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Research article

A vulnerability-based vehicle routing approach for solving capacitated arc routing problem in urban snow plowing operations

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Abstract: Vehicle drivers usually perceive a higher risk when driving on snow covered roads. The city cleaning efficiency would directly influence the risk and mitigation of wintertime events, especially for snow covered roads. Under the risk-informed approach background, more attention is paid to the capacitated arc routing problem (CARP) of urban snow plowing operations. Current algorithms mainly relies on the topology of road network without considering snow covered pavement's negative effect on road capacity and traffic flow. This paper proposes a vulnerability-based parallel heuristic algorithms applied for the CARP by implementing risk-informed approach. First, a method is proposed to set service priorities based on the vulnerability evaluation by considering the added cost of travel demands. Second, a sub-process path-scanning approach is developed to avoid redundant path scans. Then verification and comparison between this newly proposed constructive heuristic and existing algorithms of whole-process path-scanning and sequential processing are conducted. Results show that the sub-process path-scanning approach obviously costs less service completion time than the existing algorithms for solving the CARP. However, this improved algorithm would also cause an increase of deadhead time upon dispatch. The balance between service completion time and deadhead time for more routing problems would be discussed in the near future.

Keywords: capacitated arc routing problem; climate-resilient transport; risk-informed approach; snow and freezing event; urban snow plowing operations; vulnerability evaluation

1. Introduction

Snow and freezing event is one of the most serious influenced hazards for urban residents and vehicles [1]. Snow covered roads greatly influence the driving safety and driving speed, which significantly increase the travel cost and lower the transportation efficiency [2]. Aiming at the wintertime event risk reduction strategies, many researchers have concentrated on discussing appropriate vehicle routing strategies for dealing with urban snow event, especially in urban snow plowing operations.

Assessment and reduction of the risk of snow covered roads can provide a guide and improve the resilience against snow and freezing events [3]. Vulnerability analysis associated with road network originally aims at reducing traffic congestion, decreasing environmental pollution and maximizing the rational use of resources. Transportation operation strategies contributing to maintaining sustainable urban development and realizing the optimal traffic efficiency with minimum travel cost are urgently needed [4]. Due to this context of climate-resilient transport, we can build a risk-informed perspective on mitigation of snow and freezing event.

Increasing urban snow plowing operation efficiency directly reduces the risk of traffic accidents associated with snow and freezing event [5]. Further considering the urban snow plowing operation productivity and network flows' mobility, the capacitated arc routing problem (CARP) of urban snow plowing operations is thus put forward as a quantitative model problem to address the actual operation efficiency. During the past decades, specific models, solutions and strategies in view of winter road maintenance operations have been proposed [6]. However, decision makers are always grappling with myriad challenges resulting from local-specific amounts of snow and pavement conditions. This means that each operation's plan should shift to better meet the needs of a number of hard or soft constraints, such as priorities, time limits, driving conditions [7]. Therefore, using risk-informed approach to design heuristic algorithms to solve CARP is quite necessary for realizing efficient urban snow plowing operations.

Generally, an expected result of effectual snow plow operations would be a quicker traffic flow recovery and an appropriate algorithm would prompt snow plowing to operate more quickly. Based on such considerations, two typical algorithms, the sophisticated mathematical programming decomposition algorithms [3] and the heuristics algorithms [8], were then put forward for the solution of CARP and also other routing problems [9,10]. Among them, the exact algorithms usually apply shortest path relaxations and combine them through finding a minimum-cost subset of edges. In practice, instances encountered in city road networks usually consist of more than 20 segments and should be addressed quickly. However, using the exact algorithms to solve CARP may not be flexible enough to deal with multiple objectives and side constraints, especially for such a non-deterministic polynomial problem [11]. Compared to the exact algorithms, the heuristics algorithms could conduct simpler calculation processes and avoid addressing superfluous objectives and side constraints [12].

This paper focuses on enhancing the processing steps of heuristic algorithms to solve the CARP in a more efficient way, and then realize effective urban snow plowing operations. Several measures can be taken, such as setting service priorities, avoiding redundant path scans, reducing search space, etc. Taking a deep inspection of the heuristic algorithms, two main stages are covered for solving CARP in the urban snow plowing operations. One is constructing feasible loops or clusters with segment dependencies and load balancing constraints. This stage is actually based on the saving criterions to update the partial class of subproblem. The other one is scanning the feasible service routes of sub-network based on continuous solution procedures. Aiming at these two stages, this paper desires to make two aspects of improvements through proposing vulnerability-based parallel heuristic algorithms to solve CARP in the urban snow plowing operations.

