Paper

Energy Efficient Train Trajectory in the Railway System with Moving Block Signaling Scheme

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High-frequency train operation with a moving-block signaling system has begun to be introduced mainly in urban rail transit. Under high-frequency operation, however, subsequent trains can repeatedly be forced to slow down according to deceleration pattern generated by the signaling system to avoid collision with preceding trains, which increases the energy consumption of subsequent trains. In this paper, train trajectory optimization with dynamic programming is applied to evaluate the effect of considering preceding trains' trajectory on subsequent trains' energy reduction in a line with moving-block signaling system. The result shows that the method reduces the increase in energy consumption compared to the preceding train 1/3 times more than when not considering the position of the preceding train.

Keywords: high-frequency train operation, moving block signaling system, energy efficiency, automatic train operation

1. Introduction

A moving block signaling system can achieve better operation of a railway system by enabling operators to constantly track the positions of trains using a robust telecommunication system.

Meanwhile, high frequency of operation might increase the energy consumption per train because the position of a preceding train is not completely predictable throughout its operation, and a subsequent train may be unexpectedly forced to decelerate according to deceleration patterns (Fig. 1).

Recently, methods to achieve energy efficient train trajectories were proposed in (1)–(7). However, most of these methods did not consider the influence of a signaling system on the subsequent trains. In particular, in the CBTC (Communication-based Signaling System) signaling system, the influence of the signaling system was considered to calculate an energy efficient driving method in (1); however, optimization in terms of energy consumption was not firmly considered. Therefore, the objective of this study is to calculate energy efficient train trajectories considering deceleration patterns in the railway network using a moving block signaling system. A train trajectory optimization method with dynamic programming is utilized and energy consumption under this method is compared with the method that regards deceleration pattern as an unpredictable disturbance. First, the mechanism of a moving block signaling system and high-frequency operation with such a system are explored. Second, the train trajectory optimization method with dynamic programming, which is used to simulate a train's energy consumption, is described. Third, the simulation condition used in this study is explained. Finally, simulation result with and
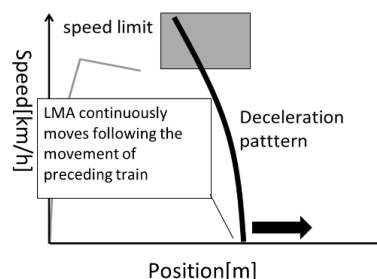

Fig. 1. Train trajectory in railway with moving-block signaling system

without prediction of a preceding train are compared.

2. Moving Block Signaling System

2.1 Mechanism of Moving Block Signaling System

Conventionally, a track circuit is mainly used for train detection, which electrically divides the rail into several sections, and detects the positions of trains by checking the current in each section of the rail. This system is commonly used for controlling a signaling system called a fixed block system (Fig. 2). In the fixed block signaling system, each train is separated by allowing only one train to proceed in each track circuit. However, the accuracy of positioning a train depends on the number of track circuits per railway line; thus, shorter track circuits are required for trains that operate in close proximities.

In a moving block signaling system (Fig. 1, Figs. 3, 4), telecommunication systems are mostly applied to estimate individual train locations and their limit of movement authority (LMA). The LMA defines the position that a subsequent train can proceed to and is calculated based on the train's profile, such as speed and length. Upon receiving a preceding train's LMA, a subsequent train can calculate the deceleration pattern required to be able stop within the LMA. When a subsequent train approaches a preceding train, the subsequent train

