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IMPACTS OF SNOW ACCUMULATION ON A FACILITY LOCATION MODEL –FOCUSING ON THE ROAD NETWORK IN NAGAOKA, NIIGATA, JAPAN–

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Abstract. *Snow cover on road surfaces is considered an adverse driving condition and has been shown to reduce traffic capacity. This reduction in traffic capacity can be interpreted as an increase in perceived travel distance. Thus, snow cover indirectly affects the optimal location of various facilities, as most models calculate the optimal locations based on traveling distance. In this study, we investigate the effects of snow cover on the accessibility of existing facilities and on optimality in the problem of selecting a location for new facilities, especially the p-median problem. Regarding the effect on existing facilities, the results showed that snow cover increased the total effective travelling distance to existing facilities by a factor of 1.5. To consider impacts on the facility location problem, we evaluated facility locations calculated with the effective summer and winter distances by comparing the total travel distance ratio in winter to that of summer. The results of a simulation with 100 different road network patterns showed that the mode and median values were less than 1.0. We conclude that using effective winter distances is preferable to obtain an optimal facility location in terms of the course of an operating year.*
Keywords: Uncertainty in optimization problems, p-median problem, Traffic capacity under snow conditions

1. **Introduction.** Urban areas typically include commercial facilities such as grocery stores, shopping malls, and restaurants as well as public facilities such as hospitals, fire stations, and evacuation centers. In considering the location of these facilities, planners and decision-makers must ensure equitability and accessibility for public facilities, whereas private facilities generally emphasize profitability or other priorities. The facility location problem is conventionally formulated as an optimization problem regarding the selection of a location for such facilities. Owen and Daskin comprehensively summarized various facility location problems [1].

In areas that regularly experience heavy snowfall, such as Niigata Prefecture in Japan, the effect of snow cover on road surfaces has been quantified in terms of a variable rate

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of reduction in traffic capacity [2]. Studies have been conducted to measure the rate at which traffic capacity is reduced owing to snow cover, such as those by Ishii and Saito [3] in Japan and He and Zhu [4] in China. Besides, Kaku et al. [5] and Terauchi et al. [6] reported that snow cover affects the amount of traffic and speed of cars, respectively. Although they are not studies on a snowfall, Edward et al. [7] further noted that rainfall and sunshine can affect traffic capacity, and Zhang et al. [9] reported the effect of rainfall on a traffic in Beijing. Oguchi and Nakamura comprehensively summarized research on traffic capacity in Japan [8].

Reductions in traffic capacity can be interpreted as an increase in the perceived distance traveled or time taken. Therefore, we can consider that two (experiential) distances may obtain between travel destinations depending on road conditions, weather, and seasonal variations. Alternatively, varying distances between points in summer and winter could be represented as intervals.

Most facility location problems focus on the distance and time required to determine the optimal facility location. However, because the experiential distance or traveling time between points may differ depending on weather conditions between different seasons, as mentioned above, optimal placement may differ as well when solving the facility location problem for a period of time spanning multiple seasons. There has been no research investigating the effect of snow cover on facility location problems. To investigate these issues, we examined the extent to which the accumulation of snow on road surfaces in winter affects the facility location problem using the p-median problem (PMP), which is one of the classic facility location problems, as a basic model.

The PMP model was proposed by Hakimi [10] and formulated as a mixed-integer programming (MIP) problem by ReVelle and Swain [11]. PMP considers facility location models on a directed or undirected network. Assuming that users (demand) at each node use the nearest facility, p facilities are located to minimize the sum of the travel distance to the facilities for all users. Besides PMP, the location set-covering problem (LSCP) is the traditional facility location problem for static demand [12]. LSCP aims to search facility locations covering all demand in any area with a minimum number of facilities, and extended models have been proposed [13, 14]. In addition to location models for static demand, such as PMP and LSCM, some models concerned with traffic flows exist [15, 16, 17].

The PMP model has been extended in various ways. Stefanello et al. [18] proposed a method to efficiently solve large-scale problems of capacitated PMP, such as a problem having upper limits in the number of capable users at each facility. Recently, the obnoxious facilities planar based on PMP has been proposed by Kalczynski and Drezner [19], and Imran et al. [20] extended the PMP to consider some environmental footprints, like the total emission of CO_2. In addition, some extended models of PMP based on robust optimizations that can account for uncertainty in the demand and distance have also been proposed. Along these lines, Serra and Marianov [21] formulated a PMP with uncertainty in terms of both demand and distance using robust optimization and applied it to the allocation of fire stations in Barcelona. Takahagi et al. proposed a facility location model that considered potential future declines in population [22].

Aiming to build on these findings, in this study, we mathematically verified two related points. First, we calculated the extent to which effective traveling distances to existing facilities such as grocery stores and evacuation centers increase when measured in terms of winter distances affected by snow cover; second, we considered the problem for a real road network. The latter entailed a comparison and validation of the optimal layout of the road network in Nagaoka City, Niigata Prefecture (excluding the area occupied by the former Kawaguchi City) in terms of summer and winter distances. In this validation, we quantified the effect of snow cover on the PMP. In other words, it is possible to consider the extent to which snow cover should be considered in the PMP in a simple comparison of two distances between two points in summer and winter.

The remainder of this study is organized as follows. In Section 2, the effects of snow cover on road conditions are described in detail, with a focus on reviewing Ito et al.'s work [2]. Section 3 presents a model for the PMP and describes the necessary preliminaries for the three validations. Two numerical validations are presented in Section 4. Finally, Section 5 summarizes our findings.

