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MODEL FOR PREDICTING CONSTRUCTION TIME BY USING GENERAL REGRESSION NEURAL NETWORK

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Abstract

Construction time is an element of every construction contract. Thus, its prediction is of particular interest. This paper presents a construction time prediction model by using General Regression Neural Network. Key data on a total of 70 constructed buildings have been collected through field studies. Chief engineers of construction companies have been interviewed on contractual and actually incurred construction times, contractual and actual construction costs, type of facilities and construction year.

General Regression Neural Network (GRNN) from predictive modelling software named DTREG, as new approach in forecasting, was used for building the predictive model to predict the real construction time. Prediction was very accurate with mean absolute percentage error, MAPE, around 2.19 which means that the error of the model is around 2.19%, the coefficient of correlation between the actual and the predicted values is very high, r = 0.99 (rounded) and the coefficient of determination which measures the global fit of the model R^2 is 0.97875 (or 97.88%).

This paper contributes to and can be useful for the decision process on planning the construction time in construction companies and in the construction industry in general.

Key words

construction time; DTREG software; general regression neural network; predicting

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1 INTRODUCTION

Construction time is one of the basic elements of each contract for building construction, particularly contracts between investors with contractors, and contractors with sub-contractors. This is of utmost importance for most of key construction participants, such as investors, contractors, and project managers as well. The reasons for such type of interest are primarily of financial nature.

Numerous researches [1-3] point to frequent construction projects completion delay. Their reasons have also been the subject of researchers' interest [4]. These delays have numerous consequences, primarily financial, but also others, e.g. social and political. Minimizing the risk of delays demands undertaking adequate measures and procedures, as earlier as possible. One of the important factors is best possible realistic time planning in the initial phase of the project, prior to contracting. Although it is subject to a number of impacts, archiving and monitoring of realized time and attempt to establish certain regularities depending on the characteristics of the project, this topic has been researched continuously by a lot of researchers [5-30]. By using different mathematical methods and tools, e.g. simple and multidimensional linear regression, neural networks etc. they have been trying to establish adequate time prognostic model for certain type of structures. In a similar attempt the authors of this paper used the neural network to explain the benefits of its application for solving this problem.

Until now numerous scientific studies indicate certain relationship between construction time and the group of other factors, e.g. construction costs, area, number of storeys, volume of works, construction resources, design solutions etc. of course depending on structure type, but according to the study results, the costs have been pointed as the most important factor. Construction time usually depends on activities delays that are a worldwide common issue during construction project realization [4]. Delays usually increase project schedules and costs, and, despite the availability of various software and techniques for construction time control [5, 6], many construction projects do not achieve their time and cost objectives [5-8]. Therefore, project realization in contracted time is a challenge for each project participant. Time has become one of the most demanding and important tasks that should be considered in each construction project [9, 10], i.e. construction time has been acknowledged by industry practitioners and construction researchers as one of the most important project performance criteria. Hence, for measuring the construction time contractors, clients and consultants increased their concern particularly about measures of construction time performance [10, 11].

Construction time prediction failure can directly affect the building project participants' work and sometimes their business. Therefore, construction time prediction is of particular interest for all building project participants. Due to a range of parameters that influence the construction time it is impossible to acknowledge all of them at the time of construction planning, especially in cases when a fast prediction of construction time is needed [12].

Regarding the above mentioned, the research was driven by the question: can the construction time be modelled using data from finished buildings projects? Therefore, the aim of the paper is to develop a model for fast prediction of the construction time for buildings by using general regression neural network (GRNN) and find out which model can be useful for project' participants, particularly during the early designing project stage, then the processes of building project' tendering, bidding and contracting.

2 LITERATURE REVIEW

Construction time, as well as its overrun, together with construction cost is among issues that are highly pronounced in construction practice and their investigation is of research interest for many authors worldwide [13-17]. Also, it is in research interest to compare the results with those from the past forty-year period which indicate a significant increase in the speed of construction.

Numerous scientific studies indicate that there is a dependency between the contracted construction time and the contracted price. The Australian Bromilow was the first who investigated time and financial execution for a total of 329 structures in the building construction area which were built in Australia between 1963 and 1967. The research resulted in establishing the so-called "time-cost" model [15].