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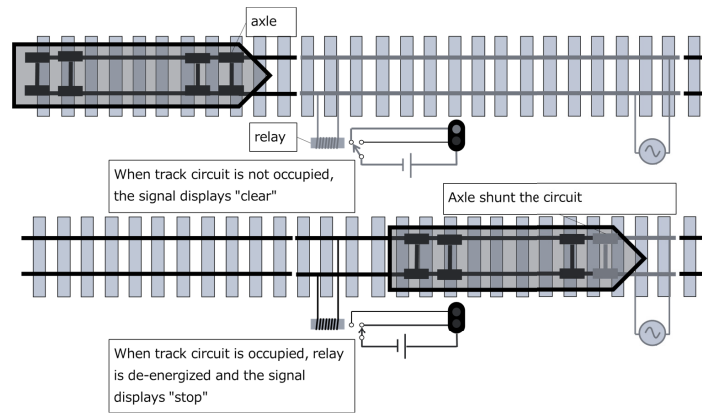
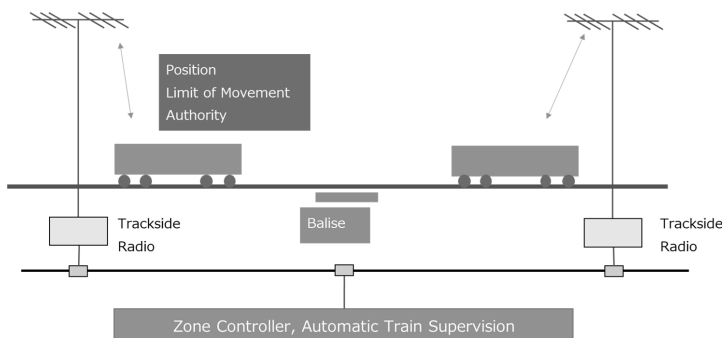Fig. 2.   Fixed block signaling system

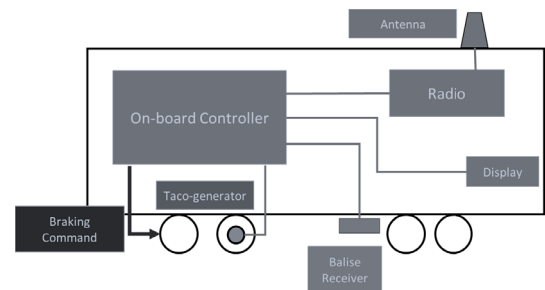Fig. 3.   Trackside equipment of moving block signaling system

Fig. 4.   Onboard equipment of moving block signaling system

decelerates according to the deceleration pattern.

2.2   Concerns Regarding Train Trajectories in High Frequency Operations   In a high frequency operation line with a moving block signaling system, a shorter distance between the trains can affect the energy consumption of the subsequent train. The distance between the trains will decrease rapidly, and the chance of exceeding the deceleration pattern of the signaling system will increase. On approaching the preceding train, the subsequent train is forced to decelerate according to the deceleration pattern. This additional deceleration and acceleration (for recovering the time lost owing to the deceleration) is a waste of energy. On the other hand, if the position of the preceding train can be accurately predicted throughout the operation, more efficient train trajectories would be possible, with lower speeds for the deceleration pattern and smaller rates of deceleration and acceleration, which reduce the energy consumption of the subsequent train.

Using the continuous train control mechanism, the moving block signaling system is often introduced with an automatic train operation (ATO) system, and an additional operation mode for energy efficient train operation is required to save energy accounting for the effects on the signaling system during high frequency operation.

Some reported literature such as (1) and (2) consider the energy efficiency of train tracking under CBTC in a high frequency operation condition; very few studies have used the prediction of a preceding train to achieve train control. Considering the influence of the preceding train's position on the subsequent train, a two way approach is proposed: (A) the position prediction method for the preceding train considering the stochastic fluctuations of arrival and departure times, and (B) the train trajectory optimization method considering the position of the preceding train. The goal of this research is to develop an energy efficient train trajectory that guarantees robustness to the delays of the preceding train and achieves the efficient operation of the subsequent train in a high frequency line. As the first phase of this research, this study focuses on the train trajectory optimization method considering the position of the preceding train. In the next section, the feature of dynamic programming is explained as a method for deriving an energy efficient train trajectory under these conditions.

3.   Train Trajectory Optimization with Dynamic Programming

3.1   Dynamic Programming and "The Bellman Principle of Optimality"   Dynamic programming is an algorithm for obtaining the optimal solution in a multistage decision process and was developed by R. Bellman based on the principle called "The Bellman Principle of Optimality" [8]. (The principle states that "An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision.").

