Automation in Construction 71 (2016) 283–293

Contents lists available at ScienceDirect

Automation in Construction

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

Hazard-based model for concrete pouring duration using construction site and supply chain parameters

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ARTICLE INFO

Article history:
Received 14 October 2015
Received in revised form 28 June 2016
Accepted 13 August 2016
Available online 24 August 2016

Keywords:
Concrete pouring duration
Ready mixed concrete
Linear regression
Cox proportional hazard

ABSTRACT

Duration of concrete pouring task is typically considered from the arrival time of the first Ready Mixed Concrete (RMC) truck until the end of the pouring process of the last truck. In practice, the concrete pouring duration does not only depend on site features. In fact, the duration is also affected by other parameters such as supply process, location of the project and traffic conditions, particularly in cities with heavy traffic. This paper investigates impacts of supply chain parameters on predicting concrete pouring duration that have been typically excluded from such analyses. Unlike other studies which are limited to construction site parameters in predicting concrete pouring duration, this study not only considers construction site factors at a general level but also investigates the impact of supply related parameters. To test the effectiveness of considered variables a field dataset of an active RMC in Adelaide, Australia with four batch plants and around 40 trucks is used. The dataset covers a period of a month which includes 2658 deliveries to >500 locations. In terms of the modeling practice of this study, first a preliminary linear regression is developed and then it is modified to satisfy crucial assumptions of heteroscedasticity and residuals normality. Finally, a hazard-based model where the assumption of residual normality is relaxed, is developed. The results show that severe bias occurs when assumptions associated with linear regression are overlooked. Moreover, in the developed models the supply parameters are found to have significant impacts on concrete pouring duration.

1. Introduction

Demand for concrete is globally increasing [1] such that the current demand is forecasted to double by 2050 compared to 2002 [15]. Due to space limitations at construction sites as well as technical obligations, fresh concrete is frequently mixed at Ready Mixed Concrete (RMC) batch plants, and then hauled to receiver sites by trucks. Therefore, when predicting the perceived duration of concrete pouring, three types of parameters should be accounted for; (i) parameters that can reflect traffic patterns, (ii) parameters that can reflect the supply conditions (iii) and parameters reflecting receiver's conditions. There are a few studies looking at predicting the duration of concrete pouring [5,6,11,22,28,44]. However the findings of these studies are considerably affected by the small size of the used data and ignoring traffic pattern and receiver's attributes. Nonetheless, the impact of traffic conditions and supply chain process on the concrete placement process is not negligible, particularly in large cities and congested areas.

In the RMC literature the main focus has been devoted to the RMC dispatching problem, which includes developing mathematical modeling formulations, or proposing meta-heuristic approaches to solve the models [36]. The RMC dispatching problem is a complex assignment problem which can be categorized as a generalized Vehicle Routing Problem (VRP) [27,32]. Large scale RMC dispatching problems are characterized as NP-hard problems for which obtaining the exact assignment solution with the existing computing facilities is computationally intractable [41,47,51,52]. To tackle this issue, a wide range of heuristic methods have been implemented such as Genetic Algorithms (GA) [3,8–10,19,31,33,38], Particle Swarm Optimization [17,23,50], Ant Colony Optimization (ACO) [43], Bee Colony Optimization (BCO) [45], Tabu Search (TS) [45], Variable Neighborhood Search (VNS) [2,39], benders decomposition [24], column generation [25,26]. There are also studies that only aim to provide more insight about the concrete delivery process rather than proposing new mathematical formulations [4,7,19,21,30,34,35,44,47,53]. Most recently [29] introduced a new method that trains machine learning algorithms by observing experts' decisions in RMC dispatching rooms. They showed that can match the experts` decisions with a high accuracy but within a very short

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http://dx.doi.org/10.1016/j.autcon.2016.08.012
0926-5805/

computing time. As it has been previously discussed, computing time is the main practical obstacle for the majority of optimization based method in this context.

The research group at the University of Edinburgh modeled the concrete placing process with Discrete Event Simulation (DES) [44] and evaluated their models with a field dataset (202 observations) that were collected from three sites in Scotland. They conducted a statistical analysis on the collected data to identify the key characteristics of concrete delivery and placement process [5,6]. Given their relatively small sample, although this has been the largest sample examined in this domain, the transferability of their results can be questionable. There are a few more papers that do not particularly focus on duration of concrete pouring; nonetheless, they are related to fresh concrete supply process. Tommelein and Li [46] discussed the concept of Just-in-Time in concrete delivery context. They primarily attempted to provide more insights about the concrete supply process by modeling two scenarios; (i) a RMC supplier produces fresh concrete and hauls it to construction sites, (ii) contractors deliver concrete to sites. Naso et al. [37] used a meta-heuristic approach to provide quick response to any disruption (e.g. delay or facility breakdown) in the RMC dispatching system. Liu et al. [18] mathematically modeled the entire RMC process including the production and delivery process and hired the GA method to minimize the total costs.

However, supply chain parameters has not been accounted for in RMC assignment problems yet, and the impact of transport network related parameters on concrete pouring duration needs to be further investigated. The importance of accurately estimating concrete pouring duration and accounting for all of the influential factors on that comes from the fact that the concrete pouring duration can significantly change the final assignment solution in RMC dispatching problems.

To address this lacuna in the literature, this paper employs a large scale dataset gathered from an active Ready Mixed Concrete (RMC) in Adelaide (Australia). The size of data is considerably larger than the size of datasets used in previously conducted studies. This data enhances the reliability of findings and the generalizability of the developed models. The data is analyzed using a linear regression formulation, in which the aforementioned parameters are incorporated as explanatory variables to accurately model the concrete pouring duration. Then a hazard-based model is constructed to relax some of the regression assumptions while capturing the stochasticity in the concrete pouring duration.

Built environment variables and supply related variables have not yet been included in the modeling process of concrete duration estimation [6,12], although the significance of these variables on the duration is quite obvious. For example, the duration of a concrete pouring task in a project that is located in a city with dense traffic would be different from a similar one in a small city with light traffic. Furthermore, travel time varies during the day between rush hours and off peak hours. Travel times from/to some locations during weekdays vary considerably than weekends. The precise prediction is more important when concrete pumps and workers are around idle. Graham et al. [12] demonstrated that 12% idleness of concrete pouring crew in a typical site resulting in an additional 14% cost. Consequently, it is necessary to have precise predictions for the duration of operation.

