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# Travel-time prediction model of ready-mixed concrete trucks for improving transportation efficiency

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**Abstract**

Ready-mixed concrete transportation planning is regarded as a core aspect of the construction industry, for which the key success factor is its effective time management. Travel time is the primary indicator of increased efficiency in advanced delivery scheduling. Therefore, this study aims to create a travel-time prediction model for ready-mixed concrete business that have, insufficient knowledge of transportation, have recently started a business, or are expanding their factories to new locations. We prioritize the model calculation speed while the accuracy within acceptable ranges becomes secondary. Data were collected, -on the travel history of trucks within the area of the bypass ring road in, Udon Thani province, Thailand, from GPS devices installed in the trucks that transmitted signal every minute. Multiple linear regression (MLR) was selected for this model because it is reliable, widely accepted, and consistent with instant decisions made within business constraints. The obtained result was the optimal travel-time prediction model with confidence interval for an adjusted $R^2$ of 81.35. The model was validated by using the remaining data, which demonstrate that RMSE was equal to 0.0868 hours or 5.208 minutes.

**Keywords:** Travel time prediction, Multiple linear regression, Ready-mixed-concrete truck

## 1. Introduction

Travelling information is an important component that affects transportation efficiency [1]. Travelling time is a key factor for businesses to ensure quality of service and efficient scheduling [2, 3]. An industry in which transportation is the main affair is RMC industry which has five performance stages, 1. Mixing of raw materials, 2. Preparing trucks, 3. Travelling to the site, 4. Pouring concrete and 5. Travelling back to the factory. The vital problem is the delivery is not always on the due date. The main reason for this problem is imprecise travelling time prediction. If trucks arrive at the site too early or late, the concrete expires before usage. This issue may lead damage to the structure owing to discontinuous concrete pouring, an increase in expenditure from the cost of labors and machines that are in a state of waiting and the over- or under-planning of trucks usage.

Efficient and realistic concrete-truck transport scheduling can decrease the effects of the mentioned problem and significantly increase the income of the entrepreneur [4]. The significant variables that affect travel-time prediction are traffic congestion, traffic flow and weather [5]. Considering concrete manufacturing procedures, the truck travel-times to the site and back to the factory contribute the most to the above issue. Therefore, an efficient and precise time prediction tool is required. In real scenarios, concrete delivery issue typically occurs in community areas with network traffic and various types of roads. Furthermore, few travelling time prediction models use data from community area research is. The majority of studies used data on short community area roads or highways between cities to simulate travel-times as shown in Table 1.

**Table 1** Road classification

| Vehicle Type | Highway | Urban Short-term | Urban Road Network |
|---|---|---|---|
| Passenger car | [1, 6] | [7-9] | - |
| Taxi | - | - | [10, 11] |
| Bus | - | - | [12, 13] |
| Heavy Truck | [14, 15] | - | - |

Table 1 illustrates that traffic from different road network types in real life should be considered to improve travel time prediction models. Previous studies have illustrated that PC and HV travel-time prediction models have been developed for highway and urban short-term road networks, whereas taxi and bus travel-time prediction models have been developed for urban road networks. Moreover,

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taxi and bus mode can be categorized as service vehicles; likewise concrete trucks can be considered as service customers in the road network. In some areas, heavy vehicles are typically have been under a 'truck-ban policy' which indicates that concrete trucks as a type of heavy vehicles may be limited in their access to the road network at specific times of day. Therefore, an RMC truck travel-time prediction model should be developed for urban-road networks.

