Technical Note

Assessing the Accuracy of Expert-Based Decisions in Dispatching Ready Mixed Concrete

Mojtaba Maghrebi[1]; S. Travis Waller[2]; and Claude Sammut[3]

Abstract: In ready mixed concrete (RMC) dispatching, common practice is to rely on human experts for any necessary real-time decision making. This is because of the perceived complexity of RMC dispatching and the general lack of highly applicable optimization tools for the task. Critically, the accuracy of expert decisions (compared to optimization approaches) has not been comprehensively examined in the literature. To address the question of current practice expert accuracy in the context of optimized outcomes, this paper first mathematically models the RMC dispatching problem according to methods introduced in the literature. Two approaches are taken: integer programming (without time windows) and mixed-integer programming (with time windows). Further, the constructed models are tested with field data and compared to the decisions made by experts. The RMC data set has four depots and approximately 40 trucks that typically supply 40–200 deliveries per day. The results show that, on average, experts' decisions are 90% accurate compared to the optimization models under examination. Finally, further investigation suggests that at least a portion of this optimality gap between expert and optimization models occurs because experts in critical situations accept a higher cost to ensure a more stable dispatching system. **DOI:** 10.1061/(ASCE)CO.1943-7862.0000853. © *2014 American Society of Civil Engineers.*

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Introduction

Resource management in ready mixed concrete (RMC) companies is a significant task because they try to supply concrete to their customers at the lowest possible cost. Typically, in RMC resource allocation, tasks are handled in dispatching rooms by human dispatchers. To maximize profit, the experts try to find appropriate matches between demands and available resources. For example, for a common 5 m^3 concrete order, a dispatcher makes the decision to supply it from a specific depot, with a specific truck, at a specific time. Before that decision is made, however, many parameters must be taken into account by a dispatcher to ensure a lower cost while meeting customer constraints. Relevant RMC parameters have been indicated in the literature (Maghrebi et al. 2013a; Feng et al. 2004). There are two broad questions about common RMC practices: (1) why such complex dispatching is still handled by human experts, and (2) to what degree the experts' decisions are accurate.

As discussed in the literature, RMC dispatching suffers from a lack of practical solutions for automation (Feng et al. 2004; Maghrebi et al. 2013a, b, 2014; Naso et al. 2007; Tatum et al. 2006). Therefore, this concern will not be addressed further within this paper. Rather, this paper attempts to answer the second question regarding the accuracy of expert decisions in RMC applications. To this end, the optimization model of RMC dispatching is discussed, and the behavior of experts and optimization models are compared within a real database. Theoretically, optimization provides the best possible solution and the gap between expert and optimization reveals the accuracy of the expert's decisions. Assessment in this paper is performed based only on travel distance. This means that the cost function consists of the sum of distances travelled by trucks.

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Expert Dispatcher

As mentioned previously, because of a lack of existing, practical, automated solutions, most RMC dispatching tasks are completed via human decision making. Regardless of the dependency of RMC on the experts, the accuracy of these expert decisions has not been rigorously studied.

To begin a study of expert accuracy, the objective of the problem must be defined. In practice, the primary task of the RMC dispatcher is to deliver all received orders within the day. For this purpose, they receive up-to-date information about the system. Such information is provided by sensors, global positioning systems (GPSs), and other telecommunication devices that are embedded in the trucks and depots. The information is updated regularly and important data—such as idle resources—can be highlighted systematically. However, the accuracy of the expert in RMC has not been studied before now.

Optimization

In the past few years, some research has been devoted to mathematically modeling RMC dispatching (Asbach et al. 2009; Lin et al. 2010; Yan and Lai 2007; Yan et al. 2008). However, complex RMC dispatching is a nondeterministic polynomial time (NP)-hard problem. Therefore, obtaining optimum decisions is computationally intractable (Asbach et al. 2009; Maghrebi et al. 2014).

This concern is empirically investigated with real data. To overcome this problem, heuristic methods have been widely used in the literature (Land and Doig 1960; Lin et al. 2010; Naso et al. 2007; Yan and Lai 2007; Yan et al. 2008; Yang et al. 2011; Maghrebi et al. 2013b). Heuristic techniques are not able to guarantee the optimum solution, but can achieve a near optimum result. In other words, there is no proof that it is possible to analytically measure the accuracy of heuristic methods because the problem is NP-hard. In this paper, with superior computation facilities, an attempt is made to optimally solve this problem for examples with sizes of up to 197 deliveries.

A constrained optimization model is used that consists of an objective function and constraints. The dispatching system is represented as a graph with depots and customers as its nodes. To depict a delivery, an arch is drawn between a depot (u) and a customer (v) (Fig. 1).

