

Exploring Experts Decisions in Concrete Delivery Dispatching Systems Using Bayesian Network Learning Techniques

Mojtaba Maghrebi

School of Civil and Environmental Engineering
The University of New South Wales (UNSW)
Sydney, Australia
maghrebi@unsw.edu.au

S. Travis Waller

School of Civil and Environmental Engineering
The University of New South Wales (UNSW) and NICTA
Sydney, Australia
s.waller@unsw.edu.au

Abstract—Optimally solving large scale Ready Mixed Concrete Dispatching Problems (RMCDPs) in polynomial time is a crucial issue and, in the absence of automated solutions, experts are hired to handle resource allocation tasks in concrete dispatching centres. Therefore, in the Ready Mixed Concrete (RMC) industry, the performance of experts is accepted as the only practical solution, although there is no benchmark for assessing the quality of their decisions. This paper aims to discover the experts' decisions in the RMC context by using Bayesian Network. Finding the optimum graph in Bayesian Network is NP-hard; therefore, this research uses a wide range of heuristic search algorithms (Hill Climbing, K2, Look Ahead Hill Climbing, Repeated Hill Climbing, Tabu Search, Simulated Annealing and Genetic Algorithm). A large scale dataset gathered from an active RMC was used for evaluating the proposed idea. Results show that Simulated Annealing search algorithm outperformed other search algorithms, although there is not a significant difference between them. However, interpreting the network obtained by Simulated Annealing involves much more effort than other networks with similar accuracy, such as K2.

Keywords—Ready Mixed Concrete; Bayesian Network; Experts' Decisions

I. INTRODUCTION

Ready Mixed Concrete Dispatching Problems (RMCDPs) suffer from a lack of practical solutions and, in the absence of automated approaches, experts are hired to handle the resource allocation in concrete delivery dispatching centres ([1], [2], [3], [4]). In the last decade, several attempts have been made for mathematically modelling RMCDP (such as [5], [6]). RMCDP can be classified as a generalized Vehicle Routing Problem (VRP) [5], [7]. The main problem is that these mathematical models cannot solve large scale RMCDPs in polynomial time and are characterized as NP-hard ([8], [9]). This means that with the available computing facilities medium and large scale RMC dispatching problems in polynomial time cannot be solved ([10], [11]).

As mentioned above, typically experts handle dispatching tasks in the Ready Mixed Concrete (RMC) industry. This paper attempts to discover the experts decisions using Bayesian Network Learning (BNL) and consists of four sections, excluding the introduction. First, the related works in RMCDP will be reviewed. Second, the variations of Bayesian Network Learning used in this paper will be discussed. Third, the

gathered field dataset and its attributes will be presented. Fourth, the achieved results will be reported and discussed.

II. LITERATURE REVIEW

Mathematical modelling and heuristic approaches have received more attention in the RMC domain. Ready Mixed Concrete Dispatching Problems (RMCDPs) can be modelled as special Vehicle Routing Problems (VRPs) ([2], [6], [12]; in general, a VRP in itself is a kind of Travelling Salesman Problem (TSP) ([13], [14])). The main differences between VRP and RMC that must be taken into the account are: (i) in RMC a truck can only supply concrete to one customer on each trip while in VRP a truck normally can supply more than one customer (ii) concrete cannot be hauled for a long time because fresh concrete is a perishable material. Based on these differences, a set of new constraints needs to be added to the original VRP formulation. Several attempts have been made to model the RMC dispatching effectively, such as ([5], [1], [2], [8], [9], [6], [3]). It has been proved that an RMC optimization problem is an NP-hard problem ([5], [2], [8], [3]). Therefore, to deal with this problem, heuristic methods have been widely used in the literature. The implementation of Genetic Algorithm (GA) has been highlighted more than other heuristic methods. Garcia et al. [15] implemented a GA-based method for solving a single depot RMC problem. Similarly, Feng et al. [16] modelled a single depot problem but used larger instances for validating their model; the instances they considered are much smaller than the instances that are used in this paper. Naso et al. [2] introduced a GA algorithm which is very similar to the methods that were presented earlier, but their model can deal with multi-depot RMC problems. Lu [17] presented the concept of integrating Discrete Event Simulation (DES) with evolutionary methods and this idea has been tested with different methods such as GA ([18], [19]) and Particle Swarm Optimization (PSO) ([20], [21]). Silva et al. [22] compared GA with Ant Colony Optimization (ACO) and suggested a GA-ACO method for solving RMC problems. More recently, Srichandum and Rujiranyong [23] compared Bee Colony Optimization (BCO) and Tabu Search (TS) with GA in this context. Despite developments in this area, the solution structure among most introduced methods remains much the 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 or after achieving a premature solution. Then, via supplementary algorithms, any infeasibilities in the achieved solution can be adjusted, mostly by out-sources or idle resources. To overcome this issue, Maghrebi et al. [7] presented an evolutionary based method which can solve the RMC dispatching problem without needing any supplementary algorithm.

