Predicting construction project scheduling issues using LSTM neural network (long-term short-term memory)

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ABSTRACT

As the purpose of monitoring the project is to make accurate decisions that can have significant effects on the project's success, predicting the project's characteristics becomes more important. According to experts, schedule delays are a frequent issue in many construction projects. The aim of this research is to propose a model that can address project scheduling problems. For this purpose, this study proposes new applications of recurrent neural network architectures based on short-term long-term memory (LSTM) prediction models. Subsequently, the prediction results of the presented models are compared and verified with the historical data of a real project. The data used in this study has been obtained from the South Extension Project of Tehran Metro Line 6. The project started in October 2016 and ended in July 2018, lasting for a total of 21 months. In this study, the training dataset consisted of the initial 14 months' data, which accounted for 83 percent of the total data. We used the construction project progress as a forecasting variable. To evaluate the performance of LSTM models, we used the mean square error (MSE) metric as the evaluation criterion. The results show that the model accurately forecasts the project's future progress based on its past progress.

KEYWORDS

Project management, Scheduling, Artificial intelligence, Short term long term memory, Forecasting

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Introduction

According to published statistics by the Office of Supervision and Evaluation of Plans, more than 50% of the country's construction projects face delays every year. The typical duration for project execution is nearly eight years, whereas it was originally expected to be completed within a three-years. Scheduling is crucial in construction projects as it enables effective project management, resource allocation, and timely completion. Uncertainty in project planning refers to the unpredictable events that can affect the project's scope, quality, schedule, or budget [1]. Furthermore, accurate forecasting allows for enhanced project monitoring. scheduling under uncertainty is primarily investigated through the utilization of stochastic optimization methods. Additionally, to overcome project scheduling challenges, several approaches based on genetic algorithms have been proposed [2]. However, deep learning models are a more effective way to handle the uncertainties of project scheduling. They can forecast the uncertainties better than other methods [1]. By utilizing deep ensemble networks, it is possible to achieve high-quality uncertainty estimation with a small value of the prediction interval width and a high confidence of prediction interval coverage probability [3]. Another approach in the prediction problem involves the use of neural networks and machine learning. Artificial neural networks are inspired by the brain, and their computations could be implemented in biological neurons. These artificial neural networks, with their non-linear mapping capability and effective topology, are widely used in pattern recognition, data prediction, and more [4]. Among the existing models in neural networks, Recurrent Neural Networks (RNNs) have the ability to consider sequential observations. In other words, this category of RNN models processes sequential data as time series [5]. The main drawback of RNNs is that they have difficulty in learning long-term dependencies in sequential data [6]. The Long Short-Term Memory (LSTM), which is a special kind of RNN that can overcome this problem by using the gates to control the amount of information that flows into and out of the memory cell, which prevents the gradients from vanishing or exploding. Therefore, in this research the progress of civil engineering projects is predicted by applying the LSTM method.

Framework of LSTM Model

The LSTM consists of unique units known as memory blocks, which replace the hidden layer found in neural networks. The input gate, forget gate, output gate, and input modulation gate are the features of the LSTM structure. This study used three hidden layers. The equations governing these are

$$i_t = \sigma(w_i X_t + U_t h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(w_f X_t + U_f h_{t-1} + b_f) \tag{2}$$

$$o_t = \sigma(w_o X_t + U_o h_{t-1} + b_o) \tag{3}$$

$$c_t = f_t C_{t-1} + i_t \tanh(w_c X_t + U_c h_{t-1} + b_c) \tag{4}$$

$$h_t = o_t \tanh(C_c) \tag{5}$$

where X_t represents the current input; h_{t-1} denotes the previous hidden state; σ denotes the logistic sigmoid function; i_t, f_t, o_t, g_t, c_t, c_{t-1}, and h_t refer to the input gate, forget gate, output gate, input modulation gate, cell state, previous cell state, and current hidden state, respectively. The weight matrices are represented by w_i, w_f, w_o, w_c and the biases are denoted as b_i, b_f, b_c, and b_o.

Experiments, results, and their discussion

This section describes the simulation experiments to evaluate the effectiveness of the proposed approach.