First, this proposed algorithm lies in the service priorities for segments through vulnerability evaluation. This improvement relates to the solution space of constructive heuristics. Current existing heuristic algorithms usually solve the CARP through generating a set of promising routes. Then a starting solution should be initialized from random manner, proximity criterion or direct artificial geometric segmentation [13,14], which thus ignores the actual road network states featured with deteriorative pavements and snow covered road capacity. Compared to the existing heuristic algorithms, the proposed method starts from vulnerability evaluation of invalid segments through considering the total added cost of travel demands. In this way, service priorities of road segments would be purposefully set and realize snow plowing in a reasonable order.

Second, an improvement relating to stream processing of parallel heuristic algorithms is mainly made by applying sub-process path-scanning. Since service priorities of road segments are not the final vehicle routing results, more work are needed to complete service paths for all segments. Considering this, both sequential algorithm and parallel algorithm are suitable to solve those mathematical models of CARP. Among them, the sequential algorithms, mainly regarded as a cluster-first, route-second algorithm, usually divide segments into clusters with roughly equal work load. Compared to sequential algorithms, the parallel algorithm constructs several routes in parallel by sequentially solving a multiple vehicle rural postman problem (m-RPP) with vehicle road segment dependencies, turn restrictions, and load balancing constraints for each class [3], which presents higher efficiency by boosting computational performance. Therefore, this paper depends on the parallel algorithm concept and aims to propose a sub-process path-scanning method in a piecewise way to avoid redundant global path scanning.

Based on the previous methods mentioned above, this paper newly proposes a vulnerability-based parallel heuristic algorithm for CARP, and expounds it in several sections. Section 2 summarizes the typical constraints of CARP in the urban snow plowing operations, and then proposes a new vulnerability-based method for setting service priorities. Section 3 develops a new path-scanning strategy to divide the whole continuous process of parallel heuristic algorithms into three sub-processes. Section 4 uses actual computational experiments to compare the service completion time and deadhead time difference caused by applying three different algorithms. These improvements made in this study are actually expected to form an effective and universal method framework to solve series of CARPs under various environment-influence pavement states and driving conditions.

2. Vulnerability-based heuristic for setting service priorities

2.1. Reasons for applying the priority rule

In actual urban snow plowing operations, the model and algorithms of CARP are rather complicated [15]. Aiming to avoid traffic accidents and traffic jams in snow covered roads, dispatching vehicles to remove snow with faster operations seems very important. Due to the emergency of snow event and the limitations of professional vehicles' service capability, it is necessary to make an overall plan to suit certain objectives, such as dispatching vehicles to remove snow in the shortest time [16], minimizing fuel use [17] or vehicle pollution emissions [18].

In order to clearly describe CARP in urban snow plowing operations, this study first synthetically analyses the elements constituting decision-making process of urban snow plowing operations, including variables, constraints and objective components. The decision-making process of urban snow plowing operations mainly includes service standard establishment, division of operation area, site selection of station, route planning for operation vehicle, arrangement of operation personnel, etc. The primary purpose of formulation of snow removal service standards and division of operation areas is to ensure that each segment is assigned a rational service priority. Thus, by means of service priorities, a set of promising routes to relax real complex constraints can be found.

In practical applications, indeterministic settings may come from different sources, including expected different driving conditions caused by snow covered pavements or unexpected traffic conditions [19]. If traffic conditions do not take the snow covered pavements into account in advance, the original established operation routes performed by snow-removal vehicles may turn out to be infeasible due to the unexpected delay. When faced with such traffic conditions, additional decisions should be made to produce a feasible solution by prioritizing operations for important road segments and postponing secondary tasks. Therefore, the need to account for such additional feasibility requirements when solving CARP entails developing approaches by allowing schedules and priorities to change early on in the operation task.

2.2. Existing methods for setting service priorities

Several efforts have been made to tackle the issue of priority setting for snow plowing operations in the past decade. Among them, a classical process of Eulerian path generation to set service priorities is commonly used [3]. Define the CARP on a connected mixed graph $G=(V, A \cup E)$, where $V=\{v_0, v_1, ..., v_n\}$ is the vertex set, v_0 corresponds to the depot, A is the arc set, E is the edge set. In snow plowing operations, since each lane must be serviced separately, the mixed graph G should be translated into a directed graph $G'=(V, A')$. The arc set A' is partitioned into $\{A^1, A^2, ..., A^K\}$ with $A^1 \cup A^2 \cup ... \cup A^K = A'$ and $A^i \cap A^j = \varnothing$ for $i \neq j$. Classes $1, ..., K+1$ represent road segments which are assigned given priorities, whereas class K represents road segments that can be serviced anywhere in the sequence. In this way, the set of arcs of class A^1 is generated by making the subgraph of A^1 Eulerian, while the connectivity of other subgraphs gradually decreases.