Many authors tested Bromilow's log-log time-cost model, e.g. in 1991 Kaka and Price [18] examined and confirmed the credibility of the Bromilow model on a sample of 661 building construction structures and 140 roads constructed in Great Britain from 1984 till 1989.

Other authors in [19] tested and refitted the Bromilow's log-log time-cost model showing that for different types of projects different parameter estimates are needed. This research has shown that smaller industrial facilities require shorter completion time than smaller educational and residential buildings. As a result, two models have been developed. Authors also found that factors such as the selection of the contractor, type of contract, type of clients do not affect the value of the parameters.

C. Pusic [20], as well as C. Pusic and Radujković [21-22] developed a few regression models for fast sustainable construction time evaluation suitable for specific structure and building groups in Croatia.

Regression analysis was also used by Chan P.C.A. [23] for modelling building durations in Hong Kong. Bromilows' relationship has been applied to 110 projects using time and cost to establish the model which can be used to predict construction time for buildings. It is interesting to point out that the private sector builds faster.

In 1994 Chan and Kumaraswamy [24] conducted a research on different types of structures built in Hong Kong from 1990 until 1993. 111 projects were divided into three different categories: government buildings, private buildings and civil engineering structures. The analysis shows different behaviour of those three categories. Government buildings and civil engineering structures fit into the model much better than private buildings. Some investigation results are comparable to those obtained from the previous researches, with the specific conditions taken into consideration [22].

Starting from 1997 Chan and Kumaraswamy developed the model for standard residential blocks, Harmony type, height 30 to 40 floors, built in Hong Kong during the period from 1990 to 1994 [13][25]. As Nkado [26], they assume that for a particular type of structure, all work activities can be grouped into several groups, the foundation, superstructure, main construction, installation and finishing work, whose duration has to be determined, as well as their start times clearly defining total construction time. Furthermore Chan P.C., A. and Chan W.M., D. [10-11] performed multiple regression analysis to analyse the collected data about construction time for high-rise public housing projects and to establish a benchmark construction time prediction model on the basis of a set of scope factors for housing scheme chosen and construction method. They also identified a set of critical factors that influence the construction time of high-rise public housing projects.

Several regression models for actual construction time and cost forecasting were made by Skitmore and Ng, [7]. Models depend on knowledge of the contractor selection method, client sector, project type, contract sum, contract period and contractual arrangement. Authors used different forms of regression analyses that include the cross validation regression and standard regression. Selection was made of the cross validation regression model with smallest deleted residual sum of squares.

An exponential equation model for assessing and testing the construction time was developed in [12]. The model is useful for water supply system construction projects for assessing and testing the time of the construction at work contracting, and also in the early planning stage.

The functional relationship between construction time and cost for highways was explored by the Shr and Chen W.T. [27]. They developed a quantifying model that provides contractors and State Highway Agencies with increased control regarding the time value of construction projects for highway.

For construction projects in [8] a prediction model is presented for estimating time based on a new neuro-fuzzy algorithm. Additionally, for predicting projects duration and costs based on historical data of similar projects, authors in [28] proposed a probabilistic model for prediction of risk effects on cost and time in construction projects. At a probability of the model of 95%, the model predicts project time and cost with a precision of ± 0.035% of the mean time and cost.

Artificial neural network was also used in [29] for developing a model for predicting the expected building projects construction time in their early stage when detailed planning isn't available. The model whose maximum error is 14% is developed using the MATLAB program. Furthermore, authors in [30] developed a multilayer perceptron neural network model for construction time prediction which is based on real data.

3 METHODOLOGY

Statistical data for 70 buildings were obtained through survey in construction companies in 2015. The questionnaire consisted of questions related to: building type, contracted and realized construction time for buildings' projects, contracted and realized construction cost and year of construction. The goal of the survey was to collect data for buildings' projects in order to create a model for construction time prediction.

The construction companies that were surveyed were contractors. According to the companies' type, the companies were small enterprises with up to 49 employees which had engaged sub-contractors and, some of them engaged consultants for some construction needed works. The survey was done by personal handover of the questionnaire to the companies representatives. They were asked to use data for buildings constructed in the last five years.

The buildings have been built on the entire state territory, by domestic investors and contractors.

The collected data were used as input in the general regression neural network (GRNN) from the predictive modelling software called DTREG [31, 32].

