Optimality Gap of Experts' Decisions in Concrete Delivery Dispatching

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ABSTRACT

Concrete delivery dispatching suffers from a lack of practical solutions and therefore, in the absence of automatic solutions, experts are hired to handle this task. In addition, the concrete delivery dispatching problem can be modelled mathematically but it can only solve up to medium sizes of this problem within a practical time. This paper attempts to answer the question of how much we can rely on experts' decisions. First, the concrete delivery problem is presented. Second, a benchmark for the problem is achieved; the heuristic approach is implemented for those instances where exact solutions are not computationally intractable. Finally, the experts' decisions are compared with the obtained benchmarks to assess the optimality gap of the experts. A field dataset which belongs to an active Ready Mixed Concrete (RMC) is used to evaluate the proposed idea. The results show that experts' decisions are near to optimum, with an average accuracy of 90%. However, after comparing individual decisions between optimisation models and the experts' decisions, we can conclude that optimisation models only try to achieve the lowest cost, while the expert prefers a more stable dispatching system at slightly higher cost.

Keywords: Concrete Delivery, Ready Mixed Concrete, Experts' Decisions

INTRODUCTION

In order to assess the experts' decisions in concrete delivery dispatching we need to compare their decisions with the best possible decisions. Optimisation is used to find the best solution but obtaining the optimum solution for a large scale Ready Mixed Concrete Dispatching Problem (RMCDP) with available computing facilities is computationally intractable as RMCDP is characterized as being NP-hard (*1-5*). In the literature, the main challenge for implementing optimisation and also the automating RMCDP process have been discussed, such as (*3; 4; 6-9*), which can be summarized into two issues (*10*): (i) a large number of variables, (ii) dealing with an uncertain and dynamic environment. In the absence of fast and optimum solutions, in practice experts are hired to handle concrete delivery resource allocation tasks (*10-12*). In this paper, for the purposes of acquiring an exact solution two models are used: (i) IP (hard time window), (ii) MIP (soft time window). Two heuristic approaches are used in the absence of optimum solutions and then best the obtained solutions are set as a benchmark and are used to assess the experts' decisions.

PROBLEM FORMULATION

In the past decade, a few attempts have been made to effectively model the RMCDP which is a generalized Vehicle Routing Problem (VRP). The main differences between RMCDP and VRP can be summarized as follows:

- In RMCDP in each trip a truck can haul concrete to only one customer.
- In RMCDP a truck can not travel longer than a specific time because fresh concrete is a perishable material.
- In RMCDP only one customer at a time can accept a truck.
- In RMCDP a truck serves one customer on each delivery.

A few RMCDP formulations have been introduced, such as (*3-8; 13; 14*). To simplify the formulation, in some methods (*4-6*) the depots and customers are divided into sets of sub-depots and sub-customers, each based respectively on the number of loads at depots and the number of required deliveries. The compact formulation of RMCDP can be stated as follows (*6; 15*) if we assume RMCDP to be a graph $\mathrm{G} = (\mathrm{V}, \mathrm{E})$ in which V is the set of vertices belonging to start points, customers, depots and end points $\mathrm{V} = \{\mathrm{u_s} \cup \mathrm{C} \cup \mathrm{D} \cup \mathrm{v_f}\}$. Additionally, E is the set of edges delineating the distance between vertices.

$$Minimize \sum_{u}\sum_{v}\sum_{k} z_{uvk}x_{uvk} - \sum_{c} \beta_c(1 - y_c) \tag{1}$$

Subject to:

$$\sum_{u\in u_s}\sum_{v} x_{uvk} = 1 \qquad \forall k \in K \tag{2}$$

$$\sum_{u}\sum_{v\in v_f} x_{uvk} = 1 \qquad \forall k \in K \tag{3}$$

$$\sum_{u} x_{uvk} - \sum_{u} x_{vuk} = 0 \qquad \forall k \in K, v \in C \cup D \tag{4}$$

$$\sum_{u \in D} \sum_{k} x_{uvk} \leq 1 \qquad \forall v \in C \tag{5}$$

$$\sum_{v \in C} \sum_{k} x_{uvk} \leq 1 \qquad \forall u \in D \tag{6}$$

$$\sum_{u \in D} \sum_{k} q_k x_{uvk} \geq q_c y_c \qquad \forall c, v \in C \tag{7}$$

