Master's Thesis
석사 학위논문

An Approach to Handling Irregular Oversaturation in Urban Subway Stations

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Department of
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Advisor: Professor Sang Hyuk Son
Co-advisor: Professor Kyung–Joon Park

by

Minji Kim
Department of Information and Communication Engineering
DGIST

A thesis submitted to the faculty of DGIST in partial fulfillment of the requirements for the degree of Master of Engineering in the Department of Information and Communication Engineering. The study was conducted in accordance with Code of Research Ethics[1]

11. 25. 2019

Approved by

Professor Sang Hyuk Son (signature)
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Professor Kyung-Joon Park (signature)
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[1] Declaration of Ethical Conduct in Research: I, as a graduate student of DGIST, hereby declare that I have not committed any acts that may damage the credibility of my research. These include, but are not limited to: falsification, thesis written by someone else, distortion of research findings or plagiarism. I affirm that my thesis contains honest conclusions based on my own careful research under the guidance of my thesis advisor.

An Approach to Handling Irregular Oversaturation in Urban Subway Stations

Minji Kim

Accepted in partial fulfillment of the requirements for the degree of Master of Engineering.

11. 25. 2019

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ABSTRACT

This thesis presents a data-based approach for a train scheduling that aims to minimize passenger waiting time by controlling train departure time and the number of skipped trains. In contrast to existing approaches that rely on a statistical model of passenger arrival, we develop a model based on real-world automated fare collection (AFC) data from a metro line in Daegu, a Korean city. The model consists of decomposing the travel time for each passenger into waiting, riding, and walking times, clustering of passengers by trains they ride and calculating the number of passengers in each train for any given time. Based on this, for a given train schedule, the passenger waiting time of each passenger for the entire AFC data period can be calculated. The problem is formulated using the model under realistic constraints such as headway, the number of available trains, and train capacity. To find the optimal solution, we employed a genetic algorithm (GA). The results demonstrate that the average waiting time is reduced up to 56% in the highly congested situation. Moreover, letting the trains directly go to the congested station by skipping previous stations further reduces the maximum waiting time by up to 19%. The effect of the optimization varies depending on the passenger arrival pattern of highly congested stations. This approach will improve the quality of the subway services by reducing passenger waiting time.

Keywords: Train timetable, Passenger waiting time, Oversaturated condition, Genetic algorithm.

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I. INTRODUCTION

Due to the advantages of the urban rail systems, including environmentally friendly transportation as well as the capability it provides to travel at a faster and more consistent speed than road-based public transport, there has been an expansion and expected growth of the urban rail transit system. Despite these positive benefits, subway transit is a complex system that integrates both mobility and commercial services where operating costs and service quality is of great importance.

Figure 1. A highly congested subway train.

The service quality of the subway system has a lot to be improved. For example, as shown in Figure 1, highly congested urban rail transit causes a deeply negative experience for passengers about the urban rail system. Occasionally, some passengers are not even able to board because there is no space on the train. The problem is that this is also a disadvantage for the operator. As more passengers accumulate on the platform, more energy is consumed to maintain a more pleasant environment. Given the fact that the heating, ventilation, and air-conditioning (HVAC) system may represent more than 30 percent of the total expenditure which is generally responsible for the highest energy consumption in subway systems [1], it will inevitably increase the energy consumption for train operations which can generate substantial cost. Reducing a few percentages on energy consumption of HVAC systems would save an impressive quantity of electricity.

Therefore, our objective is to reduce the passenger waiting time and the oversaturation time by adjusting the set of train departure times to improve service quality. However, it is difficult to estimate the oversaturation time of the station since the passenger volume inside the coming train is uncertain. Oversaturation time is the time length that at least one passenger at the station is unable to ride an incoming train due to congestion. It is essential to consider the train oversaturation in the train scheduling problem because it directly affects the passenger travel time. As a result, we face a key challenge to estimate the oversaturation time for efficient and practical subway train scheduling. Moreover, counting people without violating the privacy of individuals is also a challenge that must be considered.

To address these challenges, we propose a new approach to handling the train oversaturation problem by optimizing the passenger waiting time by controlling the train departure time from the start terminal station and, if necessary, letting the trains directly go to the congested station skipping previous stations (train skip plan). To estimate the waiting time and oversaturation time, passenger volume information is required to determine if a train is overcrowded. We estimate the passenger volume on the platform and on the train by utilizing the density-based spatial clustering of applications with noise (DBSCAN) [2]. DBSCAN is used for classifying passengers in the same carriage and travel time decomposition [3] for tracking passengers' location by time with automated fare collection (AFC) data. The AFC system is a smart card-based payment and fare collection method which automates the ticketing system for a public transportation network, and it has been widely adopted in many metropolitan cities around the world. Utilizing AFC data is with far less privacy concerns and a cost-effective method compare to existing sensor-based estimation [4][5][6]. In addition, existing researches about the train scheduling considering passenger demand typically use passenger arrival rate of each station rather than use more fine-grained data when calculating the passenger waiting time[7][8].

Specifically, the contributions of this work are as the following:

- To our best knowledge, this is the first work to optimize the subway train scheduling by controlling train departure time and applying the train skip plan by utilizing large scale real traffic data from the AFC system.
- In order to improve the service quality of the urban subway system, train scheduling optimization problem is formulated to minimize the passenger waiting time and oversaturation time
- Our experiment results show that the train skip plan and adjusting the train departure time yield better results in highly congested situations. Especially, to reduce the maximum passenger waiting time, it is desirable for the train to skip certain stations and go straight to the congested station.
- Our experiment results indicate that the degree to which the passenger wait time is reduced depends on the passenger arrival pattern and the objective function applied.

II. RELATED WORK

We provide a summary of previous research close to our work, within the area of passenger volume estimation and train scheduling optimization.

2.1. Passenger Volume Estimation

There have been existing studies that estimate the passenger volume in the subway by using sensor-based approaches such as image sensing [4], CO_2 sensing [5], and Radio Frequency (RF) -based [6] techniques.

To accurately estimate the crowd size, the most standard solutions are using images from the camera [4], However, not only digital cameras are expensive in cost and require high computational overhead, but also, each camera can cover a limited field of view which restraints the system to monitor beyond designated areas. Additionally, the reliability of these techniques can easily be affected by noise in practical settings where lighting levels can vary, and occlusions may be present. Utilizing CO_2 levels [5] is another common approach to estimate the passenger population in subways. Despite the advantages this method has in predicting demand for ventilation with far less privacy concerns than that of utilizing RGB information, the estimation accuracy is low and, hence, the approach does not significantly support in predicting cooling or warming demands. There are also techniques for estimating the number of people using RF sensing [6]. Although various wireless devices can easily obtain signal strength many factors must be taken into account such as diffraction, multi-path, reflection issues. Overall, since the sensors that are used in all of these approaches may not already exist in the subway, separate deployments may be required which require additional cost and maintenance for reliable operation over time.

Those existing methods that estimate the passenger volume not only are privacy-invasive but since the sensors that are used may not already exist in the subway, separate deployments would be required. Additionally, these devices require high computation and are expensive in cost. In this study, we estimate the passenger waiting time and the number of passengers in the subway system using transaction records of AFC data for minimizing privacy concerns that people might have.

2.2. Train Scheduling Optimization

Mathematical optimization is the most popular method of solving the train scheduling problem. Many researchers have proposed lots of subway scheduling optimization models with various objectives such as passenger waiting time minimization [8], energy consumption[8][9] and delay time [10].

In this research, we propose a train timetable scheduling model by considering service quality and operation safety. We compare our approach with three related studies.

Shi et al. proposed a method for optimizing the train timetable considering the oversaturated metro line to minimize total passenger waiting time [11]. Their model does not consider passenger walking time and they assumed that the train running time is pre-given in minute units.

Niu and Zhou presented an integer programming model to adjust train timetables for a heavily congested subway system [12]. Their model requires running time among stations. However, both of these studies do not mention the passenger walking time.

Wang et al. proposed a train scheduling model with the objective of minimizing the total travel time of passengers and the energy consumption of trains [7]. They take into account passenger walking time and even passenger transfer time from other lines. However, they did not evaluate their model with real data. They need the physical distance between two adjacent stations to calculate the train running time and train capacity.

Our approach optimizes the train timetable to minimize the passenger waiting time by placing the number of skipped trains as decision variables as well as the train departure time in heavily congested situations. In contrast to existing approaches [7][8] that rely on a statistical model of passenger arrival, we develop a model based on real-world AFC data in a metro line of Daegu, a Korean city. The train running time between two adjacent stations and the passenger walking time are estimated from the passenger data of the AFC system, and the estimated values are much finer-grained than the existing pre-given data in other studies. Therefore, we can expect more accurate results even if less data is provided in advance.

Moreover, we compare how the optimization effect depends on the passenger arrival pattern. Especially under oversaturation, we classify passenger arrival patterns into single peaks, double peaks, and box-shaped peaks and compare how the decrease in passenger waiting time depends on the objective function such as average waiting time and maximum waiting time for each pattern. Accordingly, the operator may predict how the optimization effect will vary depending on the passenger arrival pattern before applying the optimization.

III. PROPOSED APPROACH

3.1. Overview

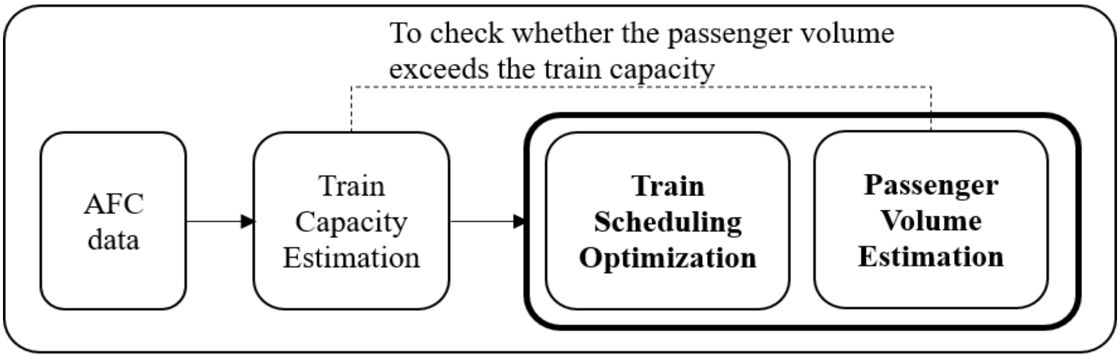


Figure 2. System overview.

The proposed model aims to optimize the train departure time from the first station to minimize passenger waiting time. As shown in Figure 2, our system consists of two major parts: train scheduling optimization and passenger volume estimation. First, we estimate the train capacity. Next, we estimate the passenger volume and optimize the train timetable. While performing optimization, we continuously check whether the passenger volume exceeds the train capacity.

To estimate the train capacity, we have to calculate the passenger waiting time and the passenger walking time for each station and the train running time between two adjacent stations. Those times can be estimated by utilizing the travel information, which is including origin, destination, tap-in/out time of each passenger from the AFC data. To calculate the passenger waiting time, by utilizing the DBSCAN, passengers are clustered to group passengers traveling to the same origin-destination and taking the same train. Passengers with the minimum travel time among passengers in the same group are assumed to have a waiting time of zero. Waiting times for other passengers are obtained by subtracting their travel time from the smallest travel time of who is on the same train and in the same OD group. The passenger walking time for each station is obtained by comparing the smallest travel time between each OD group. Train riding times between two adjacent stations are estimated by comparing minimum travel time for each OD group minus passenger walking times. The train capacity is estimated based on the number of people on the train when the passengers' travel time differs even though passengers enter the station at the same time.

The optimization model is formulated using the passenger waiting time estimated from the data. In the model, train departure times are decision variable and the objective function is to minimize passenger waiting time and oversaturation time. When the passenger volume exceeds the train capacity, the late passengers are set to wait for the next train.

To evaluate the model, we reconstruct the hypothetical passengers using only the origin, destination, and tab-in time of the passenger in the AFC data. Genetic algorithms are used to solve the model. The genetic algorithm changes the train departure time for each iteration to minimize passengers' waiting and oversaturation times.

3.2. Dataset

Our data set is the subway smart card transaction data from AFC from the city of Daegu, Korea. The Daegu City subway has 85 stations (82 if stations connected by transfers are counted as single stations) serving 3 subway lines.

Figure 3. Daegu subway network.

Passenger transaction data from May 02, 2018, to May 29, 2018, was used as the dataset in this study. For the sake of simplicity, we select the 10 stations as the station for optimization and those stations are displayed in Figure 3.

The abbreviation of each station and their average daily boarding and alighting passenger volume for the period are listed in Table 1. We have minimized the waiting time for a single station and for all stations. We will call this the local case and the global case. To address the local case, the DR station was chosen. This is because the DR station is located in a popular residential area and a large park.

Table 1. Average daily ridership (May 2018).

Station number	Station name	Boarding	Alighting
2210	Seongseo Industrial Complex (SSIC)	6,217	6,179
2220	Igok(IG)	4,999	4,484
2230	Yongsan(YS)	9,742	9,429
2240	Jukjeon(JJ)	6,129	6,129
2250	Gamsam(GS)	8,539	7,893
2260	**Duryu(DR)**	**9,439**	**9,912**
2270	Naedang(ND)	4,968	5,000
2280	Banggogae(BGG)	4,638	4,752
2290	Cheongna Hill(CNH)	6,029	5,668
2300	Banwoldang(BWD)	28,929	26,460

3.3. Scenario Analysis

In the subway system, the passenger demand usually varies between the peak-hours and off-peak hours. Generally, the frequency of service trains is increased during peak hours and decreased during off-peak hours. Taking the Daegu subway system as an example, the head-way time for peak hours is 6 minutes and that for off-peak hours is 10 minutes. Therefore, we assume that 10 and 6 trains per hour are available for peak and off-peak hours, respectively.