This set partitioning method of the CARP relies on the topology of the transportation network and road segment lengths from the directed graph. However, this makes the execution of the algorithm difficult, especially while solving Euler loop in the first-phase solution of whole CARP procedure.

2.3. The proposed method for evaluating the vulnerability of road segments

This paper proposes a vulnerability-based method for setting service priorities by identifying the critical road segments which usually weaken the road network performance on snowy days. This proposed priority setting process is convenient to implement in practice and it makes sense to reveal the effects of the deteriorative pavement conditions on driving conditions and road capacity. The vulnerability-based improvement made for priority setting process is described as follows.

2.3.1. Quantifying snow covered pavement's negative effect on road capacity

On snowy days, road capacity of road segments in network can be reduced greatly than usual. Generally, compared to normal conditions, the road vehicular capacity on slippery surface would suffer a significant decline. The formula of road capacity can be modified as below [20].

$$C = \frac{1000V}{L_1 + L_2 + L_3 + L_4} = \frac{1000V}{\frac{V}{3.6}t + \frac{V^2}{254(\varphi \pm i)} + L_3 + L_4} \tag{1}$$

where V (veh/s) is the traffic flow in a certain speed, safe headway consists of vehicle driving distance L_1 (m), vehicle braking distance L_2 (m), length of vehicle body L_3 (m), and safe braking distance L_4 (m) during the driver's reaction time t (s), φ is the friction coefficient between wheel and pavement, i is the road longitudinal slope. In Eq (1), the road capacity is a function of the average speed of traffic flow and the coefficient of friction. Based on this function, more realistic road capacity can be obtained to provide a basis for calculating road impedance under the snow covered pavement conditions.

When vehicles travel in urban road network, travel cost is usually not in direct proportion to distance. Especially on snowy days, delayed traffic volumes and weakened road capacity would seriously impact on total travel cost. Therefore, a road impedance function for calculating travel cost is then applied. The road impedance function model adopted in this paper is displayed as follows.

$$t_a = \frac{s_a}{v_0}\left[1 + \theta\left(\frac{q_a}{C_a}\right)^{\beta}\right] \tag{2}$$

Where s_a is the length of segment a, v_0 is the free-flow speed, q_a is the traffic volume of segment a, C_a is the road capacity of segment a, θ and β are retardation coefficients.

2.3.2. A newly proposed priority setting process based on vulnerability evaluation

The criticality of vulnerable road segments are actually the evidence for measuring the vulnerable road segments’ potential risks [21]. These potential risks may cause a degree of degradation in transportation efficiency of road network. For example, the road capacity on snowy days would be greatly depressed due to accumulated snow, which then further aggravate traffic jams or segment failures.

According to the principle of user equilibrium, travelers always choose paths that cost the least from origin to destination. However, if random segment e becomes invalid, travelers must re-choose paths. When network flows approach equilibrium, the criticality of vulnerable road segments can be evaluated by comparing the difference in travel costs before and after a road segment is marked invalid.

Therefore, under the known traffic demands of road network, the traffic distribution of road network can be obtained by using the Beckmann model, and then the distribution results would be used to calculate total travel costs of road network before and after the segments become invalid. The established model is depicted as follows.

$$\min \sum_{a\in L}\int_0^{x_a} t_a(\omega)d\omega \tag{3}$$

s.t.

$$\begin{cases} \sum_{k\in W_{rs}} f_k^{rs} = q_{rs}, \ \forall r\in R, s\in S; \\ f_k^{rs} \geq 0, \ \forall r\in R, s\in S, k\in W_{rs} \\ x_a = \sum_{r\in R}\sum_{s\in S}\sum_{k\in W_{rs}} f_k^{rs}\cdot \delta_{a,k}^{rs} \ \ \forall a\in L \end{cases} \tag{4}$$

where x_a is the traffic volume of segment a, t_a is the road impedance of segment a, which is travel time of segment a, $t_a(x_a)$ is the function of traffic volume x_a of segment a, f_k^{rs} is the traffic volume of path k from origin r to destination s, u_{rs} is the minimum road impedance among paths from origin r to destination s, $\delta_{a,k}^{rs}$ is a 0–1 variable, if the segment a belongs to path k from origin r to destination s, then $\delta_{a,k}^{rs}$ =1, otherwise it is 0, L is the set of segments, R is the set of origins, S is the set of destinations, W_{rs} is the set of paths from origin r to destination s, q_{rs} is the traffic volume from origin r to destination s.

Based on the Beckmann model, traffic volume x_a and road impedance t_a were calculated. Furthermore, the minimum road impedance among paths from origin r to destination s can be also calculated through $u_{rs} = \sum_{a\in L} t_a \delta_{a,k}^{rs}$. According to the principle of user equilibrium, the cost of any vehicle from origin r to destination s is equal to u_{rs}. After segment e becomes invalid, a new road impedance u_{rs}^e was calculated through the principle of user equilibrium. Then the increased total travel cost can be evaluated by $\sum_{r\in R}\sum_{s\in S} q_{rs}\left(u_{rs}^e - u_{rs}\right)$.