Various methods are typically used to solve travel-times predictions problems. Many studies have placed importance on this matter, proposing travel-time prediction models as a result of various data analysis techniques. A mixed-structure neural-network (NN) model was proposed to facilitates travel-time prediction; without using data detectors, and it yielded similar results to those of travel-time prediction using loop detectors [16]. An advanced neural network (ANN) model was developed to improve the efficiency of this technique. The ANN technique was used in travel-time estimation and prediction experiments, proving that it was practical and relatively effective. Moreover, applying the ANN technique yielded an approximately ≈ 4% error in travel-time prediction compared to the actual travel time, thereby demonstrating the potential of this technique [17]. Several studies used heuristic techniques, genetic algorithms [18], NN [19], and machine learning [20]. The application of these techniques has advantages, such as high cost when applied to all lines of a transport network and poor scalability when handling large volumes of data. This is because the traffic data are derived from the measurement of induction loop protectors. The recursive cell processing model (RCP model) was built to predict travelling time on the highway, giving 8% accuracy measured by the mean absolute percentage error [21]. However, this model is practical only under normal traffic conditions. Based on the same principle, using travelling speed as an influential variable provided better results with an approximately ≈ 0.18 root mean square error proportional [22]. Moreover, traffic data were obtained from the measurement of probe vehicles and double-loop detectors to develop a linear model for travel-time prediction on highways, resulting in a prediction error of 5%-10% using a small amount of data and 8%-13% using a large amount of data [23]. Regarding to the selection of analysis techniques for modeling, the methods that provided a better performance are yet to be confirmed. A previous model compared the accuracy of the travel-time prediction model of three wheelers in India using both regression analysis and NN approaches with six controlled variables; $R^2$ values were 91.8% and 99%, respectively [24]. In contrast, a cost estimation predictive model was proposed using the cost function from the relationships between business variables [25]. A comparison between these two techniques showed that the prediction equation from the NN approach was challenging to validate through users; that is, users were unable to give reasons for choosing their answers. Additionally, in the case of a change in the context of data processing methods, even a small change led to significant differences and results. Furthermore, the limited quantity of data used for the analysis was considered a major factor affecting precision. Because of insufficient data, when receiving newly arrived information, the NN approach could not provide accurate answers until the data underwent a training process.

Additional to creating a more precise delivery due date, which is a benefit of this study, this approach may be used as a secondary system for calculating the travelling time for transport planning in the case of a lack of internet to save service time. In addition, many studies have showed the benefits of travel-time prediction. In addition to its importance in travel time models, the study can be extended to other applications to minimize travel expenses. The truck- platooning system model analyzes trucks of various styles compared to the regular model on the highways of South Korea based on the indicator of reduced expenses related to travel time saving. As a result of this study, the travelling costs were reduced to KRW 187.6 billion in 2020 [14].

The aim of this study is to develop a reliable concrete-delivery-time prediction process and apply this information to obtain more efficient and realistic delivery due dates by creating a simulation using regression analysis. Accurate travel-time prediction is an important problem because it enables the planning of cost-effective vehicle routes and departure times, with the aim of saving time and fuel while reducing pollution. There are different components of the study are as follows:

- Specific consideration of the travelling time of concrete trucks in an urban road network, as the efficient and realistic information is required for the RMC industry.
- Creating a prediction on the RMC criteria that is connected to the other factors and realistic. Then, the RMC

## 2. Materials and methods

### *2.1 Travel-Time prediction model factors*

Creating an accurate travel-time prediction model is complicated, and the requirements for a large amount of traffic information and appropriate selection of variable types are crucial. The variables used in this study were categorized into two groups, based on sources of information as the criteria, including traffic data obtained from a survey of the actual travel behavior of vehicles. Additionally, geographical features of the road, and environment data were used, which were defined as information from the external environment or regulations in research areas. The variables were as follows.

#### *2.1.1 Subsection*

These variables are the direct traffic data that are widely used in many studies. A travel-time prediction model using traffic flow characteristics and traffic signal coordination as parameters [17] focused on the effects of travel time due to changes in travel speed, signal impacts, traffic volume and travel time [3]. Furthermore, data was collected on the total distance, average speed, red time, volume, % of classes, and queue length to predict the travel time of two-wheelers and three-wheelers in India [24].

In this study, the travel history information of trucks was used. A GPS was installed on each truck in the coordinate system, which revealed the location of the trucks every minute. Thus, distance, speed, and travel time could be computed from this information in conjunction with an actual area survey, which assisted in classifying road types according to road width. The study was conducted near the bypass ring road in Udon Thani Province, Thailand (Figure 1). Data analysis was performed, based on the data recorded from the GPS installed in each truck in the coordinate system of the truck movement with a resolution of 1 min as well as the data from a physical survey of each production unit. The data were analyzed using ArcGIS software before the input data for the environmental data analysis was determined, as shown in Table 2.

