Journal of Building Engineering 2 (2015) 17–23

Contents lists available at ScienceDirect

Journal of Building Engineering

journal homepage: www.elsevier.com/locate/jobe

Optimality gap of experts' decisions in concrete delivery dispatching

Mojtaba Maghrebi [a,*], S. Travis Waller [a], Claude Sammut [b]

[a] School of Civil and Environmental Engineering, The University of New South Wales, Kensington, NSW 2216, Australia
[b] School of Computer Science Engineering, The University of New South Wales, Kensington, NSW 2216, Australia

ARTICLE INFO

Article history:
Received 13 October 2014
Received in revised form
2 April 2015
Accepted 2 April 2015
Available online 4 April 2015

Keywords:
Concrete delivery
Ready Mixed Concrete
Experts' decisions
Integer Programming
Mixed Integer Programming
Robust-GA
Sequential-GA

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; two heuristic methods are used for those instances that their exact solutions are not available. 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.

1. 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 [26,9,23,28,29]. In the literature, the main challenge for implementing optimisation and also the automating RMCDP process have been discussed, such as [1,5,21,23,28,30], which can be summarised into two issues [16]: (i) a large number of variables, (ii) dealing with an uncertain and dynamic environment. In the absence of fast and optimum solutions, in practise experts are hired to handle concrete delivery resource allocation tasks [7,14]. 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.

* Corresponding author. Fax: +61 2 9385 6139.
E-mail address: maghrebi@unsw.edu.au (M. Maghrebi).

http://dx.doi.org/10.1016/j.jobe.2015.04.001
2352-7102/

2. Problem formulation

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

1. In RMCDP in each trip a truck can haul concrete to only one customer.
2. In RMCDP a truck can not travel longer than a specific time because fresh concrete is a perishable material.

A few RMCDP formulations have been introduced, such as [1,4,5,15,21,23,28,29]. To simplify the formulation, in some methods [1,28,29] 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 [1,18] if we assume RMCDP to be a graph $G=(V,E)$ in which V is the set of vertices belonging to start points, customers, depots and end points $V=\left\{u_s \cup C \cup D \cup v_f\right\}$. Additionally, E is the set of edges delineating the distance between vertices.

$$\text{Minimize} \sum_u \sum_v \sum_k z_{uvk} x_{uvk} - \sum_c \beta_c (1 - y_c) \tag{1}$$

Subject to:

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
U_u	Upperbond of time winodow for node u
W_u	Lowerbond of time winodow for node u
x_{uvk}	1 if route between u and v with vehicle k is selected, 0 otherwise
y_c	1 if total demand of customer c is supplied, 0 otherwise
$Z(u,v,k)$	cost of travel between u and v with vehicle k

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

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

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

$$\sum_{u\in D}\sum_{k} x_{uvk} \le 1 \quad \forall\, v \in C \tag{5}$$

$$\sum_{v\in C}\sum_{k} x_{uvk} \le 1 \quad \forall\, u \in D \tag{6}$$

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

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

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

$$U_u < w_u < L_u \cdot \quad \forall\, u \in D \tag{10}$$

The objective function (Eq. (1)) forces optimisation to find feasible solutions for all customers and penalises 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. Eq. (2) ensures that a truck at the start of the day must leave once from its base, and similarly Eq. (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 Eq. (4) ensures this issue if $u \in C$ then $u \in D$ and $j \in C$ but if $u \in D$ then $v \in D$ 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, Eqs. (5) and (6) respectively certify the sending only of one truck to each customer and only one depot supplies each customer. Eq. (7) checks the demand satisfaction of customers. Eqs. (8) and (9) are designed to control timing issues. Eq. (8) ensures that concrete will be supplied to customers within the specified time, and similarly Eq. (9) ensures that fresh concrete is not hauled more than a specific time which varies according to the type of concrete, because the fresh concrete is a perishable material and its hardening process will be started γ minutes after the loading. 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 Eq. (10); U_u and L_u define the boundaries of the time window for each customer (u).

3. 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. [6] 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 et al. [4] also modelled a single depot RMC and assumed some parameters such as loading/unloading times as fixed parameters. Further, the

Table 2
Comparing IP, MIP, Robust-GA, Sequential-GA and experts' decisions in the test domain in terms of optimialty gap.