The contributions of this study are two-folded. First, this study examines the impact of supply related variables on concrete pouring duration. More specifically, this paper investigates the impact of exogenous variables such as traffic condition on concrete pouring duration. Second, this study utilizes Cox proportional hazard-based models to introduce a new way of capturing and interpreting the impact of exogenous variables on concrete pouring duration. The main advantage of hazard-based models is relaxing the assumption on the distribution of the dependent variable (e.g. concrete pouring duration in this study). In fact, the application of the introduced hazard-based model is not limited just to concrete pouring duration. As it is explained in details in the methodology section, this hazard-based model specification does not need any assumptions about the distribution of the dependent variable (or its residuals) which possibly will provide a better fit to the data. The hazard-based approach is aimed to take into account both construction and supply parameters in modeling concrete pouring duration. The output of modeling practice in this paper can provide a chance to construction managers to effectively handle the concrete pouring process by giving them more insight on precisely estimating concrete pouring duration.

This paper consists of three main sections excluding the introduction. In the next section, the utilized dataset is described, then methodology is explained and finally the results will be discussed and summarized.

2. Data structure

This paper aims at exploring the effectiveness of the operation and supply chain parameters to model the concrete pouring duration. Typically, fresh concrete is hauled by trucks from batch plants to construction sites and then placed in frames to construct concrete elements. A project might need several deliveries; therefore, required trucks must arrive at the site consecutively. This paper considers both site (receiver and provider) related parameters and traffic related parameters to address concrete pouring duration. More specifically, the following variables are examined in modeling the duration of concrete pouring.

- **"Weekday"** is a binary variable indicating if the pouring is taking place on weekday. Travel time in some regions is considerably different between working days and weekends. This binary variable is defined to take into account the impact of different traffic condition during weekdays.
- **"Start"** is a continuous variable representing the starting time of first delivery. The impact of traffic condition on the duration of an operation would vary depending on whether it commences during rush hours or not. In this regard, the time of arrival of the first truck to the site is utilized as one of the explanatory variables for modeling.
- **"TAOC"** is a continuous variable which shows the total amount of ordered concrete. For each project the total amount of delivered concrete is extracted from the available database. This variable is one of the construction site features that affect concrete pouring duration.
- **"NRD"** is an integer variable indicating the number of required deliveries. NRD can be considered as a construction site related feature, as well as, a supply chain related variable. On one hand, it reflects the size of the task, and on the other hand, it shows how much the concrete pouring duration is related to road network conditions.
- **"Latitude and longitude of the site location"** are two continuous variables indicating the location of the site. Predicting travel time cannot be approximated by solely using the distance between the origin and destination because the speed of trucks on some routes fluctuates during the course of a day. Moreover, some parts of metropolitan areas have different traffic patterns during the day. It is believed that geo-location data that includes longitude and latitude can indirectly provide this information. Each location (depots or projects) has unique coordinates that are extracted from the available database with arithmetic precision of six digits.
- **"TNROR"** is an integer variable indicating total number of received orders by RMC Supplier. This attribute becomes important when an RMC accepts large number of deliveries in a day, specifically, when available resources are not sufficient and demand is greater than supply. In such situations, RMCs stretch the inter-arrival times to balance demand and supply which makes it possible to supply more deliveries. This variable can reflect how busy the RMC is.
- **"TNADSD"** is an integer variable indicating total number of assigned deliveries to the source depot. The former attribute shows the density of orders throughout the day; however, this attribute can reflect the same issue but particularly for the allocated depot which is

chosen to supply concrete to the project. Instead, the TNADSD attribute is selected when, for instance, an RMC supplier has received many orders but orders are not evenly distributed in the supply area. In other words, a depot can provide service to many costumers in some areas but very few orders to other areas; in such cases it is expected that this attribute reflect some information, which is not captured otherwise. For large projects with >30 deliveries, concrete is normally supplied from more than one depot.

As it was stated earlier, the current study does not directly incorporate all the construction site features in the model. For example: the proposed model does not associate the pouring system (crane or pump) or type of construction operation (wall, column or base) in the calculation, while it focuses more on supply and traffic related parameters.

The proposed approach was tested with data collected from an RMC in Adelaide (Australia). There are 4 active batch plants and around 40 trucks in this region. A minor portion of these records are deliveries to regions other than Adelaide metropolitan region which have been excluded from the study as they are outside urban areas. To understand the size of an RMC it can be noted that 27 days of operation includes 2658 deliveries supplied to the 980 unique locations. In around 70% of instances, >5 trucks are included in the order. A preprocessing task has been conducted to clean the dataset and make sure that there is no missing values or duplication among the selected instances.

Table 1 presents descriptive statistics of the variables used in this study. The top part of this table shows the mean, standard deviation, minimum and maximum values for the continuous variables. These variables include pouring start time, TAOC, latitude and longitude of the construction site, distance from depot to construction site, NRD, TNADS, TNROR and the duration of concrete pouring task. The bottom part of this table shows the details of the categorical variables, including the dispatching depot and the day of the operation.

Fig. 1 depicts the correlation between concrete pouring duration and the rest of the considered variables. According to this figure, TAOC and NRD are positively correlated with the concrete pouring duration. In Fig. 2, the distributions of explanatory variables are presented which shows that depots 1 and 4 service more construction sites compared to depots 2 and 3. Finally, the heatmap of customers' locations is shown in Fig. 3. This figure illustrate the regional distribution of the site locations across the region.

Table 1
Descriptive statistics of the available variables.

Numerical variables				
Variable	Mean	Standard deviation	Minimum	Maximum
Start	9.26	2.18	0.00	16.27
TAOC (m^3)	13.50	29.84	0.40	349.10
Latitude	−34.88	0.13	−35.28	−34.36
Longitude	138.60	0.08	138.26	138.90
Distance (km)	13.53	7.41	1.25	55.51
NRD	2.70	4.40	1.00	53.00
TNADSD	32.14	18.57	4.00	87.00
TNROR	110.53	36.42	30.00	187.00
Duration (hr)	2.17	2.06	0.05	14.45

Categorical variables			
Variable	Classes	Frequency	Percent
dispatching depot	Depot 1	331	33.74
	Depot 2	179	18.25
	Depot 3	168	17.13
	Depot 4	303	30.89
Day	Monday	118	12.03
	Tuesday	184	18.76
	Wednesday	170	17.33
	Thursday	189	19.27
	Friday	212	21.61
	Saturday	108	11.01

3. Methodology

3.1. Linear regression

Regression is a core tool in econometric studies, and is vastly employed to study the relationship between the dependent variables and independent variables. Linear regression has been massively used in the fields of engineering, physics, economics, management, life science, biology, and social sciences both for estimation and prediction purposes. Researchers and practitioners have tremendously employed linear regression; however, testing the hypothesis behind linear regression is not always considered.