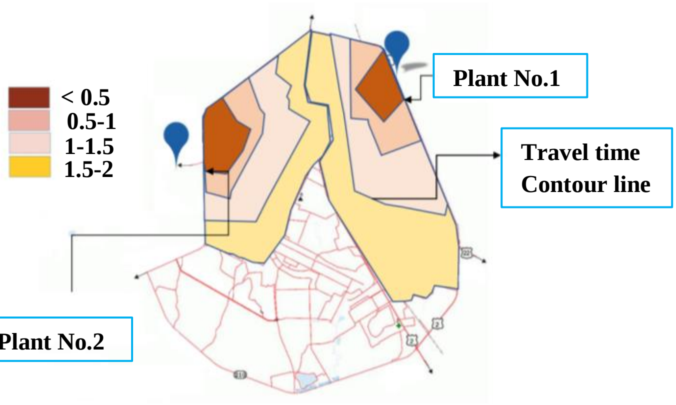


**Figure 1** Travel-Time map: Udon Thani, Thailand.

**Table 2** Data Classification

| Item | Description |
|---|---|
| Road name | Routs |
| Departure time | 6:00 – 19:00 |
| Road type | 3 types |
| Time zone | 3 zones and 6 zones |
| Average speed | Kilometer per hour |
| Distance | Kilometer |
| Travel time | Hour |

*2.1.2 Environment data*

Environment data refers to information that affects traffic but is irrelevant to vehicles. Several studies have analyzed these data to prove the connection between travel-time and certain variables, such as weather conditions [26], day offs and special holidays [27], demand, route length, type of road and population center [28]. In addition, we investigated the influences of different vehicle types on travel time, showing that the travel time prediction of passenger cars is currently the most developed because passenger cars are used more frequently than other vehicle types [2]. Therefore, the findings of the accurate travel-time prediction model should be categorized according to the vehicle types.

In this study, the travel time of RMC trucks, which has not been investigated in previous study, was reviewed. Other variables that have not been widely explored, such as – incomprehensive time zone and environmental data on days off and special holidays – were investigated to determine their effects on travel time in this model. The 12 hour - working period (7.00 – 19.00) was divided into six intervals based on different traffic conditions. The time-zone classifications listed in Table 3. Regression analysis was selected as the analytical technique to create the model because it is widely accepted as an effective approach for rapid and easy analysis without too many complications to validate the models.

**Table 3** Data classification

| Zone | Class 1 | Class 2 |
|---|---|---|
| Zone 1 | 06:00-09:00 | 07:00-08:00 |
| Zone 2 | 09:01-15:00 | 08:01-09:00 |
| Zone 3 | 15:01-19:00 | 09:01-10:00/ |
| | - | 15:01-17:00 |
| Zone 4 | - | 10:01-15:00 |
| Zone 5 | - | 17:01-18:00 |
| Zone 6 | - | 18:01-19:00 |

*2.2 Model development and analytical results*

*2.2.1 Model development concept*

The travel-time prediction of vehicles is complicated because the influence of multiple variables that affect model accuracy. An actual field data collection can also cause problem with model formulation. This model relied on information from the GPS attached to each RMC truck because this method is convenient and reliable. It is considered the only method that can easily and quickly retrieve and update data on travel history. Techniques suitable for the prediction model, linear regression and nearest neighbors method for predicting travel times on freeways [29] must be easy to use, convenient, able to engage users and widely accepted. Multiple linear regression (MLR) is considered the most suitable method for predicting the travel time of RMC trucks because it places great importance on advanced transportation planning. Furthermore, this approach can help users receive increased purchase orders if truck trips can be estimated clearly. In addition, the unique nature of this business is that the delivery appointment does not necessarily have to be strictly punctual, and a little delay is acceptable. However, rapid decision making is re-quired when receiving purchase orders, depending on the fast data processing method used to yield acceptable results that are consistent with the MLR technique.

*2.2.2 Results of multiple linear regression analysis*

In this study, the data were analyzed and processed using the statistical software STATA, and then categorized into two parts: 50% of the data were used for model analysis and the remaining data were used for model validation. Four influential variables were employed: average speed, distance, road type, and time zone. The average speed and distance were sourced from the processed GPS data. Additionally, the Highway Requirements Department focused on the study of road type. Moreover, the time zone could be defined on-site. The variables were utilized to determine the relationship between travel time and both the identifying individuals and crosstabs. The analytical results were classified into two groups based on the 14 linear equation patterns of each group, as shown in Tables 4 and 5, with the following representations of the variables: Y = travel time, ×1 = avg speed, ×2 = distance, ×3.2 = road type 2, ×3.3 = road type 3, ×4.3 = time zone 3, ×4.4 = time zone 4, ×4.5 = time zone 5, ×4.6 = time zone 6.