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

Table 1
Comparing IP, MIP, Robust-GA, Sequential-GA and experts' decisions in the test domain in terms of cost.

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

Table 3
Comparing the best solutions with 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

instances that have been considered by them are much smaller than the instances that are used in this paper. Naso et al. [21] modelled a more realistic RMC problem by considering multi-depots and penalising 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. [6] and Feng et al. [4]. However, the instances that Naso et al. have tested are larger than in previous research [8,9] 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 [2,11,20], Particle Swarm Optimisation (PSO) [12,27] and real GPS (Global Positioning System) data of trucks [10] in order to make a more powerful tool. Feng and Wu [5] and Cheng and Yan [3] had a similar approach by integrating DES with a fast messy GA algorithm. Silva et al. [24] compared GA with Ant Colony Optimisation (ACO) and suggested a GA-ACO method for solving RMC problems. Pan et al. [22] proposed an improved Discrete PSO (DPSO) for solving RMC dispatching problems and recently Srichandum and Rujirayanyong [25] 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

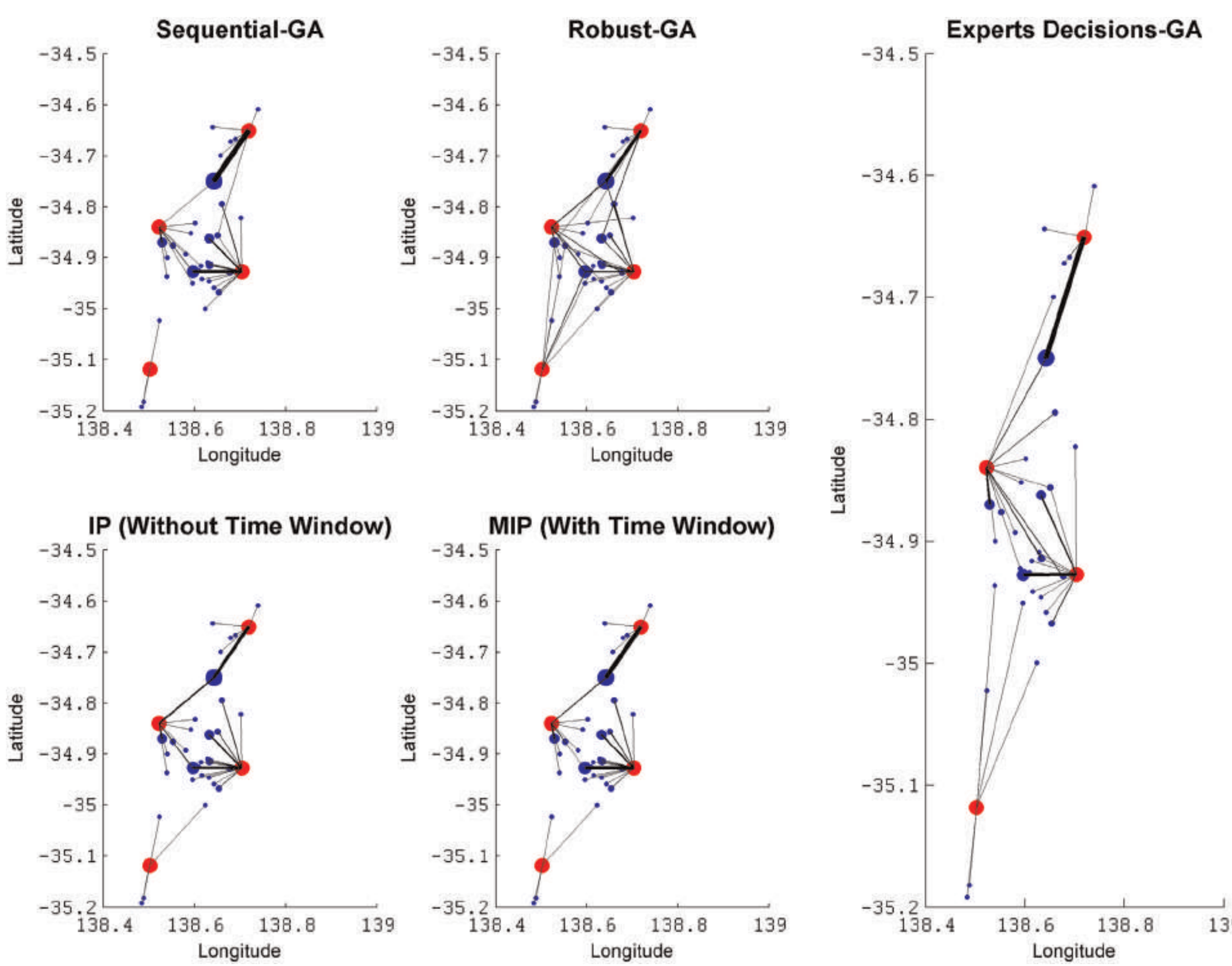

Fig. 1. Graphic summary of Sequential-GA, Robust-GA, IP, MIP and experts' decisions for D1 instances with 63 deliveries.

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. Most recently Maghrebi et al. [14] introduced a Bender decomposition solution for RMCDP and also Maghrebi et al. [13] evalutionary compared GA and Column Generation in this context.

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 [17] which was inspired by optimisation where some scholars such as [1] 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 [19] 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.

4. Comparative analysis and discussion

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 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 [18]. Eq. (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.

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 Table 1, 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 2, which is used in the following for finding the best available