Eq. (1) shows the general format of a multivariable linear model. In this equation y_i is the value of the dependent variable for instance i, x_{ij} is the value of independent variable j for instance i, and β_j is the corresponding parameter to independent variable j. β_0 is the intercept of the linear relationship and ϵ_i indicates the error of the model, which is also referred to as residual. There are several methods to estimate the model's parameters including Ordinary Least Square of errors (fOLS). In OLS, it is assumed that ϵ has a normal distribution with expected value of zero [13].

$$y_i = \beta_0 + \sum_{j=1}^{m} \beta_j x_{ij} + \epsilon_i, \forall i \tag{1}$$

The goodness-of-fit for linear regression models is typically measured by R^2 which reflect the ratio of deviation of the observed values from the mean compared to what the model provides. In other words, this statistic measures how close the model's prediction is to the observed values. The decision on which variables to include into the model is made based on a statistical test known as t-test jointly with the contribution of the variable in the model and several other indicators such collinearity. The t-test examines whether the corresponding parameter of a variable is statistically different from zero or not.

Usually, when researchers and practitioners develop linear regression models they concentrate on increasing model's accuracy while including statically significant independent variables. However, there are some caveats in linear regression that if ignored, the result of regression would be unreliable and can be misleading. In general, there are two major assumptions in linear regression that sometimes are overlooked: normality of residuals, and heteroscedasticity.

3.1.1. Normality of residuals

When developing a linear regression, it is assumed that residuals are normally distributed. This assumption is not essential in OLS but it is important for using the statistical tests such as t-test. If this assumption is not met, the t-test analysis would not be valid; therefore, the conclusion on a statistically significant relationship between independent variables and the dependent variable in the model would be questionable. Statistical tests for normality are abundant. This study utilizes two well-known test of Shapiro-Wilk test [42] and Kolmgrov Smirnov (fKS) [13] for normality. KS is a non-parametric test of equality of continuous probability distributions and testing normality is one of the specific applications of KS. Shapiro-Wilk on the other hand is specifically developed for normality test.

3.1.2. Homoscedasticity

Homoscedasticity is the assumption of constant variance for residuals across the whole range of the independent variable. This is a basic issue that can significantly affect the results of OLS. Similar to the assumption of residuals normality, if homoscedasticity is not met, the estimated test-values would not be reliable. Note that, homoscedasticity is

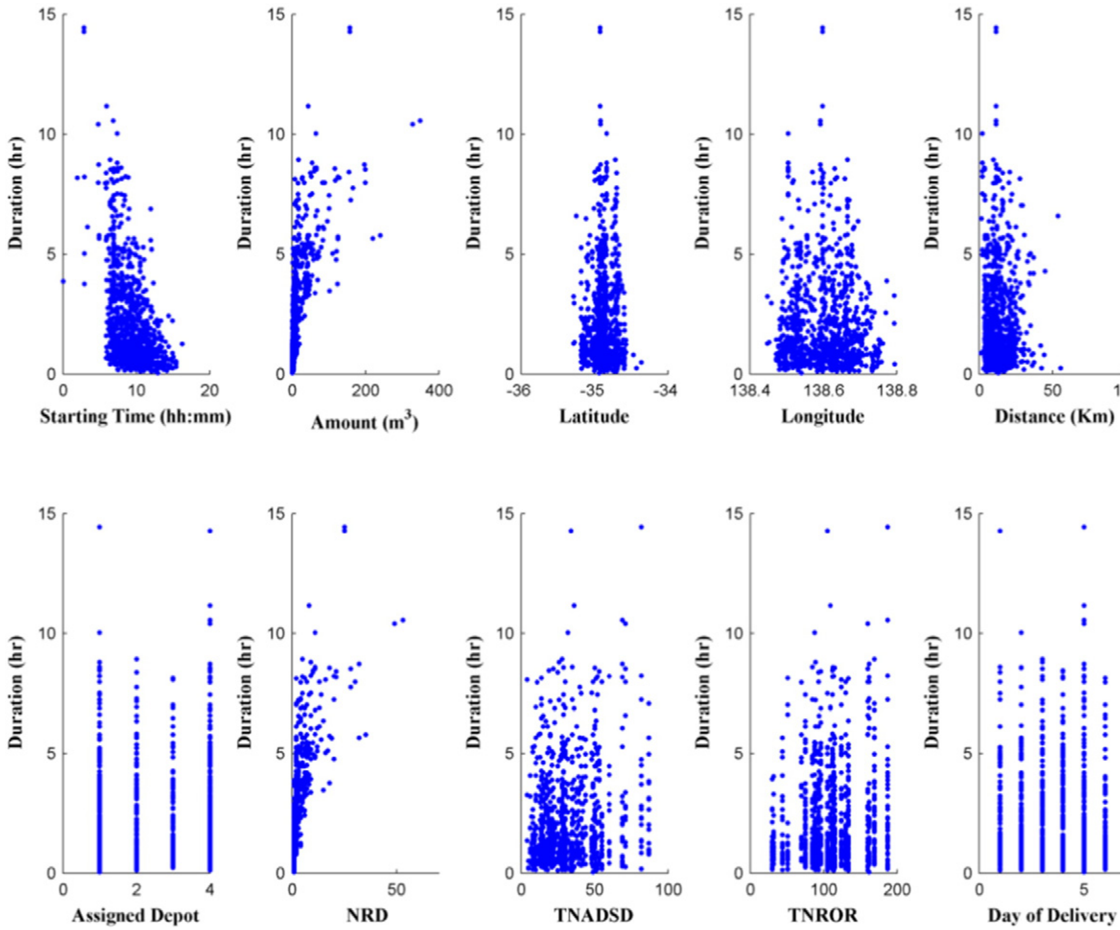


Fig. 1. Correlations between the attributes and duration.

not required for the unbiased estimations by OLS, nonetheless the estimated parameters are no longer efficient. The commonly used statistical test for homoscedasticity is White test [48]. The null hypothesis of White test is that the variance of the residuals is homogenous.