To mathematically model the network, it is assumed that each delivery starts from u and ends at v; $z(u,v,k)$ is the cost function, which is calculated based on the distance between u and v with truck k. Also, x and y are the decision variables, which are defined as follows: $x_{uvk}=1$ if the route between u and v with vehicle k is selected, 0 otherwise; $y_{c_i}=1$ if the total demand of customer c_i is supplied, 0 otherwise.

Because the model is static, all required data must be available before running the optimization.

The modeling process used here is the same as the modeling process that was introduced by Asbach et al. (2009) and used by other researchers, such as Yang et al. (2011):

$$\min \sum_u \sum_v \sum_k z(u,v,k) x_{uvk} + \sum_c (1-y_c)\beta(c) \quad (1)$$

Subject to:

$$\sum_{u\in u_s} \sum_v \sum_k x_{uvk} = 1 \quad \forall\ k \in K \quad (2)$$

$$\sum_u \sum_{v\in v_f} \sum_k x_{uvk} = 1 \quad \forall\ k \in K \quad (3)$$

$$\sum_u \sum_v x_{uvk} - \sum_v \sum_j x_{vjk} = 0 \quad \forall\ k \in K, \quad \forall\ v \in C \cup D \quad (4)$$

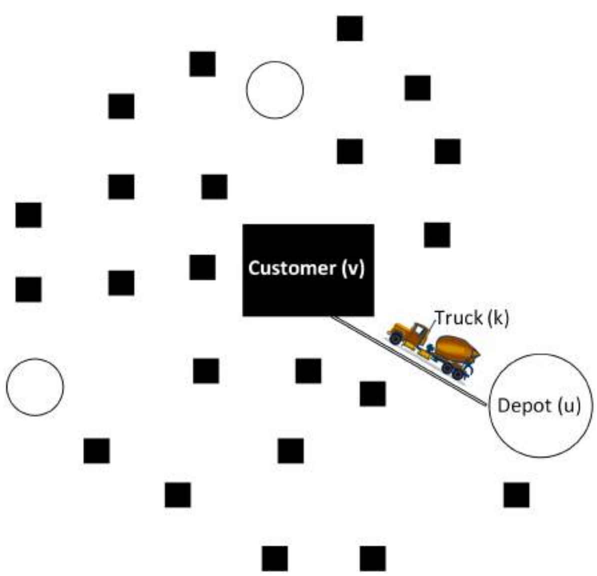

Fig. 1. Dispatching network

$$\sum_v \sum_k x_{uvk} \le 1 \quad \forall\ u \in C \quad (5)$$

$$\sum_v \sum_k x_{uvk} \le 1 \quad \forall\ u \in D \quad (6)$$

$$\sum_u \sum_v \sum_k x_{uvk} q(k) \ge q(c_i) y(c_i)$$
$$\forall\ v \in C, \quad u \in D \quad \text{and} \quad k \in K \quad (7)$$

$$-M(1-x_{uvk}) + s(u) + t(u,v,k) \le w_v - w_u$$
$$\forall\ u \in D, \quad \forall\ v \in C, \quad k \in \mathrm{K} \quad (8)$$

$$(1-x_{uvk}) + Y + s(u) \ge w_v - w_u$$
$$\forall\ u \in D, \quad \forall\ v \in C, \quad k \in K \quad (9)$$

The objective function [Eq. (1)] forces the optimization to find feasible solutions for all customers and provides a penalty if a feasible solution for the customer (c_i) cannot be found by applying zero to y_{c_i}. The first part of Eq. (1) only addresses the costs of the travels between u and v with trucks k so that their corresponding x_{uvk} is not zero. This phrase sums the lengths of all valid arcs in the network, which can also reflect the size of the operational cost. The primary objective in the second part of Eq. (1) is to minimize the number of unsupplied customers. In this phrase, $\beta(c_i)$ is used to force the model from unsatisfied customers. $\beta(c_i)$ is used to penalize the objective function if the demand for customer c_i is not satisfied. As will be discussed in the following, according to the model, only a customer can accept a delivery; therefore, in this paper, $\beta(c_i)$ is the same for all customers and is equal to a large constant. Eq. (2) ensures that a truck at the start of the day must leave once from its base; similarly, Eq. (3) necessitates the return of a truck just once to the depot by the end of the day. In reality, a truck arrives to 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 $v \in D$ 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 subdepots based on the number of possible loadings at that depot. Similarly, a customer is divided into a set of subcustomers according to the number of required deliveries. Therefore, Eqs. (5) and (6) certify that only a truck is sent to a customer and that only a depot supplies a customer, respectively. Eq. (7) checks the demand satisfaction of customers. Eqs. (8) and (9) are designed to control timing concerns. Eq. (8) ensures that concrete will be supplied to customers within the specified time; similarly, Eq. (9) ensures that the travel time for each customer will not exceed the permitted time for delivery (Υ), because fresh concrete is a perishable material and it is not advisable to haul it more than Υ, which varies according to the type of concrete.