$$-M(1 - x_{uvk}) + s_u + t_{uvk} \leq w_v - w_u \quad \forall (u, v, k) \in E \tag{8}$$

$$M(1 - x_{uvk}) + \gamma + s_u \geq w_v - w_u \qquad \forall (u, v, k) \in E \tag{9}$$

$$U_u < w_u < L_u \qquad \forall \mathrm{u} \in D \tag{10}$$

The objective function (equation 1) forces optimisation to find feasible solutions for all customers and penalizes if a feasible solution for customer (c) cannot be found by applying zero to y_c. Therefore, due to the value of M which is a large constant, optimisation attempts to avoid unsupplied customers. The (equation 2) ensures that a truck at the start of the day must leave once from its base, and similarly (equation 3) necessitates the return of a truck just once to the depot by the end of day. In reality, a truck arrives at either a depot or a customer then leaves that node after loading/unloading. This concept is called conservation of flow and (equation 4) ensures this issue if $u \in C$ then $v \in D$ and $j \in C$ but if $u \in D$ then $v \in C$ and $j \in D \cup v_f$. In this formulation a depot is divided into a set of sub-depots based on the number of possible loadings at that depot. Similarly, a customer is divided into a set of sub-customers according to the number of required deliveries. Therefore, (equation 5) and (equation 6) respectively certify the sending only of one truck to each customer and only one depot supplies each customer. (equation 7) checks the demand satisfaction of customers. (equation 8) and (equation 9) are designed to control timing issues. (equation 8) ensures that concrete will be supplied to customers within the specified time, and similarly equation (9) ensures that the travel time for each customer will not exceed the permitted time for delivery (Y) because fresh concrete is a perishable material and it is not advisable to haul it more than (Y), which varies according to the type of concrete. Due to the uncertainties in real delivery situations, RMCs are not able to guarantee supplying concrete at precise fixed times. Therefore, typically there is flexibility in most deliveries, which can occur either a little earlier or a little later than the times requested by customers. This issue is modelled in equation (10); U_u and L_u define the boundaries of the time window for each customer (u).

HEURISTIC APPROACHES

Heuristic methods have been widely used in the literature to tackle RMCDP. The implementation of Genetic Algorithm (GA) has been highlighted more than other heuristic methods. Garcia et al. (*16)* modelled the RMC for a single depot and solved it via optimisation and GA. However, their approach relaxes some realistic constraints and only considered small instances. Feng, Cheng and Wu (*13)* also modelled a single depot RMC and assumed some parameters such as loading/unloading times as fixed parameters. Further, the instances that have been considered by them are much smaller than the instances that are used in this paper. Naso et al. (*8)* modelled a more realistic RMC problem by considering multi-depots and penalizing the waiting times (loading/unloading) in the objective function. They also introduced a GA algorithm which is very similar to the methods that were presented earlier by Garcia et al. (*16)* and Feng, Cheng and Wu (*13)*. However, the instances that Naso et al. have tested are larger than in previous research. (*17; 18*) developed a software package called HKCONSIM to deal with real RMC problems. It mainly concerned the discrete event simulation (DES) tool but in its recent versions was coupled with heuristic solvers such as GA (*19-21*), Particle Swarm Optimisation (PSO) (*22; 23*) and real GPS (Global Positioning System) data of trucks (*24*) in order to make a more powerful tool. Feng and Wu (*7)* and Cheng and Yan (*25)* had a similar approach by integrating DES with a fast messy GA algorithm. Silva et al. (*26)* compared GA with Ant Colony Optimisation (ACO) and suggested a GA-ACO method for solving RMC problems. Pan et al. (*27)* proposed an improved Discrete PSO (DPSO) for solving RMC dispatching problems and recently Srichandum and Rujirayanyong (*28)* compared Bee Colony Optimisation (BCO) and Tabu Search (TS) with GA in this context. Despite developments in this area, the solution structure among most introduced methods is pretty much same, especially in the GA based method where the chromosome structure consists of two merged parts: the first part defines the sources of deliveries; the second part expresses the priorities of customers. The solution structure in these techniques is quite simple and easy to understand. However, a cumbersome computing process must be completed in each iteration to check the constraints after achieving a premature solution.

