Evaluation of an existing bus network using a transit network optimisation model: A case study of the Hiroshima City Bus network

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Abstract

This study evaluates an existing bus network from the perspectives of passengers, operators, and overall system efficiency using the output of a previously developed transportation network optimisation model. This model is formulated as a bi-level optimisation problem with a transit assignment model as the lower problem. The upper problem is also formulated as bi-level optimisation problem to minimise costs for both passengers and operators, making it possible to evaluate the effects of reducing operator cost against passenger cost. A case study based on demand data for Hiroshima City confirms that the current bus network is close to the Pareto front, if the total costs to both passengers and operators are adopted as objective functions. However, the sensitivity analysis with regard to the OD pattern fluctuation indicates

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[1] This research was carried out when the first and the second author were affiliated with Hiroshima University.

that passenger and operator costs in the current network are not always close to the Pareto front. Finally, the results suggests that, regardless of OD pattern fluctuation, reducing operator costs will increase passenger cost and increase inequity in service levels among passengers.

***Key words**:* bi-level optimisation formulation, existing bus network, numbered ticket-based travel demand data, transit assignment model, transit network configuration, frequency design.

1 Introduction

Environmental concerns are becoming more important, and many public transportation systems are being improved because they are more energy-efficient than private vehicles. To encourage travellers to switch from private cars to public transportation, many public transport operators have reduced off-peak fares or increased capacity during congested periods. Hiroshima City, the study area, has established car-free days three times each month and has appealed to commuters to refrain from using private vehicles. However, the number of bus riders in the study area has actually been decreasing annually. One reason for this might be an inefficient service configuration. Indeed, in many cities, including the study area, bus networks overlap in the central business district (CBD). Therefore, it may be possible to configure the network more efficiently; In 2004, Seoul's bus network was reorganised, resulting in an 11% increase in the number of bus passengers. Optimal public transportation route configuration can thus be used to address what is commonly referred to as the "transit route network design problem" (TRNDP) (Kepaptsoglou et. al., 2009).

Most of the transit planning models are formulated as a bi-level optimisation problem whose lower problem describe the passengers' behaviour. Although many of the transit network planning models regarded the transit route as fixed (Zhou and Lam (2000), Gao et al. (2004), Shimamoto et. al. (2005), Ibeas et. al. (2010)) due to the expensive computation cost, several researchers nowadays treat the transit routes as the policy variable. Yang et al. (2007) proposed a bus network optimisation model the objective function of which is maximising the ratio of passengers travelling without transfer; the model was based on a parallel ant colony algorithm and then applied to the Dalian city bus network. However, the model does not clearly describe passenger behaviour. Prabhat et al. (2006) proposed a model for optimising the feeder bus route, where the transfer point from the railway to the feeder bus is fixed and transferring between the feeder buses is not allowed. Guan et al. (2006) formulated a simultaneous optimisation problem for railway line configuration and passenger assignment as a linear binary integer problem. Because line frequencies were not determined in the model, the researchers charged a prior given transfer penalty as an additional waiting time. In this model, additional waiting time for transfers should be dependent on service frequency: that is, passenger waiting time should be short if the service frequency is high. Another feature of this model is that it uses a branch-and-bound method as a solution algorithm to obtain an exact solution, whereas all previous models applied heuristic algorithms to obtain solutions. However, the researchers simplified the network to enable the model to obtain a solution within a reasonable time; the real world is generally more complex than a railway network optimisation problem, and it would be difficult to apply a strict solution algorithm to a real bus network optimisation problem. Kepaptsoglou et al. (2009) published a structured review of TRNDP approaches, distinguishing between objective variables, parameters, and methodologies.

To date, most studies have not described passenger route choice behaviour accurately or otherwise, but most assume that fewer transfers are desirable for passengers. Transfers can certainly be troublesome for passengers in many cases, but passengers would be less likely to mind transferring if the frequency of alternative lines was sufficiently high, as in the CBD area of many major cities. Thus, it is important to include more accurate depictions of passenger route and transfer choice behaviours. Nachtigall and Jerosch (2008) combined a line planning model and traffic assignment model and developed a solution algorithm, based on the column generation method. However, their assignment model is very similar to the traditional assignment model and does not consider the 'common lines problem,' which is essential for transit assignment in networks for which uniform passenger arrival can be assumed. Petrelli (2004) developed a model framework that combined the TRNDP and a transit assignment model considering common lines (although some details of the transit assignment model were omitted). Beltran et al. (2009) extended their model to determine the allocation of a limited number of environmentally friendly vehicles and applied the model to a real-size network. Ibeas et al. (2010) proposed a model for deciding the optimal location of bus stops and applied the model to a real network. One of the authors also proposed a TRNDP model (Shimamoto et al., 2010), which was applied to a toy network. As in previous research (Shimamoto et al., 2005), the model developed in this study was formulated as a bi-level optimisation problem the lower problem of which was a transit assignment model considering the common lines (Kurauchi et al., 2003). The upper problem in the proposed model was also defined as multi-objective. Although multi-objective problems generally require much more computational cost than single objective problems, they can explicitly consider tradeoffs among different stakeholders. In most cases, transportation policies affect more than two stakeholders. For example, after the virtual liberalisation of bus service was introduced in Japan, many transit operators withdraw service from unprofitable routes, causing further inconvenience to passengers. Thus, transportation policies need to consider tradeoffs between all the stakeholders.

In addition to the tradeoffs among various stakeholders, transportation policies need to incorporate equity issues (Victoria Transport Policy Institute, 2010). Viegas (2001) discussed problems related to implementing road pricing from the perspective of effectiveness and acceptability. He introduced the following four dimensions of equity:

- horizontal equity, associated with the equality of opportunities;
- territorial equity, associated with the right to mobility and provision of identical conditions for citizens living in all parts of a given country;
- vertical equity, associated with the protection of those in the worst conditions; and
- longitudinal equity, associated with the comparison of conditions between present and past (balance between gains and losses).

Boscmann et al. (2008) enumerate three dimensions of equity; egalitarianism, horizontal equity and vertical equity. While horizontal equity and vertical equity might cause unequal benefit with socioeconomic status (or geographic location), egalitarianism, which is defined as all persons are created equal and should be treated as such, causes equal benefit regardless of socioeconomic status. In this sense, the idea of egalitarianism is similar with that of territorial equity. Several equity indexes, such as the Gini coefficient, Theil index, and Atkinson index, have proposed quantitative evaluations of equity. Thus, some researchers have applied an objective function in a bi-level optimisation problem. Sumalee (2004) used minimisation of inequity among drivers as an objective function when developing an optimal charging cordon design model. Shimamoto et al. (2005) applied minimisation of inequity among passengers within a similar model framework. Both of these models used only the Gini coefficient as an indicator of (in)equity, but Feng et al. (2009) compared various equity indicators as objective functions of a road network design model. Feng et al. found that differing inequity indicators produced differing solution patterns, but did not reach any conclusions about which inequity indicator(s) should be used when implementing transportation policies.

Within this framework, this study evaluated the current bus network in Hiroshima City by comparing model outputs. Evaluation indicators included both aggregated values (e.g., total cost to passengers) and equity among passengers. The rest of this paper is organised as follows: Section 2 provides a brief description of the capacity constrained transit assignment model proposed by Kurauchi et al. (2003); Section 3 provides a mathematical formulation and a solution algorithm for the bus network optimisation model; Section 4 describes the current situation in the study area and evaluates the existing bus network using the model output; and finally Section 5 provides conclusions and directions for future research.

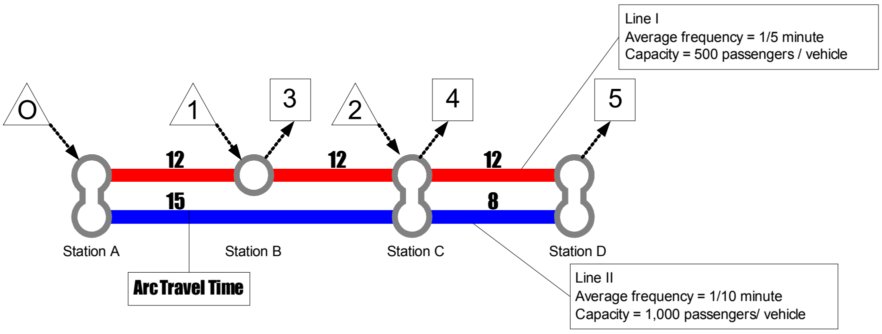
2 Capacity constrained transit assignment model with common lines

This section provides a brief description of the capacity-constrained transit assignment model with common lines (CapCon-CL; Kurauchi et al., 2003), which is applied in the lower problem of the proposed model.