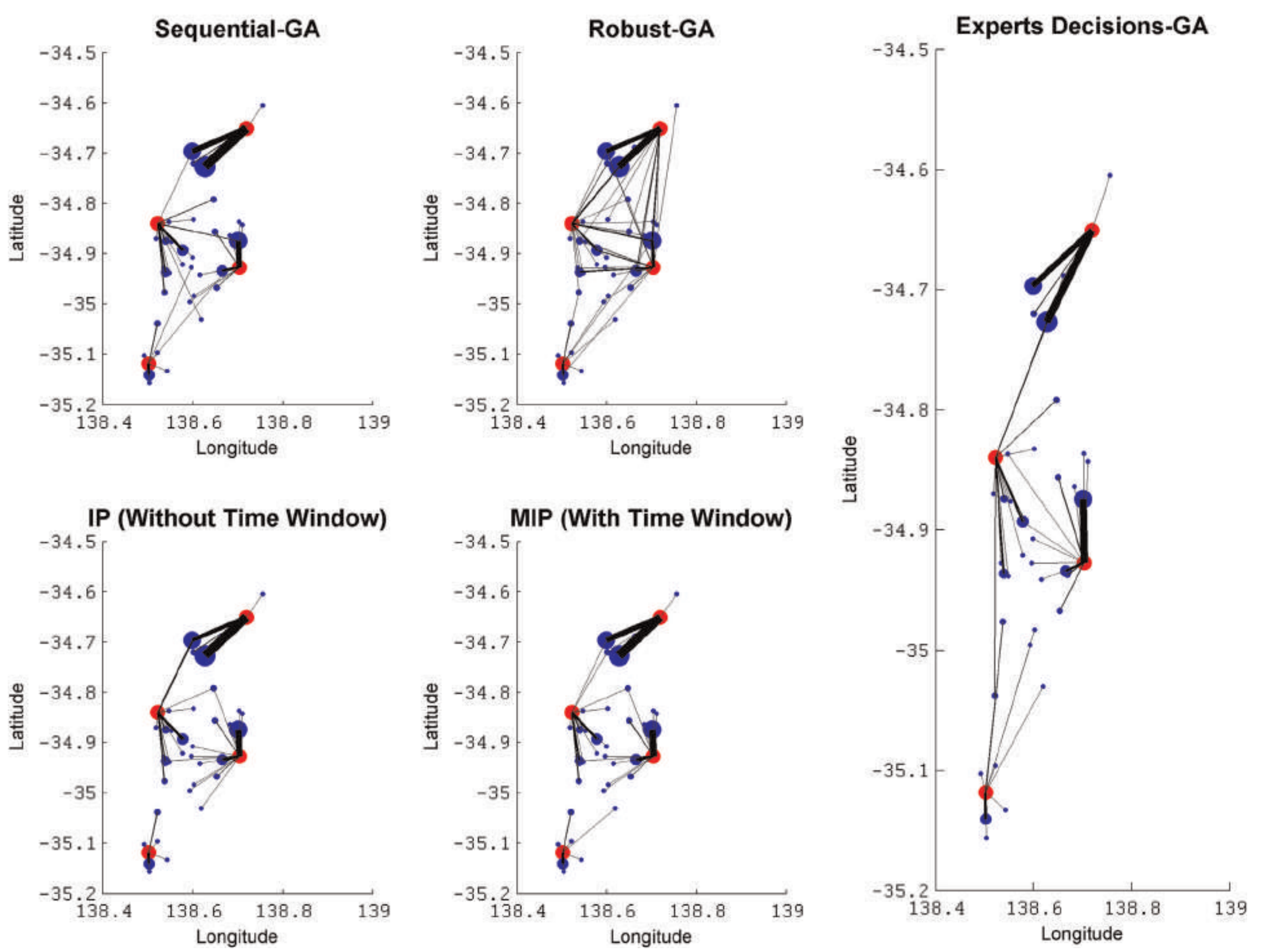

Fig. 2. Graphic summary of Sequential-GA, Robust-GA, IP, MIP and experts' decisions for D2 instances with 112 deliveries.

solution for each instance in the test domain.

According to Table 2, 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.

Now, the best obtained solutions are compared with the experts' decisions to determine the quality of decisions made by the experts. Table 3 is a summary of these comparisons.

The gap between experts' decisions and optimisation models is not negligible but significant (Table 3). 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 [18].

Additionally, during comparisons of IP, MIP, Robust-GA, Sequential-GA and the experts' decisions for each single delivery (Figs. 1–4), an interesting point was found: generally, an expert's decision is more similar to MIP than it is to IP. In these figures, the red dots are the depots and the blue dots are the customers; the size of the blue dots reflects the number of required deliveries. The travel distance between a depot and a customer is shown by an arc with its thickness representing the number of times the route is repeated. This means that the expert understands the importance of the flexible time window, which assists them in