Because of uncertainties in reality, RMC dispatchers are not able to guarantee that concrete will be supplied at precise, fixed times. Therefore, typically, there is flexibility in most deliveries, which can occur either slightly earlier or slightly later than the times requested by customers. This issue is modeled in Eq. (10); $a(u)$ and $b(u)$ define the boundaries of the time window for each customer (u).

Two models have been described: an RMC dispatching problem without time windows (integer programming, or IP) and an RMC dispatching problem with time windows (mixed-integer programming, or MIP). The IP model includes all equations with the exception of Eq. (10); the MIP model includes all described equations. To reiterate, in IP, only the best delivery choices are required, but in MIP, with more than the optimum arcs on the graph, the optimum delivery times are also needed. In the next section, these models will be tested with real examples. In this study, both IP and MIP models are used and their results are compared with those of the expert. This is the only way it is possible to take into account the flexibilities in delivering times. This will reveal two concerns: (1) the possible difference between IP and MIP in practice, and (2) the possible similarity between an expert's decisions and those of IP or MIP.

Field Example

To determine the extent to which experts' decisions on RMC dispatches are accurate, the described models (IP and MIP) are tested via a real data set. The data belong to one of the largest RMC companies in Australia; for further investigations among the data sets, the study particularly focuses on the Adelaide metropolitan area. The available database covers four months in 2012.

To increase understanding of the size and specifications of the problem, some useful information is given in the following. Regarding the size of the RMC dispatcher, there are four batch plants and approximately 40 trucks in the designated area. Fig. 2 shows the number of deliveries per day in a histogram. As is obvious from this figure, for most observed days (approximately 70%), the number of deliveries exceeds 60. Moreover, fewer than 60 deliveries in a day means that most fleets on that day have not been used. Thus, resource allocations on these days are not a cumbersome job for experts and their optimization models can be solved very quickly, often within a few seconds. To focus on more challenging problems, days with fewer than 60 deliveries will not be studied. Consequently, among the available data set, four days were selected for further tests. For an unbiased selection, the available instances are divided into four categories based on the number of deliveries in each instance. The four instances were chosen at random: days with 63, 112, 153, and 197 deliveries.

The following figures in this section assist in clearly specifying the available database. Fig. 3 uses dots to show the distribution of projects across the metropolitan area, and also illustrates the locations of depots with numbers. This figure is enhanced by two histograms on the axes that emphasize the locations with high demand. Fig. 4 demonstrates that distances between assigned depots to the projects are mostly less than 20 km, which corroborates that the RMC dispatcher can effectively cover the entire area. Fig. 5 shows the fluctuation in the numbers of daily orders received. It can be deduced from this graph that there is no specific pattern for the number of orders on days of the week. Fig. 5 illustrates that Depots 2 and 3 are more involved than the other two depots. This can also be deduced from Fig. 3. Moreover, it is shown in this graph that less than 1% of the orders were supplied from loan depots. Again, this highlights that the experts effectively handle this RMC dispatcher.