Some preliminary introduction to the neural networks will be given first, and after that some most important characteristics of GRNN.

3.1 Artificial Neural Networks

In the last several decades artificial neural networks (ANNs) have made remarkable contribution to the advancement of various fields of endeavour, solving wide variety of problems, modelling large quantities of data in many scientific areas and practice, for example recognizing objects and speech, classification, predicting, control of processes, etc. In civil engineering they have been used over past two decades as very powerful tools for solving different type of problems such as data retrieval, optimization, pattern recognition, function approximation, forecasting, automatic control or classification, in the cases where traditional analytical methods are difficult to be used, or they show inferior performances [33]. Neural networks (NNs) are based on simple computational models in comparison with traditional computer logic which requires comprehensive programming in order to accomplish a given task.

The NN have self-learning ability and they can easily identify the relationship between multivariable input and output. When the data, which are representative for the underlying process which should be implemented is provided, NN are able to infer valuable information for the task.

ANNs are computational models which are composed of n processor units called neurons, which are models of biological neurons. Fig. 1 shows the structure of biological neuron, and Fig.2 shows an artificial neuron [34].

From Fig. 1 we can see that neuronal cell bodies (soma) are connected with another neuronal cell with many input and output channels (dendrites and axons). Dendrites are used to transfer the electrochemical signals from one neuron to another. The neuron excites only when the total signal, which is received at the cell body, exceeds certain level. The neuron can be only at two states: it is excited or not excited.

ANN architecture is based on this model. Artificial neurons have several inputs (synapses), but only one output (axon) (Fig. 2). The output of a neuron can have branches and can be input in many other neurons. Neurons compute a function $\mathbf{y} = \mathbf{f}(\mathbf{x}, \mathbf{w}, \theta_j)$, where **y** is the value of the output of the neuron, **f** is some (usually) nonlinear function, **x** is input vector with n components, **w** is vector whose components are called weights of the inputs, and θ_j is some parameter often called threshold of giving output.

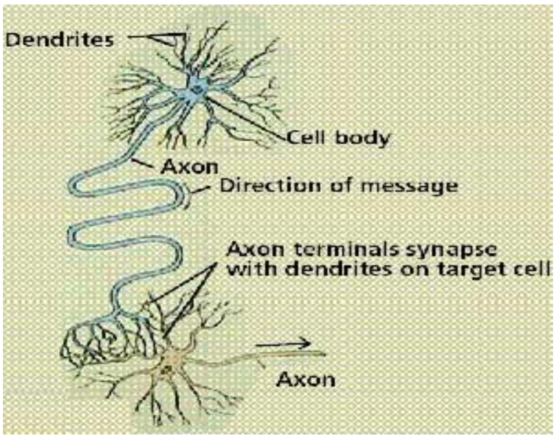

Fig.1: Biological neuron

The neural networks have ability to learn from examples and this makes them able to find the relationship between input and output variables when their relationship is not known in advance, and specifically when that relationship is not linear, so they are very useful in solving regression problems in nonlinear processes.

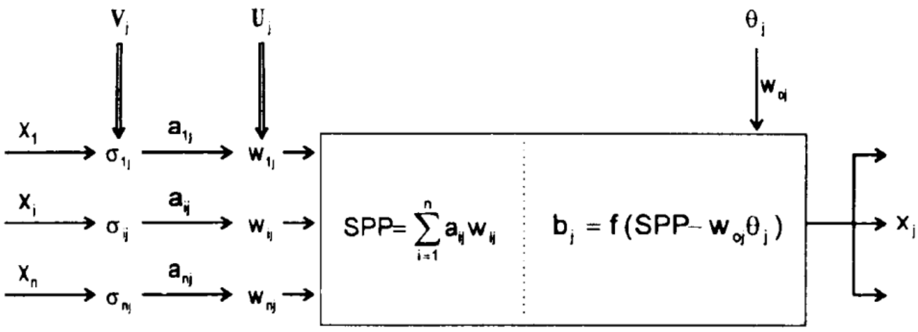

Fig. 2: Mathematical model of an artificial neuron

NN are trained to learn the relationship between input variables and the output variable, till that network output variable matches the target. Training procedure is being accomplished while the difference between the desired output and output obtained by the NN is not less than some threshold value. After the training procedure, validation procedure follows when the NN is ready to be tested on new input variables which were not used during the training (learning) procedure. NN usually contains 3 layers of neurons: input, hidden and output layer. Several hidden layers can be added, in order to obtain more powerful performance of the network, depending on the task which is being accomplished.