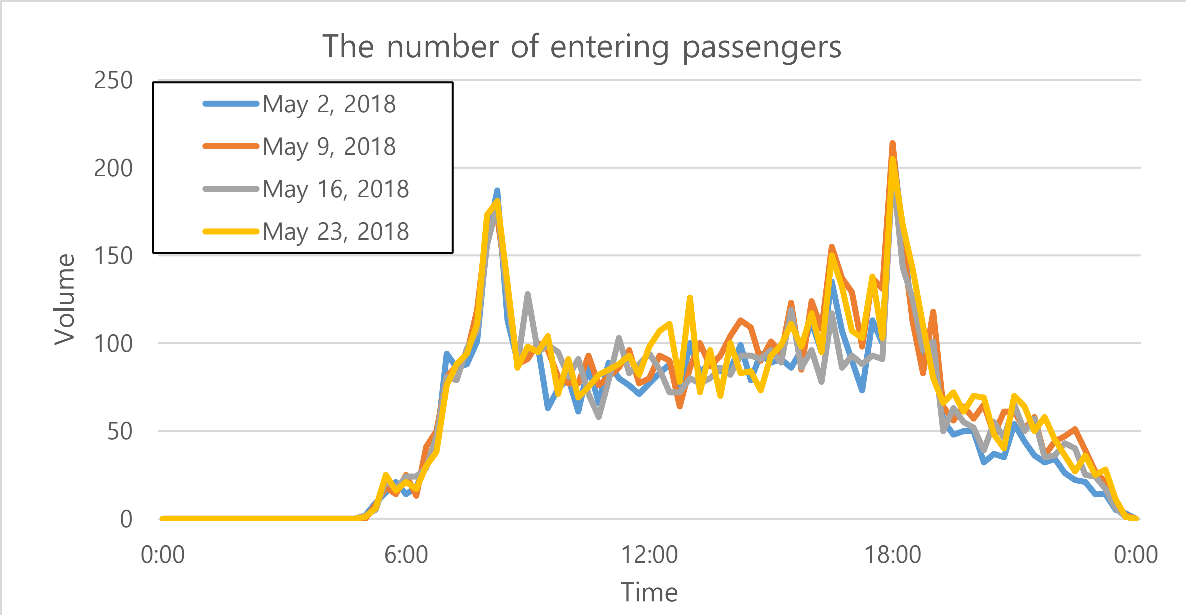


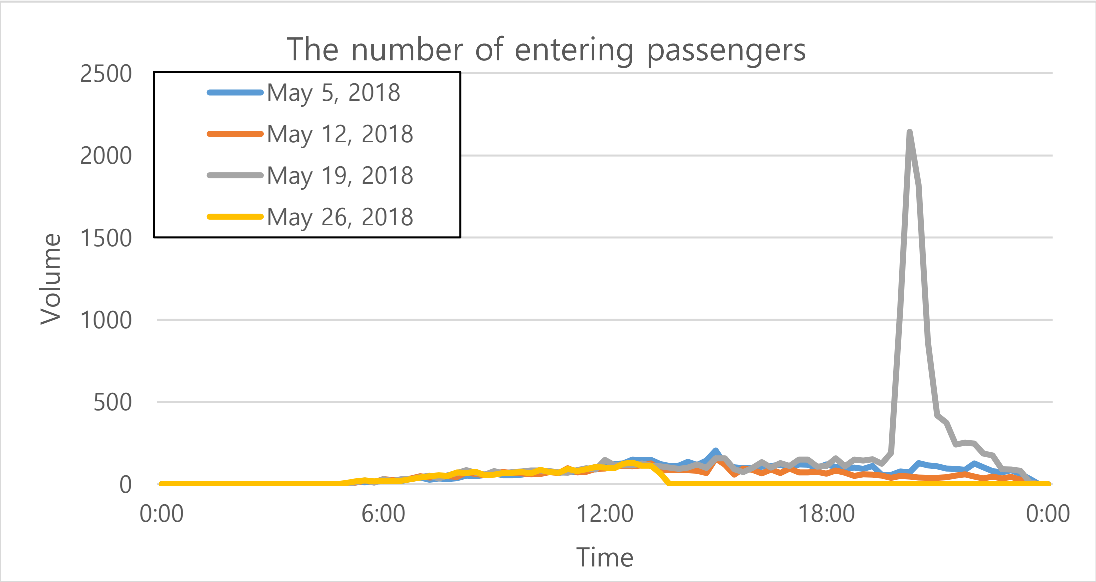
Figure 4. Daily ridership at DR station on Wednesday, May 2018.

3.3.1. Peak hours Scenario

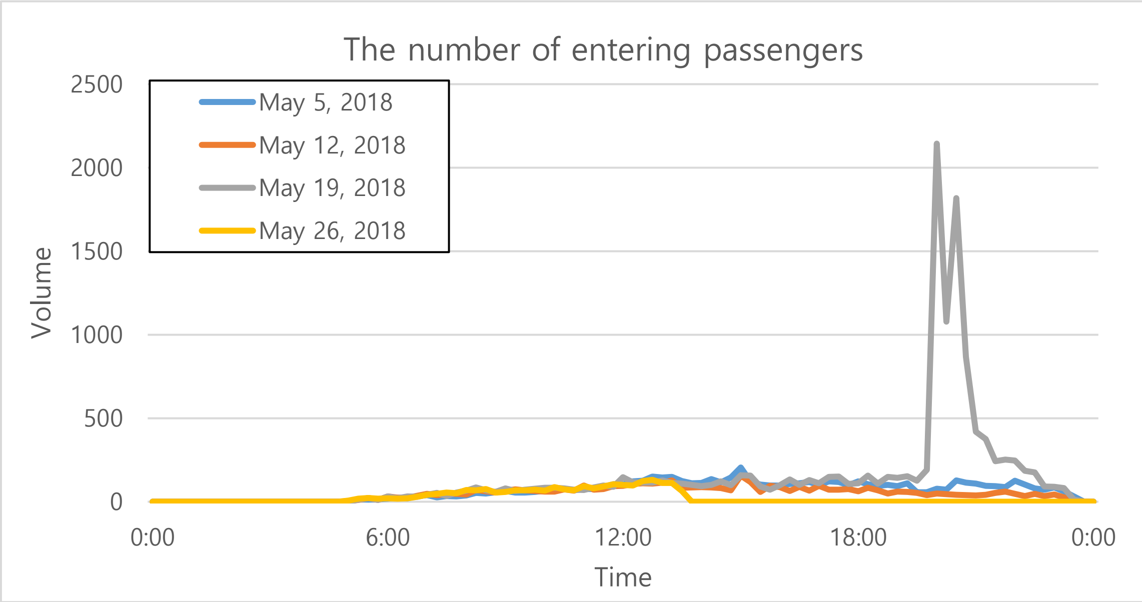
Many commuters take the subway to and from their company and home in the morning and the evening (called peak hours). At the typical peak hours, the passenger demand is steadily higher than ever. And the time interval between trains is shorter than at other times. In the experiment, we used the evening peak on 23 May in the experiment shown in Figure 4.

3.3.2. Congested Off-peak Hours Scenario

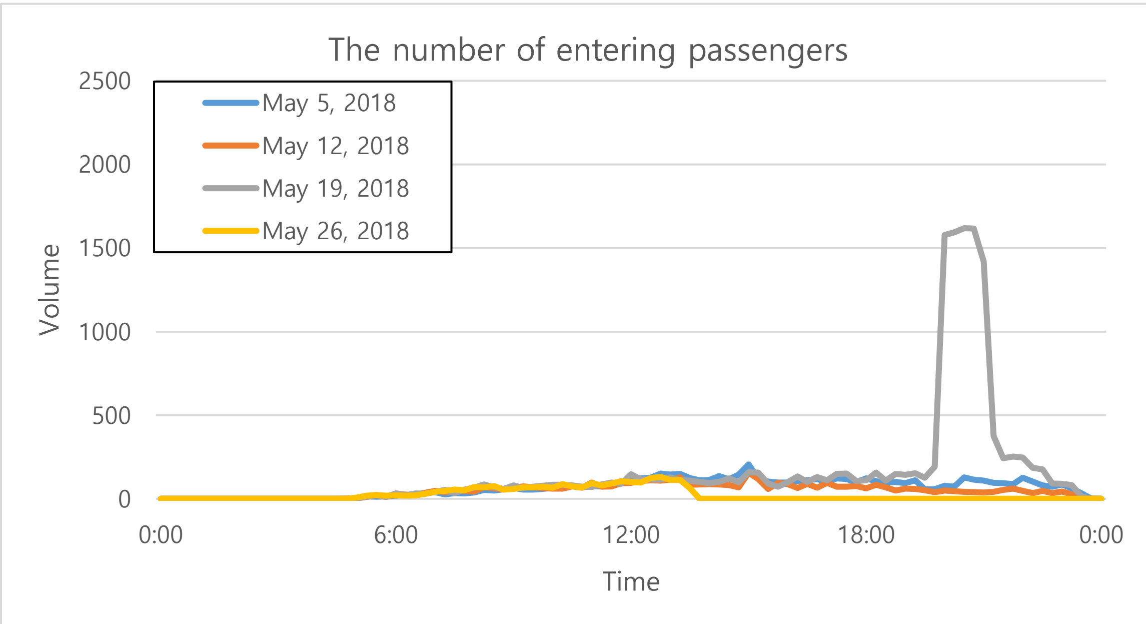
When festivals or concerts are held in certain places, passenger volume at nearby subway stations increases more than other times. Often these events take place during off-peak hours. On May 19, shown in Figure 5(a), a big lantern festival was held in a park near the DR station. The organizer estimated that 20,000 people participated in the festival. The original data for the oversaturation case is shown in Figure 5(a), to evaluate the optimization effect according to the pattern of passenger arrival rate, we synthesized two more passenger data from the original data, which is shown in Figures 5(b) and (c). Figure 5(b) shows the data with double peaks and Figure 5(c) shows the data with a box-shaped peak. With those synthesized data, we compare the effect of the waiting time optimization according to the passenger arrival pattern.



(a)



(b)



(c)

Figure 5. Daily ridership at DR station on Saturday, May 2018 (a) Single peak (SP) scenario (b) Double peak scenario (c) Box-shaped peak scenario.

IV. PROBLEM FORMULATION

4.1. Assumptions

To reduce the complexity of computation, we used passenger data that used only 10 stations in Figure 3. Also, we make several assumptions to make the problem more tractable. Assumptions are explained as follows:

Assumption 1. Each passenger satisfies the first-in-first-out (FIFO) property. Passengers who first enter the subway station earlier can board the train earlier.

Assumption 2. The number of alighting people has no effect on passenger’s walking up/down time.

Assumption 3. The walking time of a normal passenger from the turnstile to the platform is the same as that from the platform to the turnstile.

Assumption 4. The passenger cannot board on the train if the number of passengers in the train exceeds the capacity of the train.

Assumption 5. Passengers are distributed uniformly in each carriage. There is no case that one carriage is oversaturated and there is space for passengers in the other carriages.

The parameters and notations used in this research are summarized in Table 2.

Table 2. Parameters.

Notation	Description
t_{in}	Time a passenger enters a station via turnstile
t_{out}	Time a passenger exits a station via turnstile
t_{on}	Time a passenger enters a train
t_{off}	Time a passenger exits a train
$T_{ij}(t_{in})$	Total travel time from station *i* to station j when a passenger taps in at station *i* at time t_{in}(sec)
T_i^K	Walking time from the platform of station *i* to the turnstile
T_i^D	Dwell time of station *i*
$T_i^W(t_{in})$	Waiting time for a train on the platform when a passenger taps in at station *i* at time t_{in}
T_{ij}^R	Riding time in the train when traveling from station *i* to station *j* (sec)
N_{tr}	Number of available trains on the time horizon
$\tau = \{td_1, td_2, \cdots, td_{N_{tr}}\}$	Set of train departure times (sec)
a_{ik}	Time train *k* arrive at station *i*
$V_k(t, td)$	Passenger volume on train *k* at time *t*
$V_i(t)$	Passenger volume on platform i at time *t*
C_{max}	Maximum capacity of a train
N_{sk}	Number of skipped trains

4.2. Train Capacity

We perform the experiments only in a single subway line. To represent a more realistic situation, train capacity needs to be scaled down. We filter out the passengers who transfer to other lines and it has the same effect as the train capacity becomes larger. Before downsizing the system, it is important to determine how much to reduce train capacity. It is important to determine how much to reduce train capacity. To determine the train capacity, we used the following procedure. First, the train schedule is maintained. Then we adjust the train capacity such that the expected passenger waiting time in the scaled-down system is equal to the average waiting time in the original system. (The procedure for calculating passenger waiting time is described in detail in the next subsection.) Following this process, we resized the train capacity from 1902 to 397 passengers.

4.3. Passenger Volume Estimation

To minimize passenger waiting time, it is necessary to consider the passenger volume and train capacity. This is because the oversaturated train causes long waiting time for passengers and potential accident risks on the platform. In this paper, the oversaturation time is defined as time length that at least one passenger at the station is unable to ride the coming train due to many people on the train. In the following, the detailed passenger volume estimation will be proposed.