3.1. Dataset

The data used in this study has been obtained from the South Extension Project of Tehran Metro Line 6, which includes parking, station construction, ventilation systems, and emergency exits. The project started in October 2016 and ended in July 2018, lasting for a total of 21 months. In this study, the training dataset consisted of the initial 14 months' data, which accounted for 83 percent of the total data. The remaining three months' data, equivalent to 17 percent of the total, were used as the test dataset to evaluate the model's performance after the training phase. We used the construction project progress as a forecasting variable.

3.2. Experimental setting

The simulation is carried out using a system running on the Windows 8 operating system, equipped with an Intel(R) Core(TM) i7-2600 CPU operating at 3.40 GHz and 8 GB of RAM. The implementation of the LSTM was done using Python language via Keras library and TensorFlow at the back-end. Google colab API environment was used for the implementation.

3.3. Performance evaluation metric

To evaluate the performance of LSTM models, we used the mean square error (MSE) metric as the evaluation criterion. The smaller percentage value of the MSE metric expresses better performance.

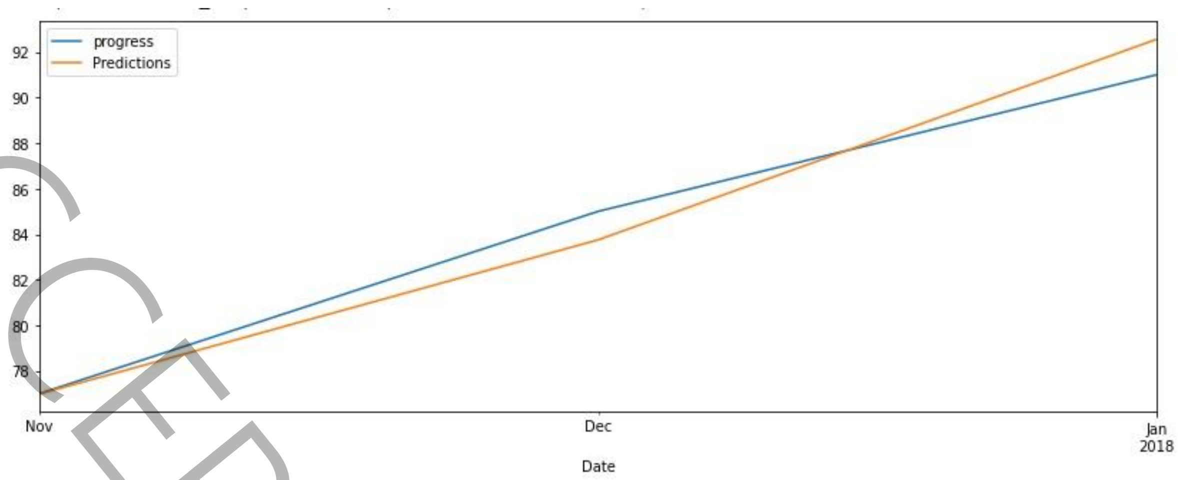

Figure 1. Comparison of actual versus predicted project progress

3.4. Results and discussion

The implementation of proposed approach and the forecasting results are presented in this section. Figure 1 illustrates the actual and forecasted results of construction project progress from LSTM model. This figure compares the actual progress of the project (blue line) and the LSTM model's prediction (orange line) for months 15, 16, and 17. As the figure illustrates, the model accurately forecasts the project's future progress based on its past progress. As the project nears its completion, the pace of progress tends to decline. Additionally, the model's forecasts are based on data from earlier stages of the project. Consequently, the accuracy of the model's predictions may be slightly affected during the final months, leading to slight deviations from the actual outcomes. However, each project is unique and its progress, especially in the last months, is influenced by various factors that this study does not account for these variables.

Conclusions

The ability to forecast the physical progress in the scheduling of construction projects provides project managers with valuable insights to adapt and adjust the initial schedule. By accurately predicting the progress, project managers can identify potential delays or advancements, enabling them to make informed decisions and implement necessary modifications to the schedule. This proactive approach helps enhance project management, optimize resource allocation, and improve overall project efficiency. In this research, we utilized the Long Short-Term Memory (LSTM) model, a type of recurrent neural network architecture designed to capture long-term dependencies, for predicting the project's progress. We used the construction project progress as a forecasting variable. To evaluate the performance of LSTM models, the mean square error (MSE) metric was used as the evaluation criterion. The results indicated that the Long Short-Term Memory (LSTM) method yielded reliable predictions of the project's progress by effectively considering long-term dependencies.

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