2. **Previous Studies on the Impact of Snow Cover on Traffic Capacity.** Ito et al. [2] described the rate of decline in traffic capacity with increasing snow cover. They also analyzed the saturation traffic flow rate and effective green time for different winter road surface conditions and calculated the traffic capacity of straight and left straight lanes at intersections with signal lights. The study was conducted on roads in Nagaoka City, Niigata Prefecture. To enable the authors to analyze differences in levels of snow removal, the intersections were classified in terms of different types of road (directly controlled roads, auxiliary national roads, prefectural roads, or municipal roads) and whether snow-melting pipes were installed. The total sample size was 665 cycles, with 9,883 vehicles. Their analysis of traffic capacity at signalized intersections was carried out in accordance with road surface conditions in winter. They classified winter road conditions as dry, slippery (powdery snow), compacted snow (smooth), compacted snow (uneven), or frozen.

The calculation of traffic capacity requires values such as the saturation traffic flow rate and headway time. The saturation flow rate was calculated from a set of headway data for each intersection and road surface condition measured from images captured in video observation to obtain the average headway for each stop line passing order. The average value was calculated using a linear regression formula derived from the relationship between the cumulative average headway time from the start of saturation, excluding vehicles affected by starting, and the cumulative number of vehicles proceeding at green traffic lights. Similarly, Oguchi et al. [23] stated that the saturation state is obtained as the expected value from the fourth vehicle onwards. In contrast Ito et al. [2] judged saturation based on other measures concerning vehicle headways, and obtained results similar to those of Oguchi et al. [23].

The clearance lost time T_c is calculated as follows:

$$T_c = G + Y - \sum_{i}^{n} T_i, \tag{1}$$

where G is the green time, Y is the yellow time, T_i is the headway of the i-th vehicle, and n is the number of vehicles that passed before the end of the yellow signal. From the above, the traffic capacity c_s of the straight (left) lane is given as

$$c_s = S_A \times g/C \tag{2}$$

where S_A is the measured saturation traffic flow rate, g is the effective green time, and C is the cycle length. The effective green time g was measured from video observations.

The saturation traffic flow rate decreased on snow-covered surfaces in winter, the start-up lost time was reduced on snow-covered surfaces in winter, and there was no significant difference in the clearance lost time. Based on these results, the traffic capacity was reduced in relation to dry road surfaces, with a 20% reduction for powder and freezing conditions, and a 30% to 50% reduction for compacted snow conditions. The rate of reduction in traffic capacity was almost the same independent of road type and installation of snow-melting pipes. However, under the same 'snowfall' conditions, the conditions of the road surface differ in practice depending on the level of snow removal, which depends on the effectiveness of such services and the amount of traffic. This means that under the same snowfall conditions, different types of road and traffic capacity reduction rate are related to the degree of snow removal and road surface condition; conversely, the rate of reduction in traffic capacity owing to snowfall in winter can be estimated based on road types.

Specifically, the traffic capacities mentioned above were those at observed at signalized intersections. The traffic capacity of an ordinary road segment is generally the same as that of a signalized intersection, according to Tsukada et al. [24]. Based on this idea, in this study, we consider the traffic capacity of a signalized intersection as a segment, that is, the traffic capacity between nodes in the road network.

Next, we show that a decrease in traffic capacity can be interpreted as an increase in perceived travel distance or traveling time. First, following Oguchi [25], we express the traffic volume Q as

$$Q = K \times V, \tag{3}$$

where K is the traffic density and V is the traffic speed. The traffic volume, density, and speed are then described as follows. In general, as the traffic density approaches zero, its speed reaches a maximum value (free speed), and as the speed approaches zero, the traffic density approaches a maximum (saturation density). Thus, certain traffic densities (critical densities) and speeds (critical speeds), the traffic volume reaches a maximum value. When the traffic density is higher than the critical density (i.e., the traffic speed is lower than the critical speed), traffic is congested. Furthermore, Equation (3) and the monotonically decreasing nature of the traffic density with traffic speed give rise to the existence of the maximum traffic volume. This maximum traffic volume is the definition of traffic capacity. Therefore, the traffic capacity $Q_{\max}$ can be expressed as

$$Q_{\max} = K_{\text{critical}} \times V_{\text{critical}}, \tag{4}$$

where K_{critical} is the critical density and V_{critical} is the critical speed. However, according to Oguchi [25], the traffic speed is a representative speed of a traffic flow comprising individual vehicles with different speeds. For this representative value, the 'spatial average speed' of individual vehicles is used. This is the average time taken by individual vehicles to travel a given distance divided by the length of that distance.

Let Q_{s} and Q_{w} (s: summer, w: winter) denote the traffic capacity of a given network in summer and winter, respectively (in both cases, we consider basic traffic capacity). The relationship between traffic capacity in summer and winter can be expressed as

$$Q_{\text{w}} = cQ_{\text{s}}, \tag{5}$$

where c is the rate of decrease of the traffic capacity in winter relative to that in summer. According to Oguchi [25], traffic density is the number of vehicles present at a given time converted into the number of vehicles per unit distance [vehicles/km], generally using a distance of 1 km or less in the direction of road extension as the aggregate unit. The traffic density K is

$$K = \frac{N}{d} \tag{6}$$

where N is the number of vehicles present at a given time and d is the length of the section along which the number of vehicles is measured. Thus, winter traffic capacity Q_{w} can be expressed as

$$Q_{\mathrm{w}} = cQ_{\mathrm{s}} = c\frac{N_{\mathrm{critical}}}{d} \times V_{\mathrm{critical}}, \tag{7}$$

where N_{critical} is the number of vehicles present at a given time in summer, corresponding to the critical density. Thus, we obtain the following:

$$Q_{\mathrm{w}} = c\frac{N_{\mathrm{critical}}}{d} \times V_{\mathrm{critical}} = \frac{N_{\mathrm{critical}}}{d/c} \times V_{\mathrm{critical}}. \tag{8}$$