4.3.1. Passenger Volume on the Train

In this step, we estimate the passenger volume on the train by utilizing the AFC data. We use the DBSCAN and the travel time decomposition for calculating the passenger volume. The DBSCAN is chosen for clustering passengers on each train because it does not need the number of clusters in the data in advance and it is robust to outliers. The travel time decomposition is employed since it is conceptually simple and requires low computation.

The procedure to estimate the passenger volume is as follows. First, we extract each component of the travel time from the AFC data, such as walking, waiting and riding as shown in Figure 6. When a passenger travels from the station i to the station j, we decompose the travel time of the passenger as

$$T_{ij}(t_{in}) = t_{out} - t_{in} = T_i^K + T_i^W(t_{in}) + T_{ij}^R + T_j^K. \qquad (1)$$

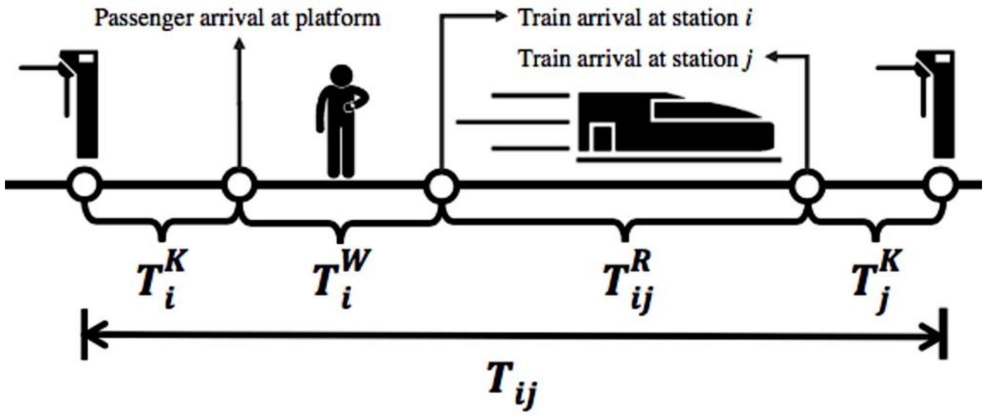


Figure 6. Travel time decomposition.

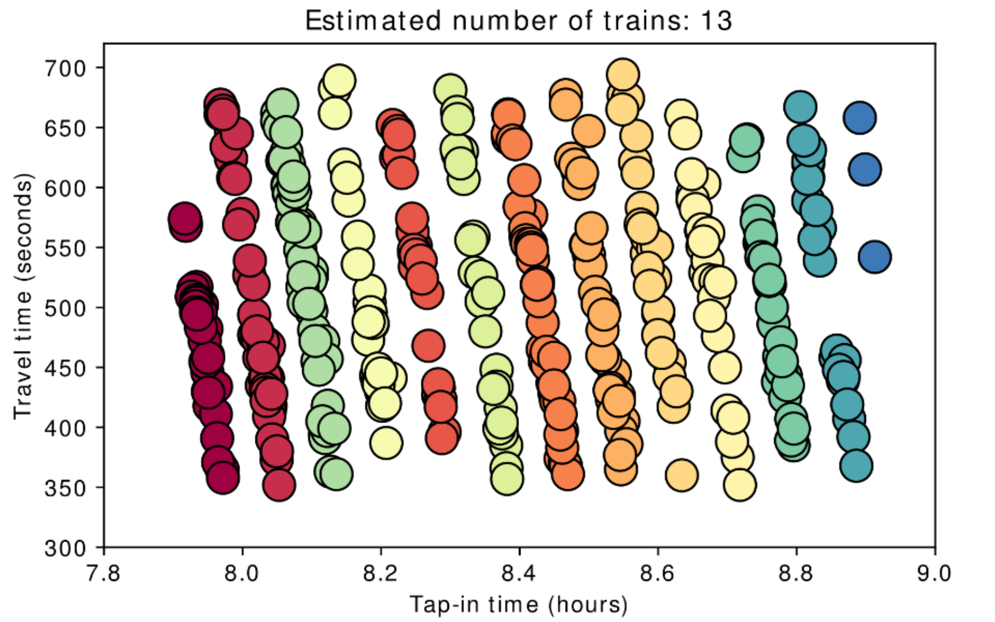


Figure 7. Clustered passengers who traveled from station *i* to station *j*.

In Figure 7, data points that are represented with the same color indicate the passengers riding the same train. We assume that the point with the smallest travel time, denoted by T_{ij}^{*}, in a cluster has zero waiting time. Then, the waiting time of each passenger in the same cluster is calculated by subtracting the smallest travel time from each travel time as follows

$$T_i^W(t_{in}) = T_{ij}(t_{in}) - T_{ij}^*. \tag{2}$$

The same procedure is repeated for other clusters. The trend lines for the clusters is mathematically expressed by the equation

$$y = -x + T_{ij}^* + a_{ik} \ \left(a_{i(k-1)} \leq x \leq a_{ik}\right). \tag{3}$$

The walking time of passenger at station j is obtained by

$$T_j^K = \frac{T_{ij}^* + T_{jk}^* - T_{ik}^* + T_i^D}{2}, \tag{4}$$

when the train travels in the order of the station i, j and k. We assume that the dwell time T_i^D is 30 seconds at peak hours scenario and one minute at off-peak hours scenario.

The riding time is calculated by subtracting walking time and riding time from the travel time as

$$T_{ij}^R = T_{ij}(t_{in}) - T_i^K - T_i^W(t_{in}) - T_j^K. \tag{5}$$

As a result, components of the travel time are obtained for a passenger who is traveling from station i to j who enters station i at t_{in}.

To calculate the number of passengers on each train by using each component of travel time, Heaviside function H(t), defined by 0 when t<0, and by 1 otherwise, is used. Thereafter, the passenger volume on the train is calculated by summing each passenger riding time [9] as

Figure 8 shows the passenger volume in each train obtained from the AFC data.

$$
\begin{aligned}
V_k(t,h) &= \sum_{train=k} H(t-t_{on}) - H(t-t_{off}) \\
&= \sum_{train=k} H(t-t_{on}) - H(t-(t_{on}+T_{ij}^R)\ ) \\
&= \sum_{train=k} \begin{matrix} H\left(t-(t_{in}+T_i^K+T_i^W(t_{in})\right) \\ -H(t-(t_{in}+T_i^K+T_i^W(t_{in})+T_{ij}^R)). \end{matrix}
\end{aligned} \tag{6}
$$

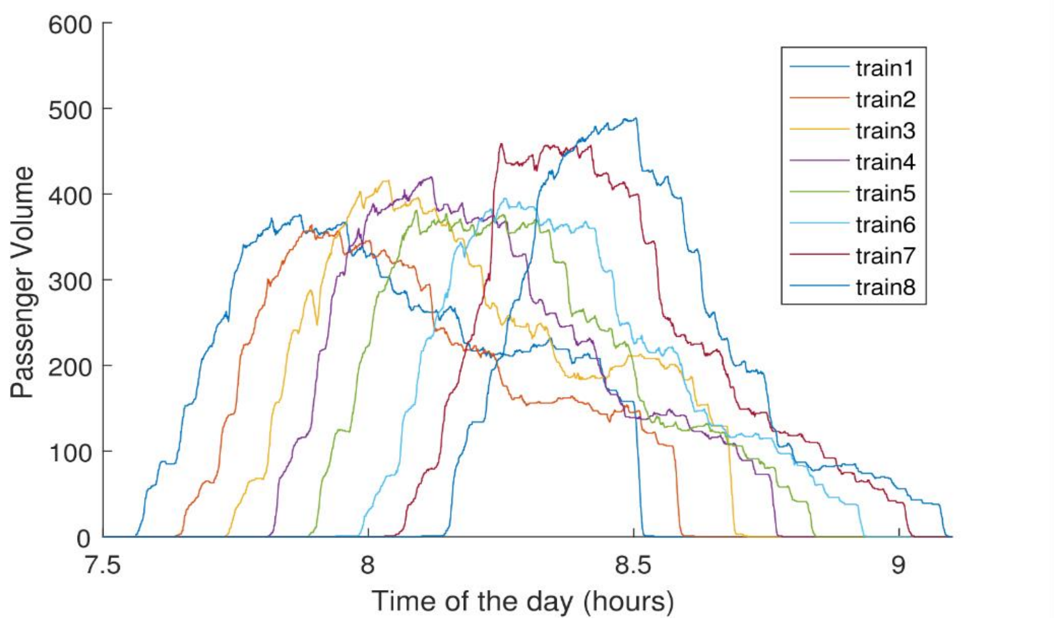


Figure 8. Passenger volume in each train.

4.3.2. Passenger Volume on the Platform

Passenger volume on the platform is used to determine the number of passengers waiting for a train at the station. It is calculated in the same way from Equation (1) to (5). In this case, instead of the riding time in the Equation (6), the walking time and the waiting time of each passenger at the station are summing.

4.4. Timetable Optimization Model

In order to minimize the passenger waiting time and oversaturation time, we develop a model to optimize the train. In this study, we assume that the train speeds are the same as usual. Therefore, the most important decision variables are the departure time of each train at the start terminal. We aim to minimize the average waiting time and the maximum waiting time by controlling the train departure time and applying the train skip plan. The optimization is performed for both local and global cases. The local case minimizes the passenger waiting time of a specific station, while the global case minimizes the passenger waiting time of all stations in the system. In addition, when the oversaturation occurs, we minimize the passenger waiting time and oversaturation time by controlling the train departure time and the number of skipped trains.

4.4.1. Train Departure Time Control

4.4.1.1. Passenger Waiting Time Minimization Problem

The goal is to minimize the passenger waiting time by controlling the set of train departure times. We set the headway constraint to prevent train car collision and long passenger waiting time. The headway is defined as the time interval between trains as follows.

$$h = td_i - td_{i-1} \tag{7}$$

where $i-1$ is the number given to the preceding train and i is the number given to the train immediately following the train $i-1$. We formulated several optimization problems according to the values that should be minimized. When the goal is to minimize the average of the waiting time for passengers at a particular station, the optimization problem for average passenger waiting time is defined as Equation (8) In this problem, the objective function is to minimize the average of the waiting times for passengers at a station *i,* which is called as LAWT (Local Average Waiting Time).

$$\begin{aligned} \min_{\tau = \{td_1, td_2, \cdots, td_{N_{tr}}\}} \quad & \sum T_i^W(t_{in})/V_i(t) \ \text{ for } i \\ \text{subject to} \quad & a \le h \le b, \\ & h = td_j - td_{j-1}, \\ & j = 2, \ldots, N_{tr}, \\ & h \in \mathbb{Z}. \end{aligned} \tag{8}$$

When the goal is to minimize passenger waiting time at all stations in the subway system, then the optimization problem for average passenger wait time is defined as Equation (9). In this problem, the objective function is to minimize the average waiting time of all passengers in the subway system which is called GAWT (Global Average Waiting Time).

$$\min_{\tau = \{td_1, td_2, \cdots, td_{N_{tr}}\}} \sum T_i^W(t_{in})/V_i(t) \quad \text{for } \forall i$$
$$\text{subject to} \quad \begin{aligned} & \mathrm{a} \le h \le \mathrm{b}, \\ & h = td_{\mathrm{j}} - td_{\mathrm{j}-1}, \\ & \mathrm{j} = 2, \ldots, N_{tr}, \\ & h \in \mathbb{Z}. \end{aligned} \tag{9}$$

When the goal is to minimize the maximum passenger waiting time for a particular station, the optimization problem for maximum passenger wait time is defined as Equation (10). The objective function is to minimize the maximum value of waiting times for passengers whose station *i* is the origin, which is called LMWT (Global Maximum Waiting Time).

$$\min_{\tau = \{td_1, td_2, \cdots, td_{N_{tr}}\}} \max\{\, T_i^W(t_{in}) \,\} \quad \text{for } i$$
$$\text{subject to} \quad \begin{aligned} & \mathrm{a} \le h \le \mathrm{b}, \\ & h = td_{\mathrm{j}} - td_{\mathrm{j}-1}, \\ & \mathrm{j} = 2, \ldots, N_{tr}, \\ & h \in \mathbb{Z}. \end{aligned} \tag{10}$$

To minimize the maximum passenger waiting time in the subway system, the optimization problem for maximum passenger wait time is defined as Equation (11). The objective function is to minimize the maximum waiting times for passengers at all stations in the subway system. This is called GMWT (Global Maximum Waiting Time).

$$\min_{\tau = \{td_1, td_2, \cdots, td_{N_{tr}}\}} \max\{\ T_i^W(t_{in})\ \}\ \text{ for }\ \forall i$$
$$\text{subject to}\quad \begin{aligned} & a \le h \le b, \\ & h = td_j - td_{j-1}, \\ & j = 2, \ldots, N_{tr}, \\ & h \in \mathbb{Z}. \end{aligned} \tag{11}$$

The decision variable in this optimization problem is the set of train departure times. The relationship between the passenger waiting time and the train departure time is expressed as Equation (12). The passenger waiting time for passengers who entered at t_{in} in station i is obtained by subtracting the sum of the time that the passenger entered the station and passenger walking time from the sum of the train departure time at first terminal and time length that the train ran from the first terminal to station i.

$$\begin{aligned} T_i^W(t_{in}) &= td_k + T_{ai}^R - (t_{in} + T_i^K) \\ & \text{for}\quad td_{k-1} + T_{ai}^R < t_{in} + T_i^K \\ & \qquad \le td_k + T_{ai}^R\ ;\, a > 1;\ i > a. \end{aligned} \tag{12}$$