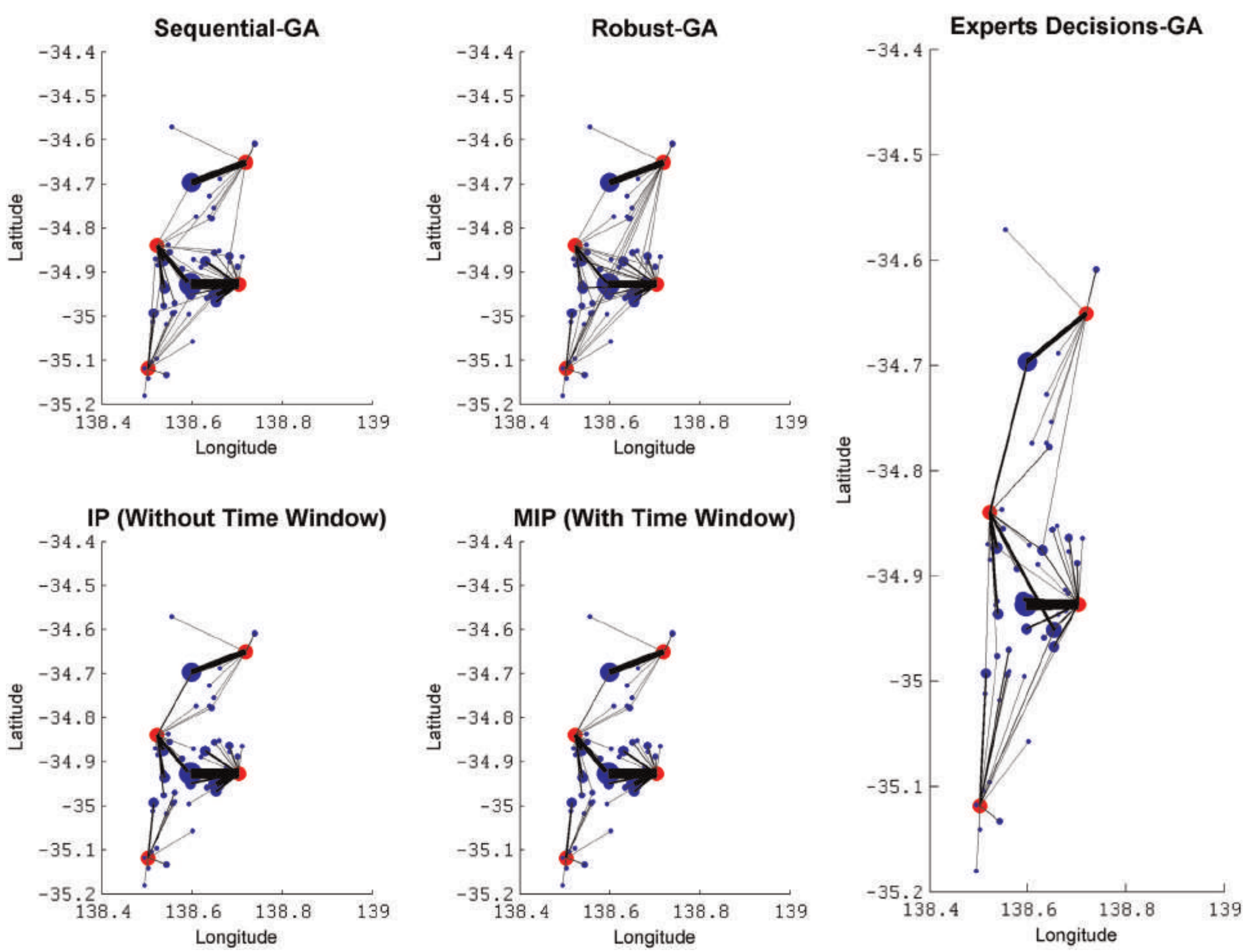

Fig. 3. Graphic summary of Sequential-GA, Robust-GA, IP, MIP and experts' decisions for D3 instances with 153 deliveries.