The denominator d/c can then be interpreted as the length of the section weighted by the inverse of the traffic capacity reduction rate, i.e., the amount by which the distance between points is perceived to have increased in the winter season compared to the summer season. Of note, no individual correction for each road is considered. In reality, for example, people may take a detour to reach their destination rather than the shortest route on roads that are heavily congested at certain times of the day. This could be quantified as a reduction in traffic capacity in the same way as for snow cover; however, because we aimed to consider the impact of snow cover on a real road network, we did not consider this situation and assume that people travel at the same speed on each road. Note that if the impact of different events could be quantified as a reduction in traffic capacity rather as with snow cover, then the methodology of this study could be applied for different conditions.

3. **Preparation of PMP and Numerical Experiments.** In this section, we describe the PMP and define the parameters and variables required for the numerical experiments.

3.1. **PMP modeling.** The PMP can be formulated using a graph $G(N, E)$, where N is the set of nodes that represent the intersections of the road network and E is the set of edges that comprise the roads connecting the intersections. The parameters and variables are listed in Table 1 and formulated for the PMP as follows:

$$\min \sum_{i,j \in N} P_i d_{ij} X_{ij} \tag{9}$$

$$\text{s.t.} \sum_{j \in N} X_{ij} = 1, \quad \forall i \in N, \tag{10}$$

$$X_{ij} \le Y_j, \quad \forall i,\, j \in N, \tag{11}$$

$$\sum_{j \in N} Y_j = p, \tag{12}$$

$$Y_j \in \{0, 1\}, \quad \forall j \in N, \tag{13}$$

$$X_{ij} \in \{0, 1\}, \quad \forall i, j \in N. \tag{14}$$

Equation (9) is the objective function for minimizing the total travel distances for all travelers to their nearest facility. Equation (10) is the constraint that travelers at each node must be assigned to only one of the nodes. Equation (11) is the constraint that

Table 1. Parameters and decision variables used in PMP

Set	N	Set of the nodes
Parameters	p	Number of facilities allocated
	P_i	Demand (e.g., population) for node $i \in N$
	d_{ij}	Distance between nodes i, j (shortest path length)
Decision variables	X_{ij}	Variable that takes 1 if the person at node i uses the facilities present at node j, and 0 otherwise.
	Y_j	Variable that takes 1 if a facility exists at node j, and 0 otherwise.

people cannot be assigned to nodes at which facilities do not exist. Equation (12) is the constraint that the number of facilities is p. Equations (13) and (14) are constraints where the decision variables are 0-1 variables.

3.2. **Traffic capacity reduction rate allocated to each road.** Next, we describe the assignment of the traffic capacity reduction rates, as described in the previous section, to the edges in the road network. Summarizing the discussion thus far, the road type of each edge determines its traffic capacity reduction rate c. Specifically, the traffic capacity reduction rates are determined based on the previous research by Ito et al. [2]. As we are interested in the case that the effect of snow cover is significant, we use the values corresponding to the worst case. The correspondence between road types and traffic capacity reduction rates c in the acquired road network is presented in Table 2 (note that there are no secondary_links).

TABLE 2. Road type and traffic capacity reduction rate c

Road type	Summary of road types	Roads	c
unclassified	Particularly small or unimportant roads that do not fall into other categories.	28,869	0.5
service	Roads for accessing buildings, gas stations, coastlines, campgrounds, industrial zones, business districts, parking lots, etc.	1,685	0.5
track	Roads used primarily for activities such as agriculture, forestry, and outdoor recreation on open land.	20,328	0.5
residential	Roads entering and surrounding residential areas that vehicles can travel on.	12,290	0.5
tertiary	Roads designed to be at least 4 m wide with sufficient two-way traffic for vehicles and usually with a centre line.	730	0.7
tertiary_link	Connections to public roads (including acceleration lanes and ramps), where the connection is to a road of a class below tertiary.	1	0.7
trunk	National roads and major roads that are not highways, usually managed by the state rather than local authorities.	2,824	0.8
trunk_link	Connections to national roads (including acceleration lanes and ramps), where the connection is a class below trunk.	110	0.8
secondary	Roads connecting small towns and villages, including subsidiary main roads.	3,557	0.8
primary	Main roads controlled by local authorities, generally connecting larger towns.	2,202	0.8
primary_link	Connections to main roads (including acceleration lanes and ramps), with connections to classes below primary.	10	0.8
motorway	Motorways, motorways and toll roads.	14	1.0
motorway_link	Connections to motorways, acceleration lanes or ramps to motorways (access/exit connections).	47	1.0

We consider the quantification of the impact of snow cover based on the above discussion. First, the network is affected by seasonal variations, and conditions differ between summer and winter. The summer road network is denoted by $G(N, E)$ in terms of the length of each edge. If the length of an edge e in summer is given by l_e^{s}, then the length of edge in winter is given by

$$l_e^{\mathrm{w}} = l_e^{\mathrm{s}} / c_{f(e)}, \quad \forall e \in E,$$

where $f(e)$ returns the road type of edge e and c_t is the traffic capacity reduction rate for road type t. Letting L^{s} and L^{w} be the sets of the lengths of edges in summer and winter, respectively, the road networks in summer and winter can be expressed by $G(N, E, L^{\mathrm{s}})$ and $G(N, E, L^{\mathrm{w}})$, respectively.