3.2 General regression Neural Network

General regression Neural Network (GRNN) has four layers; input, hidden, pattern (summation) (class nodes) and decision (Fig. 3) [31].

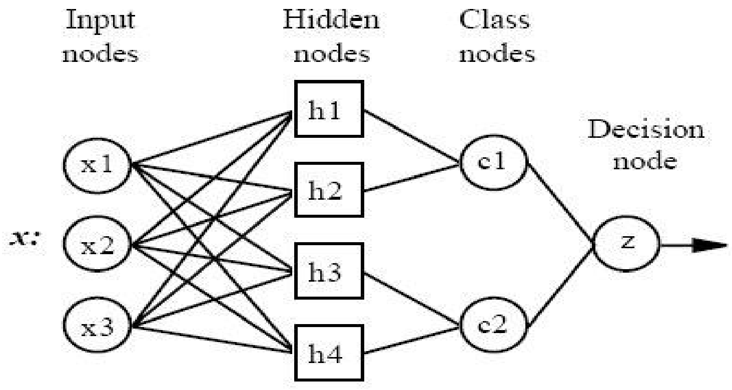

Fig.3 GRNN architecture

For each predictor variable there is one neuron in the input layer. Input neurons feed the values to the neurons in the hidden layer. The hidden layer has one corresponding neuron for each case in the training data set. Each neuron from this hidden layer stores the values of the predictor variables together with the target value. The output value of a hidden neuron is passed to the two neurons in the pattern layer where one neuron is the denominator summation unit and the other is the numerator summation unit. The denominator summation unit adds up the weight values coming from each of the hidden neurons and the numerator summation unit adds up the weight values multiplied by the actual target value for each hidden neuron. The decision layer then divides the value accumulated in the numerator summation unit by the value in the denominator summation unit and uses the result as the predicted target value [31, 35].

The author of this NN, Specht [35] has demonstrated that compared to the Backpropagation NN, GRNN needs only small number of training samples to converge to the desired function of the data, which is one of the best characteristic of this NN and which makes GRNN very popular for applications. Compared with the most popular MLP (multilayer perceptron neural network) GRNN can be trained faster than MLP network, and it can give more accurate predictions then MLP. Abhishek K. in [36] has applied MLP in stock prediction and obtained accuracy of 96 %. MLP is also applied in [37]. But GRNN is slower than MLP and require more memory space than MLP.

When we do not know in advance the relationship between the target variable and predictors, it is recommended to try several NN models in order to choose the most appropriate which will give most accurate predicting.

4 RESULTS

In the process of training GRNN learns the relationship between predictors (input) X and the target (output, dependent) variable Y from the values of X and Y which are available, in the beginning. In most cases, this dependency is not known. After the training (learning) process, in the validation process GRNN starts to estimate the predicted values for Y for new values for X.

As input variables for the GRNN the following were chosen: real time of construction – as target (dependent) variable, whose values were predicted and: contracted time of construction, real price of construction and contracted price, as predictors. Other available information from the questionnaire was facilities' purpose and the year of construction.

The values of the predictors and target variables should be stored in Excel file and this file should be formatted appropriately, as is required for DTREG software. Before starting the GRNN, some parameters for GRNN should be adjusted, such as sigma values (minimal and maximal) for the Gaussian kernel function of the GRNN, then the number of iterations and maximal time allowed for the conjugate gradient algorithm for the convergence process, as well as choosing the options for optimization and simplification by reducing the number of neurons, and choosing the type of validation of the model.

DTREG software computes the minimal, maximal, mean value and its standard deviation for each predictor and target variable with numerical values (see Table 1).

Tab. 1: Minimal, maximal, mean value and standard deviation of the predictors and the target variable

================ Continuous Variables ====================

Variable	# Rows	Minimum	Maximum	Mean	Std. Dev.
ln(real time)	70	2.70805	6.49224	4.68156	0.96156
ln(real price)	70	9.76549	15.60834	12.80734	1.40941
ln(contract. price)	70	9.72448	15.60834	12.78592	1.41069
ln(contract. time)	70	2.70805	6.57925	4.57863	0.93000

Contracted and real time of construction is given in days, and contracted and real price is given in euros. We should stress here that the figures in this table are logarithm of these values, and the reason for this is given in the Discussion section.