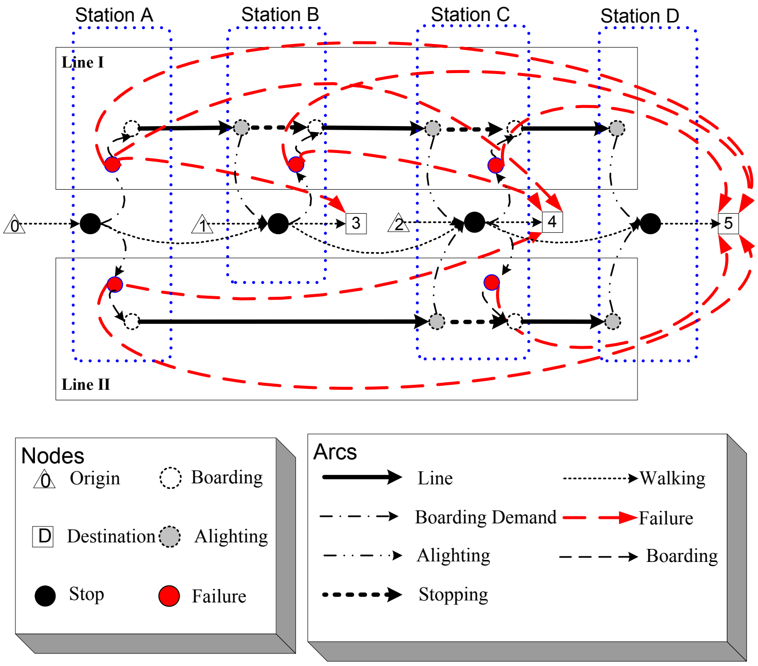
2-1. Network representation

To consider transit line capacities together with the common-lines problem, the transit network shown in Figure 1(a) can be transformed into a graph model, as shown in Figure 1(b). An *origin node* represents a trip start node. A *destination node* represents a trip end node. A *stop node* represents a platform at a station. Any transit lines stopping at the same platform are connected via boarding demand arcs, failure nodes, and boarding arcs. At stop nodes, passengers can either take a bus or walk to a neighbouring bus stop. If they take a bus, they are assigned to any of the attractive lines in proportion to the arc transition probabilities. A *boarding node* is a line-specific node at the platform where passengers board. An *alighting node* is a line-specific node at the platform where passengers alight. A *failure node* is a node that explains failure to board. When a transit line capacity is exceeded (if all passengers board), some passengers are forced to use the *failure arc*. One arc is connected to the corresponding boarding node and the others are connected to each destination node. For statistical reasons, we assumed that those who fail to board at some stations do not have priority to board at the next time step.

A *line arc* represents a transit line connecting two stations. A *boarding demand arc* denotes an arc connecting the stop node to the failure node. The flow on this arc represents the boarding demand for the transit line from a specific platform. An *alighting arc* denotes an arc from an alighting node to a stop node. A *stopping arc* denotes a transit line stopping on a platform after the passengers alight and before new passengers board. This arc is created to express the available capacity on the transit line explicitly. A *walking arc* connects an origin to a platform (access), a platform to a destination (egress) and between neighboring platforms (walk to neighbor platforms). A *failure arc* denotes the demand that failure to board. This excess demand is sent directly to its respective destination via this arc. A *boarding arc*, which represents the movement of passengers who can actually get on a vehicle, is an arc connecting a failure node to a boarding node.



a) Example transit network.



(b) Graph network.

Figure 1. Network representation.

This network representation requires considerable computer memory because of its many arcs and nodes, but this problem is not insurmountable considering recent progress in computer technology. The network can be constructed automatically once it is developed, as shown in Figure 1(a).

2-2. Notations

The following notations are used in the transit assignment model; other notations will be defined when needed.

A_p : Set of arcs on hyperpath p
L : Set of line arcs
L_l : Set of line arcs on line l
U_l : Set of platforms on transit line l
WA : Set of walking arcs
BD : Set of boarding demand arcs
S_p : Set of stop nodes on hyperpath p
E : Set of failure node
E_p : Set of failure node on hyperpath p
D_s : Set of failure arc destined to s
$OUT_p(i)$: Set of arcs that lead out of node i on hyperpath p
w_{kl} : Stopping arc of line l on platform k
b_{kl} : Boarding demand arc of line l on platform k
h_{kl} : Failure node of line l on platform k
$l(a)$: A transit line that is included in arc a
g_p : The cost of hyperpath p
c_a : Arc cost on arc $a \in A$
t_a : Travel time on arc $a \in A$
ξ : The on board value of time
ζ : The value of time for walking
η : The value of time for waiting
θ : Parameter for risk of failure to board
α_{ap} : Probability that traffic traverses arc a
β_{ip} : Probability that traffic traverses node i
q_k : Failure to board probability at platform k
f_l : Frequency of line l (1/minute)

2-3. The cost of hyperpaths

In this study, the cost of a hyperpath was considered to be a generalised cost consisting of three elements: monetary value of the travel time, monetary value of the expected waiting time, and the implicit cost associated with the risk of failure to board. The model allows passengers to walk to other bus stops by including walking arcs between every stop node. Thus, the cost for each arc, c_a, is defined as:

$$c_a = \begin{cases} \xi t_a & (a \in L) \\ \varsigma t_a & (a \in WA) \\ \infty & (a \in D_s) \\ 0 & (\text{else}) \end{cases} \tag{1}$$

Using the cost of arc a, c_a, the generalised cost of hyperpath p, g_p, can be written as:

$$g_p = \sum_{a \in A_p} \alpha_{ap} c_a + \eta \sum_{k \in S_p} \frac{\beta_{kp}}{F_{kp}} - \theta \ln\left(\prod_{k \in E_p} (1 - q_k)^{\beta_{kp}} \right) \tag{2}$$

where

$$F_{ip} = \sum_{a \in OUT_p(i)} f_{l(a)} \tag{3}$$

Note that α_{ap} and β_{kp} are obtained from the arc split probabilities in Figure 1(b). The first term of Eq. (2) represents the 'moving cost,' consisting of the monetary value of the in-vehicle time and the walking time. The second and third terms represent the monetary value of the expected waiting time and the cost associated with the risk for failure to board, respectively. The parameter for the risk for failure to board, θ, denotes risk averseness. If $\theta \to \infty$, then passengers are absolutely risk averse, so they are not interested in travel time or expected waiting time; when $\theta = 0$ passengers do not care about failing to board. As Eq. (2) can be separated by the subsequent node, Bellman's principle can be applied to find the minimum-cost hyperpath. Finally, the CapCon-CL is formulated with a complementarity problem involving hyperpath flows and failure-to-board probabilities that satisfy both user equilibrium and capacity constraint conditions. The complementarity problem can be solved by combining the method of successive averages and absorbing Markov chains (see Kurauchi et al., 2003).

3 Bus network configuration and frequency optimisation model

3-1. Outline of the model

This study focused on two stakeholders: the operator and passengers. We assumed that bus services would be provided by only one operator, who wishes to minimise the total operational cost. In the study area, the bus service is, in fact, operated by five bus companies; their objective is not minimising the operational cost, but maximising total benefit. Thus, we considered the operator not to be bus companies, but to be a public agency with the goal of realising a bus network balancing between the operational cost and the passengers' convenience. Furthermore, passengers were assumed to want to minimise their total cost, as shown in Eq.(2).

The proposed model is also based on the following assumptions:

- The position of bus stops is given and fixed, but not all bus stops must be used;

- Express services are not considered: that is, all buses stop at all bus stops they pass;
- Travel time between bus stops is constant;
- The maximum number of lines and an origin/destination of each line is fixed (due to depot constraints); and
- Origin-destination (OD) demand is fixed, regardless of the bus network configuration.

Note that no express services are provided in the study area.

3-2. Model formulation

Decision variables in the model include the route and frequency of each line, denoted as $\mathbf{r} = (\mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_{|L|})$ and $\mathbf{f} = (f_1, f_2, \ldots, f_{|L|})$ respectively. The model is formulated as:

$$\min_{\mathbf{r},\mathbf{f}} \psi_m(\mathbf{y},\mathbf{q},\mathbf{r},\mathbf{f}), m = 1,2,\cdots M \tag{4}$$

such that

$$(\mathbf{y}^*, \mathbf{q}^*) \text{ satisfies (User Equilibrium)} \tag{5}$$

$$C_l(\mathbf{r}_l) \le C_l^{\max} \tag{6}$$

$$\sum_{l=1}^{|L|} f_l C_l(\mathbf{r}_l) \le NV \tag{7}$$

where

M : The number of objective functions in the upper problem
$|L|$: The number of lines (fixed)
$C_l(\mathbf{r}_l)$: Travel time from the origin to the destination of line l
$C_l^{\max}$: The upper value of travel time on line l
NV : The available number of vehicles

Equation (4) represents the objective function of the upper problem (defined below) and Eq. (5) represents the passenger equilibrium condition under a given network configuration and frequencies, as introduced in the previous chapter. Equation(6) represents the line length constraints to avoid overly long lines and Eq. (7) represents the vehicle number constraints. The number of vehicles required to operate a certain line is assumed to be proportional to the line length and frequency, which implicitly neglects turning time or waiting time at depots.