3.3. **Generation of strongly connected subgraphs with approximately s nodes.** We describe a method for generating strongly connected (induced) subgraphs with approximately s nodes. The subgraph to be generated should be unbiased in the direction of the roads and the number of nodes should be close to s. The aim is to gradually expand the network radially until the number of nodes reaches s. Thus, the first step is to select a node at random from the nodes of the road network of the entire city of Nagaoka and let the node be v. Then, if the set of nodes in the graph to be generated is $N_{\mathrm{small}} = \{v\}$ and the set of nodes connected to $u \in N_{\mathrm{small}}$ is $M^u_{\mathrm{neighbors}}$, then N_{small} is updated as

$$N_{\mathrm{small}} \leftarrow N_{\mathrm{small}} \cup \bigcup_{u \in N_{\mathrm{small}}} M^u_{\mathrm{neighbors}}.$$

This is repeated until $|N_{\mathrm{small}}| \geq s$ (where $|N_{\mathrm{small}}|$ is of the order of N_{small}). The resulting set of nodes N_{small} is then used to generate the corresponding subgraph $G(N, E, L^{\mathrm{s}})$, $G(N, E, L^{\mathrm{w}})$ of $G_{\mathrm{small}}(N_{\mathrm{small}}, E_{\mathrm{small}}, L^{\mathrm{s}}_{\mathrm{small}})$, $G_{\mathrm{small}}(N_{\mathrm{small}}, E_{\mathrm{small}}, L^{\mathrm{w}}_{\mathrm{small}})$ (note that the distances between the nodes are calculated again). We summarized the generation method in Table 3.

Table 3. Method of generating the subgraphs with approximately s nodes

Step 1.	Let $v \in N$ be a randomly selected node from the road network of the entire city, denoted as $N_{\mathrm{small}} = \{v\}$.
Step 2.	If $|N_{\mathrm{small}}| \geq s$, extract the strongly connected components and output them as the target graph, then stop.
Step 3.	Let $M^u_{\mathrm{neighbors}}$ be the set of nodes connected to the node $u \in N_{\mathrm{small}}$.
Step 4.	Return to Step 2 as $N_{\mathrm{small}} \leftarrow N_{\mathrm{small}} \cup \left(\bigcup_{u \in N_{\mathrm{small}}} M^u_{\mathrm{neighbors}}\right)$.

4. Numerical Experiments.

4.1. **Verification of the impact of snow cover on existing facilities.** This section examines the extent to which the total distance traveled to existing facilities such as shelters and convenience stores changes between summer and winter.

4.1.1. *Experimental procedure.* First, the addresses of each facility in Nagaoka City (excluding the former Kawaguchi Town) were obtained using the NAVITIME [26] service. The latitude and longitude corresponding to the address of each facility were then obtained using the Google Maps Platform [27]. Next, the network of drivable roads in Nagaoka City was obtained from OpenStreetMap [29] using the Python package OSMnx [28]. Subsequently, a multiple-directed graph was obtained with 26,935 nodes and 80,337 edges. We removed self-loops and multiple edges by selecting the edge with the shortest distance for each link between nodes. This was performed for the networks representing summer and winter separately. In addition, edges that could not be identified with a single road type were deleted. Roads classified as path, pedestrian, footway, steps and corridor which are not accessible by vehicles, were also excluded. Finally, the strongly connected component with the largest number of nodes was extracted to form the road network to be analyzed. The final road network, which is represented by a directed graph $G(N, E)$, contained 25,283 nodes and 72,667 edges, with latitude and longitude for each node, and road type and edge length for each edge. Each facility was assumed to be located at the nearest node on the road network. The population of Nagaoka City in a 250 m grid was obtained from The Portal Site of Official Statistics of Japan, e-Stat [30]. Each grid was assigned a regional grid code to identify the grid to which a given latitude and longitude belonged. Therefore, based on the latitude and longitude of each node in the road network, we assigned the corresponding population to each node. The sum of the populations allocated to each node was 259,100. The actual population of Nagaoka City (excluding the former Kawaguchi Town) in 2020, as shown in e-Stat [30] was 262,849. This discrepancy may be attributed to the fact that only roadways were extracted to construct the model road network, and not all roads are registered in OpenStreetMap [29]. The above steps can be summarized as follows.

Step 1. Obtain the addresses of facilities in Nagaoka City.
Step 2. Convert the address of each facility to latitude and longitude coordinates.
Step 3. Obtain the road network (multiple directed graph) of Nagaoka City.
Step 4. Remove self-loops and multiple edges and extract the strongly connected component (directed graph).
Step 5. Obtain the population in each grid section.
Step 6. Assign the location and population of each facility to the relevant node.

A variable y_i is then introduced such that $y_i = 1$ if an existing facility is assigned to a node $i \in N$ on the road network and $y_i = 0$ if not. Assuming that travelers use the nearest facility, the total travel distance in summer and winter is expressed by

$$v^{\mathrm{s}} = \sum_{i \in N} P_i \min_{k \in \{j | y_j = 1\}} \left\{ d^{\mathrm{s}}_{ik} \right\},$$

$$v^{\mathrm{w}} = \sum_{i \in N} P_i \min_{k \in \{j | y_j = 1\}} \left\{ d^{\mathrm{w}}_{ik} \right\},$$

where v^{s} and v^{w} are the total travel distances in summer and winter, respectively, d^{s}_{ij} and d^{w}_{ij} are the distances between nodes i and j in summer and winter, respectively. Because the assumption that people use the nearest facility is the same as the PMP concept, we use the ratio of the total travel distance in winter to that in summer to evaluate the impact of snow cover in PMP.

The types of facilities considered included shelters (gymnasiums, schools, etc.), convenience stores, supermarkets, food stores, accommodations, hospitals/pharmacies, establishments serving gourmet food and alcohol, public facilities and institutions, and post offices. These correspond to the categories used in NAVITIME [26].