As the traffic generation of each demand node is different, the importance of each node in the network is also different. The criticality of vulnerable road segments can be weighted by actual traffic demands of multiple origin-destination network, and evaluated as follows.

$$I_e = \frac{\sum_{r\in R}\sum_{s\in S} q_{rs}\left(u_{rs}^e - u_{rs}\right)}{\sum_{r\in R}\sum_{s\in S} q_{rs}} \qquad e\in L \tag{5}$$

Through comparison of the criticality of vulnerable road segments on snowy days, the service priorities of road segments can be determined as follows.

$$\begin{cases} \alpha_1 \le \dfrac{I_e - \min\{I_e\}}{\max\{I_e\} - \min\{I_e\}} \le 1, I_e \text{ is first level;} \\ \alpha_2 \le \dfrac{I_e - \min\{I_e\}}{\max\{I_a\} - \min\{I_a\}} \le \alpha_1, I_e \text{ is second level;} \\ \qquad\qquad \vdots \\ 0 \le \dfrac{I_e - \min\{I_e\}}{\max\{I_e\} - \min\{I_e\}} \le \alpha_{K-1}, I_e \text{ is } k\text{-th level;} \\ \text{in which } 0 \le \alpha_{K-1} \le \cdots \le \alpha_1 \le 1, \ a \in L \end{cases} \tag{6}$$

Based on the priority of road segments, snow-removal vehicles could remove snow in a proper sequence. In numerical examples, the results of different values of hierarchical threshold $\alpha_1,...,\alpha_{K-1}$ could be analyzed and discussed.

In this paper, we use the increased value of total travel cost of road network to define the criticality of road segment. Road segments with the same level of criticality are grouped together sharing the same priority. A certain road segment can only be visited after all higher-priority segments have been serviced. With the proper sequence of criticality of each road segment, decision makers can draw up an overall plan for dispatching their limited number of vehicles in order to remove snow in the shortest amount of time.

A comparison between Eulerian path-based method and vulnerability-based heuristic is discussed from two aspects, shown as below.

Comparing the effects of real environmental factors.

The vulnerability-based heuristic for setting service priorities considers dynamic information on local-specific amounts of snow and also the pavement conditions which decreased the mobility of traffic network flows. The advantage of the vulnerability-based heuristic is the considerations of the negative effects of snow covered pavements on the total travel cost difference from the normal level.

Comparing the classification criteria.

The vulnerability-based heuristic considers the expected benefits from sooner recoveries of critical links and network performance while the Eulerian path-based method just considers the topology of an abstract directed graph. The vulnerability-based heuristic is more conducive to resuming critical road segments as soon as possible.

3. Path-scanning with process structure partition

In order to save search effort and reduce the negative effects of a blind and randomized manner, an admissible heuristic considering both the service priorities and the parallel computing is developed. CARP in urban snow plowing operations can be described as: operation vehicles start from stations, move to each of segments in proper sequence and finally return to the stations. The objective function of the CARP is the minimized service completion time t_m. Two-phase algorithm can be adopted for solving aforementioned objective functions with complex variables and constraints. However, the search space for an optimal or suboptimal routing will exponentially grow with the increase of problem size [22].

This section proposes a piecewise way to utilize parallel computing to boost operation performance. Both local search methods and population-based heuristics can be applied to solve the CARP, with an emphasis on driving the search towards promising solutions. Local search methods, such as tabu search, are implemented with a focus on moving at each iteration from a solution to another solution in its neighborhood. Population-based heuristics, such as ant colony optimization [18] and genetic algorithms (GAs) [23], are implemented with a focus on combining solutions together in the hope of generating better ones.

Regarding numerous local optima, this constructed vulnerability-based parallel heuristic algorithms is employed to incorporate with the genetic algorithms. The flowchart of the constructed vulnerability-based parallel heuristic algorithms is shown in Figure 1. Aiming to avoid repetitive search, the problem-solving process is divided into a set of sub-processes based on the results of service priorities. The problem-solving process is partitioned level by level from a systematic version to a group of sub-processes. Particularly, the first sub-process has the highest priority. For each sub-process, all of the synchronous sub-processes would be handled and merged into the dominant main process. As indicated in Figure 1, the sub-processes will be executed parallelly, which then could greatly decrease the number of feasible routes and improve the path-scanning efficiency for all instances.