As mentioned above, the objective function of the operator is to minimise the total operational cost (ψ_1) and the objective function of passengers is to minimise total travel cost (ψ_2), as formulated below. Generally, operator cost can be divided into direct and indirect costs. Ibeas et al. (2010) defined direct costs as the sum of four factors: rolling costs (*CK*), hourly costs due to standing still with the engine running (*CR*), personnel costs (*CP*), and fixed costs (*CF*). They defined indirect costs as the sum of exploitation, human resources, administrative/financial, depot and supplies, and management and general costs; they found that indirect costs tended to be 12% of direct costs. Furthermore, they formulated all direct costs with the exception of *CR* as being proportional to total mileage. Thus, if *CR* is ignored for simplicity, operator cost can be regarded as proportional to total mileage, as shown in Eq. (8). The total mileage for the operator is the sum of the product of line frequencies and square of the line length, because the sum of the product of line frequencies and line length (the left-hand term of Eq. (7)) represents the number of vehicles required to operate line l, multiplied by the cost for each line.

$$\psi_1(\mathbf{r},\mathbf{f}) = \sum_{l=1}^{|L|} f_l C_l(\mathbf{r}_l)^2 \tag{8}$$

$$\psi_2(\mathbf{y},\mathbf{q},\mathbf{r},\mathbf{f}) = \sum_{rs\in W} \sum_{p\in H_{rs}^*} y_p \cdot g_p(\mathbf{y},\mathbf{q}) \tag{9}$$

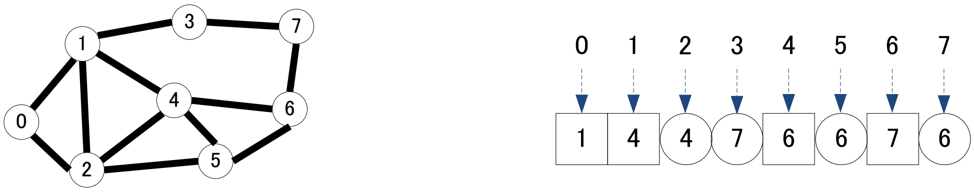
where

$\boldsymbol{W}$: The set of OD pair
H_{rs}^* : The set of hyperpath between OD pair *rs*

The results might be biased due to the possibility of multiple fixed points in the lower level problem. This bias is well-known within mixed integer non-linear programming (MINLP) and continues to be a challenging problem.

3-3. Solution algorithm

As discussed above, the proposed model is formulated with a multi-objective optimisation problem in the upper problem. We can use the elitist non-dominated sorting genetic algorithm (NSGA-II) proposed by Deb et al. (2000) to solve the upper multi-objective optimisation problem. One advantage of NSGA-II is that it requires fewer parameters than other methods; candidate bus routes and frequencies can be created separately using a GA procedure. Although it is possible to create not only the shortest route but also various alternative routes, using a GA procedure, this may result in many fatal chromosomes that do not represent the routes. Thus, we chose to use the improved GA procedure for route search proposed by Inagaki et al. (1999). Hereafter, the description of the modified GA procedure for route generation (using fixed origin and destination nodes) is based on Inagaki et al.'s work; see the example network shown in Figure 2(a).



(a) Example network. (b) Alignment of chromosomes.

Figure 2. Alignment of genes in a chromosome.

In the modified GA procedure, the number of genes in a chromosome is the same as the number of nodes in a network *N*. Each gene *m* can only take the values of the nodes to which direct links from the node *m* exist; that is, a link connecting nodes *m* and *n* is represented by assigning node ID *n* to the m^{th} gene. Therefore the alignment of the genes in a chromosome can provide the ID for nodes that make up a route, if one keeps moving ('jumping') from gene *m* to gene *n*, (in Fig.3(b), this is represented by genes with a square). Thus, the chromosome defined here consists of two types of genes: those contributing to the representation of the route and those that do not. It is always possible to obtain a valid route from the genes that contribute to the route description, unless a cyclic route is obtained; this occurs if the same node ID appears in at least two of these genes. Figure 2(b) represents the route (0 →1→4→6→7) if the origin and destination node are defined as 0 and 7, respectively. For genes that are not required for the route description, a random node ID is selected from among the available node IDs. Thus, the creation of new chromosomes consists of the well-known elements of initialisation, crossover, and mutation; see Shimamoto et al. (2010) for a detailed description of these operations. Note that the frequency of each line must be determined discretely. Also, since the bus routes and the frequencies are coded with different chromosomes in this study, the model decides the bus routes and the frequencies separately. Therefore, the number of combination of frequencies and line configuration becomes exponentially larger and consequently increases the possibility of reaching locally optimal solutions if the frequency of each line is chosen from a wider range. There is a room to improve the chromosomes coding in order to avoid premature convergence to locally optimal solutions.

4 Evaluation of Hiroshima City Bus Network

4-1. Outline of the study area

Hiroshima City is one of the core cities in the Chugoku area of Japan, with a population of approximately 1,173,000 (November 2009). Recently, Hiroshima City amalgamated its suburban areas, from which many individuals commute to the CBD area. Many bus routes are available between these residential areas and the CBD, but most of the residential areas do not spread widely and therefore reconstruction of the bus lines would be difficult. Thus, we limited the study area to the CBD, which has an area of approximately 5km (see Figure 3). Public transportation in the study area consists primarily of buses and trams, but we excluded trams from the study due to the data limitation. Figure 4 presents the distribution of boarding demand for the entire city, which was collected by Hiroshima City through a trip survey conducted in 2008. As shown in the figure, demand is greatest between 07:00-08:00; this period accounts for about 18% of the total demand. Thus, we defined the morning peak hour as 07:00-08:00.

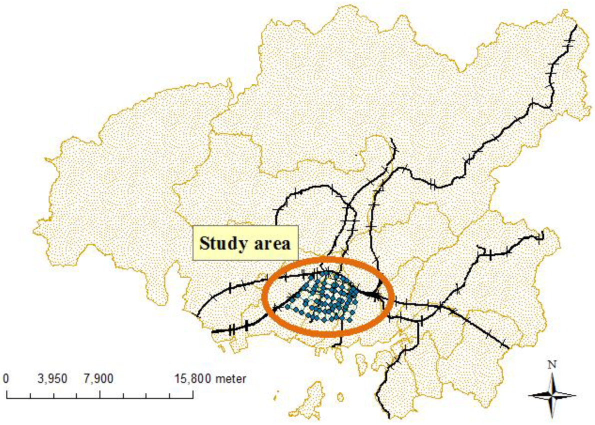


Figure 3. Map of Hiroshima City and location of the study area.

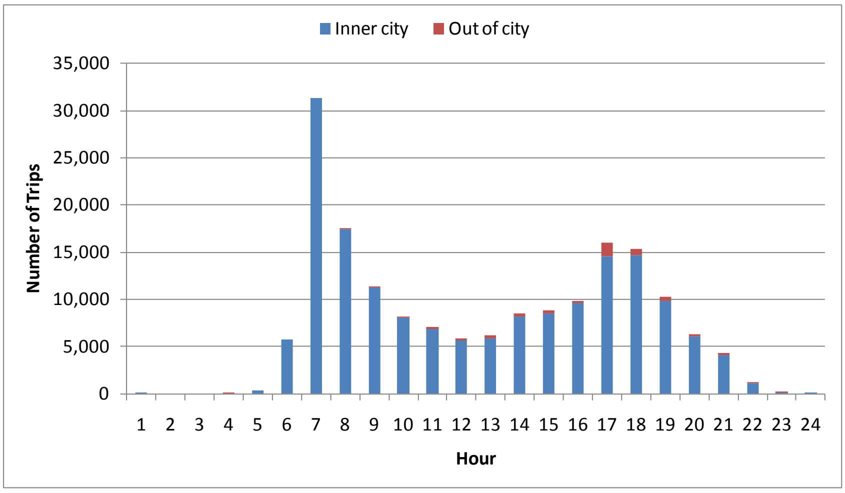


Figure 4. Distribution of boarding demand for the entire city (weekdays).

Figure 5 shows the distribution of the number of boarding and alighting passengers in the study network and Figure 6 illustrates the sum of frequencies in each road section as a result of data aggregation (described in the next section). More passengers board and alight at nodes 54, 37, and 44: node 54 corresponds to the central station (Hiroshima station) and the area between nodes 37 and 44 is the busiest downtown area. As a result, many buses run on the roads connecting node 54 and node 37 or 44, as shown in Figure 6.

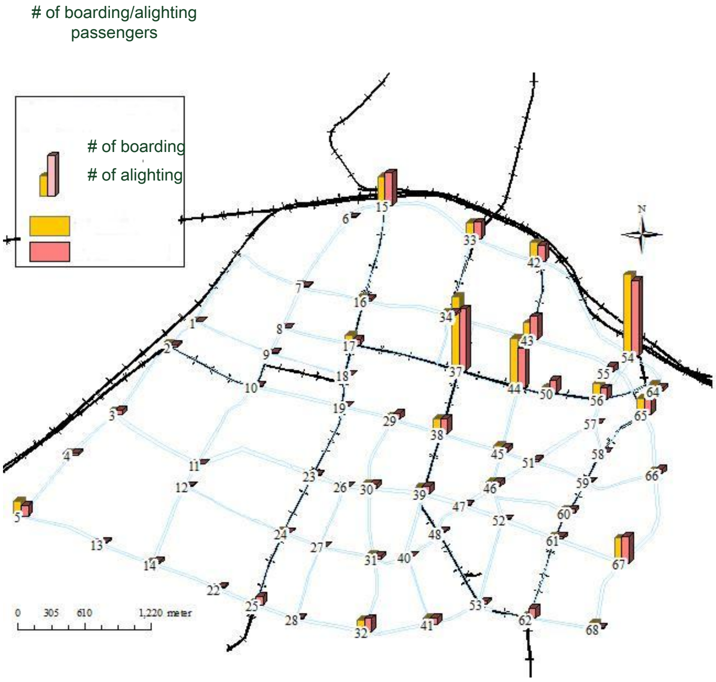


Figure 5. Distribution of the number of passengers boarding/ alighting from 07:00 to 08:00.