4.1.2. *Experimental results.* Table 4 lists the calculated ratio for each type of facility. The result shows that snow cover exhibited a general effect on access to existing facilities, increasing the total travel distance by a factor of approximately 1.6. This means that the accessibility of existing facilities decreases due to snow cover. This is particularly important for public and emergency facilities such as evacuation centers and hospitals. In addition, this shows that the traffic capacity reduction rate can be a metric for considering the effects of snow cover. The effect of snow cover should also be considered when adding new facilities.

Table 4. Calculated results of the impact of snow cover on existing facilities for each type. v^{s} and v^{w} are the total travel distances in summer and winter, respectively.

Type of facility	Facilities	Nodes	v^{s}	v^{w}	$v^{\mathrm{w}}/v^{\mathrm{s}}$
shelter	259	235	1.8×10^8	3.0×10^8	1.72
convenience store	108	106	3.1×10^8	4.8×10^8	1.58
supermarket	52	49	4.0×10^8	6.2×10^8	1.56
food stores	407	353	1.7×10^8	2.8×10^8	1.65
accommodation/onsen	122	99	3.8×10^8	6.0×10^8	1.59
hospitals/pharmacies	621	482	1.6×10^8	2.6×10^8	1.65
gourmet food and alcohol	738	510	1.8×10^8	2.9×10^8	1.62
public facilities and institutions	179	159	2.2×10^8	3.6×10^8	1.66
post offices	77	76	2.5×10^8	4.1×10^8	1.65

4.2. **Comparison of optimal facility location with summer distance and that with winter distance.** In this section, we use the PMP to calculate optimal facility location and, as in the previous section, to compare the impacts of snow cover on the total travel distance. Note that the correspondence between the road network, population data, and traffic capacity reduction rate (listed in Table 2) were used as described in the previous section.

4.2.1. *Experimental procedure.* For road networks in summer and winter ($G(N, E, L^{\mathrm{s}})$ and $G(N, E, L^{\mathrm{w}})$), the PMP is that of calculating the optimal facility locations in summer and winter ($\{Y_j^{\mathrm{s}}\}_{j \in N}$ and $\{Y_j^{\mathrm{w}}\}_{j \in N}$). Then, each of the obtained facility locations was evaluated in terms of the total travel distance for summer and winter, as in the previous section. Letting V^{s} denote the evaluation value of the obtained facility location $\{Y^{\mathrm{s}}\}_{j \in N}$, it is defined as

$$\begin{aligned} V^{\mathrm{s}} &= v_{\mathrm{s}}^{\mathrm{s}} + v_{\mathrm{w}}^{\mathrm{s}}, \\ v_{\mathrm{s}}^{\mathrm{s}} &= \sum_{i \in N} P_i \min_{k \in \{j | Y_j^{\mathrm{s}} = 1\}} \left\{ d_{ik}^{\mathrm{s}} \right\}, \\ v_{\mathrm{w}}^{\mathrm{s}} &= \sum_{i \in N} P_i \min_{k \in \{j | Y_j^{\mathrm{s}} = 1\}} \left\{ d_{ik}^{\mathrm{w}} \right\}, \end{aligned}$$

where $v_{\mathrm{s}}^{\mathrm{s}}$ and $v_{\mathrm{w}}^{\mathrm{s}}$ are the total travel distances of $\{Y_j^{\mathrm{s}}\}_{j \in N}$ for the summer and winter distances, respectively. Similarly, letting V^{w} denote the evaluation value of $\{Y^{\mathrm{w}}\}_{j \in N}$, it is defined as

$$\begin{aligned} V^{\mathrm{w}} &= v_{\mathrm{s}}^{\mathrm{w}} + v_{\mathrm{w}}^{\mathrm{w}}, \\ v_{\mathrm{s}}^{\mathrm{w}} &= \sum_{i \in N} P_i \min_{k \in \{j | Y_j^{\mathrm{w}} = 1\}} \left\{ d_{ik}^{\mathrm{s}} \right\}, \\ v_{\mathrm{w}}^{\mathrm{w}} &= \sum_{i \in N} P_i \min_{k \in \{j | Y_j^{\mathrm{w}} = 1\}} \left\{ d_{ik}^{\mathrm{w}} \right\}, \end{aligned}$$

where $v_{\mathrm{s}}^{\mathrm{w}}$ and $v_{\mathrm{w}}^{\mathrm{w}}$ are the total travel distances of $\{Y_j^{\mathrm{w}}\}_{j \in N}$ for the summer and winter distances, respectively. If V^{w} is smaller than V^{s}, the facility location Y_j^{w} obtained from the winter road network is the preferable facility location, as the one-year total travel distance is shorter.

In addition to the total travel distances, we introduce another evaluation regarding the gap between the travel distances in summer and winter. It is undesirable that the travel distance to a facility in winter differs so much compared to that in summer. Based on this way of thinking, we define the evaluation values W^{s} and W^{w} for $\left\{Y_j^{\mathrm{s}}\right\}_{j\in N}$ and $\left\{Y_j^{\mathrm{w}}\right\}_{j\in N}$ as follows:

$$W^{\mathrm{s}} = v_{\mathrm{w}}^{\mathrm{s}} - v_{\mathrm{s}}^{\mathrm{s}},$$
$$W^{\mathrm{w}} = v_{\mathrm{w}}^{\mathrm{w}} - v_{\mathrm{s}}^{\mathrm{w}}.$$

If W^{w} is less than W^{s}, the gap between the travel distances to a facility in winter and summer is more minor when using the winter road network.