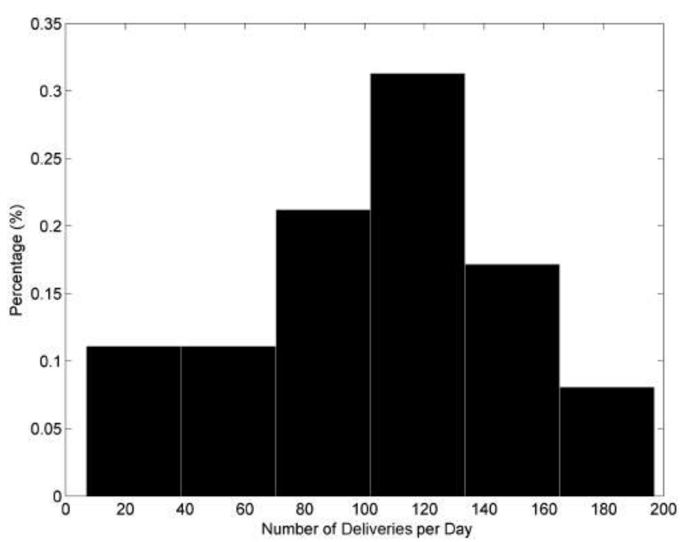

Fig. 2. Histogram of number of deliveries per day

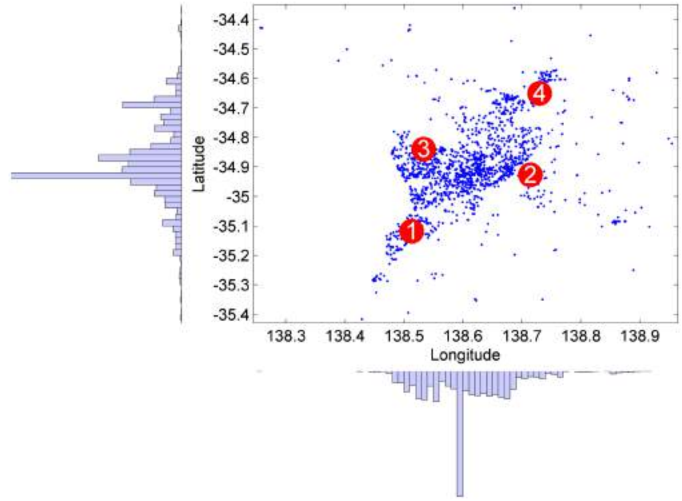

Fig. 3. Distribution of projects in metropolitan area (dots) and locations of depots (numbers)

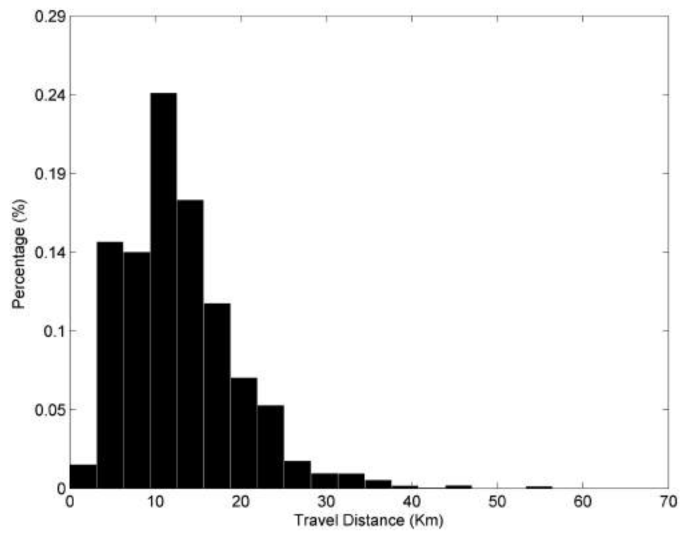

Fig. 4. Travel distance between depots and projects

Computation Metrics

In this section, the results of the optimization models are reported and compared with the experts' decisions for chosen examples. As briefly stated previously, large-scale RMC dispatching problems