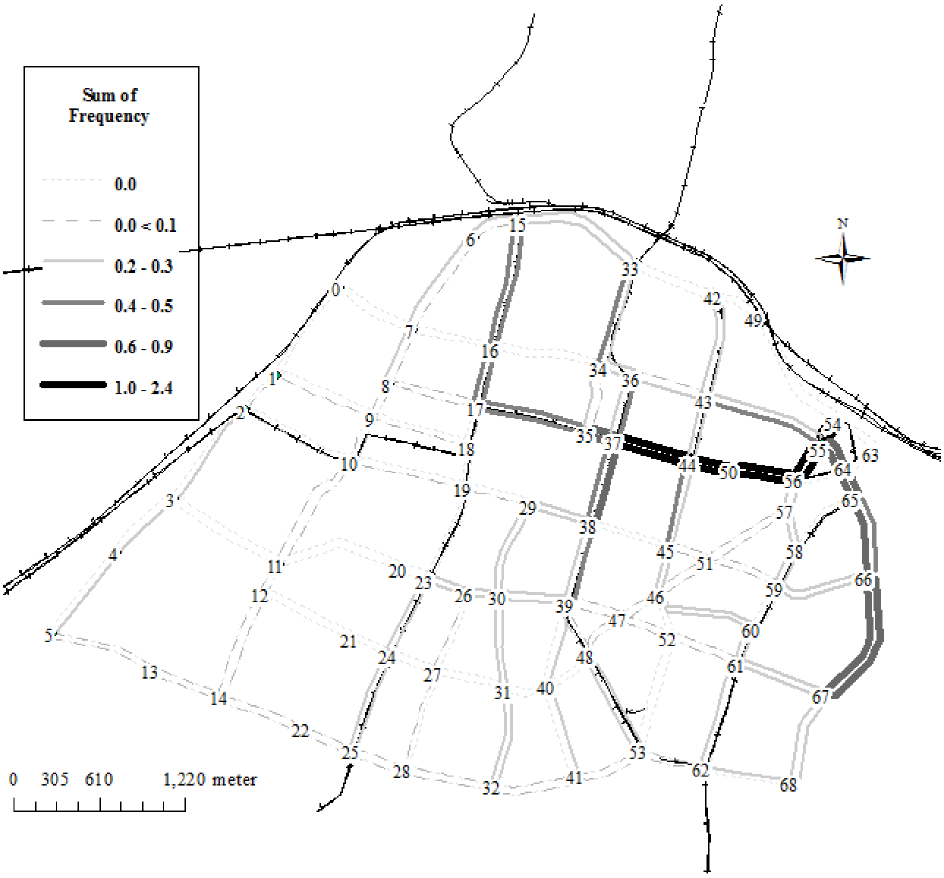


Figure 6. The sum of frequencies for each road section from 7:00 to 8:00 (current network).

4-2. Data collection and parameter setting

4.2.1 *Data collection*

Passenger demand data were obtained from the bus companies operating in the study area, based on numbered tickets used in October 2006. Five bus companies were operating in the study area, but we did not consider competition between companies and the data were treated as if only one company was operating in the area. Data limitations forced two other constraints. First, aggregated data was only available by month, so it was impossible to determine fluctuations in demand between days or hours. Thus, we first converted the original dataset to 1-day data by dividing it by 31, and then converted it to peak demand (from 07:00 to 08:00) by multiplying it by the ratio of the demand during that period (obtained from Figure 4). Second, because a sectional fare structure was used in the study area (starting at ¥150: 1 EUR is approximately 110 JPY), demand data were obtained only between different fare sections. Therefore, we consolidated bus stops to the major intersections. Because this procedure resulted in many of the fare zones having only one consolidated bus stop, the origin or destination of these fare zones can be automatically converted to that consolidated bus stop. However, if one fare zone had more than two consolidated bus stops, passenger boarding or alighting demand in this fare zone was distributed proportionally to consolidated bus stops based on the number of bus stops within this fare zone. Additionally, several boarding demands had origins or destinations outside the study area, so these origins or destinations were hypothetically moved to the closest boundary bus stop. Figure 7 shows the simplified network, which has 69 bus stops and 228 links in both directions. The result is 36 lines in both directions; frequencies and distances between bus stops were obtained from timetables and GIS data, respectively. Note that Bellman's principle does not hold in the lower model if the structural fare system is, as introduced in the study area, is considered. Therefore, the fare is not considered for the evaluation.

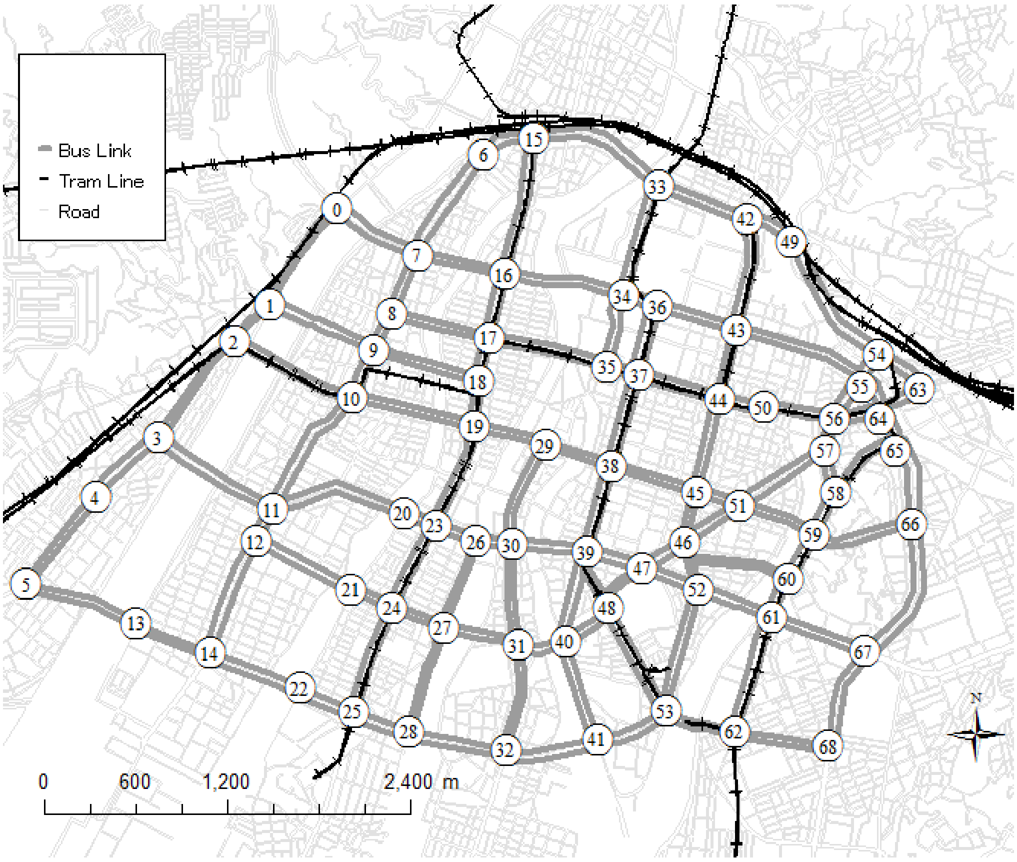


Figure 7. Study network.

4.2.2 *Parameter setting*

Although bus travel speed data were not available, the 2005 census by the Japanese Ministry of Land, Infrastructure, Transport and Tourism indicated that the average travel speed in the centre of Hiroshima City was approximately 18.8 km/h (313.3 m/min). Therefore, travel speed for each mode was estimated as shown in Table 1(a). The value of time was set as shown in Table 1(b), which was estimated by Kurauchi et al. (2004) based on SP-based mode choice survey data. The capacity of each vehicle was set at 45 passengers/vehicle, which was based on visual observations of loaded vehicles. As described previously, if the frequency of each line is chosen from a wide range, the number of combination of frequencies and line configuration becomes exponentially larger and consequently increases the possibility of reaching locally optimal solutions. Thus, frequencies were selected from four options: twice the current frequency, the current frequency, half the current frequency, and no service. Table 2 lists the parameters for NSGA-II.

Table 1. Parameters for the transit assignment model.

(a) Travel speed

Bus	300	(m/minute)
Walk	50	(m/minute)

(b) Value of time

On Board	13	(¥/minute)
Wait	26	(¥/minute)
Walk	50	(¥/minute)

Table 2. Parameters for NSGA-II.