The Bellman principle of optimality is applicable to a system with an n-stage process. That is, the system state for the Nth stage φ_N and optimal trajectory after φ_N are determined independent of the decision process from start point to the Nth process. In addition, when state φ_{N-1} transit to φ_N with control input of u_{N-1}, the optimal trajectory and evaluation

value are determined independent of φ_{N-1} and u_{N-1}, thus, the evaluation value with input u_{N-1} from the $(N-1)^{\text{th}}$ stage is calculated as the sum of the optimal evaluation value φ_N and partial evaluation value from $(N-1)^{\text{th}}$ stage to N^{th} stage.

3.2 Application of Dynamic Programming to Train Trajectory Optimization   Dynamic programming was utilized for train trajectory optimization in previous studies [7], [9]–[13]. The performances of different train trajectory optimization methods were compared in [5], and it was shown than dynamic programming is the best train trajectory optimization method with the exception of calculation time. In Ref. [14], this method was implemented in a driver advisory system operating on an Android tablet device, and it was considered that the utility of the train trajectory optimization method with dynamic programming was high in terms of the performance of the method and implementation on a device with limited computational resources. The main features of the train trajectory optimization method are as follows:

 • The track profile (speed limit, gradient, curves) parameters are taken into account throughout the optimization easily.

 • If a disturbance (such as a delayed departure) is applied during optimization, the subsequent optimal solution is able to use the neighboring point's optimal solution in calculation.

 • In solving the model with a computer, the RAM usage is linearly (not exponentially) proportional to the mesh number.

Utilizing these characteristics, train trajectory optimization with dynamic programming is applied to optimize a special type of train such as a battery train, and the optimization considers external factors such as a signaling system. The research for a Li-ion battery train and metro line by Linear Motors were conducted by Noda (2016) [10] and Watanabe (2017) [11]. Optimization considering the influence of a fixed block signaling system was studied by Oba (2017) [12]. The optimization of the timetable and train trajectory on a high speed railway line were studied by Zhoua et al. [7].

The algorithm of train trajectory optimization with dynamic programming is as follows;

A)   Discretize the state space, consisting of v (speed of train) and x (position of train), into a lattice.

B)   Discretize the operating time into N-stages, and prepare the state space for each stage.

C)   Calculate the terminal penalty φ_N for the final state space (corresponding to the time of arrival) as described below:

$$\varphi_N(x(N), v(N)) = c_1(x(N) - x_f)^2 + c_2(v(N) - v_f)^2$$

   $x(N)$: Position of train at N^{th} stage

   $v(N)$: Speed of train at N^{th} stage

   x_f: The position of destination from starting point

   v_f: The speed at destination. ($= 0$)

This penalty is applied to consider the terminal error as equivalent to an energy increase and minimize the terminal error at the destination point through optimization.

D)   Define k ($k = 1, 2, \ldots N - 1$) as the counter of stage and put $k = (N-1)$.

E)   Start calculation of partial optimal input at the kth stage according to the evaluation value from the $(k+1)^{\text{th}}$ stage, and determine the optimal inputs as shown in Figs. 5 and 6. The partial optimal solution and value of evaluation function at the kth stage are recorded.
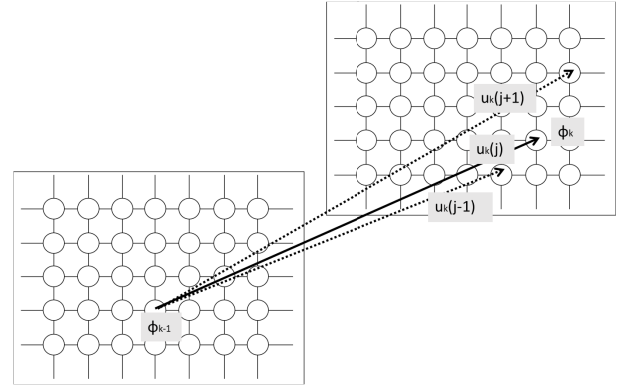