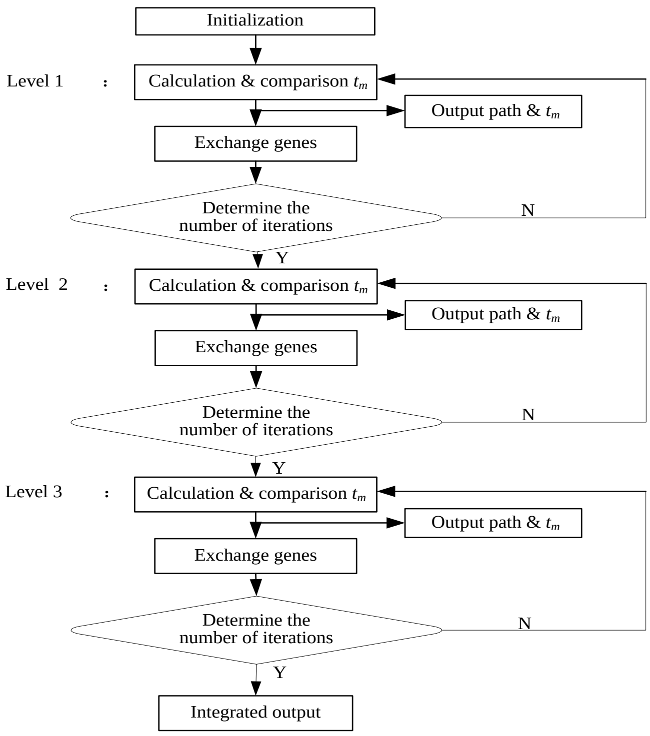


Figure 1. Flowchart of the proposed vulnerability-based parallel heuristic algorithms based on sub-process path-scanning.

The characteristic of newly proposed sub-process path-scanning based on the process structure partition can be illustrated with three steps. First, for the sub-network with first-class priority, compute the service completion time and give shortest path, and then obtain the destination nodes of serviced road segments. Second, let the forementioned destination nodes be the origin nodes of unserviced road segments in a lower priority class, compute the service completion time and give shortest path. Third, update the optimal solution of service paths and service completion time for the whole operation process.

A comparison between whole-process path-scanning and sub-process path-scanning is discussed in two aspects. First of all, comparing the path-scanning objectives of each computation task, the latter path-scanning method only considers unserviced road segments sharing the same priority class while the former one considers all road segments. That's to say, the sub-process path-scanning takes cleaning up and recovering deteriorative pavement conditions and road capacity as a priority. Then comparing the path-scanning inputs of each computation task, the latter method considers supervised information about a more likely feasible solution space, while the whole-process path-scanning just relies on random information of the instance. It means that the sub-process path-scanning prefers feasible solution space.

4. Computational experiments

4.1. Outline of case study

This paper aims to solve the CARP in urban snow plowing operations by using three methods, namely the newly proposed vulnerability-based parallel heuristic algorithms based on sub-process path-scanning, parallel algorithm based on whole-process path-scanning and sequential algorithm based on local search method. Then the solutions generated by the three different heuristics would be compared to each other to test their applications in CARP. Among them, the proposed algorithm was coded in C++ using Microsoft Visual Studio 2019 and compiled under the Windows 10 operating system.

In order to test the three different algorithms, classical Sioux-Falls road network is selected as the study location. The directed graph of Sioux-Falls network including 24 nodes, 76 road segments, in which node v_{10} represents for stations with 4 snow-removal vehicles, is shown in Figure 2. For the Sioux-Falls network, the OD travel demands are already known [24]. Based on the criticality of vulnerable road segments, service priorities of road network were classified. The traffic distribution of the road network can be obtained by using the BPR function before and after segments become invalid. After segment e becomes invalid, new road impedance and traffic volume would be calculated through user equilibrium model. Then the increased total travel cost can be evaluated.

According to the evaluation results of vulnerability, the Sioux-Falls road network can be divided into three levels from high to low, as shown in Figure 2. When the values of hierarchical threshold α_1 and α_2 in Eq (6) are 0.7 and 0.3, three sub-networks have 22, 32, 22 segments respectively.