Rather than only looking at evolutionary methods some other numerical approaches have also been studied. Yan et al. [9] introduced a numerical method for solving the RMC optimization problem by cutting the solution space and incorporating the branch and bound technique and the linear programming method. Yan et al. [24] used decomposition and relaxation techniques coupled with a mathematical solver to solve the problem. Asbach et al. [5] made the mathematical modelling much simpler by dividing depots and customers into sub-depots and sub-customers, and then used large scale instances for testing their introduced large neighborhood search and decomposition methods. More recently, Maghrebi et al. [11] implemented a Column Generation (CG) method which is amenable to Dantzig-Wolfe reformulation for solving large scale models which available computing facilities cannot optimally solve in polynomial time.

III. METHODOLOGY

In this section the principles of Bayesian Networking Learning are discussed. Bayesian based classifiers are probabilistic learning schemes that build a probabilistic model based on the features and then use this model for classifying new instances [25]. This learning scheme is a combination of Bayes theorem and naive independence assumptions. It is based on an independent feature model and always prefers simple things first. It also assumes that attributes are independent. Therefore, if $A = \{a_1, a_2, \dots, a_i\}$ the probability (likelihood) of A is conditioned on class C :

$$\begin{aligned} P(A | C) &= P(a_i | C) \times P(a_2 | C) \times \dots \times P(a_1 | C) \\ &= \prod_{j=1}^i P(a_j | C) \end{aligned} \quad (1)$$

According to Bayes theorem, posterior probability is calculated as follows:

$$P(C | A) = \frac{P(A | C)P(C)}{P(A)} \quad (2)$$

where $P(C)$ is the prior probability of class C and $P(A)$ is the predictor of prior probability. Also, if there are different classes $\{c_1, c_2, \dots, c_n\}$ then the class of new instances is obtained as follows:

$$\begin{aligned} &\underset{c_k \in C}{\operatorname{argmax}} P(c_k | a_1, a_2, \dots, a_i) \\ &= \underset{c_k \in C}{\operatorname{argmax}} \frac{P(a_1, a_2, \dots, a_i | c_k)P(c_k)}{P(a_1, a_2, \dots, a_i)} \end{aligned} \quad (3)$$

then:

$$\underset{c_k \in C}{\operatorname{argmax}} \frac{P(c_k) \prod_{j=1}^i P(a_j | c_k)}{\prod_{j=1}^i P(a_j)} \quad (4)$$

According to Maximum A Posteriori (MAP) hypothesis [26]:

$$\begin{aligned} \underset{c \in C}{\operatorname{argmax}} P(c | A) &= \underset{c \in C}{\operatorname{argmax}} \frac{P(A | c)P(c)}{P(A)} \\ &= \underset{c \in C}{\operatorname{argmax}} P(A | c)P(c) \end{aligned} \quad (5)$$

therefore:

$$\begin{aligned} c_{NB} &= \underset{c_k \in C}{\operatorname{argmax}} \frac{P(c_k) \prod_{j=1}^i P(a_j | c_k)}{\prod_{j=1}^i P(a_j)} \\ &= \underset{c_k \in C}{\operatorname{argmax}} P(c_k) \prod_{j=1}^i P(a_j | c_k) \end{aligned} \quad (6)$$

where c_{NB} is the class assigned by Naive Bayes (NB) to a test instance. Moreover, NB is not an updatable learning scheme because it classifies test instances based on analysing the training data. While the NB method is reasonably simple, in some domains it obtains competitive results [27].