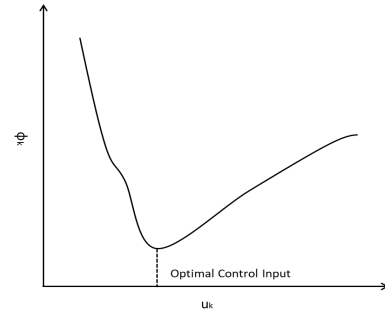Fig. 5.   Calculation of partial optimal input in state space

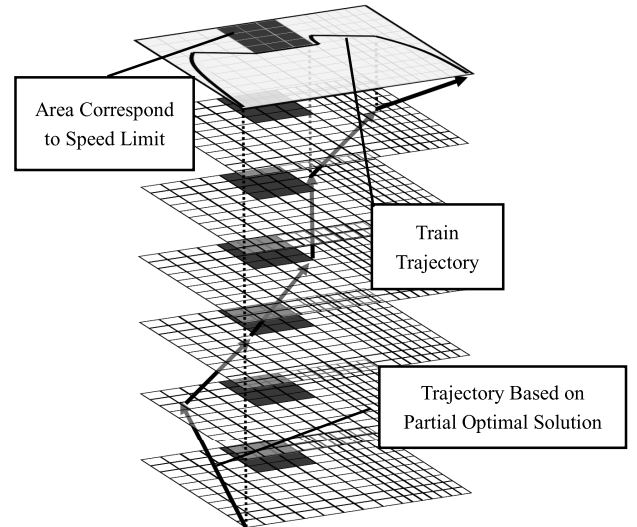Fig. 6.   Induction of optimal input u_k that minimize ϕ_k

Fig. 7.   Forward induction process. The trajectory between state space is calculated based on the partial optimal solution calculated in backward induction process

F)   Start calculation at the $(k-1)^{\text{th}}$ stage and return to E) if $(k-1) > 1$. (Steps E and F are called "backward induction")

G)   The optimal trajectory is obtained by tracking the partial optimal solution at each stage and point from the starting point at a given time. This is called "forward induction" (Fig. 7).

3.3 Train Trajectory Optimization for the Railway with Moving-block Signaling System   In this study, dynamic programming is used to directly consider the deceleration patterns of the moving block signaling system and solve for the energy efficient train trajectory considering the
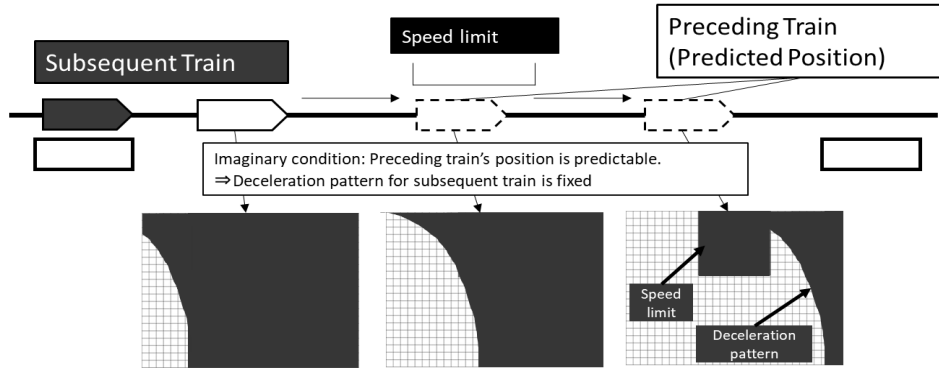
Fig. 8.   Train trajectory optimization in the railway with moving block signaling system. The deceleration pattern is considered equivalent to the permanent speed restriction

signaling system. The moving block signaling system can be modeled in dynamic programming by considering the deceleration patterns as the speed limits that change over time.

In optimization with dynamic programming, the speed limits are taken into account by setting the value of the evaluation function high to avoid the speed limit area during optimization.