3.2. Hazard-based model

Hazard-based models, also known as survival analysis, are largely utilized in medicine, engineering, economics, and sociology fields to model the time when an event occurs. Time to an event, which is also referred to as failure time, represents the time at which an event occurring or an instance changes its state. Some examples for events are marriage, death, recovery, finding a job or changing residence. In this study, the event is defined as finishing the concrete pouring process.

The main advantage of hazard-based models compared to linear regression is their ability to handle dependent variables (time to an event) which does not follow normal distribution. In fact survival analysis can model the distribution of failure time and also examine the impact of independent variables on the failure time.

Survival analysis has three main functions that explain different aspects of an event: (1) failure function, (2) survival function and (3) hazard function. Failure function is a cumulative density function indicating the probability of the event occurring before a certain time. Eq. (2) shows the definition of the failure function, $F(t)$, where T is the time of event occurrence and t is a random variable. The survival function shows the probability of the event not occurring before a certain time. The definition of the survival function and its relationship with failure function is presented in Eq. (3) (For further discussion about hazard-based models refer to [40]). When developing a hazard-based model, the first derivative of the failure function, which represent the probability of the event in an infinitesimal interval of time, also becomes important. This function is a probability density function and is typically shown with $f(t)$. Eq. (4) shows the definition of $f(t)$ and its relationship with survival and failure functions.

$$F(t) = \Pr(T \le t) \tag{2}$$

$$S(t) = \Pr(T > t) = 1 - F(t) \tag{3}$$

$$f(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \le T < t + \Delta t)}{\Delta t} = \frac{\partial F(t)}{\partial t} = -\frac{\partial S(t)}{\partial t} \tag{4}$$

The third function, the hazard function, is the primary focus of survival analysis. The hazard function describes the conditional probability of the event occurring at a certain time, conditional on the fact that it has not event up to that time (Eq. (5)). This function shows the instantaneous rate of failure. In order to clarify the difference between probability density function of failure with the hazard function, note that $f(t)$ shows the probability of failure at time t for all of the instances under study; while, $h(t)$ indicates the probability of failure at time t for those instances that has not failed before t.

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \le T < t + \Delta t | t \le T)}{\Delta t} = \frac{f(t)}{S(t)} \tag{5}$$

In the sharp contrast with linear regression, not only failure time in hazard-based models can be assumed to have any parametric distribution, but also it can be considered as non-parametric distribution.

Independent variables are typically included in the hazard function to capture the external impact of other covariates. To this point, all of the

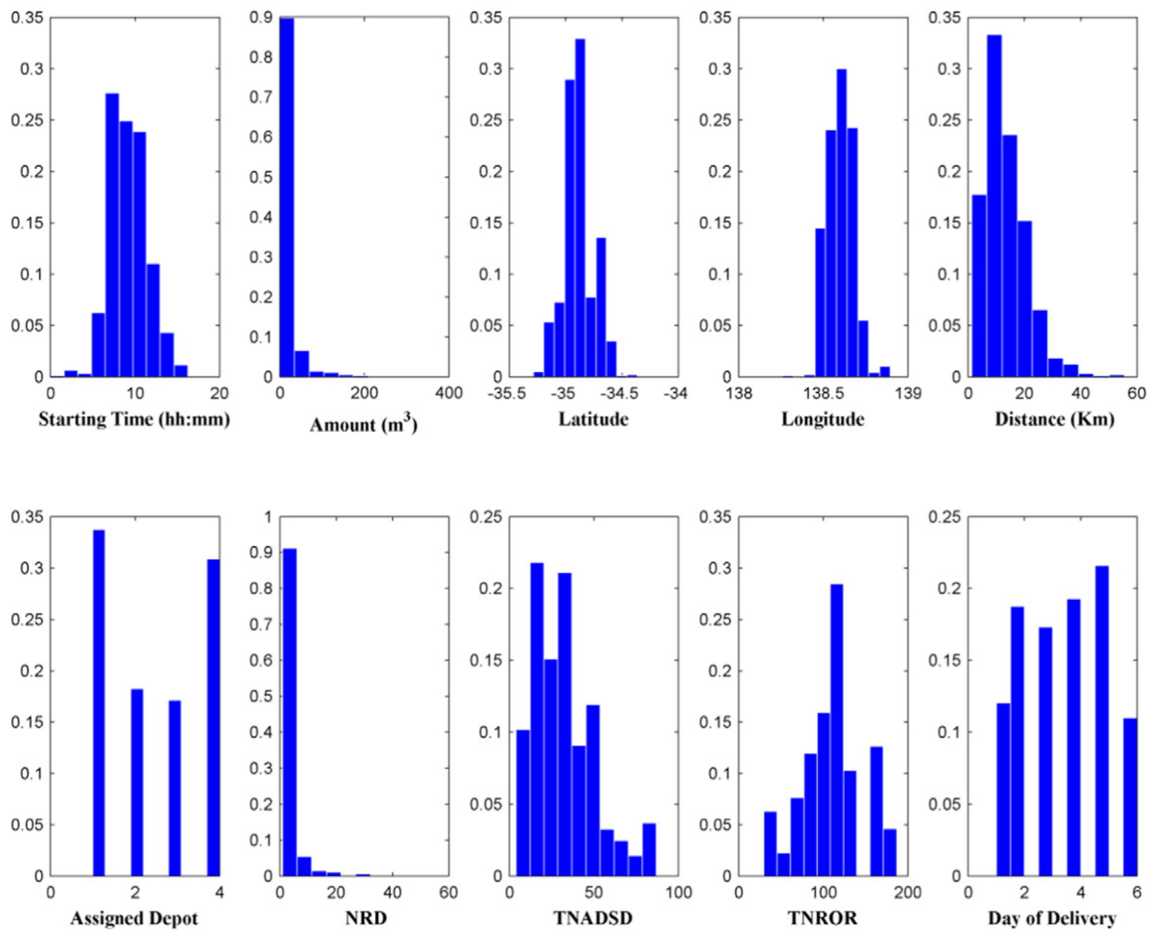


Fig. 2. Distribution of the variables.