4.4.1.2. Oversaturation Time Minimization Problem

When oversaturation occurs, we control the train departure time to minimize the oversaturation. The oversaturated time (OST) is the time length that at least one passenger at the station is unable to ride the incoming train because the train is in full capacity. OST is defined as :

$$\text{OST} = td_i - td_{i-j} \qquad \text{for } i = 2, 3, \ldots, N_{tr}. ;\ i - j > 1 ;\ C_{max} < V_k(t) \text{ for } \exists k. \tag{13}$$

Oversaturation time minimization is only performed when the passenger volume in the train exceeds the train maximum capacity. As with waiting time optimization, there is a headway constraint to prevent car crashes and long waits for passengers. The optimization problem to minimize the oversaturation time is expressed as follows.

$$\begin{aligned} \min_{\tau = \{td_1, td_2, \cdots, td_{N_{tr}}\}} \quad & td_i - td_{i-j} \\ \text{subject to} \quad & a \le h \le b, \\ & h = td_j - td_{j-1}, \\ & h \in \mathbb{Z}, \\ & i = 2, 3, \ldots, N_{tr}, \\ & j = 2, 3, \ldots, N_{tr}, \\ & i - j > 0, \\ & C_{max} < V_k(t, td) \text{ for } \exists k, \\ & N_{sk} < N_{tr}. \end{aligned} \tag{14}$$

4.4.2. Train Skip Plan Control

When oversaturation occurs at a particular station, the oversaturation time and passenger waiting time can be reduced by letting the trains directly go to the congested station by skipping previous stations. In the optimization problem to minimize passenger waiting time and oversaturation time, the decision variable is the number of trains that skip previous stations. Other parts of the equation, such as decision variables and objective functions and constraints, are similar to Equations (8)-(11) with different constraints. The optimization for LAWT is expressed in Equation (15) and the optimization for GAWT, LMW, GMWT, and OST are expressed in Equations (16)-(19) respectively.

$$\min_{N_{sk},\ \tau=\{td_1, td_2, \cdots,\ td_{N_{tr}}\}} \sum T_i^W(t_{in})/V_i(t) \text{ for } i$$

$$\text{subject to} \quad \begin{aligned} & \mathrm{a} \le h \le \mathrm{b}, \\ & h \in \mathbb{Z}, \\ & h = td_{\mathrm{j}} - td_{\mathrm{j}-1}, \\ & \mathrm{i} = 2, 3, \ldots, \mathrm{N_{tr}}, \\ & \mathrm{j} = 2, 3, \ldots, \mathrm{N}_{tr}, \\ & \mathrm{i} - \mathrm{j} > 0, \\ & C_{max} < V_k(t, td) \text{ for } \exists k, \\ & N_{sk} < N_{tr}. \end{aligned} \tag{15}$$

$$\min_{N_{sk},\ \tau=\{td_1, td_2, \cdots,\ td_{N_{tr}}\}} \sum T_i^W(t_{in})/V_i(t) \text{ for } \forall i$$

$$\text{subject to} \quad \begin{aligned} & \mathrm{a} \le h \le \mathrm{b}, \\ & h \in \mathbb{Z}, \\ & h = td_{\mathrm{j}} - td_{\mathrm{j}-1}, \\ & \mathrm{i} = 2, 3, \ldots, \mathrm{N_{tr}}, \\ & \mathrm{j} = 2, 3, \ldots, \mathrm{N}_{tr}, \\ & \mathrm{i} - \mathrm{j} > 0, \\ & C_{max} < V_k(t, td) \text{ for } \exists k, \\ & N_{sk} < N_{tr}. \end{aligned} \tag{16}$$

$$
\min_{N_{sk},\ \tau=\{td_1, td_2, \cdots,\ td_{N_{tr}}\}} \quad \max\{\ T_i^W(t_{in})\ \}\ \text{ for } \ i
$$

$$
\text{subject to} \quad
\begin{aligned}
& \mathrm{a} \le h \le \mathrm{b}, \\
& h\ \in \mathbb{Z}, \\
& h =\ td_{\mathrm{j}}\ -\ td_{\mathrm{j}-1}, \\
& \mathrm{i} = 2, 3, \ldots ,\ \mathrm{N_{tr}}, \\
& \mathrm{j} = 2, 3, \ldots,\ \mathrm{N}_{tr}, \\
& \mathrm{i} - \mathrm{j} > 0, \\
& C_{max}\ <\ V_k(t, td)\ \text{ for } \exists k, \\
& N_{sk}\ <\ N_{tr}.
\end{aligned}
\tag{17}
$$

$$
\min_{N_{sk},\ \tau=\{td_1, td_2, \cdots,\ td_{N_{tr}}\}} \quad \max\{\ T_i^W(t_{in})\ \}\ \text{ for } \ \forall i
$$

$$
\text{subject to} \quad
\begin{aligned}
& \mathrm{a} \le h \le \mathrm{b}, \\
& h\ \in \mathbb{Z}, \\
& h =\ td_{\mathrm{j}}\ -\ td_{\mathrm{j}-1}, \\
& \mathrm{i} = 2, 3, \ldots ,\ \mathrm{N_{tr}}, \\
& \mathrm{j} = 2, 3, \ldots,\ \mathrm{N}_{tr}, \\
& \mathrm{i} - \mathrm{j} > 0, \\
& C_{max}\ <\ V_k(t, td)\ \text{ for } \exists k, \\
& N_{sk}\ <\ N_{tr}.
\end{aligned}
\tag{18}
$$

$$
\begin{aligned}
&\min_{N_{sk},\ \tau = \{td_1, td_2, \cdots,\ td_{N_{tr}}\}} && td_i - td_{i-j} \\
&\text{subject to} && a \le h \le b, \\
& && h \in \mathbb{Z}, \\
& && h = td_{\mathrm{j}} - td_{\mathrm{j-1}}, \\
& && \mathrm{i} = 2, 3, \ldots,\ \mathrm{N_{tr}}, \\
& && \mathrm{j} = 2, 3, \ldots,\ \mathrm{N}_{tr}, \\
& && \mathrm{i} - \mathrm{j} > 0, \\
& && C_{max} < V_k(t, td) \ \text{for}\ \exists k, \\
& && N_{sk} < N_{tr}.
\end{aligned}
\tag{19}
$$

4.5.1. Genetic Algorithm

To solve the formulated problem, we apply the genetic algorithm (GA) [13]. GA is a heuristic search algorithm to optimize problems based on natural evolution. GA is widely applied in the train scheduling researches [14][15]. It is because GA has the advantage of requiring less computational resources and being able to perform very large calculations in a relatively short time compared to mathematical formulation approaches such as neural networks.

Table 3. Pseudocode for Genetic algorithm.

```
Function Genetic Algorithm (POP_SIZE, START, END, GENERATION, AVAILABLE_TRAIN)
As Train Scheduling
```

```
Begin
    P = Generate_Initial_Population(POP_SIZE, START, END, AVAILABLE_TRAIN)
    for i = 1 to GENERATION step 1 do
        S = Selection(P)
        C = Crossover(S)
        M = Mutation(S)
        P = S + C + M
        if i == (GENERATION-1):
            BEST_SOLUTION = Evaluate(P)
    return BEST_SOLUTION
end
```

This algorithm is applied to our research as follows. First, an initial population called P is generated when we enter the inputs such as the time window of the scheduling and the number of available trains. Each initial population is modified by applying selection, crossover, and mutation procedures. These procedures are repeated for the given generation number. If there are n solutions in the parent population, the offspring population is composed by sum of three small populations: 1) *x* selected individuals whose the fitness value, that is evaluated by the fitness function, is greater than other individuals 2) *y* individuals with crossover operation applied to the selected individuals and 3) *n-x-y* individuals with mutation operation applied to selected individual. In this experiment, two of 10 individuals were selected, four individuals crossed over, and four were mutated. During the last iteration, each individual in the population is evaluated and the solution with low waiting time (or lowest oversaturation time) is returned with the best solution.

V. EVALUATION

In order to evaluate the performance of our system, we optimize local average waiting time (LAWT), global average waiting time (GAWT), local maximum waiting time (LMWT) and global maximum waiting time (GMWT) by controlling the train departure time from the start terminal station. We evaluate the improvement for two scenarios: peak hours and congested off-peak hours. To evaluate the effect of the train skip plan, we figure out the improvement of the waiting time and oversaturation time (OST) by skipping the first 0 to 3 trains out of 6 trains operated over an hour especially in the oversaturated train scenario. We also optimize OST and then evaluate how much OST, LAWT, GAWT, LMWT, and GMWT have been decreased. All results improvement is expressed as *(old(seconds) – new(seconds)) / old (seconds) * 100 %* .

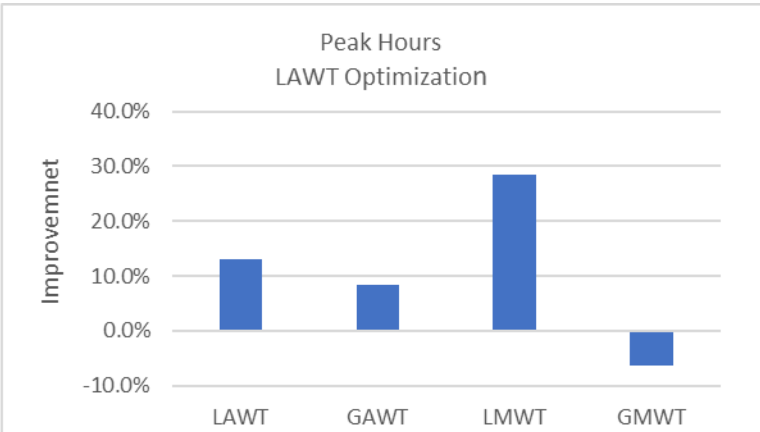
We estimated from the AFC data that there were 10 trains per hour during peak hours and 6 trains per hour during off-peak hours. The experiment was carried out with the same number of trains. To prevent car crashes and long waiting times, the minimum headway was constrained to 3 minute and the maximum headway was constrained to 15 minutes. To solve the problem, each genetic algorithm takes 100 iterations to reach the optimal solution. Each optimization was performed 5 times and more detailed experimental results are in Appendix A.

5.1. Peak hours scenario

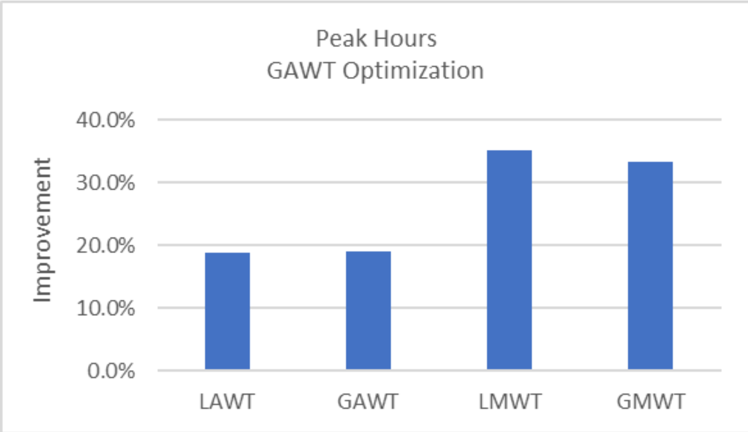
In peak hours scenarios, GAWT and LAWT are decreased by 19% and GMWT by 35% and it is most desirable to use GAWT as an objective function to reduce both AWT and MWT.

Note that LAWT is significantly reduced when GAWT is minimized compare to the case when LAWT is used as an objective function. As shown in Figure 9(a), when LAWT is minimizing, LAWT is reduced by 13%. However, in Figure 9(b) when GAWT is minimizing, LAWT is reduced by 19%. This is due to the fact that the optimization result is more likely to get stuck in a local minimum because the amount of the data used in the calculation when LAWT is used as an objective function is less than that of GAWT.

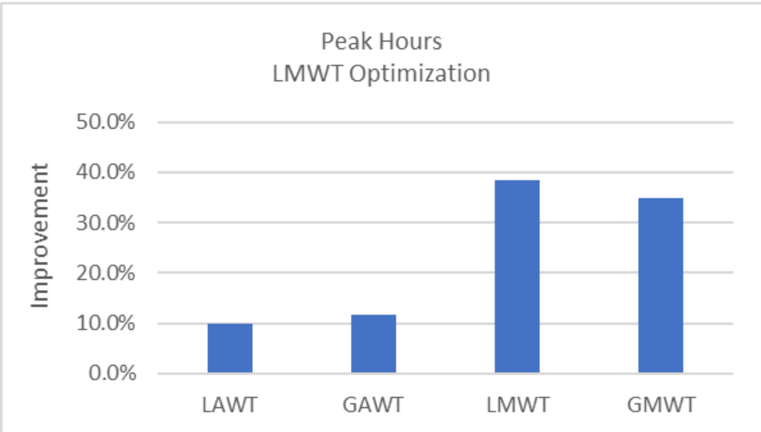
In Figure 9(a) and (b), MWT is decreased by up to 35% when minimizing AWT. However, when minimizing MWT, AWT is decreased by up to 10% in Figure 9(c), and sometimes AWT is increased as shown in Figure 9(d). This is because the objective function for AWT is to utilize the entire passenger data, whereas the objective function for MWT is to use only one passenger data of maximum waiting time.