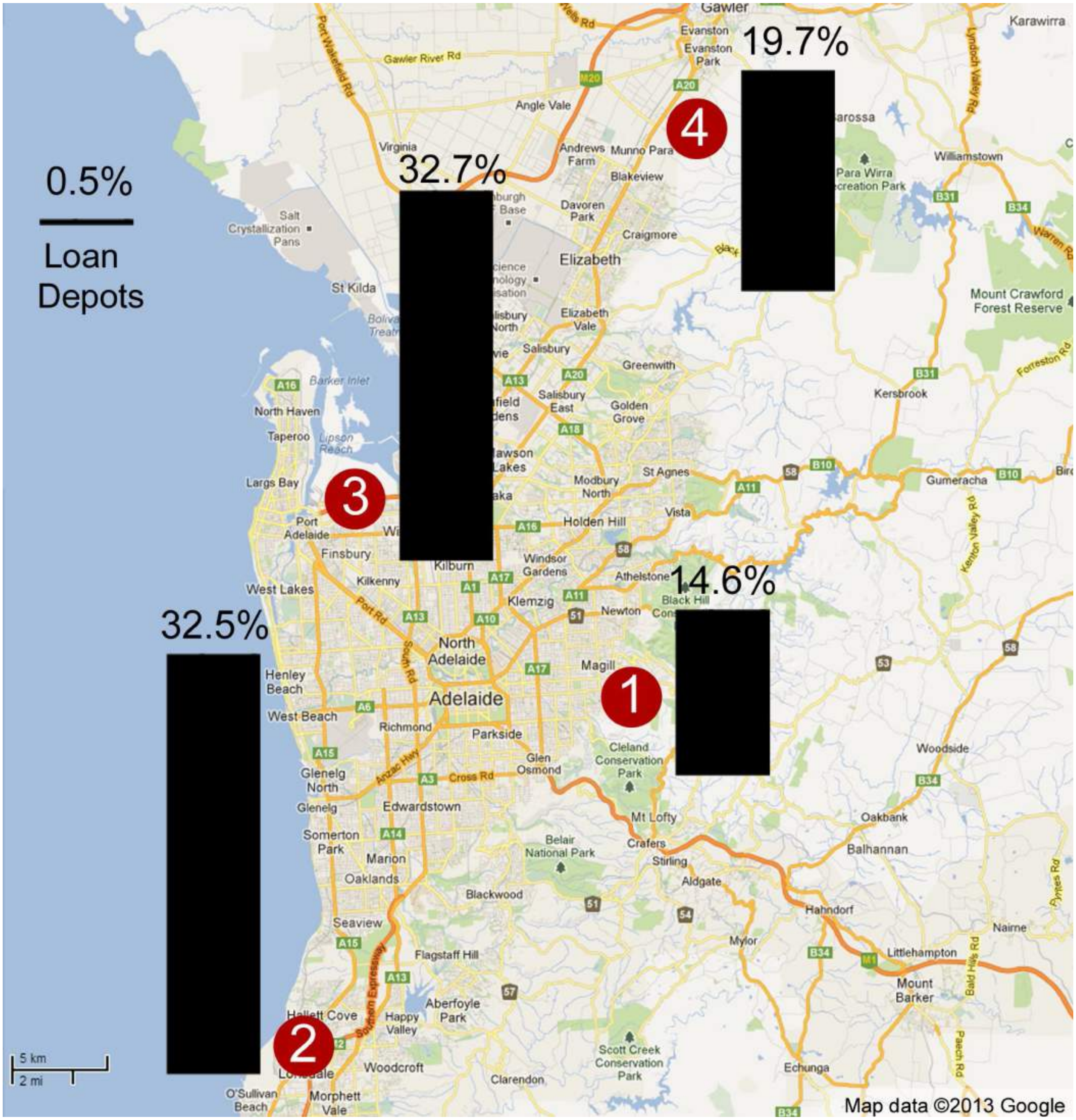

Fig. 5. Contribution of each depot in supplying concrete (map data © 2013 Google)

are NP-hard and computationally intractable. This is examined empirically in this study; a code is assigned to identify each of the instances (Table 1).

These instances are solved by using *GAMS/CPLEX* 12.0 mathematical programming software, which uses the branch-and-bound technique (Land and Doig 1960) to solve both integer and mixed-integer problems. During each optimization, the critical parameters were monitored; these included the number of variables, elapsed time, and required actual RAM. This information is summarized in Table 2.

As shown in Fig. 6, by increasing the size of the problem in both IP and MIP, the RAM and number of variables grow exponentially. This becomes critical because instances in polynomial time cannot be solved. This occurred for D4-MIP when, after a couple of weeks, the computation process was still not terminated. Fig. 7 supports this by depicting the number of iterations for both IP and MIP. Although the number is not applicable for D4-MIP, the exponential trend of instances maintains that tiny growth in the scale of the problem will cause great growth in the number of iterations. This is more crucial in MIP; for example, the size of the problem in

Table 1. Order of Coding the Chosen Instances

Chosen instance (number of orders/day)	Optimization technique	Instance code
63	IP	D1-IP
112	IP	D2-IP
153	IP	D3-IP
197	IP	D4-IP
63	MIP	D1-MIP
112	MIP	D2-MIP
153	MIP	D3-MIP
197	MIP	D4-MIP

Table 2. Monitored Parameters of Instances during Optimization

Instance code	Memory (MB)	Number of equations	Elapsed time (s)	Iteration
D1-IP	439	1,346,051	45	14,270
D2-IP	1,131	3,467,647	737	51,675
D3-IP	1,596	4,895,477	7,127	162,644
D4-IP	2,804	8,607,379	28,180	406,381
D1-MIP	514	1,346,141	3,288	199,306
D2-MIP	1,327	3,467,871	68,591	3,144,092
D3-MIP	1,876	4,895,783	264,829	16,138,119
D4-MIP	3,299	8,670,773	N/A	N/A