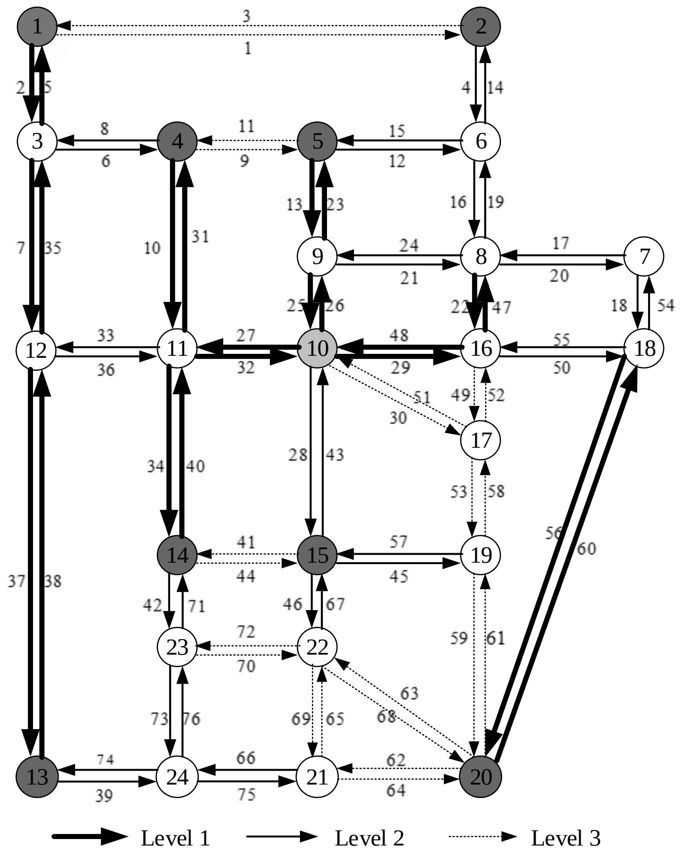


Figure 2. Hierarchical road network.

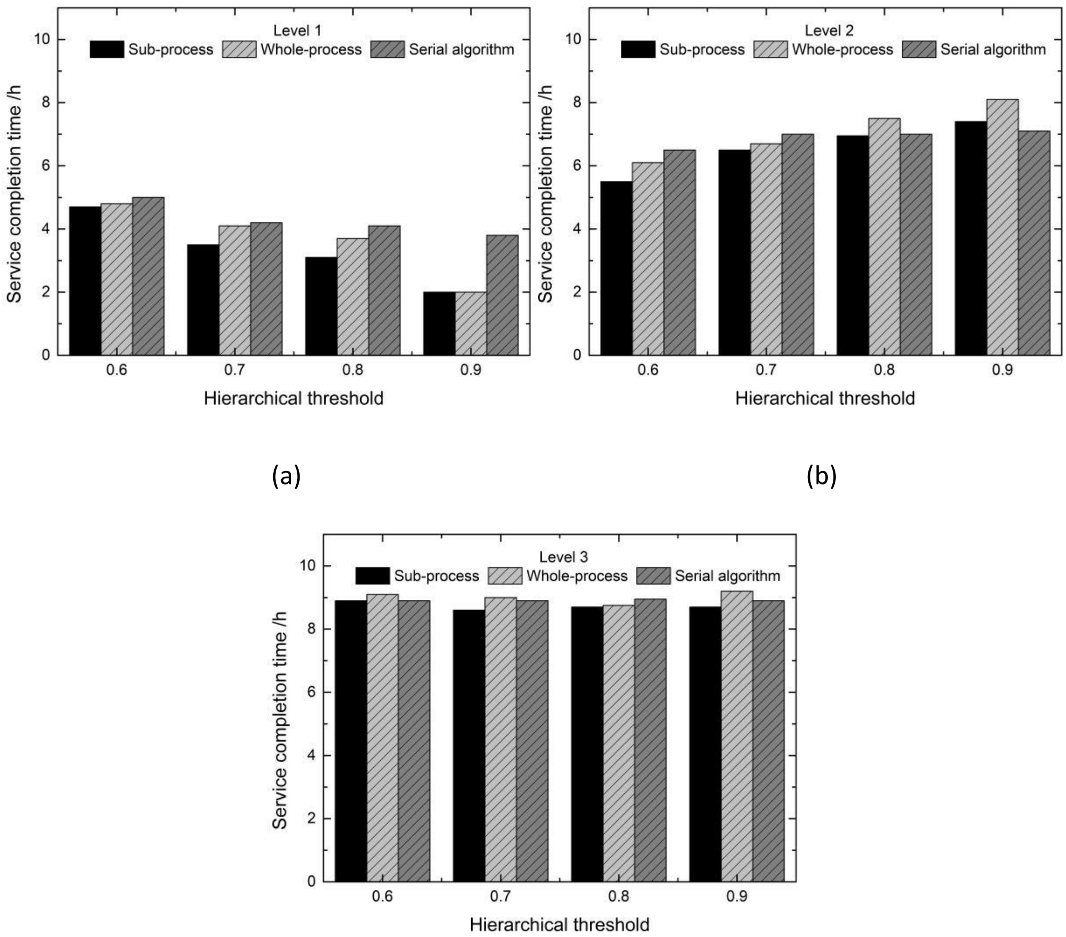
4.2. Results and comparison

To carry out the sub-process path-scanning and the whole-process path-scanning, the iterations of parallel algorithms was set 10,000 times. Then considering the road network size and the genetic algorithm efficiency, the iterations of the sequential algorithm was set 1000 times.