In this paper we selected two of the more recent heuristic methods that are able to solve RMCDP more quickly and accurately without any need for post-processing of the initial solutions, unlike in most of the introduced methods.

The first selected heuristic method is Robust-GA (*29*) which was inspired by optimisation where some scholars such as (*6*) divide depots and customers into sets of depots and customers, based respectively on the number of available loading times and the number of required deliveries. Robust-GA proposed a solution structure for an RMCDP that supposes to supply i customers consisting of a chromosome with $2\times i$ gens. The gens 1 to i are intended to find depot allocations for customers 1 to i and gens $i+1$ to $2\times i$ are dedicated to finding a proper way to allocate trucks for customers 1 to i.

The second selected method is Sequential-GA (*30*) which suggests separating the RMCDP into two detached problems that are solved separately although they are looking to find one solution. This technique consists of two one-dimensional arrays with a length of i in which i is equal to the number of customers. The first array is designed for finding a solution for the supplier depot of each customer, and the second array provides a solution for allocating a truck to each customer.

TEST DOMAIN

The instances that are used in this paper are obtained from a field dataset belonging to an active RMC in Adelaide (Australia). The test domain is limited to these instances because a huge computing effort is needed for solving the RMCDP optimisation (IP and MIP). Moreover, it cannot solve large scale RMCDP in a polynomial time. The test domain is summarised in Table 1.

TABLE 1 Features of instances in the test domain

Instance Code	Number of Deliveries in Day
D1	63
D2	112
D3	153
D4	197

ASSESSING METRICS

The operating cost is selected as the main comparison metric in this paper due to its capacity to reflect the efficiency of the resource allocation. Travelled distances by trucks have a direct impact on the operating cost in normal situations (*15*). (equation 1) is used to calculate the total travelled distances as well as the operating cost. This equation is used for all approaches and the achieved results are reported in the following section.

COMPARATIVE ANALYSIS AND DISCUSSION

In this section five different solutions obtained from IP, MIP, Robust-GA, Sequential-GA and Experts' Decisions are compared in terms of operating cost. These comparisons are made for all instances included in the test domain.

According to the Table 2, the difference between IP and MIP for the first three instances (D1, D2 and D3) is around 0.5%. However, the MIP solution for the fourth instance (D4) is not available. Therefore, this instance (D4) is compared to the other available solutions: Robust-GA and Sequential-GA. The summary of comparisons between IP, MIP, Robust-GA and Sequential-GA is shown in Table 3, which is used in the following for finding the best available solution for each instance in the test domain.

TABLE 2 Comparing IP, MIP, Robust-GA, Sequential-GA and Experts' Decisions in the test domain

Instance Code	Number of Deliveries in Day	Operating Cost (km)				
		IP (hard time window)	MIP (soft time window)	Robust-GA	Sequential-GA	Experts' Decisions
D1	63	572	565	807	575	642
D2	112	963	954	1241	978	1021
D3	153	1381	1373	1704	1561	1597
D4	197	2098	NA	2535	2380	2207

According to Table 3, MIP obtained the best solutions for the first three test instances (D1, D2 and D3) and IP acquired the best solution for the last instance (D4). The gap between the best solutions and Robust-GA solutions is around 25% on average, which is a considerable difference. However, the gap between the best solution and Robust-GA is decreased when the size of the instances is increased. From this behaviour it can be seen that Robust-GA tends to find a feasible solution rather than finding a near optimum solution. The Sequential-GA has a better performance than Robust-GA. In contrast to Robust-GA, increasing the size of the instances results in the quality of the Sequential-GA solutions decreasing. In general there is around 10% gap between the best possible solutions and the Sequential-GA solutions. Although there is a considerable gap between the IP/MIP and Robust-GA/Sequential-GA, the computation time required for IP and MIP is up to 100 times greater than the heuristic methods. It is possible that the IP solution for a larger instance than D4 is computationally intractable when the need for heuristic methods is more evident.