**Table 4** Regression analysis model in 3 time zones

| No. | Model | Adjust $R^2$ | Root MSE | P-value | Equation |
|---|---|---|---|---|---|
| 1 | Avg. speed | 18.69 | 0.1175 | < 0.001 | Y = -0.0653 + 0.0049(X1) |
| 2 | Distance | 78.39 | 0.0606 | < 0.001 | Y = 0.027 + 0.0194(X2) |
| 3 | Road type | 2.66 | 0.1285 | < 0.001 | Y = 0.0903 + 0.0435(X3.2) - 0.0395(X3.3) |
| 4 | Time zone | 0.32 | 0.1301 | 0.0255 | Y = 0.1091 + 0(X4.2) - 0.0207(X4.3) |
| 5 | Average speed+Distance | 80.07 | 0.0582 | < 0.001 | Y = 0.0826 - 0.0019(X1) + 0.0215(X2) |
| 6 | Average speed+Road type | 28.58 | 0.1101 | < 0.001 | Y = -0.143 + 0.0063(X1) + 0.0919(X3.2) + 0.0762(X3.3) |
| 7 | Average speed+Time zone | 18.64 | 0.1175 | < 0.001 | Y = -0.0672 + 0.0049(X1) + 0.0043(X4.2) - 0.0021(X4.3) |
| 8 | Distance+Road type | 78.40 | 0.0605 | < 0.001 | Y = 0.0283 + 0.0195(X2) - 0.0052(X3.2) + 0.0075(X3.3) |
| 9 | Distance+Time zone | 78.39 | 0.0606 | < 0.001 | Y = 0.0255 + 0.0194(X2) + 0.0002(X4.2) + 0.0056(X4.3) |
| 10 | Road type+Time zone | 2.94 | 0.1283 | < 0.001 | Y = 0.1039 + 0.0437(X3.2) - 0.0349(X3.3) - 0.0099(X4.2) - 0.0286(X4.3) |
| 11 | Average speed+Distance+ Road type | 81.36 | 0.0562 | < 0.001 | Y = 0.1295 - 0.0031(X1) + 0.0235(X2) - 0.039(X3.2) - 0.0393(X3.3) |
| 12 | Average peed+Distance+ Time zone | 80.06 | 0.0582 | < 0.001 | Y = 0.083 - 0.0019(X1) + 0.0216(X2) - 0.0014(X4.2) + 0.0015(X4.3) |
| 13 | Average speed+Road type+ Time zone | 28.57 | 0.1101 | < 0.001 | Y = -0.1259 + 0.0063(X1) + 0.0925(X3.2) + 0.0773(X3.3) - 0.0175(X4.2) - 0.0192(X4.3) |
| 14 | Average speed+Distance+ Road type+Time zone | 81.35 | 0.0563 | < 0.001 | Y = 0.122 - 0.0031(X1) + 0.0235(X2) - 0.0393(X3.2) - 0.0401(X3.3) + 0.0074(X4.2) + 0.0093(X4.3) |