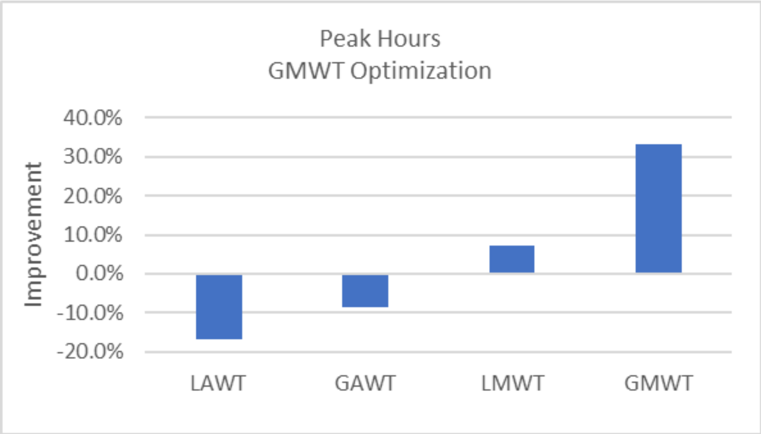
(a)


Peak Hours
GAWT Optimization
40.0%
30.0%
20.0%
10.0%
0.0%
Improvement
LAWT
GAWT
LMWT
GMWT

(b)


Peak Hours
LMWT Optimization
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
Improvement
LAWT
GAWT
LMWT
GMWT

(c)



(d)

Figure 9. Improvement comparison of waiting time by types of optimization at peak hours scenario. (a) Local average waiting time optimization (b) Global average waiting time optimization (c) Local maximum waiting time optimization (d) Global maximum waiting time optimization

5.2. Congested off-peak hours scenario

In the oversaturation scenario, we minimized AWT or MWT depending on the number of trains skipped out of six trains, along with the departure time of each train. Figures 10 to 12 indicate the outcome evaluations on the train scheduling optimization of saturated scenario.

The number of passengers in Figures 10 to 12 is the same, but the passenger arrival pattern differs by a single peak, double peak, and box-shaped peak, respectively. Each figure shows that even if the number of boarding passengers is the same, the effect of optimization can be different according to the passenger arrival pattern.

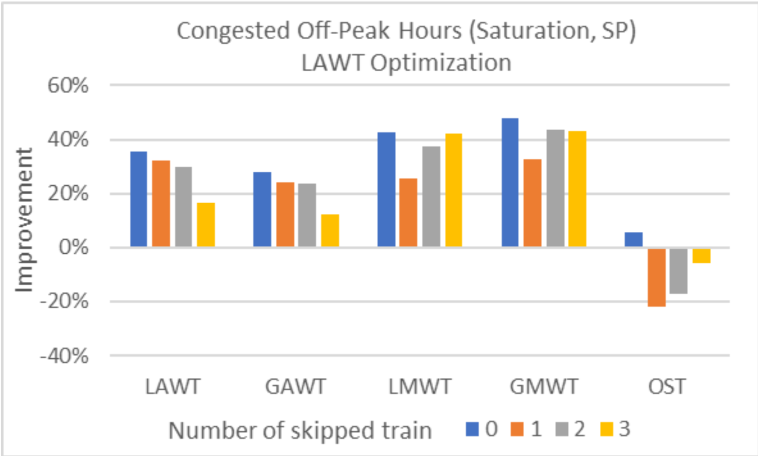
5.2.1. Single peak oversaturation

In the single peak oversaturation case, as shown in Figure 10(b), AWT is decreased by up to 36% and MWT by up to 56% when using GAWT as an objective function. In Figure 10(a), When minimizing LAWT, AWT is reduced up to 36%, which does not show a significant difference when compared with minimizing GAWT.

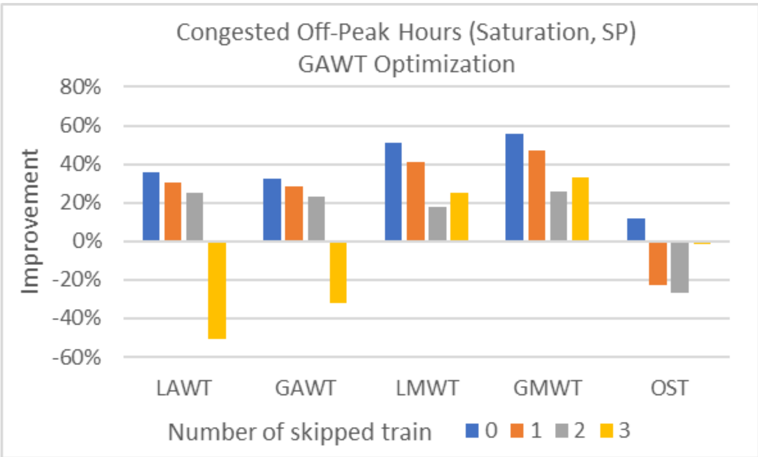
It is desirable to use AWT than MWT as the objective function to decrease both AWT and MWT with low computation at the single peak case. As shown in Figures 10(a) to (b), MWT is reduced when AWT was minimized but Figures 10(c) and (d) represent that AWT was increased when MWT was minimized. This is presumably because the headway is reduced on a single peak with the highest passenger arrival rate, and the waiting time for people arriving at the train station is longer when it is relatively less crowded. In addition, MWT is significantly reduced when AWT is the objective function than when MWT is the objective function. In Figure 10(d), LMWT and GMWT are decreased by 37% and 42%, respectively, while when the objective function is GAWT they are decreased by 51% and 56%, respectively as shown in Figure 10(b). This is because minimizing MWT requires more iterations in the GA than minimizing AWT.

When comparing GAWT and LAWT as the objective function of the optimization, GAWT yielded slightly better performance. As shown in Figure 10(b), LAWT and GAWT are decreased by 36% and 33%, respectively, when GAWT was objective function, and when LAWT was objective function LAWT and GAWT is decreased by 36% and 28% respectively which is shown in Figure 10(a). In addition, OST is also reduced by 12% when GAWT is the objective function while with LAWT it is reduced by 6%.

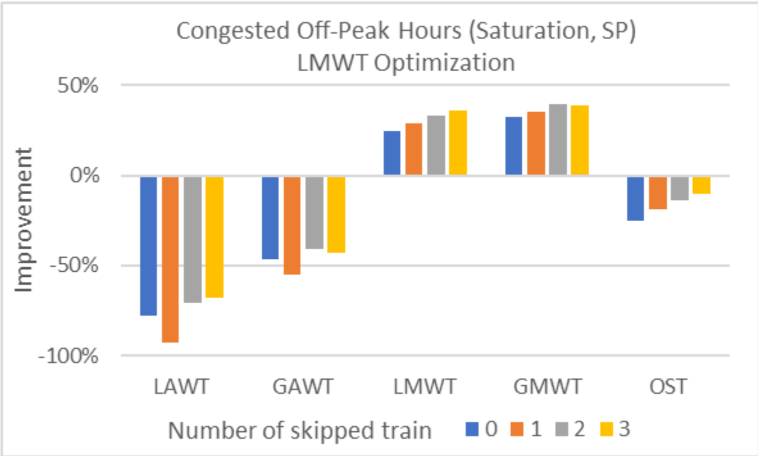
Minimizing oversaturation time has very little to do with minimizing the waiting time. As shown in Figure 10(e), OST is reduced by up to 37% when OST is the objective function. However, AWT is increased by up to 80%, and MWT is decreased up to 13%.


Congested Off-Peak Hours (Saturation, SP)
LAWT Optimization
60%
40%
20%
0%
-20%
-40%
Improvement
LAWT
GAWT
LMWT
GMWT
OST
Number of skipped train
0
1
2
3

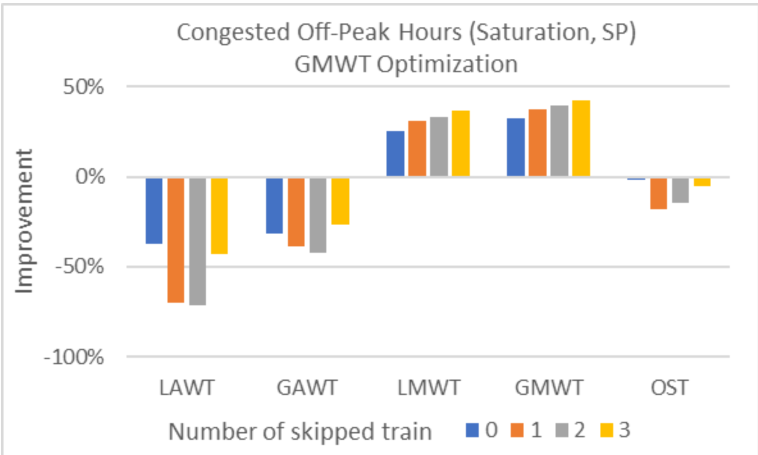
(a)


Congested Off-Peak Hours (Saturation, SP)
GAWT Optimization
80%
60%
40%
20%
0%
-20%
-40%
-60%
Improvement
LAWT
GAWT
LMWT
GMWT
OST
Number of skipped train
0
1
2
3

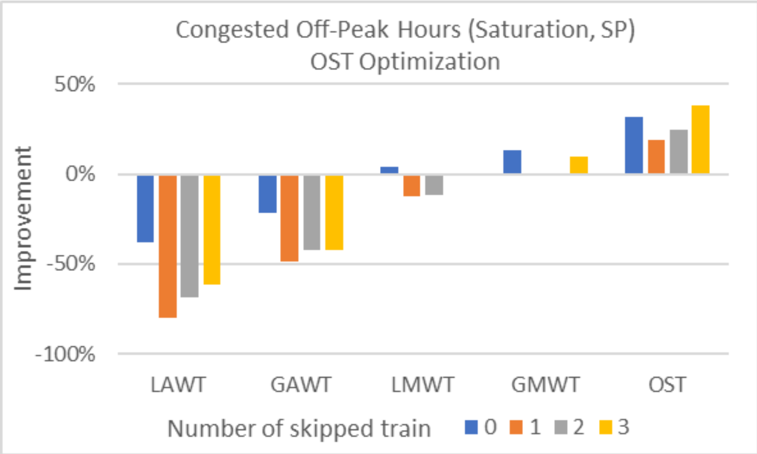
(b)


Congested Off-Peak Hours (Saturation, SP)
LMWT Optimization
50%
0%
-50%
-100%
Improvement
LAWT
GAWT
LMWT
GMWT
OST
Number of skipped train
0
1
2
3

(c)


Congested Off-Peak Hours (Saturation, SP)
GMWT Optimization
50%
0%
-50%
-100%
Improvement
LAWT
GAWT
LMWT
GMWT
OST
Number of skipped train
0
1
2
3

(d)



(e)

Figure 10. Improvement comparison of waiting time and oversaturation time by types of optimization at congested off-peak hours scenario (Single peak oversaturation). (a) Local average waiting time optimization (b) Global average waiting time optimization (c) Local maximum waiting time optimization (d) Global maximum waiting time optimization (e) Oversaturation time optimization.

5.2.2. Double peak oversaturation

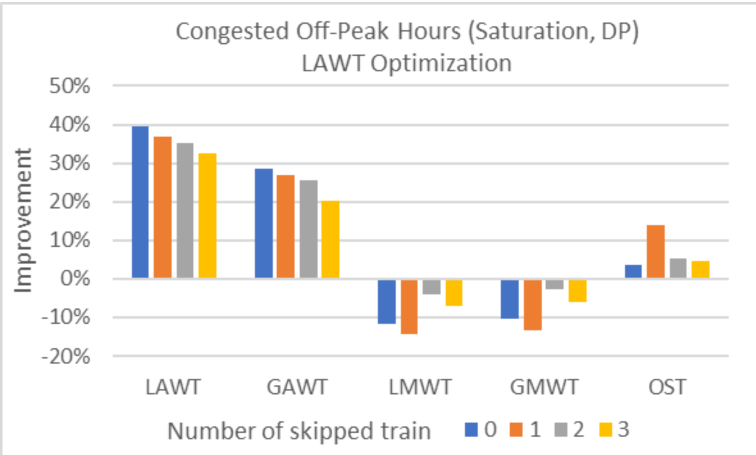
In the double peak oversaturation scenario, as shown in Figure 11 (a), LAWT and GAWT are decreased by up to 39% and 29% respectively and GMWT is decreased by 22% in Figure 11(d).

Note that MWT is increased when AWT is minimized shown in Figures 11(a) and (b). This is because that MWT increases by the time distance between two peaks. Therefore, minimizing AWT does not help reduce MWT when there is a large time interval between peaks.

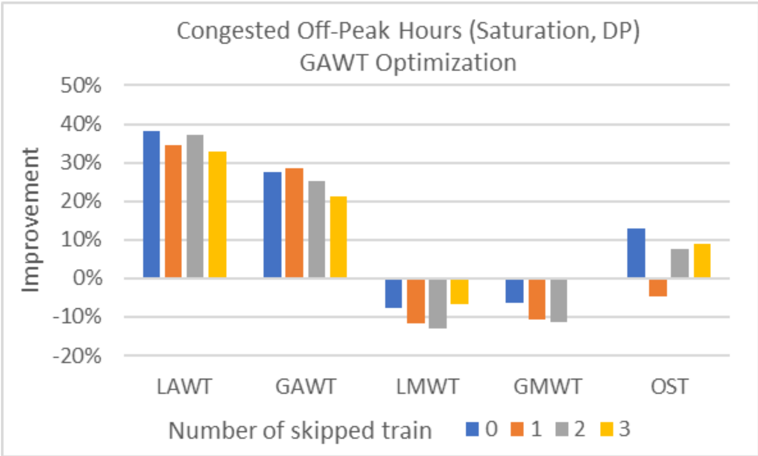
In Figures 11(c) and (d), OST is decreased by 55% when using MWT as the objective function, especially GMWT as the objective function. Using OST as the objective function in

Figure 11(e), OST is decreased by 53%, but AWT and MWT are increased. Therefore, in order to minimize AWT, MWT and OST, it is most desirable to use each of them as an objective function.