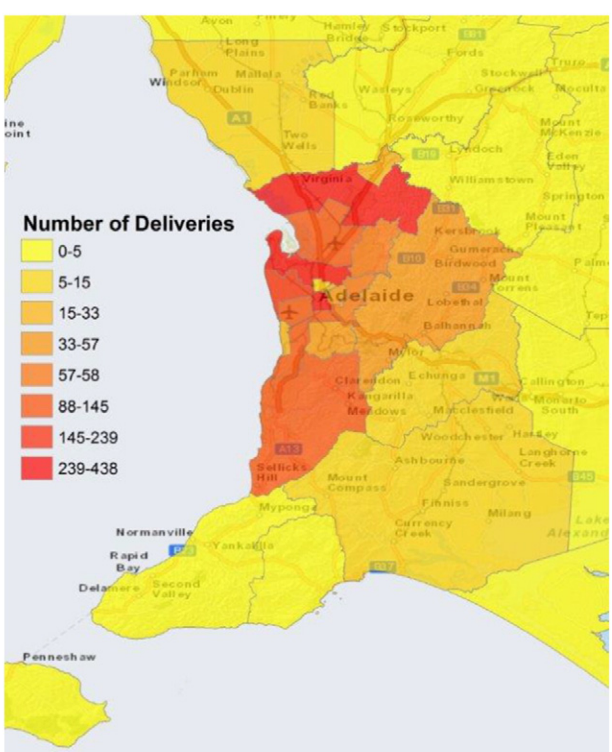


Fig. 3. Spatial distribution of orders to the RMC supplier in the Adelaide Metropolitan Area.

function in survival analysis is defined as a function of time. For incorporating the impact of independent variables, any of the three functions can be modified. Note that, the other functions can be derived from the modified function. There are several established techniques to incorporate independent variables in survival analysis, including Cox Proportional Hazard. The hazard function for Cox proportional hazard model has the form of Eq. (6). This equation shows the hazard function for instance i with independent variables of x_{ij}. In this equation $h_0(t)$ is called the baseline hazard which summarizes the pattern of duration dependence and is assumed to be common to all instances. The multiplicative term in Eq. (6) is an instance specific non-negative function of the instance's independent variables and its role is to scale the baseline hazard.

$$h(t, x_i) = h_0(t) \exp\left(\sum_{j=1}^{J} \beta_j x_{ij}\right) \tag{6}$$

When the hazard-based model is set up as Eq. (6), the ratio of hazard rates between two instances with fixed independent variables will stay constant over time. Imagine instances i and i' with identical vector of independent variables except for variable m. The ratio of hazard function of instance i over instance i', both at time t, would be evaluated as shown in Eq. (7). According to this equation, hazard rate is independent from the baseline hazard, since the baseline hazard is common for all of the instances. Besides, identical variables will cancel out.

$$\frac{h(t, x_{ij})}{h\left(t, x_{i'j}\right)} = \frac{\exp\left(\sum_{j=1}^{J} \beta_j x_{ij}\right)}{\exp\left(\sum_{j=1}^{J} \beta_j x_{i'j}\right)} = \beta_m (x_{im} - x_{i'm}) \tag{7}$$

Hazard ratio is an appropriate way to interpret the impact of independent variables. Imagine the difference between the dissimilar independent variables in Eq. (7) is one unit. In this case, the hazard ratio would be equal to β_m which is the coefficient of the independent variable. Therefore, the coefficients in a proportional hazard (PH) rate determine the hazard escalation, when their corresponding variable increases by one unite.

4. Results and discussion

This section presents a discussion on the conducted analysis on the influence of the available independent variables on the concrete pouring duration. Two linear regression models and one hazard-based model are developed to predict the concrete pouring duration. In selecting the independent variables, several combinations of variables are examined and at the end, variables that are statistically significant at the 85% confident level are included in the models.

4.1. Preliminary linear regression

For the first attempt the duration of concrete pouring is modeled as a linear function of the available independent variables. In this model, which is called the preliminary linear regression model, the variables are kept in their original format. The top part of Table 2 is devoted to the estimated parameters in this model. According to Table 2, the following four independent variables are found to be significant in the model.

- Total Amount of Ordered Concrete (TAOC)
- Number of required deliveries (NRD)
- Total Number of Assigned Deliveries to the Source Depot (TNADSD)
- Total Number of Received Orders by RMC Supplier (TNROR)).

Eq. (8) shows the preliminary linear regression model. The corresponding t-test statistics and model's goodness-of-fit are presented in the top part of Table 2.

$$T = 2.896 - 0.111 \times \text{TAOC} + 1.019 \times \text{NRD} + 0.006 \times \text{TNADSD} + 0.002 \times \text{TNROR} \qquad (8)$$

Although all variables in this model are statistically significant and the model shows an acceptable goodness-of-fit ($R^2 = 0.60$), this model is not reliable because the normality of the residuals and heteroscedasticity are not warranted. This issue is discussed in details in the following section after presenting the improved linear regression model.

4.2. Improved linear regression

In the second step, the preliminary linear regression model is improved in three directions. First, the dependent variable is transformed using a logarithm transformation. This transformation is implemented to cope with the heteroscedasticity assumption. A logarithm transformation has the potential of damping the large variations of residuals for large values of y. Second, as a classic technique to improve regression models, the following variations of independent variables are introduced to the model.

- **"Average Load"** is a continuous variable defined as TAOC divided by NRD. This variable is an indicator of the size of concrete deliveries.
- **"NRD1"** is a binary variable which is equal to 1 if the project needs

Table 2
Results of the regression models and the hazard-based model for concrete pouring duration.

Variable	Parameter estimate	Standard error	T Statistic	Pr(Statistic > Critical statistic)
Preliminary regression model				
Intercept	2.896	0.236	12.27	<0.0001
TAOC	−0.111	0.011	−10.13	<0.0001
NRD	1.019	0.074	13.82	<0.0001
TNADSD	0.006	0.003	2.16	0.0311
TNROR	0.002	0.001	1.63	0.1033
			R Square	**0.597**
			Adjusted R Square	**0.594**
Improved regression model				
Intercept	0.776	0.10	7.41	<0.0001
Ln(TAOC)	0.421	0.04	11.21	<0.0001
Average Load	−0.047	0.02	−2.54	0.0111
NRD1	−0.707	0.05	−13.24	<0.0001
Weekend	−0.182	0.05	−3.71	0.0002
Midnight	−0.158	0.11	−1.43	0.1423
CBD	0.107	0.07	1.57	0.1176
DD1	0.009	0.00	3.14	0.0017
D1	0.075	0.04	2.09	0.0369
D2	−0.071	0.04	−1.7	0.089
			R Square	**0.754**
			Adjusted R Square	**0.751**

Non-parametric proportional hazard-based model

Parameter	Parameter estimate	Standard error	Chi-Square Statistic	Pr(Statistic > Critical statistic)	Hazard ratio
TAOC	−0.008	0.002	18.651	<0.0001	0.99
D1	−0.200	0.074	7.326	0.0068	0.82
NRD1	2.326	0.103	507.010	<0.0001	10.23
Average Load	0.166	0.023	50.718	<0.0001	0.85
Weekend	0.176	0.116	2.300	0.1294	1.19
CBD	−0.434	0.141	9.415	0.0022	0.65
DD1	−0.023	0.006	13.191	0.0003	0.98
TNROR	−0.002	0.001	5.675	0.0172	1.00
				LL	**−5213.567**
				AIC	**10,445.131**

only one delivery.