Here, we conduct simulations to obtain exact solutions for small road networks based on Nagaoka City with p facilities and s nodes. We generate 100 patterns of road networks for each pair of (p, s) and compare the distribution of $V^{\mathrm{w}}/V^{\mathrm{s}}$. If multiple solutions exist for the summer road network, $v_{\mathrm{w}}^{\mathrm{s}}$ may differ depending on the solution used. In such cases, maintaining uniqueness is achieved by selecting a solution that minimizes $v_{\mathrm{w}}^{\mathrm{s}}$. The reverse is also done in the same manner.

In the calculation of solving the optimization problems, we use the CPLEX 22.1.1 [31]. A branch-based algorithm is implemented in CPLEX.

4.2.2. *Experimental results.* Here, we show the results of the simulations. Figures 1 and 2 show the distributions of $V^{\mathrm{w}}/V^{\mathrm{s}}$ and $W^{\mathrm{w}}/W^{\mathrm{s}}$, respectively, for $p \in \{10, 20, 30\}$ and $s \in \{100, 200\}$.

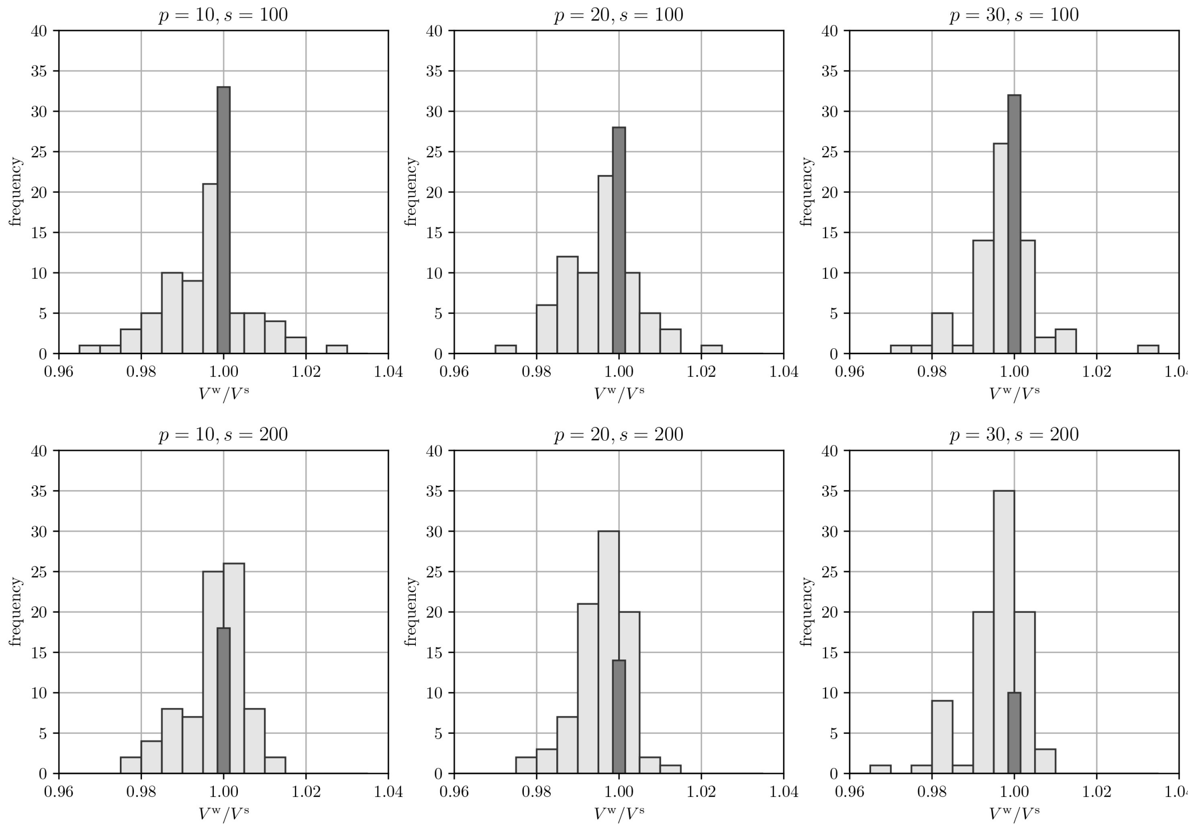

FIGURE 1. Histograms of $V^{\mathrm{w}}/V^{\mathrm{s}}$ by the simulation with 100 patterns of road networks for each of 6 combinations of the number of facilities p and the number of nodes s. The dark gray bin represents the counts of the patterns that take 1.0.