Number of indivisuals	40
Number of generations	50
Crossover rate	0.9
Mutation rate	0.05

Because it was not possible to estimate the parameter for failure to board, we first compared the Pareto front using various parameters using Figure 7. Note that $\theta = 0$ indicates that the passengers choose a route without considering the possibility of failure to board. When operational cost is around 300, positive θ values result in higher cost to passengers than when θ is equal to 0, but the three Pareto fronts remain approximately the same. This result indicates that overcapacity cannot be a serious problem even if the transit operator reduces the service level to some extent. One reason for this might be underestimation of peak demand since we did not consider differences in patterns of demand between weekdays and weekends due to data limitations. None of the results hereafter consider capacity constraints.

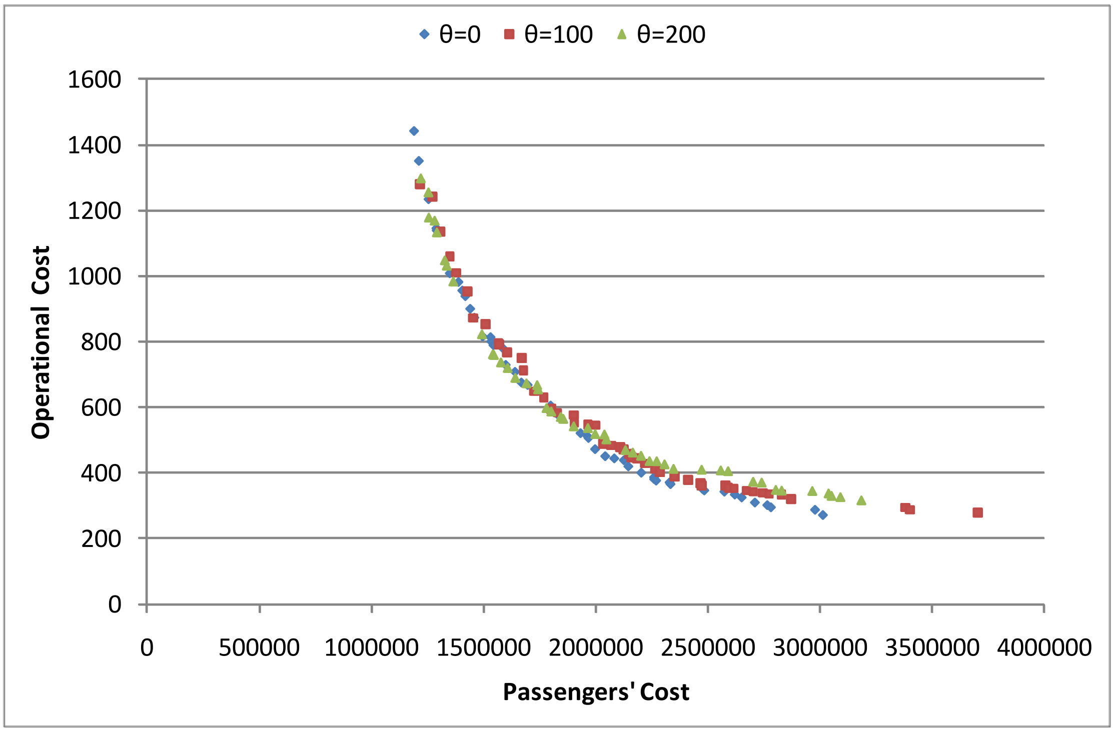


Figure 8. Pareto front with differing parameters for failure to board.

4-3. Discussion

Figure 9 shows the transition of chromosomes with regard to the number of generations which shows chromosomes disperse over the plains at younger generations. However, chromosomes accumulate to a curve with passing generations, and finally yielding a Pareto front with 46 Pareto solutions (Figure 10).

The two black dotted lines in Figure 10 represent the objective values for the current network. It is not realistic to investigate network configurations for all Pareto solutions. Thus, to determine how reducing operational costs along the Pareto front would affect service level for the entire network, the Pareto solutions are labelled in ascending order of cost to passengers. Of the 46 solutions, solutions 6 and 7 are better than the current network in terms of cost to passengers and operational costs, but the current network (where the two black dotted lines meet) is, in fact, very close to the Pareto front.

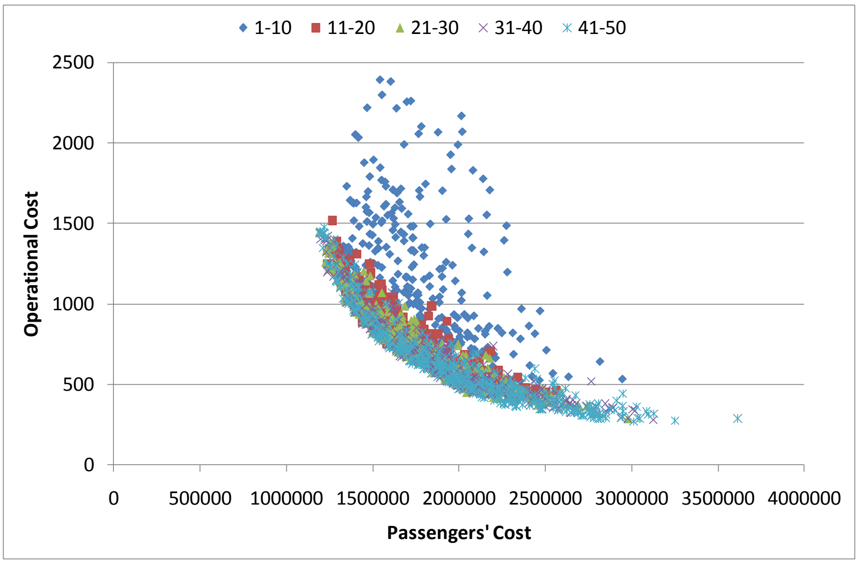


Figure 9. Transition of chromosomes.

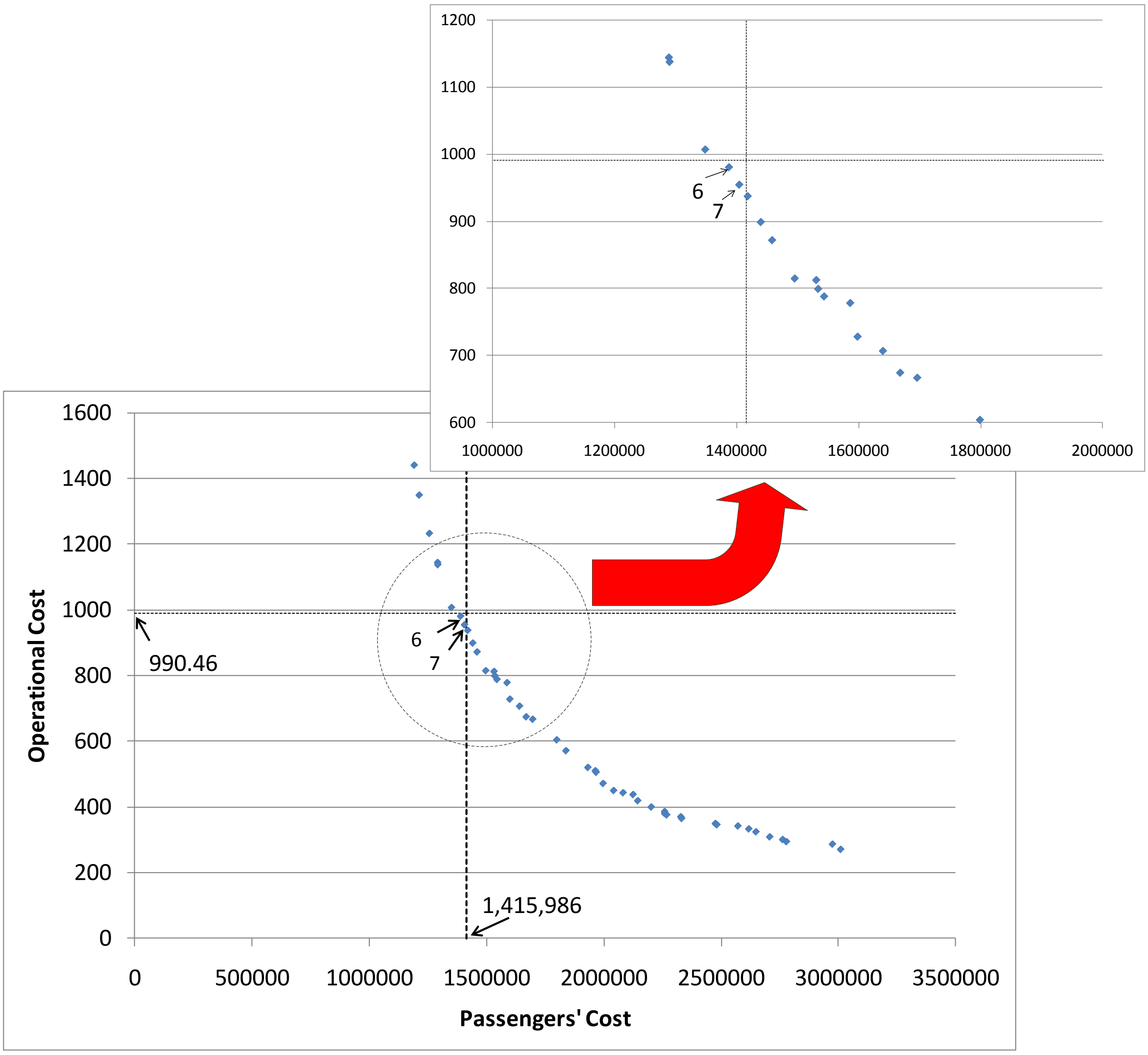


Figure 10. Pareto front with the costs of the current network.