TABLE 3 Comparing IP, MIP, Robust-GA, Sequential-GA and Experts' Decisions in the test domain

Instance Code	Number of Deliveries in Day	Best Solution Obtained by	Gap Between Best Solution and			
			IP	MIP	Robust-GA	Sequential-GA
D1	63	MIP	0.24%	0	42.83%	1.77%
D2	112	MIP	0.94%	0	30.08%	2.52%
D3	153	MIP	0.58%	0	24.11%	13.69%
D4	197	IP	0	NA	20.83%	13.44%
Average			0.48%	NA	25.99%	10.10%

Now, the best obtained solutions are compared with the experts' decisions to determine the quality of decisions made by the experts. Table 4 is a summary of these comparisons.

The gap between experts' decisions and optimization models is not negligible but significant (Table 4). This gap amounts to 14% (D1-MIP) and in the best case is 5% (D4). On average, experts' decisions are 90% accurate within the sizes of the tested RMC problems. This accuracy is important for RMCs because, on the one hand, there is a lack of practical solutions in this context and they must trust the experts. On the other hand, there is a concern for RMCs as to the extent to which an expert's decisions are the best possible ones. Daily calculation of the accuracy rate for experts, as has been stated before, is computationally intractable. Moreover, the expert performance is defensible because experts can handle RMCDP with few cancelled orders. Investigations through the available database show that the number of unsupplied orders on most of the days is zero, which means that experts have almost found a way to supply the customers with available resources within the specified day. In other words, the experts' main objective is to find a way to match the supply and the demand at a low cost if they are unable to find the optimum solution. The experts' second goal is to keep customers satisfied. However, optimization models seek to find a match between available resources and demand at lowest cost. Optimization models only prioritise given constraints and nothing beyond such conditions. Therefore, it is possible that this gap between optimization models and the experts is the result of differences between their goals (*15*).

TABLE 4 Comparing IP, MIP, Robust-GA, Sequential-GA and Experts' Decisions in the test domain

Instance Code	Number of Deliveries in Day	Best Solution Obtained by	Operating Cost (km)		Gap between Best Solution and Experts' Decisions	Gap between Experts' Decisions and Sequential-GA
			Best Solution	Experts' Decisions		
D1	63	MIP	565	642	13.63%	-10.44%
D2	112	MIP	954	1021	7.02%	-4.21%
D3	153	MIP	1373	1597	16.31%	-2.25%
D4	197	IP	2098	2207	5.2%	7.84%
Average					9.56%	0.49%

Additionally, during comparisons of IP, MIP, Robust-GA, Sequential-GA and the experts' decisions for each single delivery (Figure 1, Figure 2, Figure 3 and Figure 4), an interesting point was found: generally, an expert's decision is more similar to MIP than it is to IP. This means that the expert understands the importance of the flexible time window, which assists them in handling resource allocation more smoothly. The other interesting issue that can be seen in this chapter is that the performances of experts are very similar to Sequential-GA. In terms of cost (Table 4), by increasing the size of the test instances the gap between the experts' decisions and Sequential-GA is decreased, on average the difference being only 0.5%. When idle resources exist during small instances the experts are less likely to prioritise cost and are only concerned about serving the customers on time. But in larger instances, when there are overcapacity concerns, it seems that the experts try to find near optimum decisions at least cost. The similarity between the experts' decisions and Sequential-GA can be seen in Figure 1, Figure 2, Figure 3 and Figure 4, as well as and especially in D3 and D4.

SUMMARY

Ready Mixed Concrete Dispatching Problem (RMCDP) still suffers from a lack of practical solutions and in the absence of automated solutions, experts are hired to handle this task. This paper has tried to assess the experts` decisions in concrete delivery dispatching rooms. First, the RMCDP was modelled mathematically with IP (hard time window) and MIP (soft time window). However, this problem cannot be solved for large scale RMCDP and is characterized as NP-hard. Two heuristic methods were used when the exact solution of RMCDP was computationally intractable. The best obtained solutions have been set as a benchmark as well for assessing experts' decisions. We can thus conclude that experts' decisions are near to optimum, with an average accuracy of 90%. However, after comparing individual decisions between optimization models and the experts' decisions, we can say that optimization models only attempt to achieve the lowest cost while the experts prefer a more stable dispatching system at slightly higher cost. This is a significant consequence for any further studies in terms of trying to reconstruct experts' decisions with machine learning techniques to decrease the dependency of human resources on RMCs.