Utilizing these characteristics, the deceleration pattern of a moving block signaling system is optimized. In this study, the imaginary condition is assumed as the condition where the position of the preceding train is known (or predictable) all over the operation time, and the deceleration pattern is fixed at each time stage. Applying this condition, energy efficient operation method of the subsequent train considering the position of the preceding train is calculated (Fig. 8).

In the next section, simulations to evaluate the effect of this optimization method are described.

4.   Simulation

The imaginary railway line shown in Fig. 9 is used for simulation. The preceding train operates from station 1 to station 3 and the subsequent train operates from station 1 to station 2. The other conditions of this railway are as shown below in Table 1. During simulation, a change in energy consumption when the train headway changed is evaluated to consider the effect of predicting the preceding train's position. With this condition, simulations are performed under the following two cases.

4.1   Case 1: The Position of Preceding Train is not Predictable   In this case, the subsequent train only receives the current position of the preceding train, and deceleration pattern is not included in optimization. The deceleration pattern will be reflected as a disturbance. To simulate this condition, the deceleration pattern is applied during the forward

induction process (Fig. 10).

4.2   Case 2: The Position of Preceding Train is Predictable Throughout the Operation Time   In this case, the subsequent train knows the future position of the preceding train, and the deceleration pattern is predictable in

Table 1.   Track and train specification

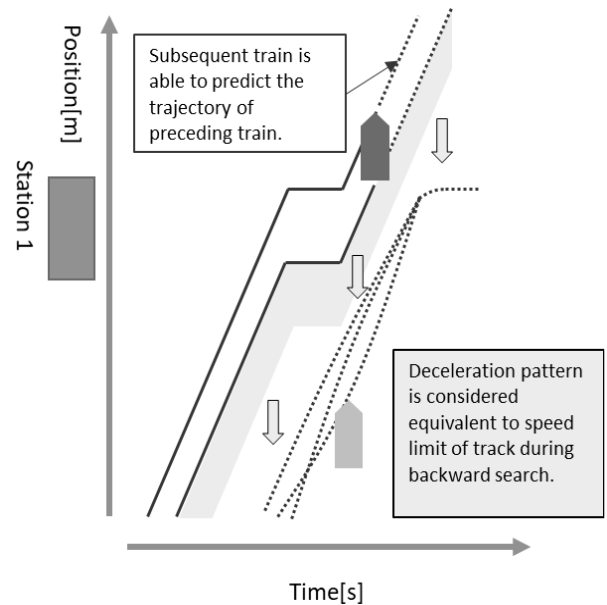| Line Profile		Train profile	
Operating time[s] (station1-2)	210	Maximum Acceleration rate[km/h/s]	2.6
Operating time[s] (station2-3)	210	Maximum Deceleration rate[km/s2]	3.16
speed limit[km/h]	60 (1200-1800[m])	Train Length[m]	200
stoppage time at station 1[s]	30	Deceleration Rate of Speed Pattern	same as maximum deceleration rate

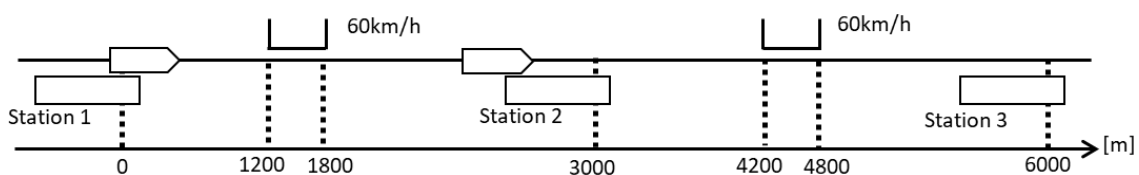Fig. 10.   Description of simulation Case 1

Fig. 9.   Target railway for simulation with three stations and two train. (Preceding train operates from station 1 to station 3 and subsequent train operates from station 1 to station 2)

advance. The subsequent train can optimize the operation profile considering the deceleration pattern as well as railway speed limit (Fig. 11).