Bayesian Network is very similar to NB, but typically is implemented to illustrate probability of every joint installation of attributes using Direct Acyclic Graph (DAG) [28]. Bayesian Network first learns a structure and then learns the probabilities among the attributes. Bayesian Network is known for being a formidable tool for troubleshooting and complex system analyses and is widely used in practice such as: ([29]–[35]).

In other words, Bayesian Network constructs a graph in which nodes are attributes and an arc represents the conditional dependency between two attributes. This graph is obtained in a process called structure learning. If we have n attributes (a_1, a_2, \dots, a_n) , and then the DAG is built using conditional independency:

$$p(X) = \prod_{i=1}^n P(a_i | a_1, a_2, \dots, a_n) \quad (7)$$

therefore for each node we have:

$$P(a_i | a_1, a_2, \dots, a_{i-1}) \quad (8)$$

then:

$$p(X) = \prod_{i=1}^n p(a_i | a_1, a_2, \dots, a_n) \quad (9)$$

It was proved in the literature (such as [36]–[40]) that the search process of Bayesian Network for large networks is NP-hard; thus, heuristic approaches are recommended to deal with this problem. In this paper the following search methods are used:

1) *Hill Climbing*: This iterative search algorithm initially generates then tries to change the arcs by local searching around the best solution. Sticking in a local optimum solution is the main drawback of this method.

2) *K2*: This search algorithm is very similar to Hill Climbing but it is restricted by an order on the variables. In this method, a prior specified probability can be allocated to some arcs and if this information is not available then all arcs are given a uniform value [41].

3) *Look Ahead Hill Climbing*: This is generalized Hill Climbing but applies scoring the best steps and configuring the number of look ahead steps as well as the number of steps. Unlike *k2* this algorithm is not restricted by the order of the variables.

4) *Repeated Hill Climbing*: This algorithm returns a network after repeatedly using Hill Climbing that is initially generated randomly.

5) *Simulated Annealing*: This method, simulated annealing is used for finding the best Bayesian Network [42]. It was inspired by the heating and cooling processes of materials. [43].

6) *Tabu Search*: This method aims [44] to obtain optimum Bayesian Network. It retains a certain number of worse solutions as a tabu list and would not consider them in the following steps.

7) *Genetic Algorithm*: This method uses Genetic Algorithm [45] generates an initial random population and then applies cross over and mutation to try to improve the population.

A. Field Data

The size and amount of data that is used in this study is much greater than the datasets that have been used in similar research studies in the literature. The richness of the data helps the authors to draw their conclusions more confidently and to introduce more generalized models. The proposed approach is tested with the field dataset of an active RMC which belongs to one of the largest RMC companies in Australia. For the collected dataset we particularly focused on the Adelaide metropolitan area. The available database covers 4 months in 2012 of the RMC which has 4 batch plants and around 40 trucks. In Figure 1, the distribution of projects across the metropolitan area is illustrated; this supports the premise that customers locations do not follow a uniform pattern. It also might be assumed that customers in a particular area are supplied from a nearby depot, but in practice this is not always true. The huge number of overlaps between the supply areas provides proof that most likely other attributes than simply the

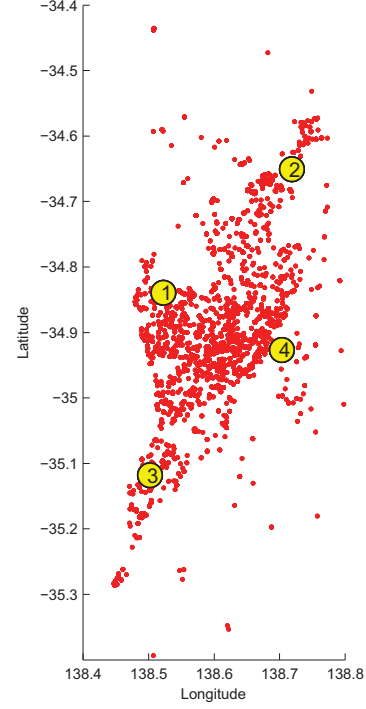


Fig. 1: Distribution of Customers in Adelaide Metropolitan Area

location of customers are taken into account by experts when assigning a depot to a customer.