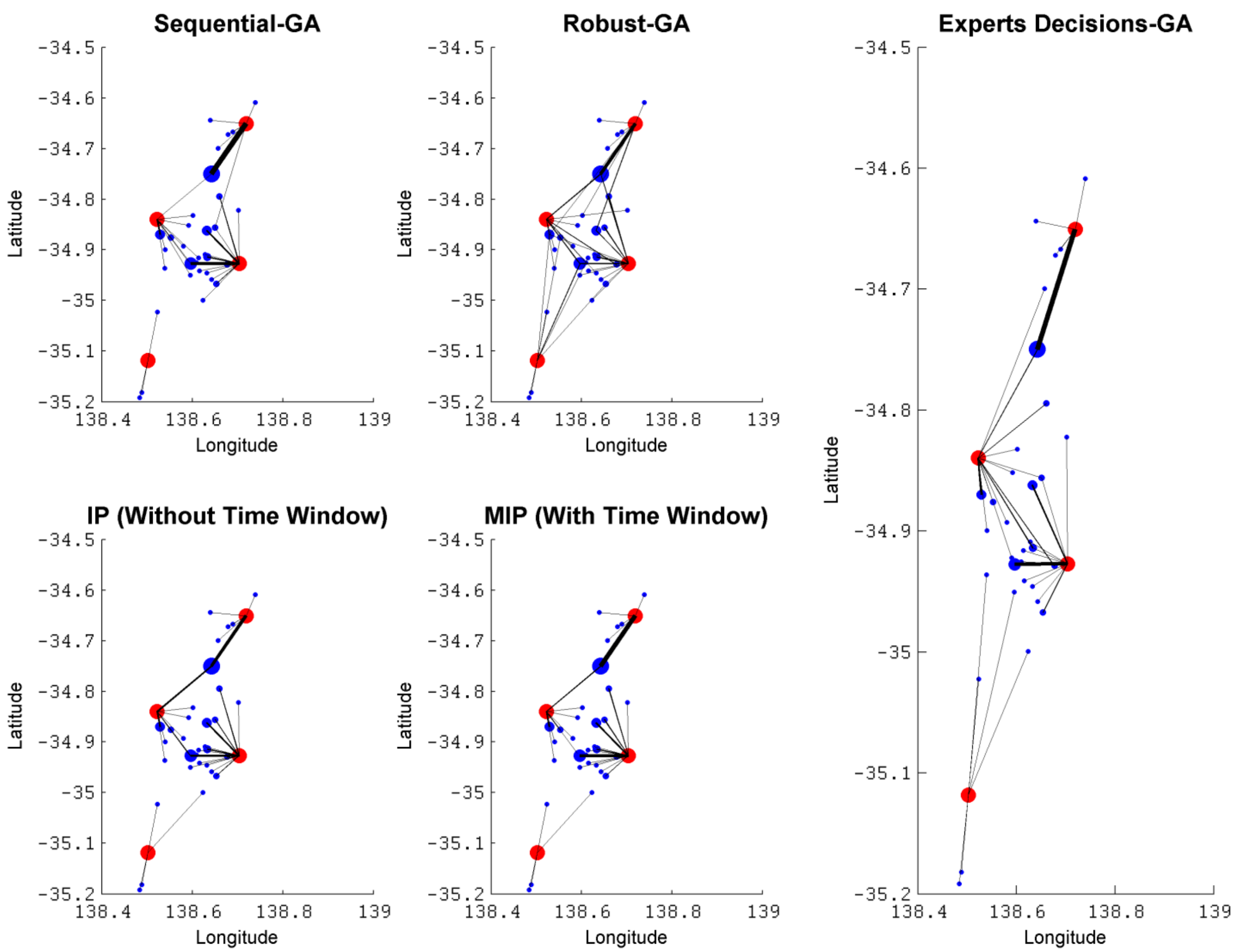

FIGURE 1 Graphic summary of Sequential-GA, Robust-GA, IP, MIP and Experts'

Decisions for D1 instances with 63 customers.