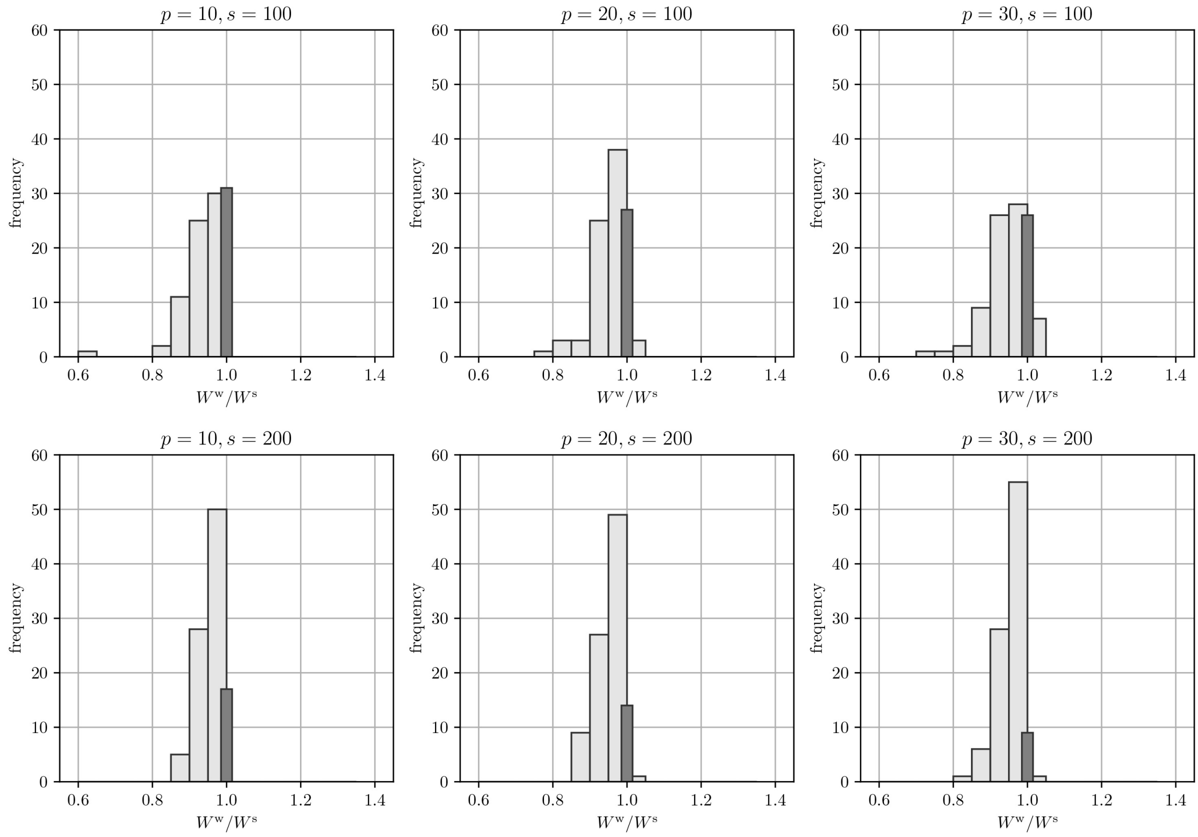

FIGURE 2. Histograms of $W^{\mathrm{w}}/W^{\mathrm{s}}$ by the simulation with 100 patterns of road networks for each of 6 combinations of the number of facilities p and the number of nodes s. The dark gray bin represents the counts of the patterns that take 1.0.

Figure 1 shows the mean and median values were less than 1.0 for all cases. This means that using winter distances was preferable on average to obtain an optimal facility location for travel times considered over the course of a full year. As for Figure 2, the preferability of using winter distances is more significant than the results in Figure 1. The gap of the travel distances in summer and winter seems to tend to be smaller when using winter road network.

Both evaluations showed that using winter distances to obtain an optimal facility location is preferable. Note that the facility location obtained using summer distances is not optimal in winter, and the location obtained using winter distances is not optimal in summer. According to the results, we showed the non-optimality of using summer distances is more serious than that of using winter distances. It means that a path to a facility in the facility location obtained using summer distances is sometimes a bad choice in winter, whereas that using winter distances is not a bad choice, even in summer. It is because the snow cover sometimes forces us to take a detour.

In conclusion, it is preferable to use winter distances on average when determining the optimal locations for facilities. However, because the difference is not so drastic, these results do not suggest that the relocation of facilities is efficient. Instead, our findings show that winter distances should be considered in terms of reduced traffic capacity on roadways when adding new facilities.

5. **Conclusion.** In this study, we have evaluated the impact of snow cover on the facility location problem. Based on a study by Ito et al. [2], we quantified the effect of snow cover

as a traffic capacity reduction rate determined by different types of road, and introduced this value into a facility location model by dividing the distances between the edges by the traffic capacity reduction rate. To evaluate this model, we conducted two simulations. In the first, we evaluated the impact of snow cover on the accessibility of existing facilities, and in the second, we determined the effects of snow cover on facility location. The results showed that the impact on existing facilities was non-negligible, and considering snow cover yielded a more optimal facility location for a one-year period on average. Therefore, considering road conditions only in the summer may lead to unexpected inconveniences in winter. For the facility location problem with emergency facilities such as evacuation centers or hospitals, snow cover should be taken into account if possible.

Although we have considered more realistic conditions than other studies on the effects of snow cover in this work, we did not fully consider all realistic factors. For example, in the evaluations, the impact of snow cover, quantified as traffic capacity reduction rate, was comprehensively considered for only two seasons, but we did not reflect detailed annual snowfall or similar meteorological data. The difference in the importance of facilities between seasons could also be introduced as a possible factor for a more realistic model, and this may vary for different types of facility. In the future, we would like to ensure that the model is more realistic to enable us to examine the effects of snow cover more closely.

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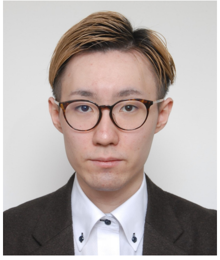
REFERENCES