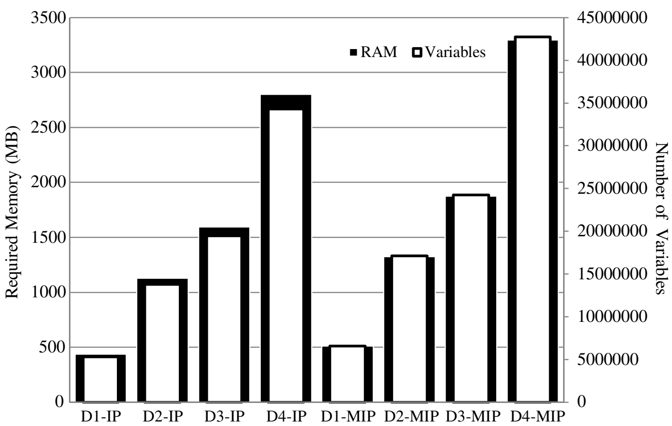

Fig. 6. Required memory and number of variables for instances

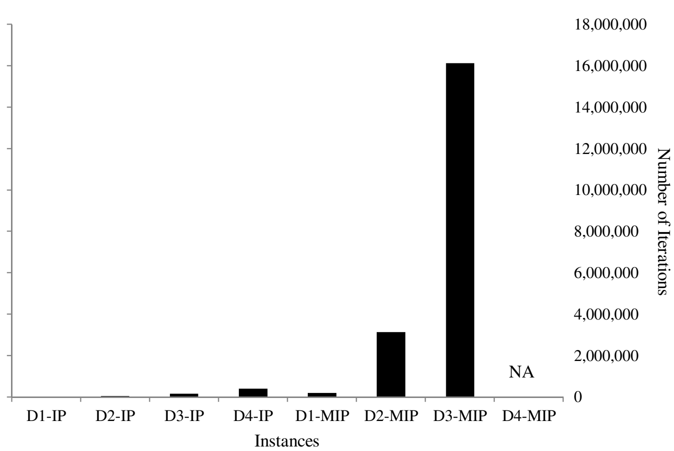

Fig. 7. Number of iterations for each instance

D3-MIP has 36% growth in comparison with D2-MIP. However, D3-MIP has four times more iterations than D2-MIP.

Results and Discussion

This section compares the results achieved by IP and MIP and the expert's decision for each instance. Fig. 8 graphically summarizes all of the results. This graph shows the geographical locations of depots (red dots) and customers (blue circles). Lines in the graph illustrate the deliveries, and the diameters of the blue circles and lengths of lines show the amount of demand and the number of delivered trucks, respectively. It is rather difficult to establish all of the differences between IP, MIP, and the expert's decisions for each instance because most of the decisions are the same. Generally, according to this figure, there is no substantial difference between the expert's decisions and those of the optimization models. However, to answer the question regarding the accuracy of the expert in RMC dispatching, the total costs of IP, MIP, and the expert are compared in Table 3.

As expected, MIP achieved the best results. The MIP model has only one more constraint than the IP model. Despite this, Eq. (10) provides an additional constraint for the MIP model in comparison with the IP model; in practice, it relaxes Eqs. (8) and (9) by providing a boundary for expected arrival times at customers. This does not mean that RMC dispatchers can supply concrete at any time, and furthermore, this flexibility is defined and determined by RMC companies and customers. For example, the desired time of unloading concrete for a customer is 8:00 a.m. The RMC dispatcher guarantees that the concrete will be supplied to the location at a time between 7:30 and 9:00 a.m. This flexibility partially relaxes the time window constraints of Eqs. (8) and (9) and allows optimization to find a feasible solution that may not be exactly the customer's desired time.

In crucial cases, MIP and IP are almost equal when the RMC dispatcher either has too many orders or too few. In the chosen instances, with the exception of D4-MIP, which is intractable, the gap between IP and MIP is less than 1.5% (Table 3). Therefore, it can be concluded that with these sizes of RMC problems, the performances of the IP and MIP models are almost the same. This consequence can assist researchers in finding global optimization results for large-sized RMC problems using the IP model. In other words, it acknowledges that there may not be a substantial gap between IP and MIP; thus, the IP result may be accepted as the best possible solution.

The gap between experts' decisions and optimization models is not negligible, but significant (Table 3). This gap amounts to 14% (D1-MIP) and 5% in the best case (D4-IP). On average, in these sizes of RMC problems, experts' decisions are 90% accurate. This accuracy is important for RMC companies because, on one hand, there is a lack of practical solutions in this context and the experts must be trusted. On the other hand, there is a concern for RMC companies about the extent to which an expert makes the best possible decisions. Daily calculation of the accuracy rate for experts, as has been investigated in this paper, is computationally intractable (Table 2). However, from a general point of view, a significant gap between the expert and the optimization has not been observed in all of the variously sized problems among the chosen instances.