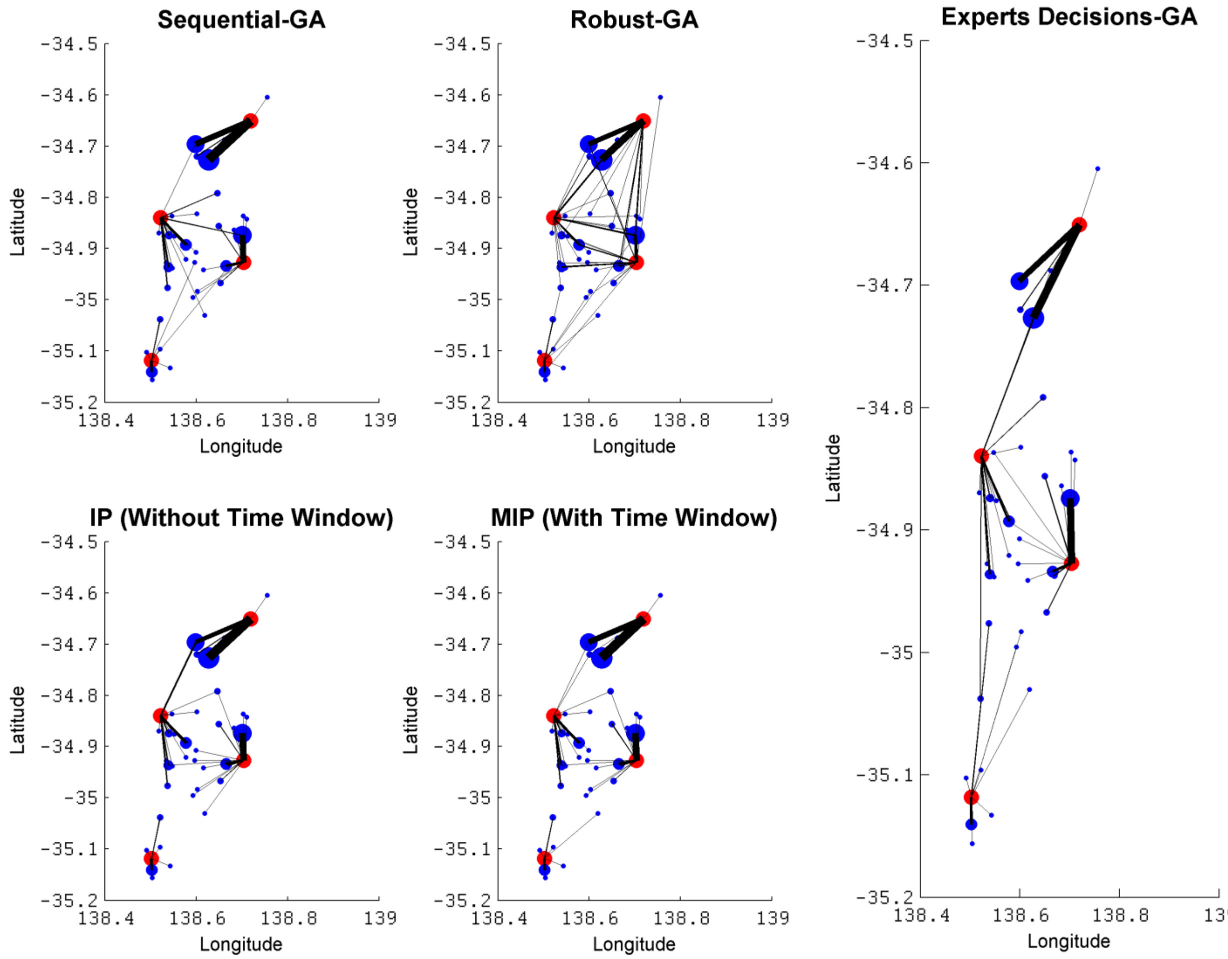

FIGURE 2 Graphic summary of Sequential-GA, Robust-GA, IP, MIP and Experts' Decisions for D2 instances with 112 customers.