**Table 5** Regression analysis model in 6 time zones

| No. | Model | Adjust $R^2$ | Root MSE | P-value | Equation |
|---|---|---|---|---|---|
| 1 | Average speed | 18.69 | 0.1175 | < 0.001 | Y = -0.0653 + 0.0049(X1) |
| 2 | Distance | 78.39 | 0.0606 | < 0.001 | Y = 0.027 + 0.0194(X2) |
| 3 | Road type | 2.66 | 0.1285 | < 0.001 | Y = 0.0903 + 0.0435(X3.2) - 0.0395(X3.3) |
| 4 | Time zone | 0.42 | 0.1300 | 0.0265 | Y = 0.1076 - 0.0064(X4.3) + 0.0021(X4.4) - 0.0259(X4.5) - 0.0582(X4.6) |
| 5 | Average speed+Distance | 80.10 | 0.0582 | < 0.001 | Y = 0.0826 - 0.0019(X1) + 0.0215(X2) |
| 6 | Average speed+Road type | 28.58 | 0.1101 | < 0.001 | Y = -0.143 + 0.0063(X1) + 0.0919(X3.2) + 0.0762(X3.3) |
| 7 | Average speed+Time zone | 18.65 | 01175. | < 0.001 | Y = -0.0673 + 0.0049(X1) + 0.0025(X4.3) + 0.0048(X4.4) + 0.0027(X4.5) - 0.0291(X4.6) |
| 8 | Distance+Road type | 78.40 | 0.0605 | < 0.001 | Y = 0.0283 + 0.0195(X2) - 0.0052(X3.2) + 0.0075(X3.3) |
| 9 | Distance+Time zone | 78.35 | 0.0606 | < 0.001 | Y = 0.0254 + 0.0194(X2) + 0.0024(X4.3) + 0.0018(X4.4) + 0.0019(X4.5) - 0.0069(X4.6) |
| 10 | Road type+Time zone | 3.23 | 0.1282 | < 0.001 | Y = 0.1016 + 0.045(X3.2) - 0.0373(X3.3) + -0.015(X4.3) - 0.0067(X4.4) - 0.0373(X4.5) - 0.0723(X4.6) |
| 11 | Average speed+Distance+ Road type | 81.36 | 0.0562 | < 0.001 | Y = 0.1295 - 0.0031(X1) + 0.0235(X2) + -0.039(X3.2) - 0.0393(X3.3) |
| 12 | Average peed+Distance+ Time zone | 80.06 | 0.0582 | < 0.001 | Y = 0.0834 - 0.0019(X1) + 0.0215(X2) - 0.0001(X4.3) + 0.0007(X4.4) - 0.006(X4.5) - 0.0124(X4.6) |
| 13 | Average speed+Road type+ Time zone | 28.64 | 0.1101 | < 0.001 | Y = -0.1263 + 0.0062(X1) + 0.0927(X3.2) + 0.0762(X3.3) - 0.0156(X4.3) - 0.0151(X4.4) - 0.0215(X4.5) - 0.0505(X4.6) |
| 14 | Average speed+Distance+ Road type+Time zone | 81.35 | 0.0563 | < 0.001 | Y = 0.1226 - 0.0031(X1) + 0.0235(X2) - 0.0392(X3.2) - 0.0398(X3.3) + 0.0075(X4.3) + 0.0089(X4.4) + 0.0038(X4.5) - 0.0019(X4.6) |

Model 1: Avg Speed. Model 2: Distance. Model 3: Road Type. Model 4: Time Zone. Model 5: Avg Speed, Distance. Model 6: Avg Speed, Road Type. Model 7: Avg Speed, Time Zone. Model 8: Distance, Road Type. Model 9: Distance, Time Zone. Model 10: Road Type, Time Zone. Model 11: Avg Speed, Distance, Road Type. Model 12: Avg Speed, Distance, Time Zone. Model 13: Avg Speed, Road Type, Time Zone. Model 14: Avg Speed, Distance, Road Type, Time Zone.

*2.3 Model validation*

The stability of the travel-time prediction model was tested for accuracy. Therefore, all models were validated by testing the models with the remaining field data using an MLR statistical technique. In all models, all values were represented using another set of prepared data to calculate the minimum value of the root mean square error (RMSE) as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{N}}, \quad (1)$$

Where $y_i$ = actual value of the dependent variable (time)
$\hat{y}_i$ = value of the dependent variable (time) from each model
N = number of datapoints used for calculation

The sample analysis results from the six time zone groups indicated that each unit of travel time obtained from the model had an error equal to the value shown in Table 6.

**Table 6** Model validation

| Model | Adjusted $R^2$ | RMSE |
|---|---|---|
| Average speed | 18.69 | 0.1321 |
| Distance | 78.39 | 0.0916 |
| RoadType | 2.66 | 0.1395 |
| Timezone | 0.42 | 0.1419 |
| Average speed+Distance | 80.10 | 0.0885 |
| Average speed+RoadType | 28.58 | 0.1280 |
| Average speed+Timezone | 18.65 | 0.1330 |
| Distance+RoadType | 78.40 | 0.0916 |
| Distance+Timezone | 78.35 | 0.0916 |
| RoadType+Timezone | 3.23 | 0.1412 |
| Average speed+Distance+RoadType | 81.36 | 0.0867 |
| Average speed+Distance+Timezone | 80.06 | 0.0886 |
| Average speed+RoadType+Timezone | 28.64 | 0.1286 |
| Average speed+Distance+RoadType+Timezone | 81.35 | 0.0868 |