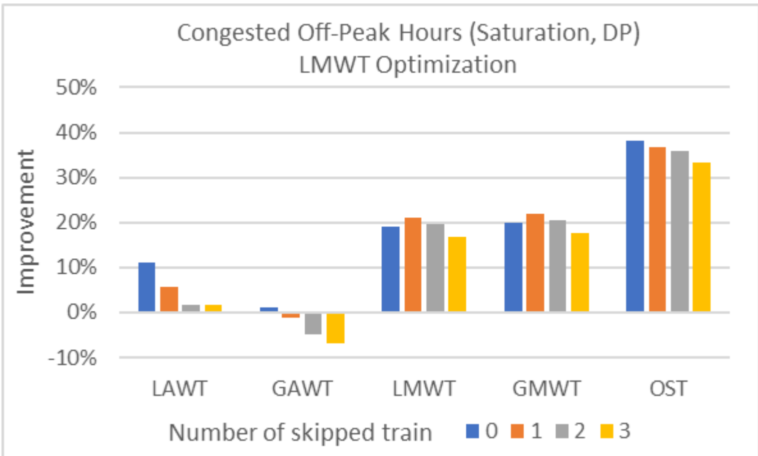
Figures 11(a) to (d) indicate that the number of skipped trains that minimizes AWT and MWT is different. To reduce AWT, we do not need to skip the train, but it is desirable to skip the train to reduce MWT further. Figure 11(e) presents minimizing oversaturation time does not help reduce the waiting time.



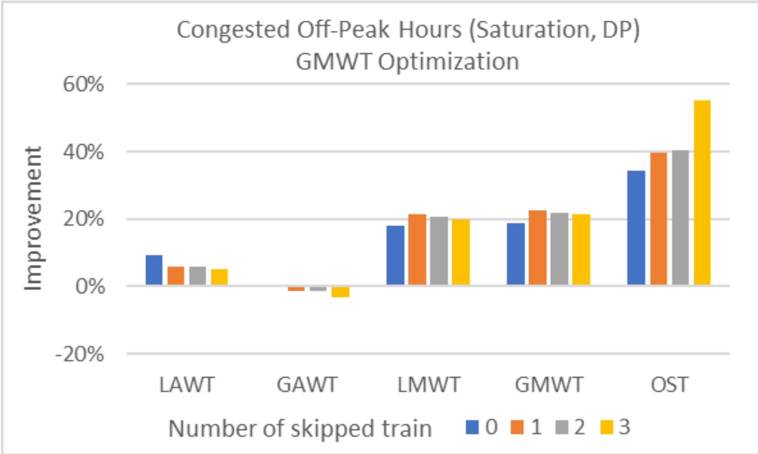
(a)


Congested Off-Peak Hours (Saturation, DP)
GAWT Optimization
50%
40%
30%
20%
10%
0%
-10%
-20%
Improvement
LAWT
GAWT
LMWT
GMWT
OST
Number of skipped train
0
1
2
3

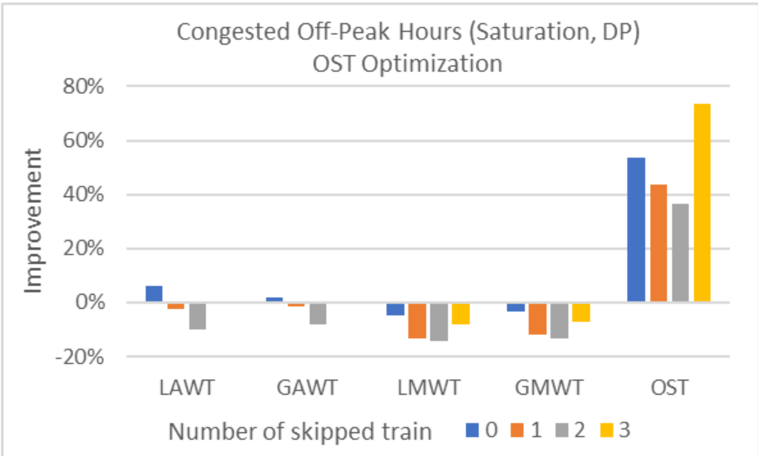
(b)


Congested Off-Peak Hours (Saturation, DP)
LMWT Optimization
50%
40%
30%
20%
10%
0%
-10%
Improvement
LAWT
GAWT
LMWT
GMWT
OST
Number of skipped train
0
1
2
3

(c)



(d)



(e)

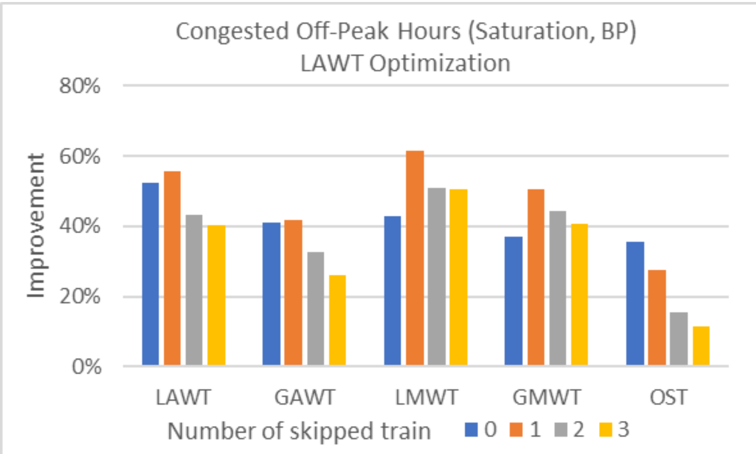
Figure 11. Improvement comparison of waiting time and oversaturation time by types of optimization at congested off-peak hours scenario (Double peak oversaturation). (a) Local average waiting time optimization (b) Global average waiting time optimization (c) Local maximum waiting time optimization (d) Global maximum waiting time optimization (e) Oversaturation time optimization.

5.2.3. Box-shaped peak oversaturation

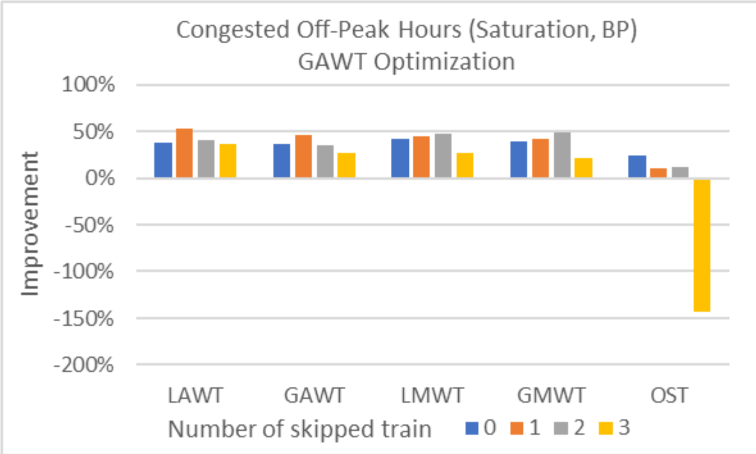
In the box-shaped peak oversaturation scenario, LAWT and GAWT are decreased by up to 56% and 47% respectively in Figures 12(a) and (b). As shown in Figure 12(c) GMWT is decreased by up to 42% when one train is skipped.

As shown in Figures 12(a) to (d), whatever the objective function is, all variables are decreased together. This is because train arrival intervals are optimized on a regular basis as passenger arrival rates are nearly constant by time.

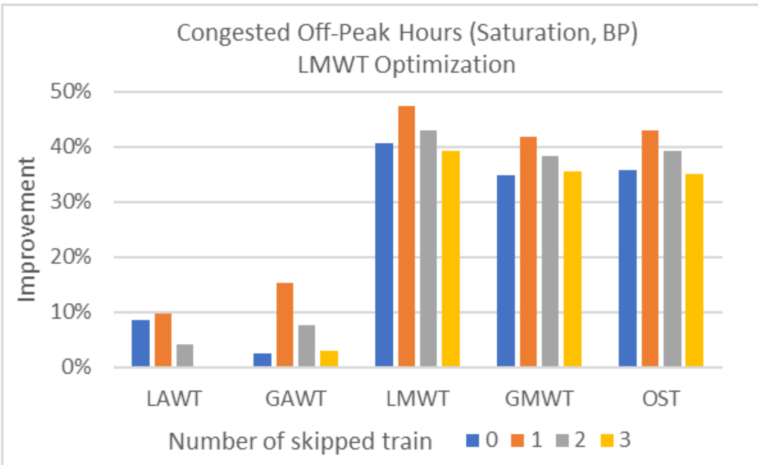
Figure 12(e) indicates that minimizing OST reduces MWT by up to 38% and increases AWT by up to 26%.



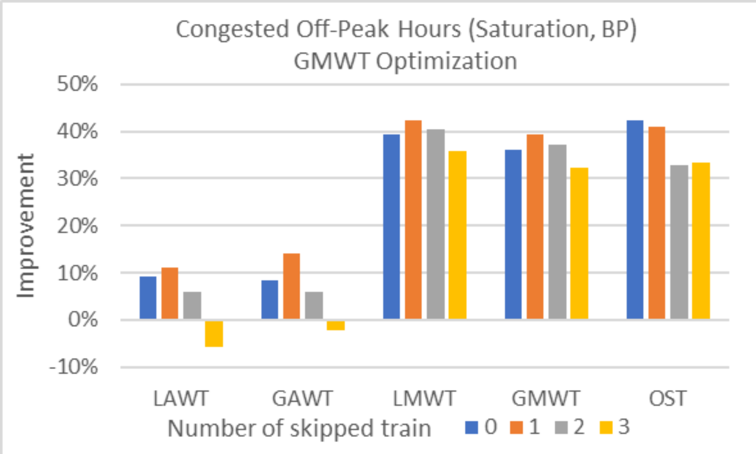
(a)


Congested Off-Peak Hours (Saturation, BP)
GAWT Optimization
100%
50%
0%
-50%
-100%
-150%
-200%
Improvement
LAWT
GAWT
LMWT
GMWT
OST
Number of skipped train
0
1
2
3

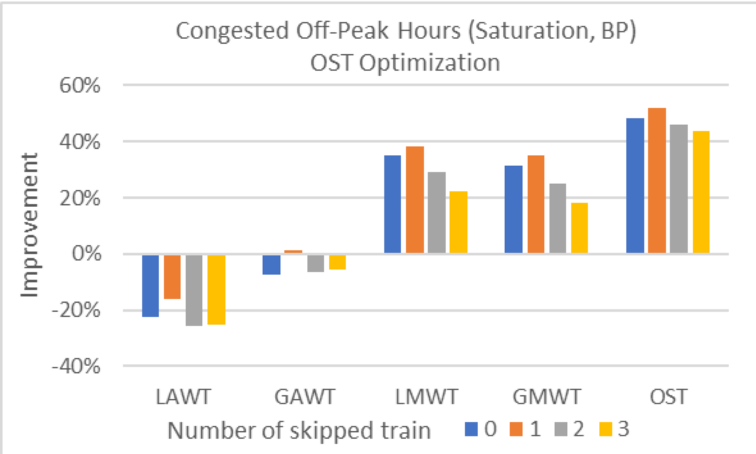
(b)


Congested Off-Peak Hours (Saturation, BP)
LMWT Optimization
50%
40%
30%
20%
10%
0%
Improvement
LAWT
GAWT
LMWT
GMWT
OST
Number of skipped train
0
1
2
3

(c)



(d)



(e)

Figure 12. Improvement comparison of waiting time and oversaturation time by types of optimization at congested off-peak hours scenario (Box-shaped peak oversaturation). (a) Local average waiting time optimization (b) Global average waiting time optimization (c) Local maximum waiting time optimization (d) Global maximum waiting time optimization (e) Oversaturation time optimization.

5.3. Discussion

We found that the effect of optimization on the objective function varies according to the passenger arrival pattern. In particular, the effectiveness of optimization in a congested situation depends on the uniformity of the passenger arrival pattern of the congested local station. In the oversaturation of the box-shaped peak, whichever is chosen as the objective function, AWT and MWT are minimized together because the arrival rate of passengers is uniform which is shown in Figure 12. On the other hand, AWT and MWT do not decrease together when the passenger arrival pattern is not uniformly distributed such as single-peaked and double-peaked oversaturation. In the case of single peaked oversaturation, AWT and MWT decreased only when AWT was used as the objective function. In double-peaked oversaturation, we observe that the closer the distance between the two peaks, the greater the decrease in AWT and MWT. Therefore, the operator may consider various decisions depending on the passenger arrival pattern and their purpose. If the operator would like to reduce AWT or MWT, they might set AWT or MWT to their objective function and minimize it. The optimization result will be a new train departure timetable that serves that purpose. However, it should be noted that if the passenger arrival pattern is not uniform, a trade-off may occur between MWT and AWT when MWT is minimized.

When it comes to the relationship between WT and OST, OST and MWT had little correlation except for the uniform passenger arrival pattern. OST decreases when MWT is reduced in double peak and box-shaped peak oversaturation. However, when the OST is reduced, the MWT is reduced only if the passenger arrival pattern is uniform.