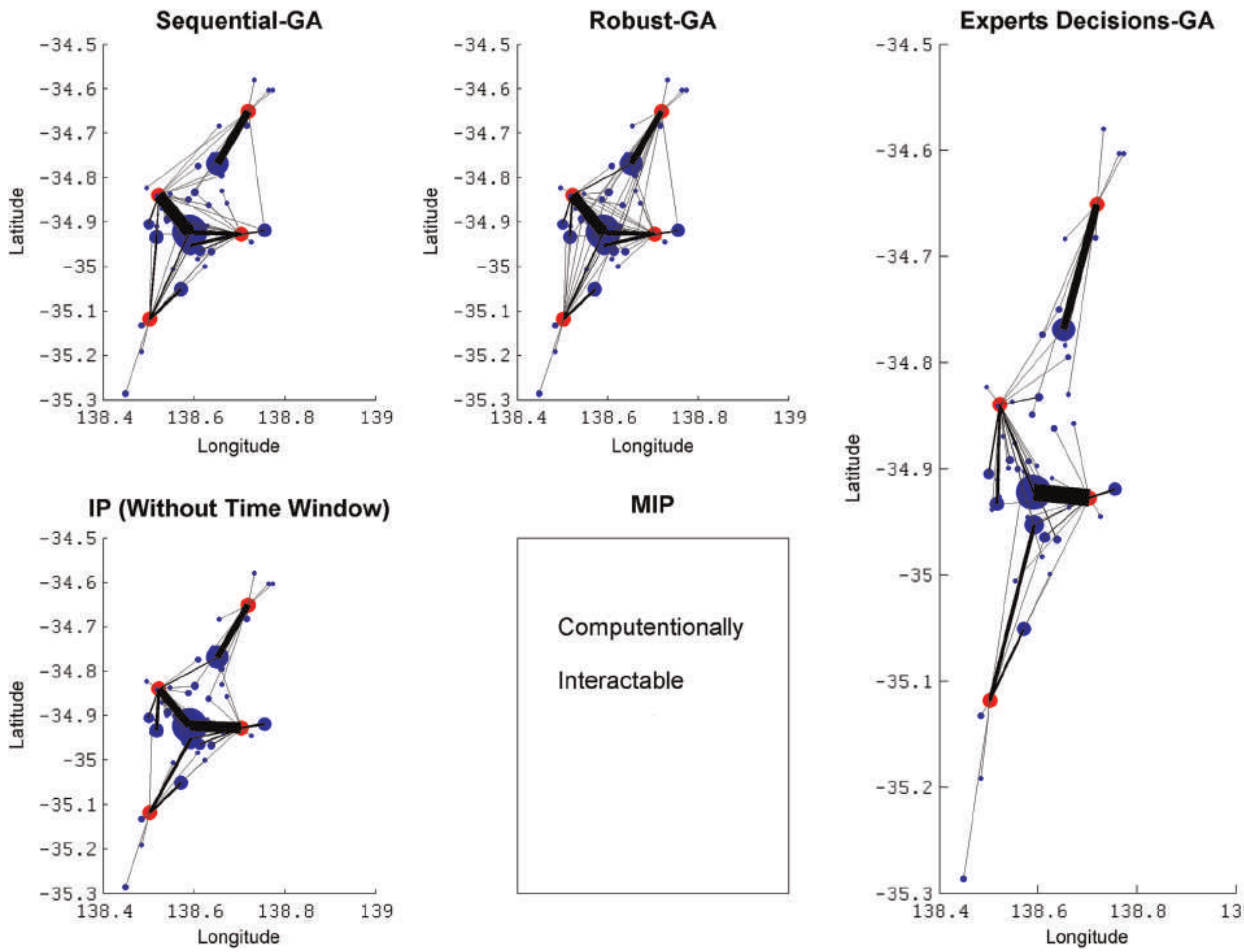

Fig. 4. Graphic summary of Sequential-GA, Robust-GA, IP, MIP and experts' decisions for D4 instances with 197 deliveries.

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 3), 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 Figs. 1–4, as well as and especially in D3 and D4.

5. Conclusion

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.

References

[1] L. Asbach, U. Dorndorf, E. Pesch, Analysis, modeling and solution of the concrete delivery problem, Eur. J. Oper. Res. 193 (2009) 820–835.
[2] M. Cao, M. Lu, J.-P. Zhang, Concrete plant operations optimization using combined simulation and genetic algorithms, in: Proceedings of the 2004 International Conference on Machine Learning and Cybernetics, IEEE, 2004, pp. 4204–4209
[3] T.M. Cheng, R.Z. Yan, Integrating messy genetic algorithms and simulation to optimize resource utilization, Comput. Aided Civil Infrastruct. Eng. 24 (2009) 401–415.
[4] C.-W. Feng, T.-M. Cheng, H.-T. Wu, Optimizing the schedule of dispatching RMC trucks through genetic algorithms, Autom. Constr. 13 (2004) 327–340.
[5] C.-W. Feng, H.-T. Wu, Integrating fmGA and CYCLONE to optimize the schedule of dispatching RMC trucks, Autom. Constr. 15 (2006) 186–199.
[6] J. Garcia, S. Lozano, K. Smith, T. Kwok, G. Villa, Coordinated scheduling of production and delivery from multiple plants and with time windows using genetic algorithms, in: Proceedings of the 9th International Conference on Neural Information Processing, ICONIP'02, IEEE, 2002, pp. 1153–1158
[7] P.-C. Lin, J. Wang, S.-H. Huang, Y.-T. Wang, Dispatching ready mixed concrete trucks under demand postponement and weight limit regulation, Autom. Constr. 19 (2010) 798–807.