Moreover, the expert believes that their performance is defendable because they have been able to handle the dispatching with few cancelled orders. Investigations through the available database show that the number of orders that were not supplied on most days is zero. Normally, when an order is not supplied by an RMC dispatcher, there is a lack of some resource; the critical resource is

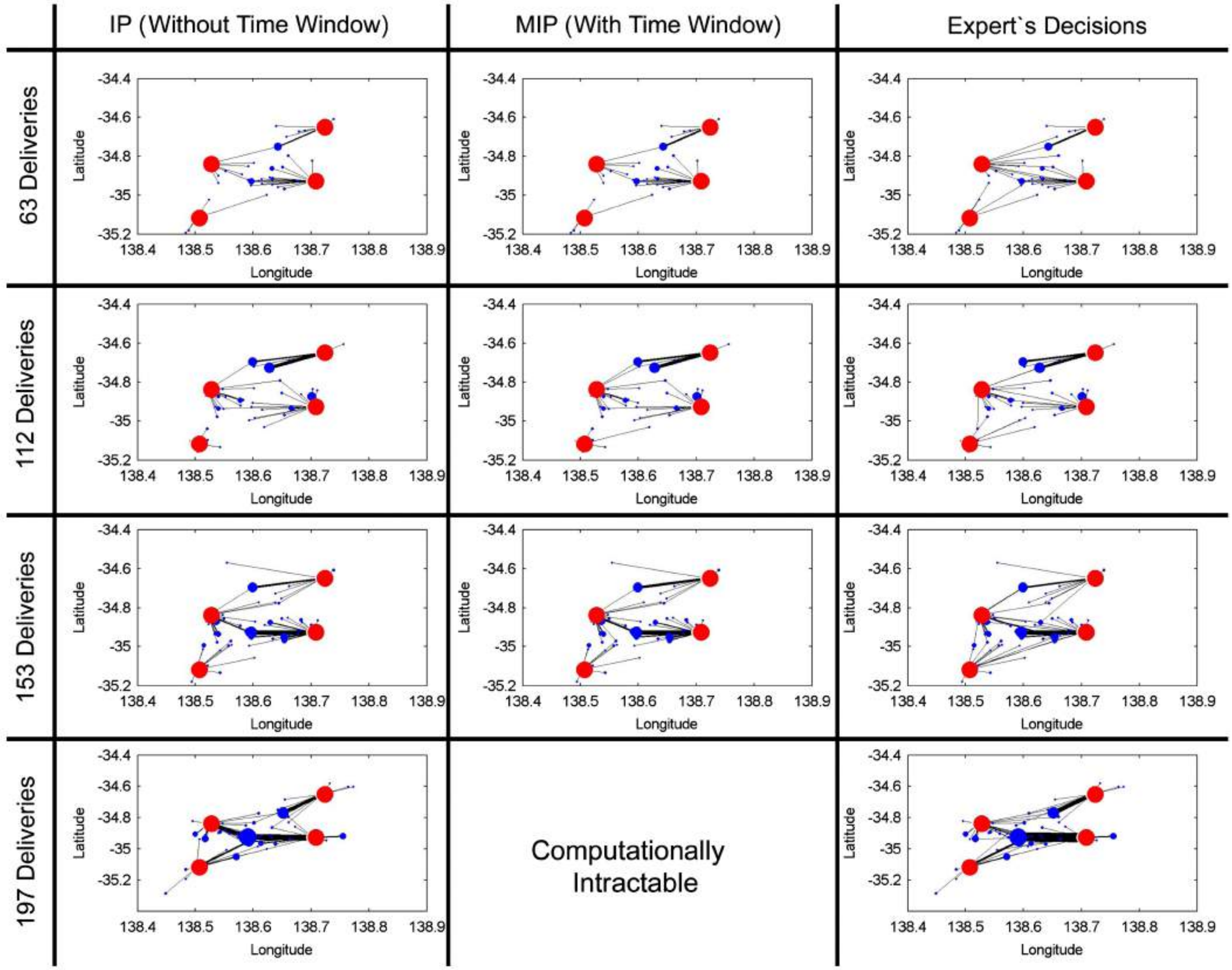

Fig. 8. Graphic summary of IP, MIP, and expert's decisions for all instances

transportation. Therefore, when the number of unsupplied orders is approximately zero, this means that experts are able to find a way to supply all received orders within the day with available resources. Moreover, this was observed by the researchers, who determined that the expert's primary objective is to find a way to match the supply with the demand, involving a low cost if they are unable to find the optimum solution. Their second goal is to keep customers pleased. However, optimization models seek to find a match between available resources and demand at the lowest cost. Optimization models only care about constraints and nothing else. Therefore, it is possible that this gap between optimization models and experts is the result of differences between their goals.