Applying the train skip plan reduces WT more, especially MWT. However, the train skip plan has the disadvantage of increasing the passenger waiting time of skipped stations. Therefore, using the train skip plan can be considered when there is an urgent need to deal with the high congestion of certain stations.

VI. CONCLUSION AND FUTURE WORK

Highly congested trains are often a major factor in poor passenger service in the subway system. To solve this problem, we optimized the train timetable to minimize passenger waiting time for each scenario of peak hours and congested off-peak hours by controlling the train departure time and the number of skipped trains. Our system reduces LAWT by up to 56% at oversaturation. The experiment results demonstrate that adjusting the train departure time and the train skip plan reduce the waiting time more in the highly congested situation. When we skipped the trains in an oversaturation scenario, AWT and MWT are further reduced up to 15% and 19% respectively in the box-shaped oversaturation scenario.

Moreover, we compared how the effect of optimization varies with each passenger arrival pattern when oversaturation occurs. As a result, we found that AWT and MWT to be minimized together when the arrival rate of passengers is uniform. The proposed approach will not only help train scheduling in congestion situations but also help to estimate the optimization effect according to the passenger arrival pattern.

Our future work will consider extending the transfer time when the single line is extended to multiple lines and the real-time operation of the system. Moreover, since we used previous data to optimize train scheduling, it will also be useful to predict the oversaturation by utilizing the real-time data. In addition, we assume that passenger walking time is not affected by passenger volume, however that assumption is not realistic. Therefore, it would be good to make a more detailed model of the passenger walking time to improve the accuracy of the model by considering the effect on the walking time of the passengers when there are a lot of passengers on the platform.

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Appendix A. Optimization Results.

Appendix A indicates how the waiting time and the oversaturation time are reduced by optimizing train scheduling and train skip plan. For each optimization, the experiment was performed five times and the improvement was calculated as the average of the results.

A.1 Peak Hours Scenario

Before Optimization

(unit: sec)

LAWT	GAWT	LMWT	GMWT
205	260	778	1228

A.1.1 LAWT Optimization

(unit: sec)

	LAWT	GAWT	LMWT	GMWT
1st	184	255	586	1356
2nd	184	236	549	1353
3rd	177	234	550	1355
4th	174	229	549	1253
5th	172	238	550	1212
Average	178.2	238.4	556.8	1305.8
Improvement	13.1%	8.3%	28.4%	-6.3%

A.1.2 GAWT Optimization

(unit: sec)

	LAWT	GAWT	LMWT	GMWT
1st	172	214	503	818
2nd	170	214	507	818
3rd	165	209	506	821
4th	164	210	506	821
5th	162	207	505	820
Average	166.6	210.8	505.4	819.6
Improvement	18.7%	18.9%	35.0%	33.3%

A.1.3 LMWT Optimization

(unit: sec)

	LAWT	GAWT	LMWT	GMWT
1st	195	235	503	818
2nd	192	225	457	795
3rd	187	239	505	819
4th	176	224	466	781
5th	174	226	467	781
Average	184.8	229.8	479.6	798.8
Improvement	9.9%	11.6%	38.4%	35.0%

A.1.4 GMWT Optimization

(unit: sec)

	LAWT	GAWT	LMWT	GMWT
1st	258	298	776	792
2nd	249	294	799	858
3rd	246	264	667	817
4th	232	283	787	825
5th	212	272	580	801
Average	239.4	282.2	721.8	818.6
Improvement	-16.8%	-8.5%	7.2%	33.3%

A.2 Congested Off-peak Hours Scenario

A.2.1 Single Peak

Before Optimization

(unit: sec)

LAWT	GAWT	LMWT	GMWT	OST
596	572	3301	3661	2180

A.2.1.1 LAWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	316	347	1340	1340	902
2nd	320	417	1885	1885	593
3rd	402	435	2207	2207	3249
4th	440	419	1861	1861	2259
5th	443	449	2210	2210	3282
Average	384.2	413.4	1900.6	1900.6	2057
Improvement	35.5%	27.7%	42.4%	48.1%	5.6%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	379	428	2222	2222	2964
2nd	394	436	2227	2227	2955
3rd	397	429	2205	2205	2714
4th	421	425	1865	1865	2292
5th	435	447	3790	3790	2346
Average	405.2	433	2461.8	2461.8	2654.2
Improvement	32.0%	24.3%	25.4%	32.8%	-21.8%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	401	431	2158	2158	1923
2nd	408	416	1676	1676	2727
3rd	417	473	2411	2411	3017
4th	429	422	1959	1959	2709
5th	430	440	2107	2107	2409
Average	417	436.4	2062.2	2062.2	2557
Improvement	30.0%	23.7%	37.5%	43.7%	-17.3%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	380	422	2138	2138	2567
2nd	517	523	1295	1725	2188
3rd	522	534	1420	1860	2308
4th	528	505	1767	1767	2174
5th	535	529	2949	2949	2350
Average	496.4	502.6	1913.8	2087.8	2317.4
Improvement	16.7%	12.1%	42.0%	43.0%	-5.9%

A.2.1.2 GAWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	316	351	1439	1441	599
2nd	349	363	1476	1496	1264
3rd	367	379	1351	1351	2428
4th	428	414	1882	1882	2267
5th	445	422	1929	1929	3029
Average	381	385.8	1615.4	1619.8	1917.4
Improvement	36.1%	32.6%	51.1%	55.8%	12.0%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	382	381	1826	1826	2772
2nd	398	413	1989	1989	2488
3rd	418	430	2060	2060	2567
4th	427	407	1870	1870	2928
5th	440	415	1927	1927	2618
Average	413	409.2	1934.4	1934.4	2674.6
Improvement	30.7%	28.5%	41.4%	47.2%	-22.7%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	417	453	3486	3486	3290
2nd	420	415	2007	2007	2806
3rd	460	443	3141	3141	2516
4th	462	436	1864	1864	2676
5th	463	442	3033	3033	2491
Average	444.4	437.8	2706.2	2706.2	2755.8
Improvement	25.4%	23.5%	18.0%	26.1%	-26.4%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	585	591	2372	2372	1393
2nd	692	639	2554	2554	1764
3rd	875	716	2512	2512	2617
4th	1161	920	2370	2370	2637
5th	1184	906	2498	2498	2628
Average	899.4	754.4	2461.2	2461.2	2207.8
Improvement	-50.9%	-31.9%	25.4%	32.8%	-1.3%

A.2.1.3 LMWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	905	728	2375	2375	2738
2nd	937	758	2468	2468	2699
3rd	1073	855	2416	2416	2745
4th	1171	900	2540	2540	2588
5th	1215	946	2598	2598	2861
Average	1060.2	837.4	2479.4	2479.4	2726.2
Improvement	-77.9%	-46.4%	24.9%	32.3%	-25.1%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1109	835	2266	2266	2445
2nd	1136	864	2411	2411	2601
3rd	1139	885	2258	2258	2507
4th	1144	882	2256	2256	2533
5th	1227	979	2588	2588	2874
Average	1151	889	2355.8	2355.8	2592
Improvement	-93.1%	-55.4%	28.6%	35.7%	-18.9%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	969	772	2143	2143	2454
2nd	990	792	2213	2213	2514
3rd	1021	799	2276	2276	2524
4th	1038	812	2242	2242	2494
5th	1071	853	2151	2151	2412
Average	1017.8	805.6	2205	2205	2479.6
Improvement	-70.8%	-40.8%	33.2%	39.8%	-13.7%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	919	768	2030	2175	2339
2nd	993	810	2099	2244	2406
3rd	1017	809	2207	2328	2442
4th	1021	835	2123	2243	2423
5th	1050	860	2105	2204	2397
Average	1000	816.4	2112.8	2238.8	2401.4
Improvement	-67.8%	-42.7%	36.0%	38.8%	-10.2%

A.2.1.4 GMWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	585	591	2372	2372	1393
2nd	292	639	2554	2554	1794
3rd	872	713	2512	2512	2617
4th	1161	920	2370	2370	2637
5th	1184	906	2498	2498	2628
Average	818.8	753.8	2461.2	2461.2	2213.8
Improvement	-37.4%	-31.8%	25.4%	32.8%	-1.6%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	840	690	2237	2237	2700
2nd	1003	770	2182	2182	2430
3rd	1028	817	2326	2326	2631
4th	1061	804	2262	2262	2454
5th	1139	881	2391	2391	2676
Average	1014.2	792.4	2279.6	2279.6	2578.2
Improvement	-70.2%	-38.5%	30.9%	37.7%	-18.3%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	893	741	2080	2080	2372
2nd	1002	802	2231	2231	2578
3rd	1034	807	2184	2184	2398
4th	1081	846	2207	2207	2488
5th	1103	865	2321	2321	2623
Average	1022.6	812.2	2204.6	2204.6	2491.8
Improvement	-71.6%	-42.0%	33.2%	39.8%	-14.3%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	798	704	2260	2260	2340
2nd	835	720	2287	2291	2466
3rd	847	714	1965	1972	2213
4th	857	719	1891	1921	2158
5th	915	764	2078	2119	2321
Average	850.4	724.2	2096.2	2112.6	2299.6
Improvement	-42.7%	-26.6%	36.5%	42.3%	-5.5%

A.2.1.5 OST Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	540	532	2775	2775	1342
2nd	696	643	2687	2687	1276
3rd	814	695	3079	3079	1659
4th	1025	786	3529	3529	1614
5th	1045	817	3817	3817	1532
Average	824	694.6	3177.4	3177.4	1484.6
Improvement	-38.3%	-21.4%	3.7%	13.2%	31.9%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1032	857	4113	4113	1623
2nd	1062	878	4179	4179	1771
3rd	1065	837	3336	3336	1873
4th	1088	831	3594	3594	1874
5th	1111	859	3314	3314	1660
Average	1071.6	852.4	3707.2	3707.2	1760.2
Improvement	-79.8%	-49.0%	-12.3%	-1.3%	19.3%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	974	765	3419	3419	1639
2nd	983	792	3076	3076	1567
3rd	996	830	4113	4113	1602
4th	996	852	4121	4121	1668
5th	1077	821	3722	3722	1763
Average	1005.2	812	3690.2	3690.2	1647.8
Improvement	-68.7%	-42.0%	-11.8%	-0.8%	24.4%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	824	744	2771	2771	1028
2nd	841	745	2576	2576	1066
3rd	1001	819	3848	3848	1698
4th	1046	852	3184	3184	1620
5th	1091	901	4121	4121	1492
Average	960.6	812.2	3300	3300	1380.8
Improvement	-61.2%	-42.0%	0.0%	9.9%	36.7%

A.2.2 Double Peak Optimization

Before Optimization

(unit: sec)

LAWT	GAWT	LMWT	GMWT	OST
1190	927	3224	3260	2294

A.2.2.1 LAWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	692	655	3834	3834	2120
2nd	717	677	3851	3851	2053
3rd	722	632	3560	3560	2477
4th	730	675	3876	3876	2388
5th	745	675	2889	2889	2005
Average	721.2	662.8	3602	3602	2208.6
Improvement	39.4%	28.5%	-11.7%	-10.5%	3.7%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	655	642	3971	3971	2173
2nd	752	670	3556	3556	1861
3rd	762	670	3556	3556	1861
4th	776	711	3925	3925	1796
5th	807	689	3442	3442	2200
Average	750.4	676.4	3690	3690	1978.2
Improvement	36.9%	27.0%	-14.5%	-13.2%	13.8%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	719	661	2954	2954	2386
2nd	750	668	3455	3455	2302
3rd	767	680	3836	3836	2217
4th	778	688	3529	3529	1818
5th	847	753	2978	2978	2154
Average	772.2	690	3350.4	3350.4	2175.4
Improvement	35.1%	25.6%	-3.9%	-2.8%	5.2%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	792	734	3691	3691	2320
2nd	797	746	2896	2896	2227
3rd	801	725	3445	3445	2338
4th	802	741	3783	3783	1631
5th	825	748	3443	3443	2442
Average	803.4	738.8	3451.6	3451.6	2191.6
Improvement	32.5%	20.3%	-7.1%	-5.9%	4.5%

A.2.2.2 GAWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	700	676	3905	3905	1700
2nd	702	644	3754	3754	2104
3rd	722	661	2966	2966	2063
4th	761	658	3446	3449	2128
5th	802	717	3290	3290	1985
Average	737.4	671.2	3472.2	3472.8	1996
Improvement	38.0%	27.6%	-7.7%	-6.5%	13.0%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	704	601	3447	3447	2264
2nd	754	640	3636	3636	2629
3rd	769	658	3449	3449	2222
4th	812	693	3741	3741	2340
5th	856	723	3751	3751	2566
Average	779	663	3604.8	3604.8	2404.2
Improvement	34.5%	28.5%	-11.8%	-10.6%	-4.8%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	675	633	3666	3666	2118
2nd	699	689	3960	3960	1977
3rd	700	684	3884	3884	1939
4th	825	738	2927	2927	2230
5th	839	729	3757	3735	2353
Average	747.6	694.6	3638.8	3634.4	2123.4
Improvement	37.2%	25.1%	-12.9%	-11.5%	7.4%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	666	661	2875	2875	2329
2nd	700	670	3741	3741	2331
3rd	788	725	2992	2992	2287
4th	912	795	3764	3794	1806
5th	926	805	3808	2908	1711
Average	798.4	731.2	3436	3262	2092.8
Improvement	32.9%	21.1%	-6.6%	-0.1%	8.8%