4.2.1. Sensitivity analysis of hierarchical thresholds

To evaluate the criticality of vulnerable road segments, the instanced road network is divided into three sub-networks corresponding to three priority levels, that is $K=3$ in the snow-removal vehicle route planning model. $T_{\max}^{1}$, $T_{\max}^{2}$ and $T_{\max}^{3}$ stand for the respective service completion time of these three sub-networks. $T_{\max}^{4}$ is the service completion time when the final task vehicle comes back to station. Hierarchical thresholds should meet the relationship $0 \le \alpha_2 \le \alpha_1 \le 1$. When making a sensitivity analysis of hierarchical thresholds, we set $\alpha_1 + \alpha_2 = 1$, and take value of α_1 as 0.6, 0.7, 0.8, and 0.9 respectively. Evaluation results of priority levels of sub-networks are used as the inputs of the vehicle routing planning model.

Service completion time of different sub-networks obtained by different thresholds are shown in Figure 3. As shown in Figure 3, different settings of α_1 and α_2 would cause varied directed arcs of sub-networks. Results in Figure 3 expresses that the service completion time $T_{\max}^{1}$ and $T_{\max}^{2}$ varied with different thresholds. But $T_{\max}^{3}$ representing the third-level sub-network service completion time are approximately equal. When α_1 and α_2 are respectively set 0.7 and 0.3, the service completion time $T_{\max}^3$ computed by sub-process path-scanning of parallel algorithm is shortest with a calculated value of 8.62 h.



(a) (b)

(c)

Figure 3. Sensitivity analysis of hierarchical thresholds.

4.2.2. Results of route planning

When α_1 and α_2 are respectively set 0.7 and 0.3, the results computed by parallel algorithm and sequential algorithm are compared. Results show that sub-process path-scanning at Level-1 sub-network reached the local minimum value of 3.52 h at the iteration number of 2411, while the sub-process path-scanning at Level-2 and Level-3 sub-networks reached the local minimum values of 2.98 h and 2.14 h at the iteration numbers of 3625 and 821, respectively. Then the whole-process path-scanning reached the local minimum value 9.12 h at the 458 iteration.

The service paths computed by sub-process path-scanning and whole-process path-scanning are respectively shown in Table 1 and Table 2. Results express the service paths of all 4 vehicles, the service completion time t_4^m, and the vehicle deadhead travel time t_d^m. For parallel algorithm, the service completion time t_4^m of each vehicle of sub-process path-scanning are shorter than those of whole-process path-scanning.

Table 1. Results of service paths computed by sub-process path-scanning.

Snow-removal vehicle number	Priority level	Service paths (number of arcs)	Service completion time t_4^m (h)	Vehicle deadhead travel time t_d^m (h)
1	1	29-48-40-35-5-2-	8.66	1.74
	2	6-8-36-28-20-		
	3	62-3		
2	1	27-32-23-10-25-	8.74	1.34
	2	24-21-35-46-67-42-71-		
	3	68-61-58-51-29-49-52-53-63-64-65		
3	1	26-31-7-37-38-22-	8.74	1.80
	2	50-55-57-43-66-74-76-		
	3	44--41-30-59-11-9		
4	1	34-13-47-56-60-	8.96	1.88
	2	54-17-19-14-4-15-12-16-33-39-75-73-		
	3	72-69-70		

Table 2. Results of service paths computed by whole-process path-scanning.

Snow-removal vehicle number	Priority level	Service paths (number of arcs)	Service completion time t_4^m (h)	Vehicle deadhead travel time t_d^m (h)
1	1	29-48-25-31-5-7-	9.12	2.06
	2	76-73-42-36-50-54-18-16-4-		
	3	3-72-52		
2	1	27-35-13-23-22-55-	9.04	1.34
	2	57-46-71-12-21-24-		
	3	9-41-44-69-64-61-58-63		
3	1	32-10-2-60-	9.08	1.94
	2	17-14-15-8-6-33-74-		
	3	11-30-51-49-53-59-62		
4	1	26-34-40-38-47-56-	9.08	2.14
	2	67-43-28-45-20-66-75-		
	3	68-70-1		

For sequential algorithm, the service completion time reached the local minimum value 9.24 h with the iteration number of 458. Then the service paths computed by sequential algorithm are described in Table 3. Through comparing the results from Table 1 to Table 3, the sum of vehicle deadhead travel time t_d^m computed by sub-process path-scanning is 6.76 h. The sum of vehicle deadhead travel time t_d^m computed by the whole-process path-scanning is 7.48 h. Yet the sum of vehicle deadhead travel time t_d^m computed by sequential algorithm is 2.10 h, which is significantly less than the former two. Therefore, the sequential algorithm would be more applicable with a target of minimizing fuel consumption under deadhead states.