For improving the accuracy of the model and its speed, DTREG software for GRNN has an option for reducing the number of the neurons of the GRNN. In this model, this option is used and the DTREG reduced the number of the neurons from 70 to 31, because the minimum error occurred with 31 neurons and the model was improved.

DTREG gives ***Validation data row report file*** where all predicted values for the actual target variable from the validation process can be read. The correlation between the actual and the predicted values of the target variable for our model is 0.99 (rounded to 2 decimal places). From the *validation data* we can read the accuracy of the model (see Table 2) [31,32].

DTREG separates the input dataset in two subsets: one subset for training and other subset for validation.

There are several methods for validation. In DTREG there are 4 choices for validation: 1) holding out a random percent of all rows from input dataset during the building of the model, and using them for validation (evaluating the error of the model), 2) using control variable to select which rows from the input dataset will be held out for testing (validation of the model); 3) performing cross validation with a specified number of folds (V-fold cross validation); 4) performing cross validation with one row left out of each model which is built (LOO – Leave One Out) [31].

For our model the best accuracy is obtained with LOO method when 69 rows are used for training and 1 row for validating, and this method requires learning and validating $C_n^1 = n$ times, where n is the number of rows in the input dataset, in our case 70 times.

The *coefficient of determination* R^2 and the *mean absolute percentage error* (MAPE) are most often used estimators of the accuracy of the model. For our model R^2 =0.97875 (or 97.88 %) and MAPE = 2.19 (rounded to 2 decimal places) (using LOO validation method), which means that the percentage error for our model is around 2.19%. The *coefficient of determination* $\mathbf{R^2}$ indicates how well data points match the approximation function which is obtained from the model – it is a measure of the general match of the model. The value $\mathbf{R^2}$**= 0.97875** can be interpreted as: around **97.88%** of the variation in the response can be explained by the predictor variables. The remaining around **2%** can be attributed to unknown variables or inherent variability.

Tab. 2: Results for the training and validation of the model

--- Training Data --- Mean target value for input data = 4.681556 Mean target value for predicted values = 4.6653081 Variance in input data = 0.9246063 Residual (unexplained) variance after model fit = 0.0180853 **Proportion of variance explained by model (R^2) = 0.98044 (98.044%)** Coefficient of variation (CV) = 0.028726 Normalized mean square error (NMSE) = 0.019560 Correlation between actual and predicted = 0.990318 Maximum error = 0.4979211 RMSE (Root Mean Squared Error) = 0.1344816 MSE (Mean Squared Error) = 0.0180853 MAE (Mean Absolute Error) = 0.0847899 **MAPE (Mean Absolute Percentage Error) = 1.8664853**
--- Validation Data --- Mean target value for input data = 4.681556 Mean target value for predicted values = 4.6650297 Variance in input data = 0.9246063 Residual (unexplained) variance after model fit = 0.0196474 **Proportion of variance explained by model (R^2) = 0.97875 (97.875%)** Coefficient of variation (CV) = 0.029941 Normalized mean square error (NMSE) = 0.021250 Correlation between actual and predicted = 0.989468 Maximum error = 0.4979211 RMSE (Root Mean Squared Error) = 0.1401693 MSE (Mean Squared Error) = 0.0196474 MAE (Mean Absolute Error) = 0.1000573 **MAPE (Mean Absolute Percentage Error) = 2.1922517**

We obtained maximal accuracy of the model when we used 3 predictors. The method for validation used was LOO when the option "Remove necessary neurons" is chosen for model optimization. Another method for validation using this option in DTREG is "Random percent" when random percent from the rows are used for validation. Maximal accuracy with this method was obtained with Random 21% when MAPE was 2.66 and R^2=97.846%. When the option "Remove necessary neurons" is not chosen, then the method for validation is "V-fold cross validation" and in this case, using 3 predictors, we obtained maximal accuracy with MAPE=2.94 and R^2=96.52%.