- **"Weekend"** is a binary variable indicating if concrete pouring during takes place during weekends.
- **"Midnight"** is a binary variable which is equal to 1 if the pouring is take place between 12 AM to 6 AM.
- **"CBD"** is a binary variable which specifies whether the project is located in Central Business District (CBD) or not.
- **"DD1"** is a continuous variable showing the distance from depot 1 to project site only if the delivery is supplied by depot 1. This variable only takes non-zero values if the source of delivery is depot 1 where it is equal to the distance between the project and depot 1.
- **"D1"** is a binary variable which indicates if the delivery is received from depot number 1.
- **"D2"** is a binary variable which indicates if the delivery is received from depot number 2.

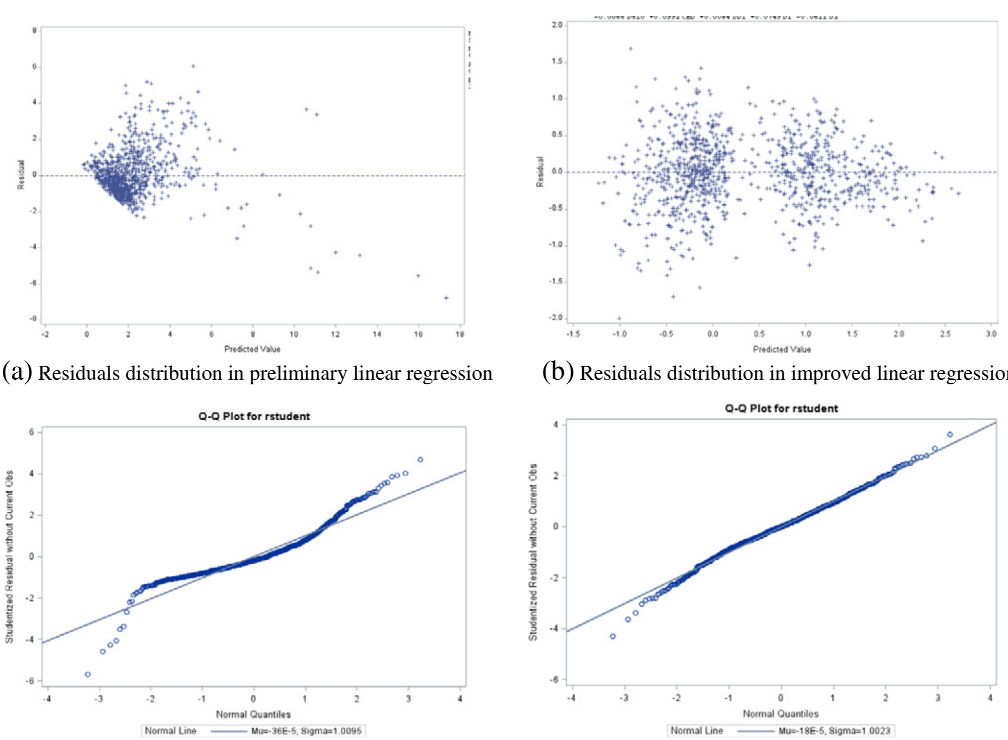
As the third improvement, logarithmic transformation of TAOC (Total Amount of Ordered Concrete) is included in the model. Logarithmic transformation is a beneficial technique dealing with residual normality assumptions in regression [13]. The emphasis of this study on logarithmic transformation is to demonstrate the advantages of this transformation in practice. Obviously, as the total amount of ordered concrete increases the concrete pouring duration also increases. However the rate of increase is not constant. For large scale projects minor increase in the amount of ordered concrete does not impact the pouring duration as it does in small scale projects. In other words, the relationship between TAOC and pouring duration is not linear; therefore TAOC is transformed.

Eq. (9) shows the improved linear regression and the statistical details of this model are provided in the middle part of Table 2. Compared to preliminary linear regression, this model has larger number of included independent variables. Besides, the adjusted goodness-of-fit has improved in this model. According to the result, the concrete pouring duration is decreased if it takes place during weekends or at midnights. In contrast, if the construction site is located in the CBD area, the concrete pouring duration increases.

$$\begin{aligned} Ln(T) = 0.776 - 0.421 \times Ln(\mathrm{TAOC}) - 0.047 \times Average_{Load} - 0.707 \times \mathrm{NRD1} \\ - 0.182 \times Weekend - 0.158 \times Midnight + 0.107 \times \mathrm{CBD} \\ + 0.009 \times \mathrm{DD1} + 0.075 \times \mathrm{D1} - 0.071 \times \mathrm{D2} \end{aligned} \tag{9}$$

Fig. 4 compares preliminary and improved regression models. Distributions of residuals versus the predicted values for preliminary regression model are shown in Fig. 4(a). Heteroscedasticity requires the variance of the residuals to be constant; thereby residuals are not expected to follow any specific pattern while plotted versus predicted values. This assumption is clearly violated since the dispersion of residuals around their average has an increasing pattern. In order to test the normality assumption of residuals, the Q-Q plot (quantile-quantile plot) of residuals versus a normal distribution for preliminary regression model is plotted (Fig. 4(c)). In a Q-Q plot, the quantiles of two probability distribution functions are plotted against each other. If the distributions are close enough, then the achieved plot would overlay $y = x$ line. But the Q-Q plot in Fig. 4(c) shows significant difference from $y = x$. Hence, the preliminary regression model does not satisfy the required statistical assumptions and is not reliable.