The training data includes the RMC monitoring data which covers all the information provided to the experts as well as the decisions that the experts have made. In particular, the dataset shows the experts decisions in several circumstances. Therefore, it is expected that the selected machine learning techniques will match experts decisions in any circumstances. In the attribute selection process, two issues have been taken into account: (i) the conducted research in this area such as [1], [4], [2], [16], [9], [46], [47] and (ii) a consideration of the data that is already provided in practice to the experts which was determined after carefully observing the experts behaviours in several RMC dispatching rooms. Then, the following parameters were selected to construct the training and test datasets.

Experts' Decisions	Experts' decisions about a selected depot for each delivery
Day of Delivery	a large constant
Volume	Volume of Delivery (m^3)
Arrival Time	Expected arrival time at customer (hh:mm)
Longitude	Longitude of customer
Latitude	Latitude of customer
Total Orders	Total number of received orders in day
Close Customers	Number of close customers to each customer

Longitude and *Latitude* follow the geographic coordinates system. For calculating *CloseCustomers*, in a day the number of customers for whom D_i is their nearest source is counted. This value is assigned to *CloseCustomers* for those instances when D_i is their closest depot. This number reflects the level of demand around each depot and also shows

the density of customers around a customer in a day. The training set is constructed from a real database whose features are studied below.

IV. RESULTS AND DISCUSSION

In this section the described dataset is tested with the mentioned Bayesian Network algorithms and the results are reported and discussed. First, the number of parents of each attribute for Hill Climbing, K2, Look Ahead Hill Climbing, Repeated Hill Climbing and Tabu Search varies from between 1 and 5 (Table I); then, the best solution for each algorithm is selected and compared with Genetic Algorithm and Simulated Annealing (Table II). 10 folds cross-validation is used for evaluating the selected algorithms, with 10 fold cross-validation being the standard way of assessing a learning scheme on a particular dataset. In this evaluation method, the datasets are divided into 10 folds, with around 9 folds used for training and the remaining 10% of the data being used for testing.

According to Table I, in all search algorithms with the exception of Repeated Hill Climbing, increasing the number of parents to more than 3 does not affect the accuracy. Possibly related to this issue is that these search algorithms are able to discover the maximum number of effective arcs in DAG. The best accuracies of Hill Climbing, K2, Look Ahead Hill Climbing, Repeated Hill Climbing and Tabu Search from Table I were selected and summarized in Table II where the results of Simulated Annealing and Genetic Algorithm also have been reported. According to Table II, Simulated Annealing outperformed other techniques, although the difference is not significant. This issue is illustrated in Figure 2. It is obvious that the performances of Simulated Annealing and K2 are much the same, although Simulated Annealing obtained slightly better results. This issue is investigated in detail in follow. For this purpose, the networks obtained by K2 for 1 parent (Figure 3), 2 parents (Figure 4) and 3 parents (Figure 5), and the network obtained by Simulated Annealing (Figure 6) are illustrated. In Figure 3, when each variable can accept only one arc, all variables have a direct link to Experts' Decisions, although with different values. In Figure 4, it is allowed for having maximum 2 parents. It can be seen from this figure that the Arrival Time has a probability correlation with Volume; as well, this issue might be related to the fact that large customers prefer to start concrete pouring sooner to make sure that they can finish the job in a day. It was also revealed by K2, that Total Orders can be affected by Day of Delivery. This issue can be justified easily because it appears that the number of deliveries on weekdays is much higher than on weekends. Similarly, this occurs for the arc between Day of Delivery and Close Customers. Because the number of deliveries on weekdays is higher than weekends, there is a chance of having a number of customers in a particular area. However, according to this justification, it can be expected that there will be an arc between Total Orders and Close Customers which has not been determined by K2 with 2 parents. In Figure 5 this issue was discovered and the link between Total Orders and Close Customers can be seen. This might