Figure 11 shows the suggested line frequencies for each of the four options. For example, 100% of lines increase their frequency for the option of "twice" (doubling the frequency on all lines). Again, solutions are arranged horizontally in ascending order of cost to passengers. The percentage of lines increasing their frequency to twice reaches 40% at solution 0 (the solution with largest operational cost) and then decreases as the solution number increases. Alternatively, the percentage of lines with the same frequency increases and has the largest value around solution 10. As the solution number increases further (consequently reducing the operational cost), the percentage of lines with the same frequency increases, and the percentage of lines halting their service increases. Finally, more than 40% of lines halt service and all lines cease to increase frequency at solution 45.

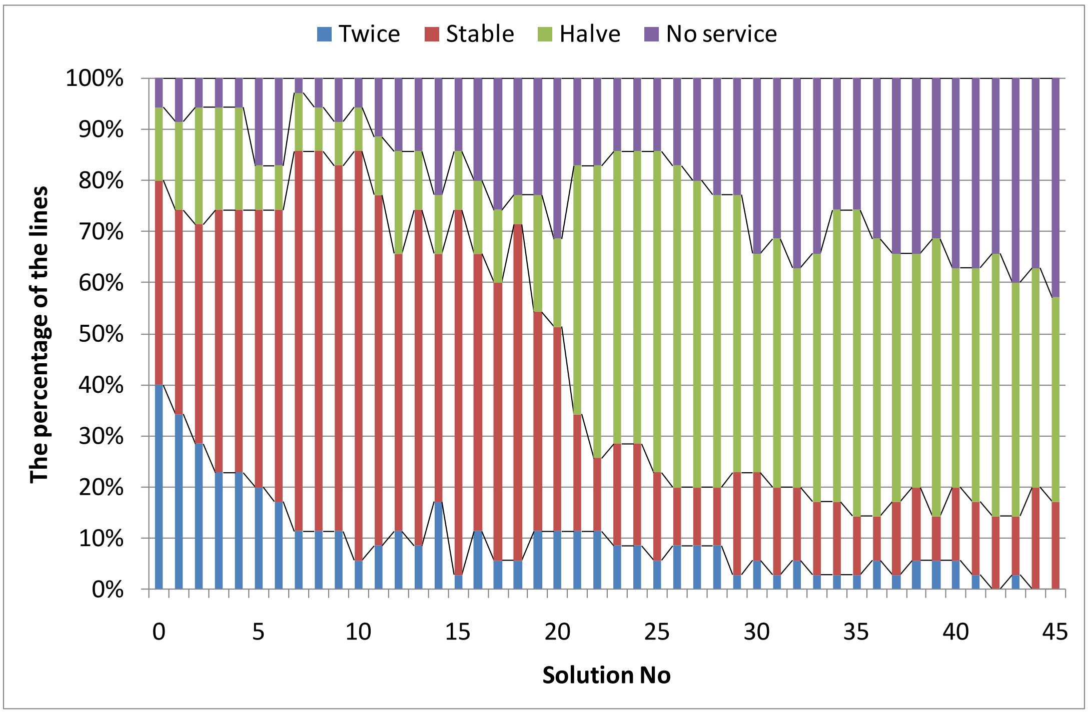
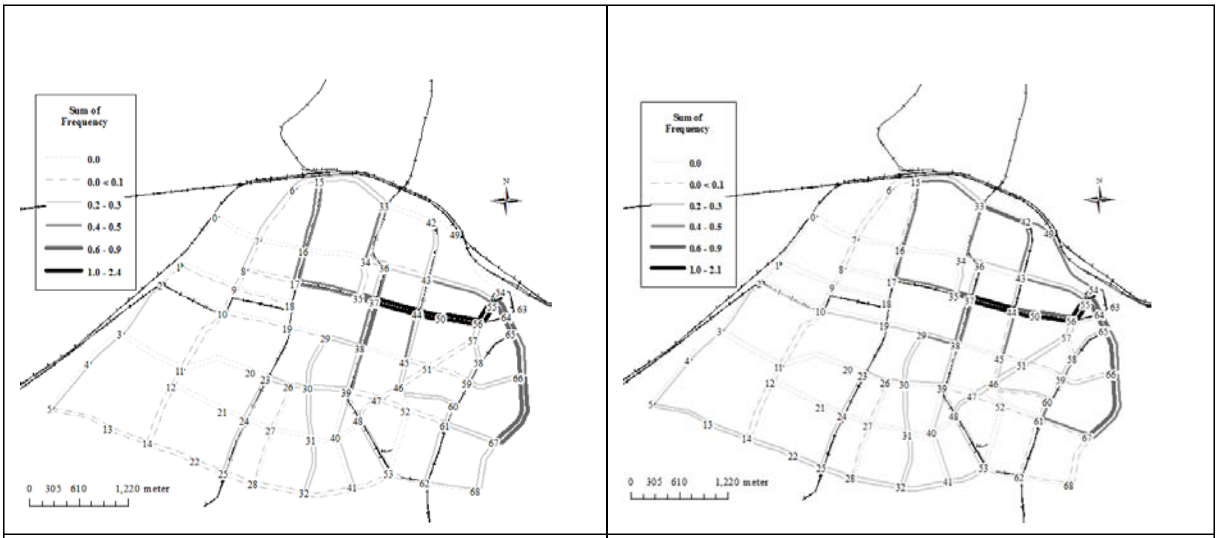


Figure 11. Suggested line frequencies for each solution.

Figure 12 shows the sum of frequencies for the current network and for solution 6 (one of the solutions in which both objective values are better than the current network.) By comparing the two figures, a new route emerges, connecting a road section between nodes 54 and 42. However, the number of road sections with high frequency seems to decrease for the entire network. Indeed, the sum of the line frequencies is 4.47min^{-1} for solution 6 but 5.28min^{-1} for the current network. Also, the variance in sum of the frequency among road sections for solution 6 and for the current network is 0.088 min^{-2} and 0.120 min^{-2}, respectively. Note that the small variance in frequency among road sections indicates that the difference of sum of the frequency among road sections is small, which implies that bus service is uniformly dispersed to the network. Therefore, this fact indicates that bus service is dispersed wider in solution 6 than in the current network. These findings suggest that the operators could provide better service than the current network from the perspective of overall passenger cost even if they reduced the overall service frequency. One reason for this is that in solution 6, operational service is dispersed thorough the network, because it has a greater variance in frequency among road sections than the current network does. Another reason may be that many lines are concentrated at a certain road section in the current network.



(a) Current network. (b) Solution 6.

Figure 12. The sum of frequencies for each road section.

To test these hypotheses, we focused on changes in frequencies at local road sections where many buses are concentrated. Figure 13 shows the sum of the frequencies for each solution at Section A and Section B. In the figure, Section B is marked with a red circle; it connects the central station and the busiest downtown area, and as mentioned above, many buses pass through the section. Section A is marked with a blue circle; it was chosen as an alternative to Section B because both sections run in parallel directions. The sum of frequencies for west-bound travel on both sections decreases for many solutions, but the ratio of decrease seems to be larger for Section B than for Section A. Furthermore, the sum of frequencies for east-bound travel on Section B decreases for many solutions, whereas the sum of frequencies for east-bound on Section A increases for many solutions. Thus, the concentration of buses on Section B is reduced in many solutions and one reason for this is the fact that some lines shifted from Section B to Section A.

In summary, dispersing service operation is one way to bring about a win-win situation for both passengers and service operators of a dense bus network. One way to make this happen is to shift some services from a section with dense service to another parallel section with less dense service.