The distribution of residuals versus the predicted values and also the Q-Q plot versus a normal distribution for the improved linear regression model are provided in Figure (b) and (d) respectively. According to these two graphs, the assumptions of heteroscedasticity and normality of residuals seem to be visually satisfactory, although it is statistically confirmed as well. The White test on the results provides a statistic of 106.1 with a degree of freedom of 65 indicating that the hypothesis of the variances not being homoscedastic cannot be rejected with a 99.9% confidence level. Moreover, the Shapiro-Wilk test suggests that the hypothesis of the residuals being normally distributed can be accepted at a 0.001 level. The result for Kolmogorov-Smirnov test also suggests that the hypothesis of normality cannot be rejected at a 0.001confidence level. In short, it can be concluded that the improved



(a) Residuals distribution in preliminary linear regression

(b) Residuals distribution in improved linear regression

(c) Q-Q plot for residuals in preliminary linear regression

(d) Q-Q plot for residuals in improved linear regression

Fig. 4. Graphical illustration of heteroscedasticity and normality of residuals in linear regression models.

linear regression model satisfies the major linear regression assumptions.

Therefore, an acceptable model to measure the impact of independent variables is achieved at this stage. However, the next part of the paper which discusses the hazard-based modeling approach, illustrate the advantages of hazard-based modeling compared to the developed linear regression models.

4.3. Hazard-based model

As the third modeling approach, a Cox proportional hazard-based model is developed using SAS statistical analysis software package version 9.4. Similar to linear regression modeling, a large number of combinations of independent variables are examined and the best model, which has the highest likelihood value with statistically significant variables, is reported. The result of this model is provided in the bottom part of Table 2. The model is shown in Eq. (10).

$$h(t,x) = h_0(t) \times \exp(-0.008 \times \text{TAOC} - 0.200 \times D1 + 2.326 \times \text{NRD1} + 0.166 \times Average_{Load} + 0.176 \times Weekend - 0.434 \times \text{CBD} - 0.023 \times \text{DD1} - 0.002 \times \text{TNROR}) \quad (10)$$

In proportional hazard models, estimating the impact of the independent variables does not depend on making any assumption on the form of the baseline hazard function, $h_0(t)$, which can be left unspecified. Therefore, regardless of $h_0(t)$, the impact of independent variables on hazard function is as shown in Eq. (10). The decision on the configuration of independent variables in the model can be supported by a non-parametric overall survival experience such as Kaplan-Meier [16]. The advantage of Non-parametric methods is that these methods do not require any assumptions about the shape of the survival function.

In order to examine the impact of an exogenous variable on survival rate (e.g. the duration of concrete pouring in this study), different non-parametric survival curves can be drawn for different values of any of the exogenous variables. If these survival curves are shown to be statistically different, then it can be concluded that the considered exogenous variable has some impact on the survival rate. Fig. 5 shows the non-parametric survival curves for the concrete pouring duration when the data is divided based on some of the available independent variables. The shaded area around the survival curves represents the 95% confidence band for each of the survival curves (refer to [14] for calculation details). In Fig. 5(a) the observations are classified into four groups based on the *Average Load* of the deliveries. Generally this graph confirms that by increasing the value of Average Load, duration also increases. For instance there are only 3 observations with $Average_{Load} < 2.2$ that their duration took >5 h and this value for $2.2 < Average_{Load} < 2.9$, $2.9 < Average_{Load} < 4.3$ and $5 < Average_{Load}$ respectively are 10, 22 and 70 h. In Fig. 5(b) survival curves are separated for the projects that are located in CBD showing that there is an acceptable correlation with the pouring duration. Similarly, Fig. 5(d) distinguishes between projects having one delivery and more. Fig. 5(c) shows survival curves for the deliveries on weekends or weekdays. In this case, the confidence boundaries for weekend projects is wider indicating higher variations in concrete pouring duration for such deliveries. This boundary covers the weekday survival curve which makes it difficult to derive any clear conclusion which urges proper statistical tests.

In this study the Wilcoxon test [49] is utilized to decide whether dividing the data based on each independent variable results in statistically different survival curves or not. The Wilcoxon test is utilized to select a set of independent variables when a hazard-based model is developed. All independent variables that pass this test and are found to be statistically influential are examined and are included in a Cox Proportional Hazard-based model.

As it was noted in the modeling section, the results of the preliminary regression model are not reliable due to the non-normality issue and the problem of heteroscedasticity; thereby they are excluded from discussion on the relationship between concrete pouring duration and the available independent variables. The variables that are found to be significant in both the improved regression and PH model are

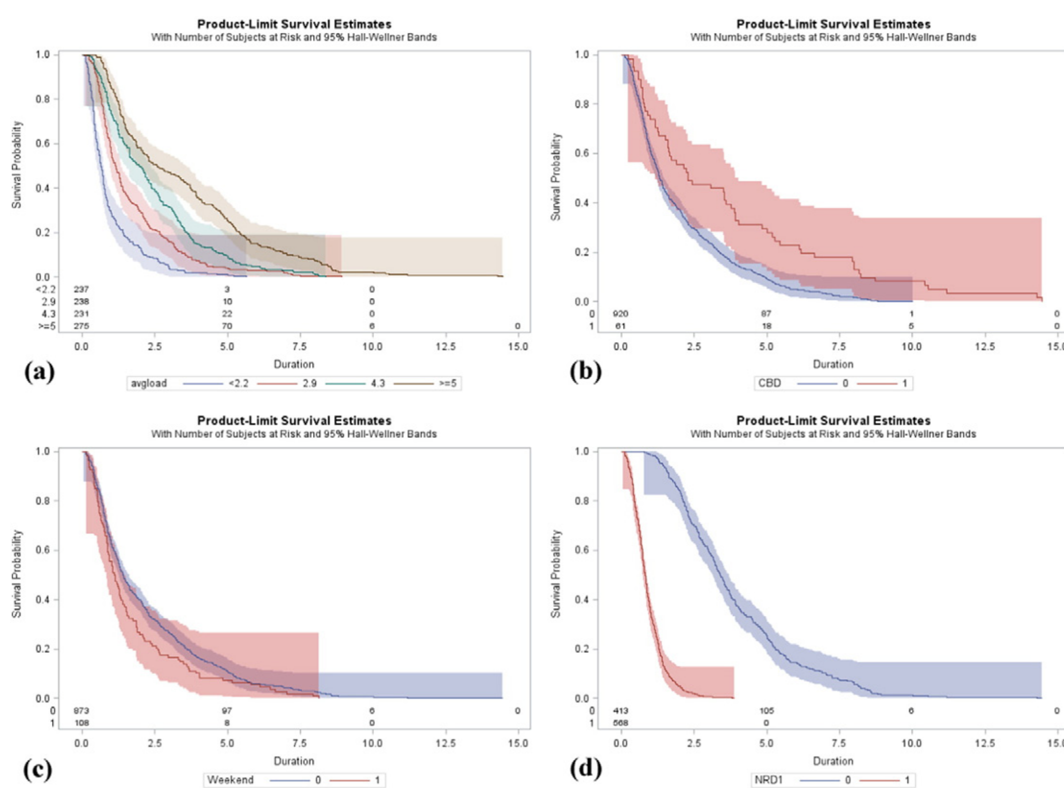


Fig. 5. Non-parametric survival functions for some of included independent variables.

assumed to have a significant impact on the duration of concrete pouring. These variables are categorized into two groups of road network related variables and others. Although the direct information of the road network is not available, the following variables can be considered as proxies for road network conditions.