Table 3. Results of service paths computed by sequential algorithm.

Snow-removal vehicle number	Priority level	Service paths (number of arcs)	Service completion time t_4^m (h)	Vehicle deadhead travel time t_d^m (h)
1	1	26-23-55-13-25-29-47-22-48-	6.38	0.12
	2	21-20-18-50-54-17-19-14-4-15-12-16-24		
2	1	27-31-5-27-35-10-32-	9.24	0.90
	2	33-36-8-6-		
	3	9-11-1-3		
3	1	34-40-74-38-	6.92	0.76
	2	42-73-75-66-37-39-76-71-		
	3	44-41-70-69-65-72		
4	1	56-60-	6.88	0.32
	2	28-67-46-43-		
	3	30-53-59-62-64-63-68-61-58-52-49-51		

4.2.3. Comparison of service completion time

Service completion time of vehicles computed by three algorithms are shown in Table 4. t_p^m is the service completion time for all segments belonging to level p served by snow-removal vehicle m, $T_{\max}^p$ is the service completion time for all segments belonging to level p. Through the comparison of different solutions from Table 1 to Table 4, service completion time computed by sub-process path-scanning is the shortest, and the segments with higher priority level can be served in the shortest time compared to the results computed by whole-process path-scanning and sequential algorithm.

Results of service paths computed by sequential algorithm in Table 3 emphasized that the directed arc 55 with priority Level 2 appeared in the service path of sub-network with priority Level 1 which snow-removal Vehicle 1 served. The reason is that sequential algorithm could make the arcs with lower priority level achieve high priority level service ahead of time. Conversely, such circumstances can never happen to the parallel algorithm because the path-scanning process of each level of sub-network should search independently.

Table 4. Comparison of service completion time.

Priority level	Snow-removal vehicle number	Parallel algorithm				Sequential algorithm	
		Sub-process path-scanning		Whole-process path-scanning			
		t_p^m (h)	$T_{\max}^p$ (h)	t_p^m (h)	$T_{\max}^p$ (h)	t_p^m (h)	$T_{\max}^p$ (h)
1	1	3.50	3.52	3.08	4.08	2.70	4.36
	2	3.50		4.02		4.36	
	3	3.50		4.08		1.86	
	4	3.52		3.42		1.92	
2	1	6.18	6.48	6.18	6.72	6.32	6.94
	2	6.48		6.58		6.94	
	3	6.46		6.72		3.50	
	4	6.48		6.66		4.28	
3	1	8.30	8.62	9.02	9.02	6.32	8.88
	2	8.54		8.84		8.88	
	3	8.58		8.84		6.68	
	4	8.62		8.74		5.88	

5. Conclusions

Traffic congestion has long been a severe issue, especially on snowy days. Snow covered pavements significantly increase the travel cost and lower the transportation efficiency. In this study, the CARP of urban snow plowing operations addressing the actual operation efficiency was used to solve target model. Traditional problem-solving methods would consume considerable computational effort in searching infeasible solutions. Therefore, this paper mainly contributed to enhancing the processing steps of heuristic algorithms to solve the CARP in a high-efficient way, and then realized effective urban snow plowing operations. Two aspects of improvements were made. First, this study gave a brief description of typical existing methods for setting service priorities, and analyzed the snow covered pavement's negative effects on road capacity. Then a vulnerability-based method for setting service priorities by identifying the critical road segments was proposed. Second, a piecewise way to utilize parallel computing to boost operation performance was developed. The problem-solving process was partitioned level by level from a systematic version to a group of sub-processes, which avoided repetitive search.

Three methods of the newly proposed vulnerability-based parallel heuristic algorithms, parallel algorithm based on whole-process path-scanning and sequential algorithm were compared with an actual case study. Results show that for parallel algorithm, the service completion time of each vehicle of sub-process path-scanning were shorter than those of whole-process path-scanning. Then the sum of vehicle deadhead travel time computed by sequential algorithm was significantly less than parallel algorithms, which demonstrated a better application of sequential algorithm in dealing with fuel fewer-optimal routing optimization. However, among the three algorithms, the service completion time computed by sub-process path-scanning was the shortest, and also the segments with higher priority level could be served in the shortest time. It revealed that the sub-process path-scanning generally obtained less service completion time for the CARP than the other two algorithms.

However, it should be noted that these improvements made in the proposed vulnerability-based parallel heuristic algorithm usually accompany with a cost of increased deadhead travel time for snow-removal vehicle dispatching. More research for balancing service completion time and deadhead travel time for dispatching would be discussed in detail in the near future.

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Conflict of Interest

The authors declare no conflict of interest.

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