5. Result

The simulation results of the headway diagram, running profile, and energy consumption (at train headway of 106 [s]) are shown in Figs. 12–14 (Case 1) and Figs. 15–17 (Case 2), and rate of increase in energy consumption for all tested train headways are shown in Fig. 18.
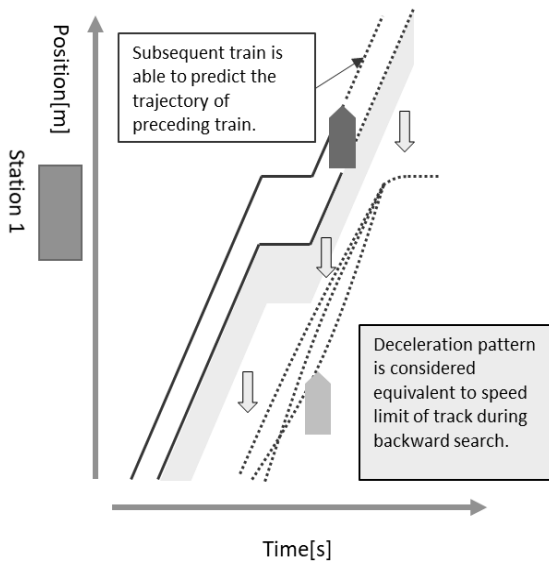

Fig. 11. Description of simulation Case 2

5.1 Case 1: The Position of Preceding Train is not Predictable The subsequent train operates similar to the preceding train before the subsequent train approaches. However, after approaching the preceding train, the subsequent train decelerates until the preceding train departs from the next station. (Figs. 12, 13). There is a large rate of energy increase after re-acceleration and causes additional energy consumption (Fig. 14).

5.2 Case 2: The Position of Preceding Train is Predictable Throughout the Operation Time The subsequent train operates at a lower speed compared to the preceding train until the preceding train departs from the next station. After the departure of the preceding train, the subsequent train re-accelerates (Figs. 15, 16). There is an energy increase after re-acceleration, but at a reduced rate compared to Case 1 due to lower rate of deceleration (Fig. 17).

5.3 Comparison of Energy Consumption between Case 1 and 2 at Various Train Headway Energy consumption generally increases when applying a shorter train headway. However, energy consumption increase in Case 1 is 1/3 of that of Case 2 (Fig. 18). The reason for this is that the subsequent train operates at a lower top speed between Stations 1 and 2 compared to that in Case 1. Although the time to commence re-acceleration and achieve top speed after reacceleration are same as that of Case 1, Case 2 operates in a more energy efficient manner by avoiding the additional deceleration caused by the signaling system. Predicting the preceding train is thus effective for reducing energy consumption rate and finding an energy efficient train trajectory.
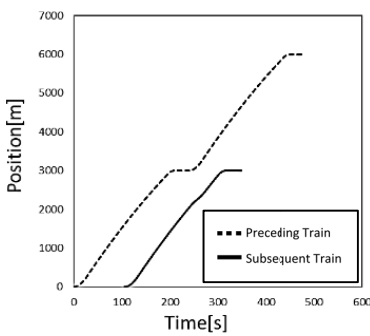

Fig. 12. Train headway diagram of preceding train and subsequent train (Case 1)
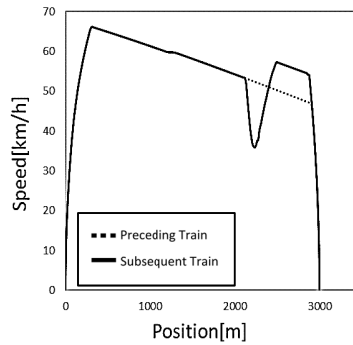