- The estimated coefficient for "**NRD1**" is found to be significant while modeling concrete pouring duration. Besides, the non-parametric survival test of Figure (d) clearly shows that projects with more than one delivery have a distinct survival curve. This observation also confirms the assumption of significant effects of road attributes on concrete pouring duration.
- The estimated coefficient for **"Average Load"** indicates as the size of delivery increases the concrete pouring duration would decrease. This is because as Average Load increases the required number of trucks for a certain amount of concrete decreases; therefore, the concrete pouring process would be less dependent on the road network situation. In other words, for two projects with the same amount of required concrete, the one with larger delivery batches would have lower concrete pouring duration.
- **"Weekend"** has a decreasing effect on the concrete pouring duration in both models which complies with the common expectations. This variable is important from the transportation perspective, since the road network is less congested during weekends.
- **"Midnight"**, similar to "weekend", is a proxy of the congestion level on the road network. Therefore it is expected that if the concrete pouring process starts overnight, it reduces concrete pouring duration.
- The importance of **"CBD"** is the special impact of central business district on the transportation system. Regularly the road network in CBD is in congestion conditions. According to the results, if the project is located in CBD, then higher concrete pouring duration is expected which is quite expectable.
- Distance was examined in different ways while eventually only the distance from depot 1 was found to be statistically significant in the final models (**"DD1"**). This is explained by the fact that this depot is located close to the central part of the city and traffic condition has significant impact on the deliveries from this depot.

Both model specifications confirm the fact that the network related variables have relatively significant impact on concrete pouring duration. This argument is inferable from the statistically significant transportation related variables in both model specifications. Moreover, the relatively large hazard ratio of these variables in the hazard-based model is an indicator of their high impact on concrete pouring duration.

The main benefit of the utilized non-parametric Cox proportional hazard-based model is the ability to separate predicting the dependent variable (concrete pouring time), from assessing the impact of independent variables on the dependent variable. The hazard-based model does not restrict the baseline hazard, which represents the concrete pouring time, but it is seeking to estimates the impact of external factors (such as road network conditions) on the concrete pouring duration. This feature differentiates the hazard-based approach from the regression models. For instance, comparing concrete pouring duration for two identical construction sites where only one is located in CBD. The modified regression model says the logarithm of concrete pouring time results an increase of 0.107 units for the CBD site. The hazard-based model instead provides insight on how locating in CBD would affect the event of completing concrete pouring. According to the estimated hazard ratio in this model, a multiplicative reduction factor of 0.65 would apply to the probability of completing concrete pouring for the CBD site. In other words, the hazard-based approach measures the impact of the exogenous variables, regardless of the distribution of completing concrete pouring duration (the baseline hazard).

5. Conclusion

Fresh concrete is typically mixed at batch plants and hauled by trucks to construction sites where it is poured into the frame to form concrete elements. Predicting the duration of concrete pouring process is always crucial because the number of required crew size and required facilities such as pumps are extremely costly. In the literature this issue has been investigated by considering only the construction site parameters. In contrast, this study considers both construction site parameters and supply chain features. Regarding the modeling practice, this paper utilized linear regression models and hazard-based models to investigate the impact of exogenous variables on the concrete pouring duration. In terms of dataset, a field dataset gathered from an active RMC in Adelaide Australia that includes both attributes of the construction site and supply process parameters are used in this study. First, a preliminary linear regression is developed as the common practice which includes five variables and achieving an R^2 of 0.6. Second, this linear regression model was modified by transforming dependent variables using a logarithm transformation function, and introducing new variations of the available independent variables led to achieving an R^2 of 0.75. The main advantage of the improved linear regression over the preliminary model was satisfying the assumption of linear regression model which was violated in the preliminary model. Finally a hazard-based model was constructed to relax the assumption of residuals normality. The main advantage of the hazard-based model was its capability in precisely capturing the impact of exogenous variables on concrete pouring time, while it does not require any assumption on the concrete pouring duration distribution.

As the main finding, this study showed that the supply related variables are not negligible while modeling concrete pouring duration, as variables such as number of required deliveries, average load per truck, delivers being on weekend and midnight and CBD located projects were found to be significant in the final model. Moreover, the hazard ratios were found be significant for supply related variables. The other important contribution of this study was utilizing hazard-based approach to introduce an example of modeling concrete pouring productivity with an analytical approach, where the time is treated as a stochastic variable. In general, this study provides decision makers with a practical tool to improve concrete pouring productivity. One of the benefits of the developed model is to approximate the duration of concrete pouring as while considering both supply chain and construction site features. Having such approximations about the project duration enables the company to manage the daily operation based on transportation cost, on time delivery benefits, late delivery costs and many other factors. This paper focused on introducing the merits of a hazard-based modeling approach for predicting concrete pouring duration as one of the human intensive jobs in construction projects. During the modeling process, it was aimed to select generalizable parameters and it has been avoided from providing any generalized conclusions because the model was built on a field dataset limited to a specific region.

The limitations of this study can be categorized in two groups of data related limitations and transferability related limitations. Regarding the data related limitations, even though one of the main purposes of this study was to investigate the impact of supply chain related variables on the concrete pouring duration; the investigated variables for this purpose are not direct measurements from road networks. Utilizing direct estimations of travel time from depots to sites can reflect the impact of supply chain variables on concrete pouring duration more accurately. For example considering travel time, reliability of travel time on road networks possibly can improve the developed hazard-based model to more precisely predicting the concrete pouring duration. This issue also can be complemented by other factors such as build form information of where customers are located. But on the other hand, data gathering practice for such a study would be time consuming and costly. In terms of transferability limitations, the modeling outcome of this study might be applicable to other metropolitan regions, but this issue needs further investigation and data collection which is beyond the scope of this paper. However, the used methodology can be applied on similar databases collected from different locations.

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