Using 5 predictors, (by adding 2 predictors: year of construction and purpose of the facility, to the 3 previously used predictors), we obtained MAPE=2.3 and R^2=97.715%, using the option "Remove necessary neurons".

When the Bromilow's model was not linearized then with the used 3 predictors the accuracy was MAPE=11.78% and R^2=97.4%. In this case, when using 5 predictors mentioned previously, the accuracy was MAPE=17.6% and R^2=97.06% and using 4 predictors: 3 predictors used before and plus the predictor – year of construction, the accuracy was MAPE=15.6% and R^2=96.99%.

5 DISCUSSION

Choosing the predictors is the most important part of the modelling with NN. This means that we should choose most representative predictors which contribute to the accuracy of the model. The percentage error for the model is around 2.19%. Considering that the data are real, the model has high accuracy. Authors in [38] have made comparison between 3 types of NN that they used for prediction construction crew productivity and obtained MAPE around 31% using GRNN and they obtained most accurate prediction with SOM-self organized map NN with MAPE around 21%.

We can also notice that we used not the values of the predictors which were known from the input data, but logarithm of them considering the equation (1) for the dependency of the cost and time of construction (Bromilow's time-cost model [15])

$$T=KC^B \tag{1}$$

where T is the time for construction, C is the price for construction and K and B are parameters of the model.

Bromilow's time-cost model for the contracted time T_1 and contracted price C_1 can be given with (2), and for real time of construction T_2 and real price of construction with (3)

$$T_1 = K_1 C_1^{B_1} \tag{2}$$

$$T_2 = K_2 C_2^{B_2} \tag{3}$$

By logarithm of equations (2) and (3), the equations (4) and (5) are obtained:

$$\ln T_1=\ln K_1+B_1\ln C_1 \tag{4}$$

$$\ln T_2=\ln K_2+B_2\ln C_2 \tag{5}$$

By summarizing (4) and (5), the equation (6) is obtained:

$$\ln T_1 + \ln T_2 = \ln K_1 + B_1 \ln C_1 + \ln K_2 + B_2 \ln C_2 \qquad (6)$$

From equation (6), if we express $\ln T_2$, the dependence of the real time from the contracted time and contracted and real price can be obtained:

$$\ln T_2 = \ln K_1 + B_1 \ln C_1 + \ln K_2 + B_2 \ln C_2 - \ln T_1 \qquad (7)$$

Because of (7), the target variable is chosen to be ln(real time), and predictors are chosen to be ln(contracted time), ln(contracted price) and ln(real price). So we obtained prediction for ln(target variable). By anti-logarithm of these values we can receive the values of the target variable (the real time of construction). This is very important, because in this way, by linearizing the equations (2) and (3), linear dependency of the target variable from the predictors is obtained, and this contributed very much for simplicity of the model and its accuracy. So, we can stress here the significance of the Bromilow's equation for the selection of the values for the target and predictors variables.

Linear regression model from DTREG was also tried for modelling of the target variable and predictors using the equation (7) in linearized form. The accuracy of the prediction was very similar to that of GRNN. The MAPE was around 2.63% and R^2 = 97,132, i.e. around 97.13%, but when the model was not linearized, the MAPE for the linear regression model was around 20%.

6 CONCLUSION

Many parameters determine the building construction time and it is impossible for all of them to be known and acknowledged at the beginning of the project when the time of construction is being estimated. Therefore, learning from previous projects experience is of particular interest. For that purpose, for the paper, a database for previously realized construction projects was formed. By applying a method from artificial intelligence, i.e. general regression neural network using DETREG software, a construction time predictive model was designed.

The percentage error for the model is around 2.19% and it should be noted that the model has high accuracy, considering that the data are real.

The limitation of the model is that it is applicable in conditions where it is not expected to have large influence from physical factors such as: incorrect or incomplete documentations, bad climate conditions, poor organisation of construction works and etc. Also, some variables of the model depend on circumstances of the considered area where the research was conducted.

The model can be used for rapid and efficient analysis of building construction time. It is not a substitution of detail planning of construction time, so it is convenient for the initial phase of building planning and construction, as well as contracting of works. It can serve for project participants and for clients as a tool for construction time prediction.

Although the model was applied in Macedonian context, the approach used may be applied for developing similar models for construction time prediction in other countries.

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