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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; 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.

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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 $V=\{u_s \cup C \cup D \cup v_f\}$. 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

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

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

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

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

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

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

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

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

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

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