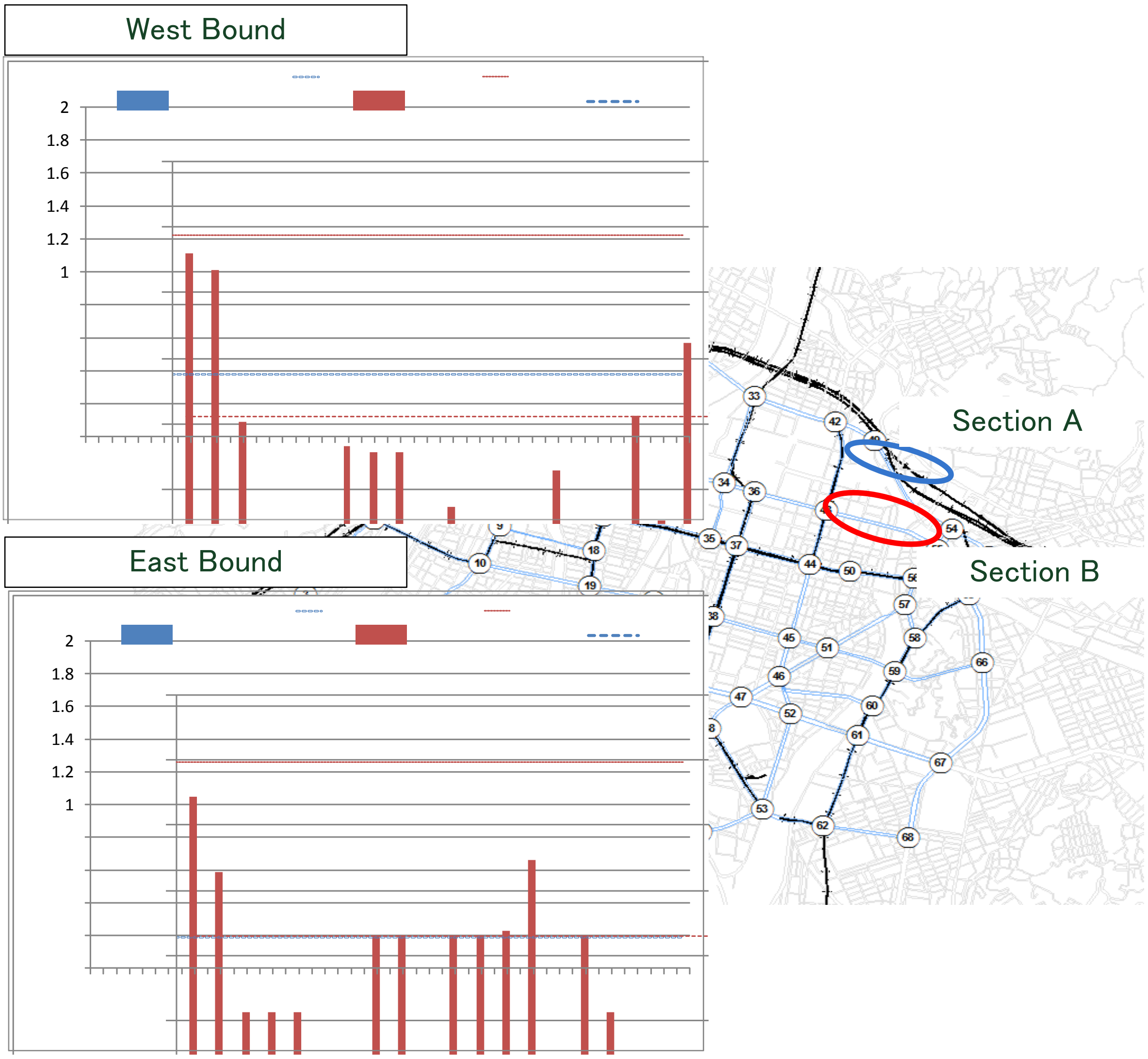


Figure 13. The sum of frequencies at Section A and Section B for each solution.

So far, the Pareto solutions have been evaluated mainly from the perspective of the operators or the overall systems; now, we evaluate the Pareto solutions from the perspective of passengers. Figure 14 illustrates the cost component for each solution. The boarding cost is stable through all the solutions, but wait times and walking times increase as the solution number increases (consequently decreasing operational costs by reducing the level of service, as shown in Figure 10 and Figure 11). Thus, passengers suffer from inadequate service as operational costs decrease, but the total boarding time is stable, presumably due to the assumption of fixed OD demand.

Finally, equity levels were compared between OD pairs using an equity indicator. As mentioned in Section 1, researchers have not reached a consensus about which equity indicator is most suitable for evaluating certain transportation policies. Some previous studies have used the Gini coefficient, and we used it here (see Appendix for a definition and formulation). We also applied the longitudinal dimension (see Section 1), based on the assumption that it is preferable to maintain a differential of the service level that is similar to the current situation. Figure 15 shows the Gini coefficient for each Pareto solution; it increases as the solution number increases (equivalent to reducing operational costs). To summarise, decreasing operational costs has the effects of increasing cost to passengers and of increasing inequity among OD pairs.

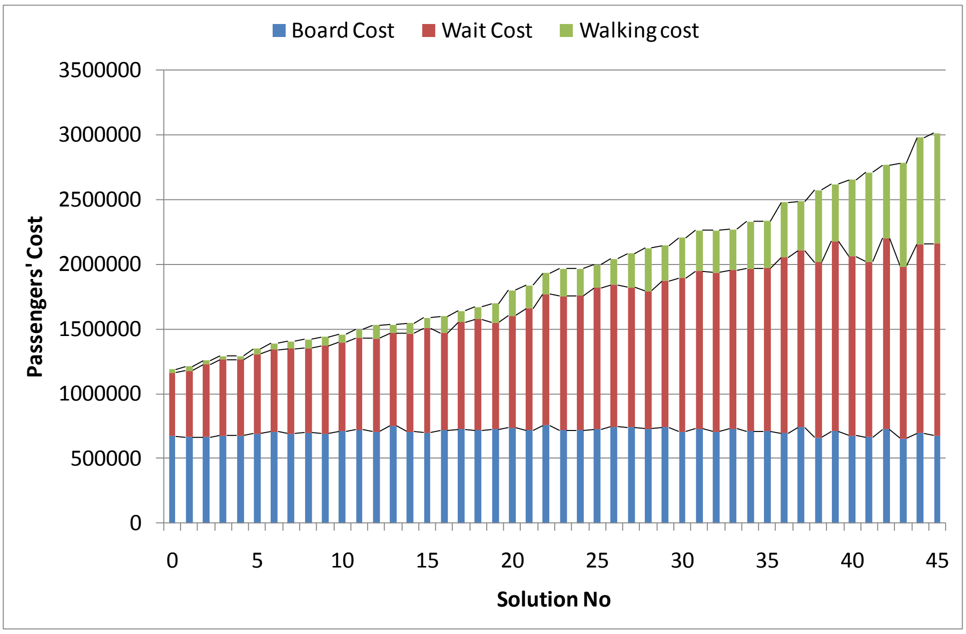


Figure 14. Cost component for each solution.

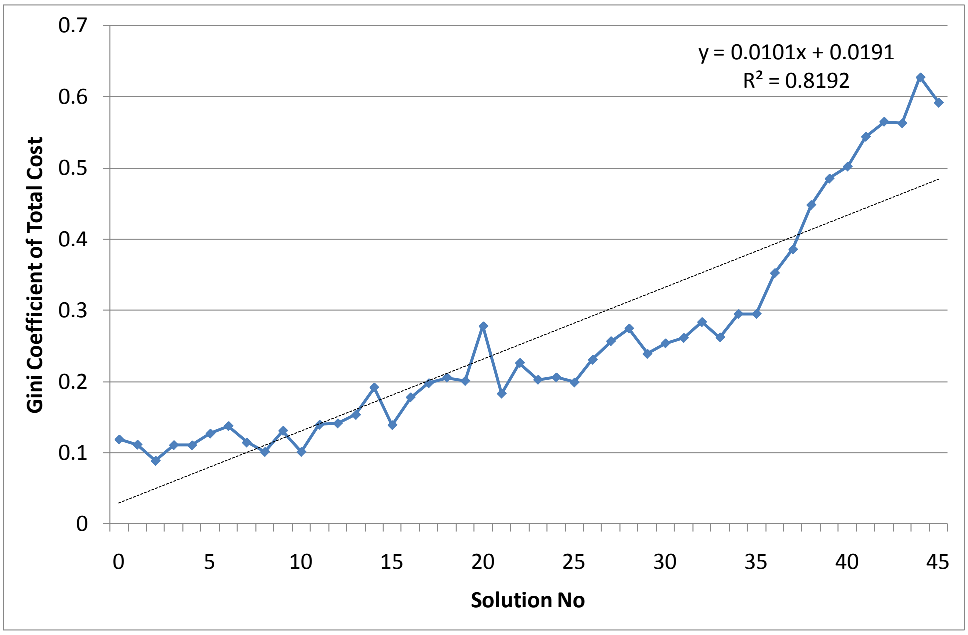


Figure 15. Gini coefficient with respect to total cost for each solution.

4-4. Sensitivity analysis of demand pattern

As mentioned in Section 4-2, only aggregated demand data were available, so it was not possible to determine fluctuation in demand between days or times of day. Thus, we conducted a sensitivity analysis of fluctuation in demand pattern. This involved generating four different types of demand patterns using the following procedure:

(Step 1) For each OD pair *ij*, define the magnification factor using the standard normal random variable as:

$$c_{ij} = 1 - \kappa r_{ij}$$

where r_{ij} is the standard normal random variable and k is a constant.

(Step 2) The new passenger demand is given by:

$$new\_demand_{ij} = c_{ij} \times demand_{ij}$$

where $demand_{ij}$ represents the passenger demand between i and j.

In the above procedure, only the demand patterns are variable, in short, total passenger demand is conserved.

