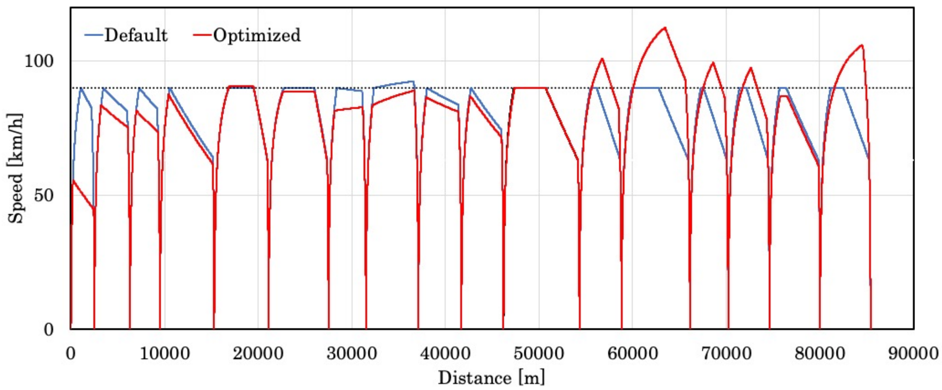

Fig.12 Speed profile according to the default and the optimized timetable

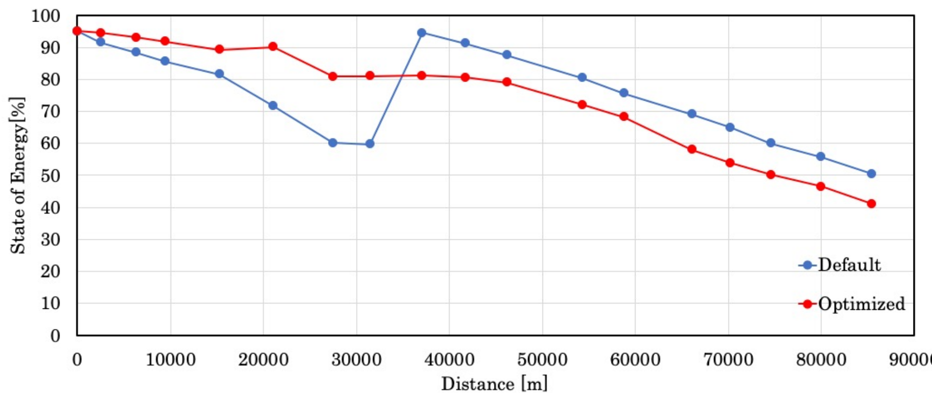

Fig.13 Transition of SOE of the default and the optimized timetable

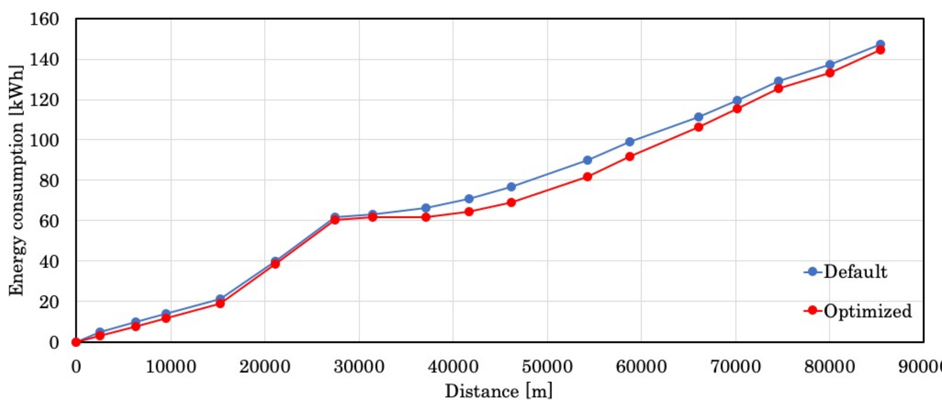

Fig.14 Transition of integrated value of the energy consumption of the default and the optimized timetable