[8] M. Lu, HKCONSIM: a sim ulation platform for planning and optimizing concrete plant operations in Hong Kong, in: Proceedings of the International Conference on Innovation and Sustainable Development of Civil Engineering in the 21st Century, 2002, pp. 278–283
[9] M. Lu, M. Anson, S. Tang, Y. Ying, HKCONSIM: a practical simulation solution to planning concrete plant operations in Hong Kong, J. Constr. Eng. Manag. 129 (2003) 547–554.
[10] M. Lu, F. Dai, W. Chen, Real-time decision support for planning concrete plant operations enabled by integrating vehicle tracking technology, simulation, and optimization algorithms, Can. J. Civil Eng. 34 (2007) 912–922.
[11] M. Lu, H.-C. Lam, Optimized concrete delivery scheduling using combined simulation and genetic algorithms, in: Proceedings of the 37th Conference on Winter Simulation, 2005, pp. 2572–2580
[12] M. Lu, D.-P. Wu, J.-P. Zhang, A particle swarm optimization-based approach to tackling simulation optimization of stochastic, large-scale and complex systems, in: D.S. Yeung, Z.-Q. Liu, X.-Z. Wang, H. Yan (Eds.), Advances in Machine Learning and Cybernetics, Springer Berlin, Heidelberg, Germany, 2006.
[13] M. Maghrebi, V. Periaraj, S.T. Waller, C. Sammut, Solving ready-mixed concrete delivery problems: evolutionary comparison between column generation and robust genetic algorithm, in: Proceedings of the International Conference on Computing in Civil and Building Engineering, 2014, pp. 1417–1424.
[14] M. Maghrebi, V. Periaraj, S.T. Waller, C. Sammut, Using Benders Decomposition for Solving Ready Mixed Concrete Dispatching Problems, in: Proceedings of the 31th International Symposium on Automation and Robotics in Construction and Minning, Sydney: UTS, 2014.
[15] M. Maghrebi, D. Rey, S.T. Waller, C. Sammut, Reducing the number of decision variables in ready mixed concrete for optimally solving small instances in a practical time, in: Proceedings of the CSCE 2014 General Conference, Halifax, 2014.
[16] M. Maghrebi, C. Sammut, T. Waller, Reconstruction of an expert's decision making expertise in concrete dispatching by machine learning, J. Civ. Eng. Archit. 7 (2013) 1540–1547.
[17] M. Maghrebi, S.T. Waller, C. Sammut, Scheduling concrete delivery problems by a robust meta heuristic method, in: Proceedings of the European Modelling Symposium on Mathematical Modelling and Computer Simulation, 20–22 November 2013, pp. 150–156.
[18] M. Maghrebi, S.T. Waller, C. Sammut, Assessing the accuracy of expert-based decisions in dispatching ready mixed concrete, J. Constr. Eng. Manag. 140 (6) (2014) 06014004-1–7.