A.2.2.3 LMWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	979	879	2421	2421	1379
2nd	1030	888	2768	2768	1474
3rd	1089	944	2512	2512	1302
4th	1092	925	2678	2678	1439
5th	1105	943	2667	2667	1505
Average	1059	915.8	2609.2	2609.2	1419.8
Improvement	11.0%	1.2%	19.1%	20.0%	38.1%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1091	908	2586	2586	1318
2nd	1110	934	2630	2630	1747
3rd	1114	934	2432	2432	1392
4th	1126	944	2495	2495	1378
5th	1170	966	2566	2566	1411
Average	1122.2	937.2	2541.8	2541.8	1449.2
Improvement	5.7%	-1.1%	21.2%	22.0%	36.8%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1097	939	2347	2347	1275
2nd	1122	942	2611	2611	1447
3rd	1143	943	2502	2502	1334
4th	1236	1001	2785	2785	1552
5th	1254	1032	2718	2718	1756
Average	1170.4	971.4	2592.6	2592.6	1472.8
Improvement	1.6%	-4.8%	19.6%	20.5%	35.8%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1080	968	2584	2584	1335
2nd	1140	981	2441	2441	1460
3rd	1165	966	2747	2747	1420
4th	1232	1024	2794	2794	1611
5th	1234	1017	2856	2856	1815
Average	1170.2	991.2	2684.4	2684.4	1528.2
Improvement	1.7%	-6.9%	16.7%	17.7%	33.4%

A.2.2.4 GMWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1060	926	2501	2501	1286
2nd	1077	911	2790	2790	1586
3rd	1080	911	2876	2876	1761
4th	1090	954	2530	2530	1640
5th	1099	944	2525	2525	1260
Average	1081.2	929.2	2644.4	2644.4	1506.6
Improvement	9.1%	-0.2%	18.0%	18.9%	34.3%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1075	916	2384	2375	1336
2nd	1076	920	2449	2449	1234
3rd	1115	964	2527	2527	1485
4th	1159	949	2669	2669	1501
5th	1170	955	2632	2632	1380
Average	1119	940.8	2532.2	2530.4	1387.2
Improvement	6.0%	-1.5%	21.5%	22.4%	39.5%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1054	892	2610	2610	1379
2nd	1107	921	2610	2610	1413
3rd	1107	947	2462	2462	1386
4th	1126	947	2383	2383	1242
5th	1216	989	2699	2699	1421
Average	1122	939.2	2552.8	2552.8	1368.2
Improvement	5.7%	-1.3%	20.8%	21.7%	40.4%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1079	944	2511	2511	1494
2nd	1086	924	2864	2864	1583
3rd	1140	965	2581	2581	1360
4th	1164	988	2756	2756	1619
5th	1183	978	2732	2732	1329
Average	1130.4	959.8	2688.8	2688.8	1477
Improvement	5.3%	-3.4%	19.9%	21.2%	55.3%

A.2.2.5 OST Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1050	850	3537	3537	1073
2nd	1050	861	3844	3844	1091
3rd	1094	910	3983	3983	1178
4th	1193	970	2663	2663	1001
5th	1199	963	2858	2858	995
Average	1117.2	910.8	3377	3377	1067.6
Improvement	6.1%	1.7%	-4.7%	-3.6%	53.5%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1113	946	4292	4292	1137
2nd	1133	882	3839	3839	1217
3rd	1170	928	2885	2885	1239
4th	1325	979	3758	3758	1252
5th	1351	972	3491	3491	1609
Average	1218.4	941.4	3653	3653	1290.8
Improvement	-2.4%	-1.6%	-13.3%	-12.1%	43.7%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1207	915	3352	3352	1180
2nd	1267	1008	2844	2877	1473
3rd	1315	1007	4005	4005	1706
4th	1323	1007	4018	4018	1448
5th	1421	1084	4212	4212	1492
Average	1306.6	1004.2	3686.2	3692.8	1459.8
Improvement	-9.8%	-8.3%	-14.3%	-13.3%	36.4%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	1145	906	3755	3755	1232
2nd	1154	878	3517	3517	1241
3rd	1165	906	3596	3596	1256
4th	1191	923	3735	3735	1301
5th	1302	1036	2983	2983	1570
Average	1191.4	929.8	3517.2	3517.2	1320
Improvement	-0.1%	-0.3%	-9.1%	-7.9%	42.5%

A.2.3 Box-shaped Peak Optimization

Before Optimization

(unit: sec)

LAWT	GAWT	LMWT	GMWT	OST
722	663	3376	3206	1962

A.2.3.1 LAWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	317	412	1075	1526	1195
2nd	356	372	2174	2174	1439
3rd	359	377	2038	2038	1148
4th	388	395	2145	2145	1353
5th	296	400	2226	2226	1188
Average	343.2	391.2	1931.6	2021.8	1264.6
Improvement	52.5%	41.0%	42.8%	36.9%	35.5%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	279	402	1184	1973	1141
2nd	302	335	1307	1352	1117
3rd	329	393	1543	1532	1858
4th	330	418	1041	1609	1108
5th	363	379	1401	1439	1867
Average	320.6	385.4	1295.2	1581	1418.2
Improvement	55.6%	41.9%	61.6%	50.7%	27.7%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	390	411	2183	2183	1723
2nd	402	475	1375	1743	1858
3rd	422	478	1474	1624	1943
4th	521	507	1448	1586	1309
5th	307	359	1796	1796	1442
Average	408.4	446	1655.2	1786.4	1655
Improvement	43.4%	32.7%	51.0%	44.3%	15.6%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	503	568	2320	2320	1769
2nd	359	423	1276	1622	1750
3rd	424	490	1274	1636	1888
4th	425	495	1249	1728	1602
5th	443	474	2198	2198	1676
Average	430.8	490	1663.4	1900.8	1737
Improvement	40.3%	26.1%	50.7%	40.7%	11.5%

A.2.3.2 GAWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	326	363	2140	2140	1644
2nd	344	350	1401	1401	1327
3rd	423	422	1994	1994	1538
4th	477	421	1915	1915	1781
5th	660	537	2269	2269	1141
Average	446	418.6	1943.8	1943.8	1486.2
Improvement	38.2%	36.9%	42.4%	39.4%	24.3%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	321	338	1877	1877	1800
2nd	323	349	1965	1965	1334
3rd	356	359	2183	2183	2519
4th	396	390	1221	1221	1552
5th	309	335	2052	2052	1551
Average	341	354.2	1859.6	1859.6	1751.2
Improvement	52.8%	46.6%	44.9%	42.0%	10.7%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	342	393	1200	1516	1536
2nd	384	408	1198	147	1544
3rd	429	432	2401	2401	1895
4th	444	434	1667	1667	1855
5th	549	491	2433	2433	1883
Average	429.6	431.6	1779.8	1632.8	1742.6
Improvement	40.5%	34.9%	47.3%	49.1%	11.2%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	373	490	1821	1839	1693
2nd	421	442	3211	3211	1640
3rd	455	487	2314	2314	17121
4th	516	519	1957	1975	1838
5th	518	503	3174	3174	1630
Average	456.6	488.2	2495.4	2502.6	4784.4
Improvement	36.8%	26.4%	26.1%	21.9%	-143.9%

A.2.3.3 LMWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	619	594	2156	2156	1408
2nd	639	635	1947	2093	1227
3rd	643	781	2100	2100	1395
4th	693	586	1896	1896	1128
5th	705	633	1916	2187	1139
Average	659.8	645.8	2003	2086.4	1259.4
Improvement	8.6%	2.6%	40.7%	34.9%	35.8%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	681	633	1990	1916	1139
2nd	728	613	1913	1990	1197
3rd	729	666	1976	1913	1169
4th	733	618	1964	1976	1246
5th	651	689	2006	1964	1363
Average	651	562	1774	1867	1117
Improvement	9.8%	15.2%	47.5%	41.8%	43.1%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	661	619	1848	2113	1102
2nd	691	602	1913	1913	1290
3rd	693	613	1902	1902	1300
4th	703	640	1940	1942	1250
5th	714	584	2013	2013	1009
Average	692.4	611.6	1923.2	1976.6	1190.2
Improvement	4.1%	7.8%	43.0%	38.3%	39.3%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	653	601	1849	1872	1214
2nd	685	612	2031	2031	1193
3rd	693	630	2078	2078	1266
4th	709	606	1771	1857	966
5th	867	769	2512	2512	1723
Average	721.4	643.6	2048.2	2070	1272.4
Improvement	0.1%	2.9%	39.3%	35.4%	35.1%

A.2.3.4 GMWT Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	693	596	1985	1985	1159
2nd	630	620	2087	2087	1112
3rd	631	583	2018	2018	1193
4th	639	609	2067	2067	1151
5th	685	633	2067	2067	1049
Average	655.6	608.2	2044.8	2044.8	1132.8
Improvement	9.2%	8.3%	39.4%	36.2%	42.3%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	586	518	1830	1830	1222
2nd	597	528	1895	1895	1038
3rd	631	541	1911	1911	1144
4th	675	611	2027	2027	1188
5th	722	647	2067	2067	1203
Average	642.2	569	1946	1946	1159
Improvement	11.1%	14.2%	42.4%	39.3%	40.9%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	591	581	1925	1925	1281
2nd	631	607	1929	1939	1205
3rd	690	635	2028	2028	1281
4th	737	597	2109	2109	1421
5th	746	701	2050	2055	1411
Average	679	624.2	2008.2	2011.2	1319.8
Improvement	6.0%	5.9%	40.5%	37.3%	32.7%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	614	592	2078	2078	1271
2nd	732	633	2080	2080	1193
3rd	761	643	1860	1860	1087
4th	818	753	2117	2117	1375
5th	888	763	2706	2706	1601
Average	762.6	676.8	2168.2	2168.2	1305.4
Improvement	-5.6%	-2.1%	35.8%	32.4%	33.5%

A.2.3.5 OST Optimization

The number of skipped train: 0

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	840	704	2178	2178	1003
2nd	867	656	1935	1935	911
3rd	884	723	2198	2198	1022
4th	914	712	2312	2312	1061
5th	921	761	2371	2371	1064
Average	885.2	711.2	2198.8	2198.8	1012.2
Improvement	-22.6%	-7.3%	34.9%	31.4%	48.4%

The number of skipped train: 1

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	748	655	2229	2229	911
2nd	808	617	2004	2004	894
3rd	816	639	2119	2119	946
4th	906	685	2031	2031	963
5th	910	683	2045	2045	1009
Average	837.6	655.8	2085.6	2085.6	944.6
Improvement	-16.0%	1.1%	38.2%	34.9%	51.9%

The number of skipped train: 2

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	874	682	2230	2230	891
2nd	880	735	1949	1990	967
3rd	901	686	2194	2194	1141
4th	928	674	3274	3274	1135
5th	957	756	2346	2346	1149
Average	908	706.6	2398.6	2406.8	1056.6
Improvement	-25.8%	-6.6%	29.0%	24.9%	46.1%

The number of skipped train: 3

(unit: sec)

	LAWT	GAWT	LMWT	GMWT	OST
1st	819	640	3499	3499	1060
2nd	865	683	2158	2158	1049
3rd	879	707	2114	2114	994
4th	900	698	2163	2163	1089
5th	1065	766	3214	3214	1309
Average	905.6	698.8	2629.6	2629.6	1100.2
Improvement	-25.4%	-5.4%	22.1%	18.0%	43.9%

요 약 문

도시 지하철역에서의 예기치 않은 혼잡에 대한 처리 방안

도시 지하철은 도로교통 상황의 영향을 크게 받지 않으며 대용량의 교통 수요를 처리할 수 있어 많은 승객들에게 이용된다. 혼잡한 지하철은 승객들에게 불편을 야기하며, 승객들의 승강장에서의 대기시간을 증가시킨다. 본 논문은 열차 출발 시간과 역들을 건너 뛴 열차 수를 조절하여 승객 대기 시간을 최소화하는 것을 목표로 한 열차 시간표 최적화 방안을 제시한다. 승객 도착 통계 모델에 의존하는 기존의 접근 방식과 달리, 이 연구는 대구의 지하철에서 수집된 교통카드 데이터들을 기반으로 하는 최적화 모델을 만든다. 모델은 각 승객의 여행 시간을 차량 대기 시간, 차량 탑승 시간 및 보행 시간으로 구분하고, 탑승한 기차에 따라 승객들을 군집화 시킨 후 각 차량마다 승객 수를 추정하는 것으로 구성된다. 이를 바탕으로 주어진 열차 스케줄에 대해 모든 승객 각각의 대기 시간들을 계산할 수 있다. 최적화 문제는 이용 가능한 열차 수, 열차가 수용 가능한 최대 승객 수, 폐색구간과 같은 현실적인 제약 조건 하에서 구성된다. 최적의 시간표를 찾기 위한 방법으로 유전자 알고리즘이 사용되었다. 그 결과 승객 평균 대기 시간은 최대 56%까지 단축되었으며, 열차 출발시간 뿐만 아니라 일부 역을 건너뛰는 열차의 수까지 최적화하면 매우 혼잡한 상황에서 더 나은 결과를 얻을 수 있었다. 혼잡한 상황에서 기차가 일부 역을 건너뛰었을 때, 그렇지 않을 때보다 승객 최대 대기 시간은 19%, 승객 평균 대기 시간은 15% 정도 더욱 단축되었다. 또한 혼잡한 상황에서 승객 도착 패턴에 따라 최적화의 효율이 달라진다는 것을 확인하였다. 본 방안은 승객 평균 대기시간을 감소시킴으로써 지하철 서비스를 향상시킬 것이다.

핵심어: 열차 시간표 최적화, 승객 대기시간, 유전자 알고리즘