Table3 Station performed charging

Default timetable	H (the 8th station)
Optimized timetable	E (the 5th station)

Table4 Total energy consumption of the default and optimized timetable

Default timetable	147.1kWh (100%)
Optimized timetable	144.6kWh (98.3%)

6. Discussion

By the optimization, running times are adjusted up to 60 seconds at each section. The location of the charging point is also changed. The total energy consumption is reduced about 1.7% by the adjustment. In this chapter, we discuss this adjustment and energy-efficient timetable for catenary-free transportation with battery train.

Location of charging point
In the default timetable, charging is performed at the station H. We can see a big recovery of SOE in the blue line of Fig.13. On the other hand, in the optimized timetable, charging point moves to the station E. The station E is located in the valley on the route model. Usually, trains consume much more energy on the uphill section than the downhill section. It can be said that the energy consumption has reduced because battery had been charged before uphill section that needs much electric energy. This change has the similar feature to the related study (Noda et al. 2015). It can be referred for the detail explanation.

Allocation of running time
See Fig.11. In the optimized timetable, running times in sections of the first half are extended. Contrary, running time in sections of the last half are shorten. The reason of this adjustment is SOE dependence as shown in Fig.5. Although the SOE characteristic depends on the route condition, it has the convex characteristic and the most energy-efficient point is at 75%. This is the highest point where the battery train can absorb all regenerative energy without restriction of regenerative power. On the red line (optimized timetable) in Fig.13, the battery train runs fast when the SOE is around 60-80%. Hence, we got the acknowledge that it's necessary to keep SOE around the most energy-efficient point to minimize the energy consumption. We calculate the average of SOE while running between the starting station and the terminal station. The average value is showed in Table5.

Table5 Average value of SOE while running

Default timetable	75.76% (+0.76% from 75%)
Optimized timetable	74.91% (−0.09% from 75%)

As shown in Table5, the average value of SOE of the optimized timetable is nearer than the default's one. This control to keep SOE around the most energy-efficient point is important to make a time table efficiently for catenary free transportation with battery train. Still, in this case study, it is not sufficient to evaluate the energy saving effect of this optimization because the effect depends on the initial timetable. Currently, catenary-free transportation is not popular in Japanese railway. Therefore, in this paper, we make the initial timetable by ourselves, and the it is difference from the timetable used in the actual operation. Moreover, the consideration of dwell time is necessary. If we add dwell time to variables this optimization program is not defined as a linear programming but a nonlinear programming. However, there is a possibility to get a new acknowledge if we can adjust simultaneously running time and dwell time so that the sum of those is constant. The effect of the number of the charging points is also considerable.

7. Conclusion

In this paper, we focus on the energy-efficient timetable for catenary-free transportation system with battery train. It is significant for catenary-free transportation system that how much regenerative energy can be absorbed in the ESS. Firstly, we investigate the characteristic of SOE by running simulation. It is clarified that the characteristic draws a convex curved line to SOE. We can draw the convex curved surface to add running time as the second parameter in the three-dimensional space. Secondly, we make the model to minimize the energy consumption and make the energy-efficient timetable. Although the characteristic of the energy consumption is nonlinear, we define this optimization programming as MILP to use a polyhedron approximation. Finally, we perform a numerical experiment using the data from real-world route model. Consequently, the optimized timetable reduced the total energy consumption by 1.7%. The optimization result of the location of charging point is at the station with a low altitude, and this is similar result to the related study. As a characteristic of the running time allocation, running time in the section where the SOE is around the most energy-efficient point is shorten. In future work, it should be more case studies in the more variable conditions to enhance this method.

There are many studies to design a suitable and energy-efficiently transportation system in the field of railway. It is expected further reduction of electric energy in catenary-free transportation and battery train.

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