Also, during the comparison of IP, MIP, and the expert for each single delivery (Fig. 6), an interesting point was found: generally, the expert's decision is more similar to MIP than to IP. This means that the expert understands the importance of the flexible time window that allows them to smoothly handle resource allocation. Notwithstanding this similarity, it is expected that the expert's decisions are quite similar to IP and MIP; in reality, this is not so. There may be two reasons for this gap.

Table 3. Total Costs of IP, MIP, and Experts' Decisions for Each Instance

			Optimization		Accuracy of expert in comparison with computation		
Picked day	Number of deliveries	Expert's decision	IP (without time window)	MIP (without time window)	IP (without time window) (%)	MIP (without time window) (%)	Gap between IP and MIP (%)
Day 1	63	642	572	565	88	86	1.2
Day 2	112	1,021	963	954	94	93	0.9
Day 3	153	1,597	1,381	1,373	84	84	0.6
Day 4	197	2,207	2,098	N/A	95	N/A	N/A

First, there is human error, which does not allow the expert to achieve a better result. Human error in a complex task such as RMC dispatching is inevitable and becomes more crucial when the system is not controlled. Moreover, the earliest time at which performance can be assessed is at the end of the day, when the number of unsupplied orders is counted. This process is already the only way for auditing by the expert in most RMC companies. Based on this assessment, an expert dispatcher might be rewarded or penalized. Nevertheless, there is no other applicable way to measure the quality of the expert during the day or before any decision.

Second, there is the conservative behavior of the expert, which was noted when researchers tried to find a relation between the size of the problem and the number of errors. According to the results (Fig. 6), this kind of error ordinarily happens when a large number of orders is accepted for a specific area. At this point, the number of loads at the nearest depot to that area will increase. This causes concerns for the expert regarding overcapacity. To prevent any unsupplied orders, they make decisions to supply some orders from other depots (Fig. 6). In practice, the expert accepts a higher cost for some orders instead of controlling an unstable dispatching system, because when a depot serves at full capacity, it is very difficult to control the system if there are any unpredicted events. Modeling uncertainties in RMC dispatching problems is a very cumbersome job and definitely increases the complexity of the computation model and threatens the computation process. Therefore, it can be concluded that although IP and MIP achieved better results, the expert semi-optimally handles the RMC dispatching system with more stability than deterministic approaches.

Also, in terms of computing time, IP and MIP are not practical solutions. These techniques cannot provide a quick solution when RMC situations are changed; for example, when an order is changed or cancelled at the last minute or there is a truck breakdown.

Conclusion

From an engineering perspective, the resource allocation problem for RMC can be modeled as an optimization model. However, it is NP-hard and computationally intractable for large-scale problems. Therefore, in practice, RMC dispatching tasks are normally handled by experts. This study examined the accuracy of experts' decisions. First, according to the methods introduced in the literature, the RMC optimization problem was mathematically formulated with two models: without time windows and with time windows. The first model is an integer problem and the second is a mixed-integer problem. Second, the constructed models were tested by using real data from an RMC dispatcher. Among the data sets, four examples of different sizes were chosen and tested. Finally, the results of the IP and MIP models were compared with experts' decisions for all chosen instances. In conclusion, experts' decisions are nearly optimum, with an average accuracy of 90%. However, after comparing individual decisions between the optimization models and the experts, it can be concluded that optimization models only try to achieve the lowest cost, whereas the expert prefers a more stable dispatching system with a slightly higher cost. This is a significant consequence for any further studies trying to reconstruct experts' decisions with machine learning techniques to decrease the dependency on human resources in RMC companies. Before any investment into experts' decisions in RMC, their accuracy must be known; this study provides a clue in this regard. Also, this study implemented a practical framework for assessing the experts in RMC dispatching, which can be used by RMC owners for assessing an individual dispatcher or even a whole dispatching team.

Notation

The following symbols are used in this paper:

$C = \{C_1, \ldots, C_n\}$ set of customers;
$D = \{D_1, \ldots, D_m\}$ set of depots;
$K = \{K_1, \ldots, K_p\}$ set of vehicles;
M = large constant;
$q(c_i)$ = required amount of concrete for customer c_i;
$q(k)$ = the maximum capacity of vehicle k;
$s(u)$ = service time at depot u;
$t(u, v, k)$ = travel time between u and v with vehicle k;
$us = \{u_{s1}, \ldots, u_{sr}\}$ set of starting points;
$vf = \{v_{f1}, \ldots, v_{fg}\}$ set of ending points;
w_i = time at node i;
$\beta(c_i)$ = penalty of unsatisfying the demand for customer c_i, which is a large constant; and
Υ = maximum time that the concrete can be hauled.

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