[19] M. Maghrebi, S.T. Waller, C. Sammut, Sequential Meta-Heuristic Approach for Solving Large-Scale Ready-Mixed Concrete–Dispatching Problems, J. Comput. Civil Eng. (2014) 04014117104014117111.
[20] L. Ming, L. Hoi-Ching, Simulation-optimization integrated approach to planning ready mixed concrete production and delivery: validation and applications, in: Proceedings of the 2009 Winter Simulation Conference (WSC), 13–16 December 2009, pp. 2593–2604.
[21] D. Naso, M. Surico, B. Turchiano, U. Kaymak, Genetic algorithms for supply-chain scheduling: a case study in the distribution of ready-mixed concrete, Eur. J. Oper. Res. 177 (2007) 2069–2099.
[22] L. Pan, W. Liya, D. Xihai, G. Xiang, Scheduling of dispatching ready mixed concrete trucks trough discrete particle swarm optimization, in: Proceedings of the IEEE International Conference on Systems Man and Cybernetics (SMC), 10–13 October 2010, pp. 4086–4090.
[23] V. Schmid, K.F. Doerner, R.F. Hartl, J.-J. Salazar-González, Hybridization of very large neighborhood search for ready-mixed concrete delivery problems, Comput. Oper. Res. 37 (2010) 559–574.
[24] C.A. Silva, J.M. Faria, P. Abrantes, J.M.C. Sousa, M. Surico, D. Naso, Concrete delivery using a combination of GA and ACO, in: Proceedings of the 44th IEEE Conference on Decision and Control, 2005 and 2005 European Control Conference, 12–15 December 2005, pp. 7633–7638.
[25] S. Srichandum, T. Rujirayanyong, Production scheduling for dispatching ready mixed concrete trucks using bee colony optimization, Am. J. Eng. Appl. Sci. 3 (2010) 823–830.
[26] S. Wang, Scheduling the truckmixer arrival for a ready mixed concrete pour via simulation with risk, J. Constr. Res. 2 (2001) 169–179.
[27] D.-P. Wu, M. Lu, J.-P. Zhang, Efficient optimization procedures for stochastic simulation systems, in: Proceedings of 2005 International Conference on Machine Learning and Cybernetics, 2005, pp. 2895–2900.
[28] S. Yan, W. Lai, An optimal scheduling model for ready mixed concrete supply with overtime considerations, Autom. Constr. 16 (2007) 734–744.
[29] S. Yan, H.-C. Lin, Y.-C. Liu, Optimal schedule adjustments for supplying ready mixed concrete following incidents, Autom. Constr. 20 (2011) 1041–1050.
[30] Z. Yang, L. Menglei, L. Zhenyuan, Vehicle scheduling and dispatching of ready mixed concrete, in: Proceedings of the Fourth International Workshop on Advanced Computational Intelligence (IWACI), 19–21 October 2011, pp. 465–472.