[1] S. H. Owen and M. S. Daskin, Strategic facility location: A review, *European Journal of Operational Research*, vol.111, no.3, pp.423-447, 1998.
[2] J. Ito, R. Ooshima, K. Sano and K. Hatoyama, A study on the traffic capacity decrease rate of signal intersection due to winter road surface condition, *JSTE Journal of Traffic Engineering*, vol.5, no.2, pp.B_34-B_41, 2019.
[3] K. Ishii and K. Saito, An assessment of reduction in capacity of signalized intersection by the change of surface condition in winter, *Infrastructure Planning Review*, vol.1, pp.123-130, 1984.
[4] Y.-M. He and B.-Q. Zhu, Simulation and analysis on traffic capacity reduction in ice or snow condition, *2010 International Conference on Computational and Information Sciences*, pp.234-237, 2010.
[5] T. Kaku, Y. Masuya and Y. Onodera, Some research on traffic volume and velocity in winter, *Bulletin of the Faculty of Engineering, Hokkaido University*, vol.68, no.2, pp.343-355, 1973.
[6] Y. Terauchi, T. Kato and Y. Honda, A study on speed and delay of road commuter's traffic in snowy season, *Proc. of Infrastructure Planning*, vol.22, pp.905-908, 1999.
[7] C. Edward, O. Ohtani, H. Warita, M. Kuwahara and H. Morita, Does weather affect highway capacity?, *The 5th International Symposium on Highway Capacity and Quality of Service*, vol.1, pp.139-146, 2006.
[8] T. Oguchi and H. Nakamura, Review and perspective of highway capacity and quality of service research in Japan, *Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management)*, vol.67, no.3, pp.217-229, 2011.
[9] W. Zhang, R. Li, P. Shang et al., Impact analysis of rainfall on traffic flow characteristics in Beijing, *International Journal of Intelligent Transportation Systems Research*, vol.17, pp.150-160, 2019.
[10] S. L. Hakimi, Optimum locations of switching centers and the absolute centers and medians of a graph, *Operations Research*, vol.12, no.3, pp.450-459, 1964.
[11] C. S. ReVelle and R. W. Swain, Central facilities location, *Geographical Analysis*, vol.2, no.1, pp.30-42, 1970.
[12] C. ReVelle, C. Toregas and L. Falkson, Applications of the location set-covering problem, *Geographical Analysis*, vol.8, no.1, pp.65-76, 1976.
[13] F. Xiang, H. S. Mahmassani and S. M. Eisenman, Sensor coverage and location for real-time traffic prediction in large-scale networks, *Transportation Research Record Journal of the Transportation Research Board*, vol.2039, no.1, pp.1-15, 2007.

[14] Y. Kakimoto and Y. Shimakawa, Rest-area location model for time-driven demands to the expend buffer time of freight vehicles, *International Journal of Innovative Computing, Information and Control*, vol.18, no.1, pp.15-28, 2022.
[15] M. J. Hodgson, A flow-capturing location-allocation model, *Geographical Analysis*, vol.22, no.3, pp.270-279, 1990.
[16] M. Kuby and S. Lim, The flow-refueling location problem for alternative-fuel vehicles, *Socio-Economic Planning Sciences*, vol.39, no.2, pp.125-145, 2005.
[17] Y. Kakimoto, Y. Shimakawa and H. Takahashi, Optimal location model of electric vehicle charging facility based on the flow-capturing location-allocation model – Case study by using the data of road network of Bangkok, Thailand, *Journal of Computations & Modelling*, vol.8, no.2, pp.111-136, 2018.
[18] F. Stefanello, O. C. B. de Araújo and F. M. Müller, Matheuristics for the capacitated p-median problem, *International Transactions in Operational Research*, vol.22, no.1, pp.149-167, 2014.
[19] P. Kalczynski and Z. Drezner, The obnoxious facilities planar p-median problem, *OR Spectrum*, vol.43, pp.577-593, 2021.
[20] A. Imran et al., A simulation-based optimisation for the stochastic green capacitated p-median problem, *Journal of Industrial Engineering and Management*, vol.15, no.4, pp.552-565, 2022.
[21] D. Serra and V. Marianov, The p-median problem in a changing network: The case of Barcelona, *Location Science*, vol.6, nos.1-4, pp.383-394, 1998.
[22] W. Takahagi, K. Sakai, Y. Omae, Y. Sumitani and H. Takahashi, Method of determining future facility location with maintaining present accessibility, *Industrial Engineering and Management Systems*, vol.15, no.3, pp.192-205, 2016.
[23] T. Oguchi, T. Yamaguchi, S. Shikata and H. Oneyama, Empirical study for estimating the lost time at signalized intersections –Case study at signal change intervals from green to protected right-turning green arrow–, *Journal of Japan Society of Civil Engineers, Ser. D3 (Infrastructure Planning and Management)*, vol.68, no.5, pp.I_1175-I_1183, 2012.
[24] Y. Tsukada, T. Kiriyama, H. Hokuhara and K. Hamaya, Study on new road design method about traffic capacity, *Technical Note of NILIM*, no.317, 2006.
[25] T. Oguchi, Chapter 4: Traffic engineering, in *Traffic and Safety Sciences*, The International Association of Traffic and Safety Sciences, 2015.
[26] *NAVITIME*, https://www.navitime.co.jp/, Accessed on Nov. 25, 2023.
[27] *Google Maps Platform*, https://developers.google.com/maps, Accessed on Nov. 25, 2023.
[28] *OSMnx*, https://osmnx.readthedocs.io/en/stable/, Accessed on Nov. 25, 2023.
[29] *OpenStreetMap*, https://www.openstreetmap.org/, Accessed on Nov. 25, 2023.
[30] The Portal Site of Official Statistics of Japan, *e-Stat*, https://www.e-stat.go.jp/, Accessed on Nov. 25, 2023.
[31] *IBM ILOG CPLEX*, https://www.ibm.com/jp-ja/products/ilog-cplex-optimization-studio, Accessed on Nov. 25, 2023.

Author Biography



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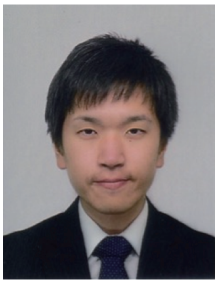

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