## 3. Results

Proper model selection relied on examining the adjusted-R2 value incorporated with a stepwise MLR. Based on the results obtained for each time zone group, Models 11 and 14 from both time zone patterns were appropriate and close together; however, they had different time- zone variables. In particular, the travel time of RMC trucks may not be affected by the time zone, owing to the constraints of size and travel time in the study area based on legal conditions. Consequently, the time-zone variable had a minor effect, which was different from that of personal vehicles. For practical applications, Model 14 of the six-time zone groups exhibited a better performance with respect to the adjusted-R2 value of 81.35, as shown in Table 4. Thus, Model 14 is considered appropriate for predicting the travel time of trucks because it covers all variables. In addition, if data on further significant changes in time zones are reprocessed, the model will provide a higher accuracy, as depicted in Equation (2).

$$Y = 0.1226 - 0.0031(X1) + 0.0235(X2) - 0.0392(X3.2) - 0.0398(X3.3) + 0.0075(X4.3) + 0.0089(X4.4) + 0.0038(X4.5) - 0.0019(X4.6) \quad (2)$$

The model selected as the optimal model to predicting travel time was validated, and its precision was confirmed; Table 6 presents the corresponding results. The representative variables in Model 14 introduced errors into the calculated travel time of the RMC trucks; thus, the calculated time differed from the real time by 0.0868 h or 5.208 min.

## 4. Discussion

The travel-time prediction models in this study were developed using linear regression [30]. Many factors were used in the model including traffic flow, traffic density, and traffic speed. The model results showed an R2 value of 91.8%, indicating high reliability. Linear regression was also employed as the solution technique in this study. Weather, car density, construction and time zone factors were observed to be significant for travel time prediction in this study. In term of the confidence of the model, the obtained result was the optimal travel- time prediction model in which the confidence interval for the adjusted R2 were 81.35 (with the time zone) and 81.36 (without the time zone). These two models generally predicted the different results based on the different numbers of factors involved [31]. The time zone was included as a factors in the travel time prediction model using the fuzzy logic technique in a study by xx. Three models were developed separately for different time zones (peak, semi peak, and off peak) associated with other factors, including the period of the day, weather, car density, and construction. The travel time from of peak model was shorter than those of other two models. This indicates that the time zone affects the prediction of the travel time of the vehicle.

## 5. Conclusions

In general, construction and customer service mostly occur in urban areas. Furthermore, RMC trucks are service vehicles that require the development of travel-time prediction in an urban area road network, similar to taxi and bus vehicle types. Therefore, heavy vehicles are required to study travel-time predictions in urban area networks to improve conformation, precision and applicability to real scenarios. RMC businesses provide make quick responses and provide and answer to clients. The main objective of this study was to predict the travel time of RMC trucks to be used for delivery planning which is more effective than using people's experiences. Consequently, a modeling concept was developed to predict travel times, emphasizing practicality, traceability based on the planner's experiences, and quick data processing. The model did not require the analysis a large quantity of data but provided accuracy within acceptable ranges. MLR is recommended as an adequate method for this industry. The variables used for this analysis included the average speed, distance, road type, and time zone, which were obtained from actual field data collected from GPS devices attached to each truck. More importantly, the time zone, a variable that had not previously been applied to RMC trucks, was analyzed. The results indicated that the time zone of the study area may not affect to the travel time because of truck-size and travel-time constraints due to traffic laws. The obtained result was the optimal travel-time prediction model in which the confidence interval for the adjusted $R^2$ was 81.35. The model was then validated using the remaining GPS data, which showed that the RMSE was 0.0868; that is, the travel time of RMC trucks, when all values from the model were calculated had a real time error of 0.0868 hours or 5.208 minutes, which are considered acceptable values for applications in the RMC industry. The confidence of the model, was compared to that of Ref [24], and the result had an R2 value of 91.8%, showing the same tendency of high reliability. However, different confidence intervals were recorded owing to the significant differences in vehicle characteristics, including all the variables that were not identical.

This study aimed to improve the efficiency of transportation planning in response to a concrete business that has expanded to a new branch in the same area. The travel time prediction model can be used as a foundation for the further development of more complex and accurate techniques for RMC dispatching and scheduling. Moreover, if the 'truck ban policy' is applied in some areas, time zones may be considered as a factor for RMC travel-time prediction. As a result, the model developed in this study can be used as a criterion for implementing a multi-plant RMC in future studies. The prediction model facilitates quick decisions, which are required in accordance with the characteristics of this industry.

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