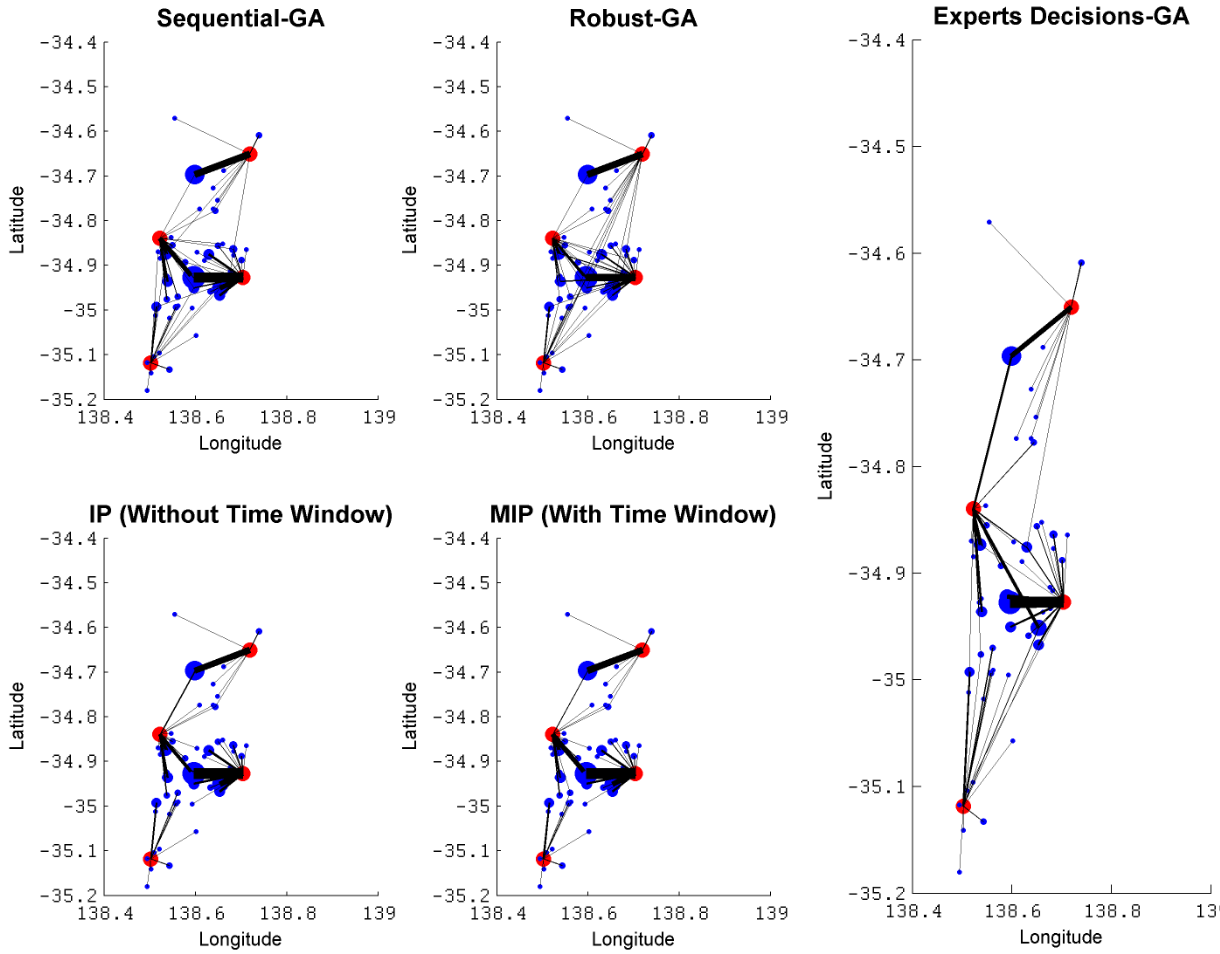

FIGURE 3 Graphic summary of Sequential-GA, Robust-GA, IP, MIP and Experts' Decisions for D3 instances with 153 customers.