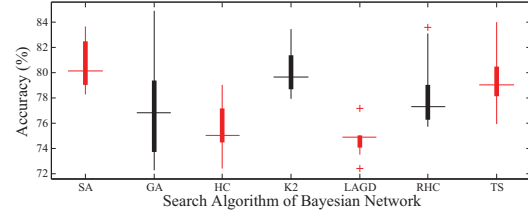


Fig. 2: Comparing the Accuracy Variation between the Bayesian Network with different search algorithms

prove that increasing the number of parents could possibly reveal more interaction between variables among the dataset. Simulated Annealing obtained a different network (Figure 6) than K2, but surprisingly those search algorithms achieved a very similar accuracy. Unlike K2, Simulated Annealing revealed that Volume only is affected by Longitude and does not have a direct link with Experts' Decisions. Also, it can be seen that Experts' Decision has direct links only with Arrival Time, Longitude, Total Orders and Day of Delivery. Longitude affects Volume, Latitude and Close Customers. Close Customer is affected by Latitude, Longitude and Total Order and only has an effect on Day of Delivery. The only similarity between Simulated Annealing and K2 is in the arcs between Total Orders and Close Customers as well as Day of Delivery which were justified above. Interpreting the network obtained by Simulated Annealing involves much more effort than networks obtained by K2. Therefore, in this context it is recommended to use K2 for discovering the dataset, although it has not achieved optimal accuracy.

TABLE I: COMPARING ACCURACY OF BAYESIAN NETWORK WITH DIFFERENT SEARCH ALGORITHMS (HILL CLIMBING, K2, LOOK AHEAD HILL CLIMBING, REPEATED HILL CLIMBING AND TABU SEARCH) WITH A DIFFERENT NUMBER OF PARENTS FOR EACH ATTRIBUTE

Search Algorithm	Number of Parents				
	1	2	3	4	5
Hill Climbing	77.65	77.2	75.53	75.53	75.53
K2	77.65	79.76	80.24	80.24	80.24
Look Ahead Hill Climbing	76.97	75.11	74.87	74.87	74.87
Repeated Hill Climbing	77.65	77.55	78.33	76.08	76.08
Tabu Search	77.81	77.90	79.46	79.46	79.46

TABLE II: COMPARING BEST SOLUTIONS OBTAINED FROM I WITH BAYESIAN NETWORK WHEN GENETIC ALGORITHM AND SIMULATED ANNEALING WERE SET AS SEARCH ALGORITHMS

Search Algorithm of Bayesian Network	Accuracy
Simulated Annealing (SA)	80.73
Genetic Algorithm (GA)	77.04
Hill Climbing(HC)	77.65
K2	80.24
Look Ahead Hill Climbing (LAGD)	76.97
Repeated Hill Climbing (RHC)	78.33
Tabu Search (TS)	79.46

V. CONCLUSION

Ready Mixed Concrete Dispatching Problems (RMCDPs) suffer from a lack of practical solutions and in the absence