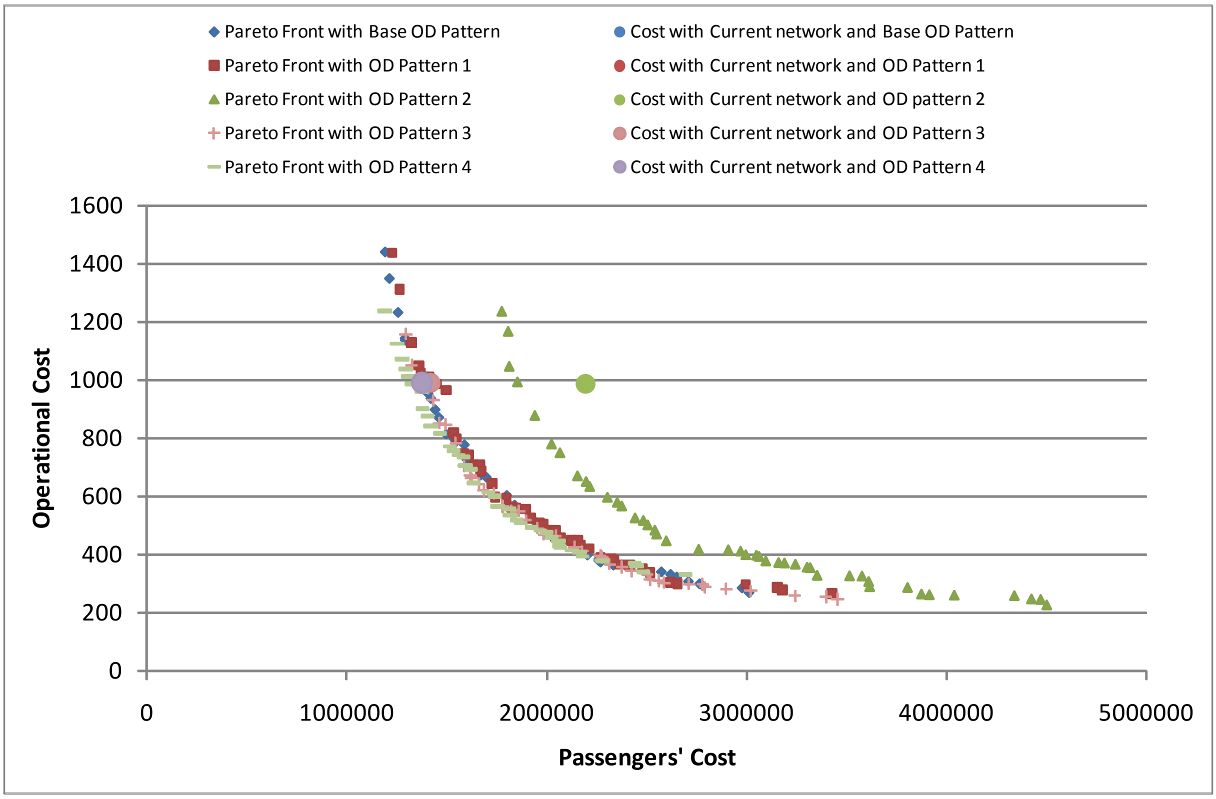


Figure 16. Pareto fronts with various origin-destination (OD) patterns.

Figure 16 illustrates the Pareto fronts for various OD patterns. The large filled circles plot passenger cost and operational cost for the current network and each OD patterns. The base OD pattern represents the OD pattern used in the previous section. OD patterns 1 and 2 are based on small OD pattern fluctuation (with κ equal to 0.1 in Step 1 above) and OD patterns 3 and 4 are based on large OD pattern fluctuation (with κ equal to 0.2 in Step 1 above). The figure reveals that OD patterns 1, 3, and 4 have Pareto fronts similar to the base OD pattern. Additionally, both passenger cost and operational cost in the current network is very close to the Pareto front with OD patterns 1, 3, and 4 as well as the base OD pattern. However, the Pareto front with OD pattern 2 is not close to that of the base OD pattern. Furthermore, passenger cost and operational cost in the current network are not close to the Pareto front for OD pattern 2, indicating that the current network is not efficient with this OD pattern. Thus, despite the small fluctuation, OD pattern 2 exhibits a different tendency with regard to the Pareto front and passenger cost in the current network. However, Figure 17 (which illustrates the Gini coefficient in each Pareto solution for OD pattern 2) shows tendencies similar to those in Figure 15; that is, the Gini coefficient increases as the solution number increases.

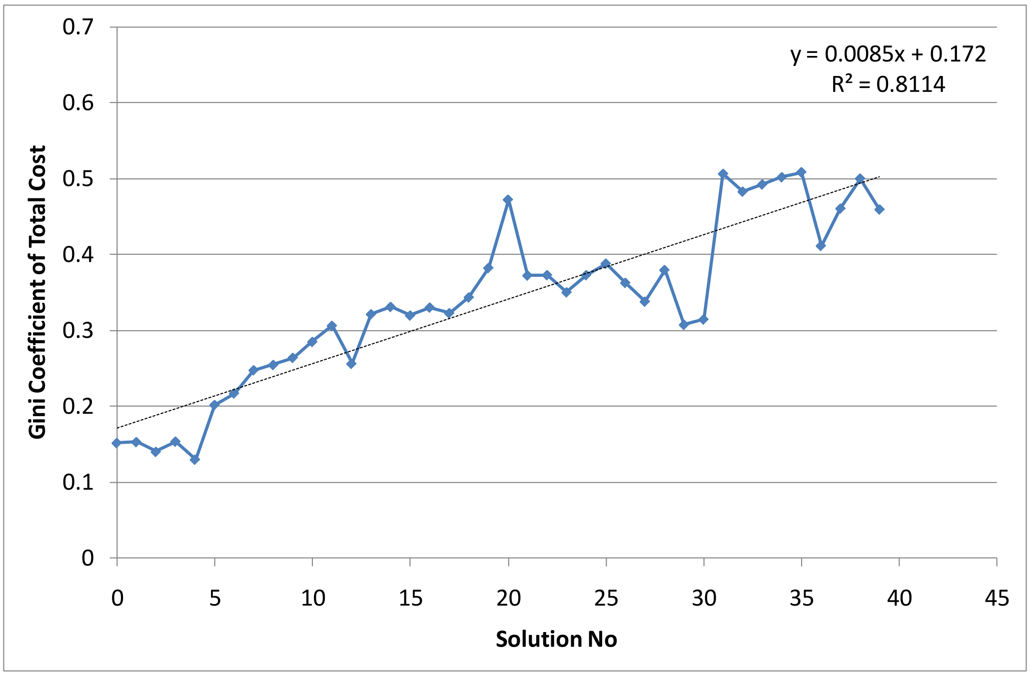


Figure 17. Gini coefficient with respect to the total cost in each solution (OD pattern 2).

To summarise, passenger cost in the current network could be increased by the OD pattern fluctuation. In such a case, the current network is not efficient because passenger cost and operational cost in the current network is not close to the Pareto front. However, despite the OD pattern fluctuation, the same tendency was confirmed: decreasing operational cost has the effects of increasing passenger cost and increasing inequity of service levels among OD pairs.

5 Conclusions

This study evaluated the bus network configuration during the morning peak hour in the central area of Hiroshima City from the perspectives of operators and passengers. The evaluation was conducted using a previously constructed bus network optimisation model, which can decide line configurations and frequencies simultaneously. In the model, transit operators were assumed to be a public agency with the goal of minimising total operational costs, but not maximising benefit; the current bus network was compared with a bus network balancing between the operational cost and the passengers' convenience.. Only aggregated demand data were available, so peak demand data was generated using simple assumptions.

The comparison of the current bus network and the model output based on demand pattern data confirmed that the current bus network is close to the Pareto front if the total costs to passengers and operators are adopted as objective functions. It also demonstrated that dispersing service operation could bring about a win-win situation for both passengers and service operators and that one way to make this happen is to shift some services from a section with dense service to another parallel section with less dense service. Thus, it is still possible to realise a more desirable network with less cost to passengers and operator. However, the sensitivity analysis with regard to the OD pattern fluctuation confirmed that passenger and operator costs in the current network can be sensitive to the demand. Finally, the results confirmed that, regardless of OD pattern fluctuation, reducing operator costs will increase passenger cost and increase inequity in service levels among passengers.

Future research should use more detailed OD data from IC card records to improve the accuracy of results. Furthermore, it would be worth comparing results based on various time periods to confirm the robustness of the network configuration with variable demands. It will be necessary to expand the model to consider elastic demand or interaction among other means of travel (such as private vehicles and taxis). Finally, it would be helpful to add other constraints to the model, such as driver scheduling, to obtain more realistic results.

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Appendix: Gini coefficient

The Gini coefficient is a value that is often used to measure income inequity; it has also been used in operations research (Shimamoto et al., 2005). The Gini coefficient is defined as twice the area between the Lorentz curve and a 45° line in the population-share and income-share plane. By definition, the Gini coefficient has a value between 0 and 1, where 0 corresponds to perfect equity and 1 to perfect inequity. The Gini coefficient regarding the total cost among OD pairs can be formulated as:

$$Gini^m = \frac{1}{2 \cdot Q^2 \cdot \overline{CR}^m} \sum_{i=1}^{I} \sum_{j=1}^{I} Q_i Q_j \left| CR_i^m - CR_j^m \right| \qquad \text{(A1)}$$

where

$$CR_i^m = g_i^0 \Big/ g_i^m$$

$$\overline{CR}^m = \sum\nolimits_{i=1}^{I} CR_i^m \Big/ I$$

where

$Gini^m$: Gini coefficient at solution *m*
I : Set of OD pair
Q_i : Passenger demand of OD pair *i*
g_i^0 : Generalise cost of OD pair *i* at current network
g_i^m : Generalise cost of OD pair *i* at solution *m*

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