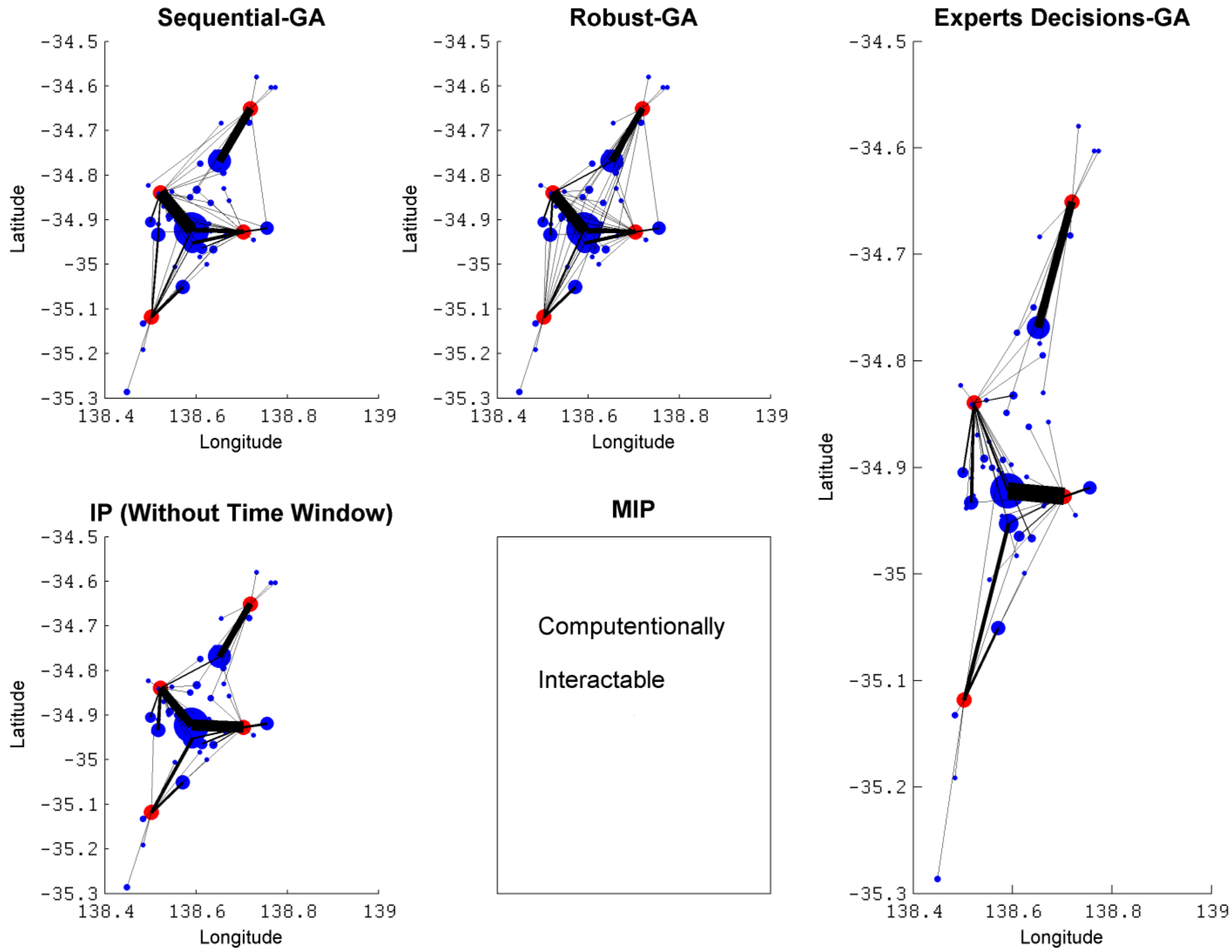

FIGURE 4 Graphic summary of Sequential-GA, Robust-GA, IP, MIP and Experts' Decisions for D4 instances with 197 customers.

Notations

Symbol	Description
C	set of customers
D	set of depots
K	set of vehicles
U_s	set of starting points
V_f	set of ending points
S (u)	service time at the depot u
t (u,v,k)	travel time between u and v with vehicle k
q (k)	maximum capacity of vehicle k
q (c)	demand of customer c
W_o	time at location o
β (c)	penalty of unsatisfying the customer c
M	a big constant
ϒ	maximum time that concrete can be hauled
x_{uvk}	1 if route between u and v with vehicle k is
y_c	1 if total demand of customer c is supplied, 0
Z(u,v,k)	cost of travel between u and v with vehicle k

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