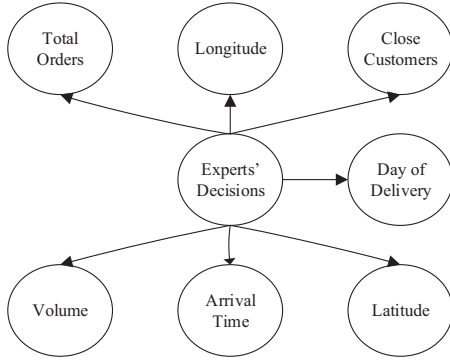


Fig. 3: Bayesian Network with K2 search algorithm - 1 parent

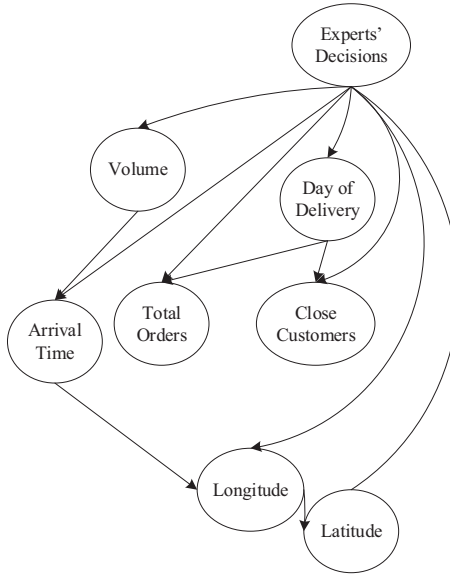


Fig. 4: Bayesian Network with K2 search algorithm - 2 parents

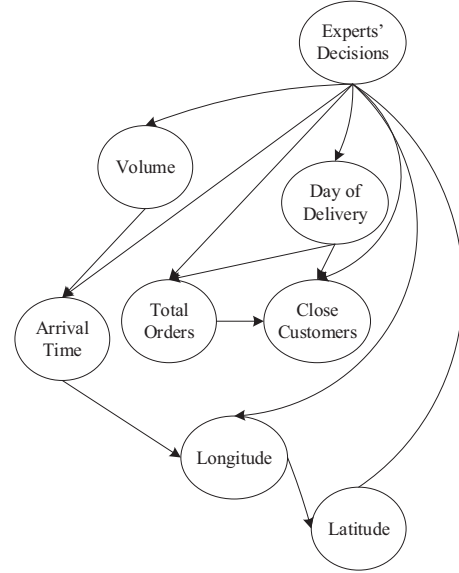


Fig. 5: Bayesian Network with K2 search algorithm - 3 parent

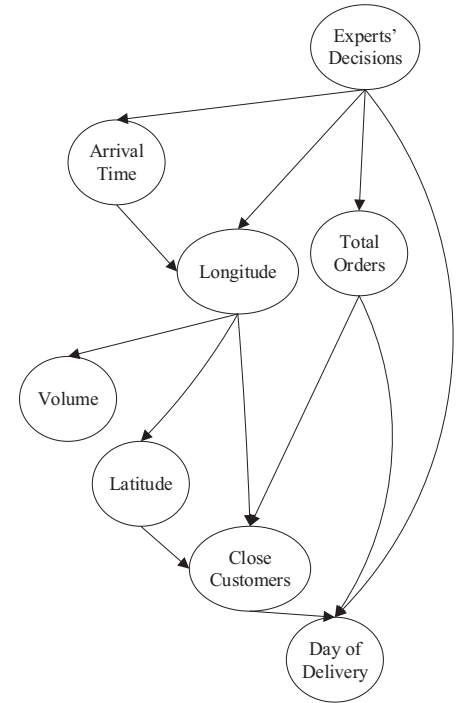


Fig. 6: Bayesian Network with Simulated Annealing search algorithm

of automated solutions, experts are hired to handle resource allocation tasks in concrete dispatching centres. Therefore, in the Ready Mixed Concrete (RMC) industry the performance of experts is accepted as the only practical solution, although there is no benchmark for assessing the quality of their decisions. This paper aimed to discover the experts' decisions in the RMC context by using Bayesian Network. Finding the optimum graph in Bayesian Network is NP-hard, therefore this research used a wide range of heuristic search algorithms (Hill Climbing, K2, Look Ahead Hill Climbing, Repeated Hill Climbing, Tabu Search, Simulated Annealing and Genetic Algorithm). A large scale dataset gathered from an active RMC was used for evaluating the proposed idea. Results show that the Simulated Annealing search algorithm outperformed other search algorithms, although there is not a significant difference between them. However, interpreting the network obtained by Simulated Annealing involved much more effort than other networks with similar accuracy, such as K2.

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