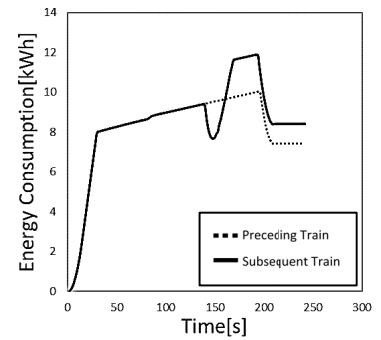Fig. 13. Running profile of preceding train and subsequent train (Case 1)

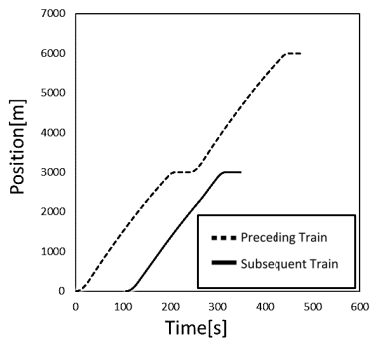Fig. 14. Energy consumption of preceding train and subsequent train (Case 1)

Fig. 15. Train headway diagram of preceding train and subsequent train (Case 2)
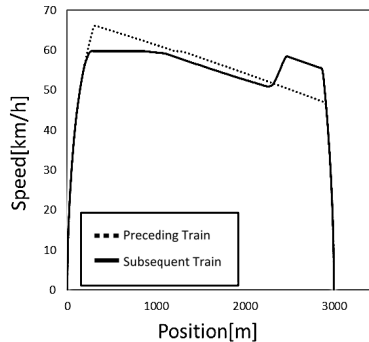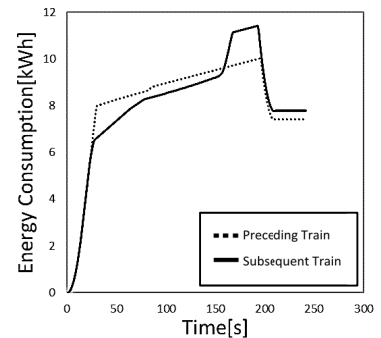

Fig. 16. Running profile of preceding train and subsequent train (Case 2)

Fig. 17. Energy consumption of preceding train and subsequent train (Case 2)
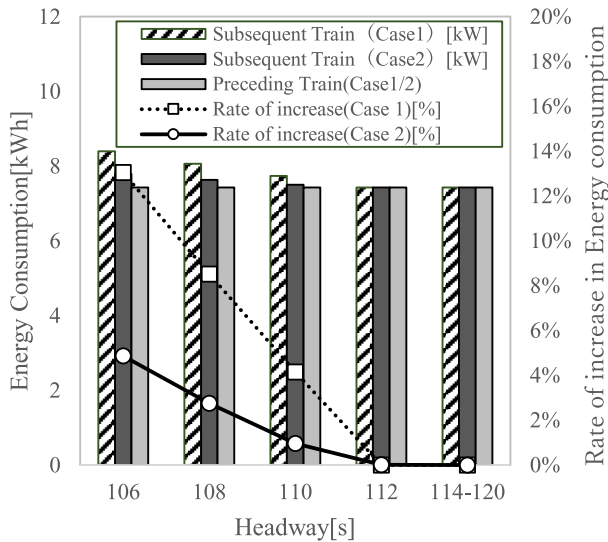
Fig. 18.　Energy consumption at each train headway

6.　Conclusion

In this study, an energy efficient train trajectory considering the position of the preceding train is calculated utilizing a train trajectory optimization method with dynamic programming. The results show that considering the position of the preceding train is effective for improving energy efficiency compared to the case where the influence of the signaling system is considered as a disturbance.

As the future work, two cases wherein (A) the subsequent train does not arrive at the next station on time, and (B) the position of the preceding train is not completely predictable will be considered. This work focused on the case where the subsequent train arrives on time and can completely predict the position of the preceding train to evaluate the influence of the preceding train's position on the subsequent train's operating profile. However, it is indispensable for a train control system to consider the case where the train does not operate according to a timetable during actual train operation. To develop this energy efficient train trajectory optimization method that is robust enough to implement for actual operation, this type of disturbance will be considered in future work.

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