Predicting Construction Costs Under Uncertain Market Conditions: Probabilistic Forecasting Using Autoregressive Recurrent Networks Based On DeepAR

Ghiwa Assaf

Rayan H. Assaad

Islam H. El-Adaway
Missouri University of Science and Technology, eladaway@mst.edu

Mohamad Abdul Nabi

Predicting Construction Costs under Uncertain Market Conditions: Probabilistic Forecasting Using Autoregressive Recurrent Networks Based on DeepAR

Ghiwa Assaf[1]; Rayan H. Assaad, Ph.D.[2]; Islam H. El-adaway, Ph.D.[3]; and Mohamad Abdul Nabi[4]

[1]Ph.D. Candidate, John A. Reif, Jr. Dept. of Civil and Environmental Engineering, New Jersey Institute of Technology, Newark, NJ. Email: ga338@njit.edu
[2]Assistant Professor of Construction and Civil Infrastructure and Founding Director of the Smart Construction and Intelligent Infrastructure Systems Lab, John A. Reif, Jr. Dept. of Civil and Environmental Engineering, New Jersey Institute of Technology, Newark, NJ (corresponding author). Email: rayan.hassane.assaad@njit.edu
[3]Hurst-McCarthy Professor of Construction Engineering and Management, Professor of Civil Engineering, and Founding Director of Missouri Consortium of Construction Innovation, Dept. of Civil, Architectural, and Environmental Engineering and Dept. of Engineering Management and Systems Engineering, Missouri Univ. of Science and Technology, Rolla, MO. ORCID: https://orcid.org/0000-0002-7306-6380. Email: eladaway@mst.edu
[4]Ph.D. Candidate, Dept. of Civil, Architectural, and Environmental Engineering, Missouri Univ. of Science and Technology, Rolla, MO. Email: mah59@mst.edu

ABSTRACT

Projects often experience cost overruns due to market uncertainty and price escalations. Traditional cost estimation methods that rely on point estimation are incapable of providing prediction intervals as well as probabilistic assessment. Thus, there is need for an innovative approach to predict the changes and uncertainties in construction material costs. This paper proposes a novel stochastic model to estimate construction material costs by applying probabilistic forecasting using autoregressive recurrent networks. First, price data was collected for four different construction materials. Second, data was divided into a training set (pre-COVID-19) and a testing test (post-COVID-19). Third, the state-of-the-art DeepAR algorithm was implemented to provide probabilistic forecasts for construction material prices under uncertain post-COVID market conditions. The results showed that the proposed stochastic model provides accurate cost estimates with a mean absolute percentage error of 1% for concrete products, of 2% for concrete ingredients, of 3% for paving mixtures and blocks, and of 4% for steel and iron materials. This paper adds to the body of knowledge by proposing a new approach for estimating construction material by providing probabilistic forecasts in the form of Monte Carlo samples that can be used to compute quantile estimates, which offers better protections against rising costs.

INTRODUCTION

The construction industry plays a major role in nations' development. However, this sector has been facing numerous challenges, especially cost overruns (Assaf and Assaad 2023). In fact, large asset projects have been experiencing up to 80% cost overruns compared to the planned budget (Assaad et al. 2020). Moreover, the recent steel tariffs in 2018, the COVID-19 in 2019-2021, and the Ukraine-Russia conflict in 2022 are one of the main causes behind cost overruns in the past years and the increase in material prices due to inflation and supply chain-related challenges (Steel Times International 2022; Assaad and El-adaway 2021). The unbudgeted additional project costs may affect the performance and the schedule of the project. To that extent, the need for an accurate method to predict or estimate the costs of construction materials is greatly needed to control price inflation and provide the construction industry with the ability to accurately estimate their budgets (Jiang et al. 2022).

Several approaches have been proposed to predict construction material costs. Yet, one of the most used approaches relies on predicting costs using the Producer Price Index (PPI). The PPI is an index that quantifies how the average selling price changes over time from the industry or producers' perspective (U.S. Bureau of Labor Statistics 2023). That being said, the PPI measures the inflation from the industry's point of view.

Thus, to accurately predict the cost of construction material, this study implements a probabilistic forecasting methodology based on autoregressive recurrent neural networks to predict the prices of construction material using their PPI time series data. Moreover, to ensure accurate forecasts, tuning of the hyperparameters of the machine learning model was implemented to minimize the prediction error. The results of this research present an approach for the construction industry to properly hedge against inflation and reduce project cost overruns as well as increase project performance. Moreover, the proposed stochastic forecasting model is capable of presenting prediction intervals rather than prediction points, which provides decision-makers with the ability to properly analyze and estimate their project costs and associated risks.

LITERATURE REVIEW

Due to the increased cost overruns affecting the construction industry, several studies attempted to predict construction-related prices to accurately estimate project budgets and prevent cost overruns. In relation to that, Shiha et al. (2020) implemented artificial neural networks along with optimization techniques, such as genetic algorithms and root-mean-square propagation, to predict the prices of construction material for 6 months ahead with a Mean Absolute Percentage Error (MAPE) that ranges from 4 to 11%. Faghih and Kashani (2018) used vector error correction models to forecast the prices of construction material while capturing the internal structure of the data set with a MAPE of 0.2901. Oshodi et al. (2017) compared two univariate models: neural network model and the Box-Jenkins model to predict the tender price index of construction projects, where the tender price index measures the changes in the tender price or the costs to clients. This comparison showed that the neural network model is more accurate in predicting the tender price index of construction projects with a MAPE of 0.82%. Jiang et al. (2013) proposed a vector error correction model with the implementation of dummy variables to predict the changes in the construction prices. The developed model was compared to the normal vector error correction model and to the Box-Jenkins model where it was shown that the proposed vector error correction model with dummy variables is the most effective and reliable method for the prediction of construction costs with a MAPE of 1.1%. Pewdum et al. (2009) developed artificial neural network models that predict the final cost of highway projects during the construction stage with a MAPE of 2.56%. Dharwadkar and Arage (2018) implemented ordinary least square regression and multilayer perceptron model to predict the cost of construction projects and concluded that multilayer perceptron models are more accurate than the regression models with an accuracy that can reach 98%. Finally, Elfahham (2019) compared three models for the prediction of reinforced concrete materials costs: the linear regression, autoregressive time series, and the artificial neural networks. This comparison has resulted in identifying the autoregressive time series model as the most accurate in predicting construction material costs with an average of absolute errors of 3.5.

Ultimately, and although numerous machine learning algorithms have been used to predict construction-related costs, the existing models are only capable of providing point estimates rather than probabilistic forecasts that can yield prediction intervals. Thus, to fill this knowledge gap, this paper develops a stochastic model using autoregressive recurrent networks to probabilistically predict construction material prices. More specifically, the state-of-the-art DeepAR model or algorithm was trained and tested on pre- and post-COVID-19 PPI data of different materials.

METHODOLOGY

Data Collection. This study aims to predict costs of construction material using their PPI data. Thus, the first step is to collect the data of the PPI of different construction materials. The construction material considered in this study are presented in Table 1. To capture pre- and post-COVID-19 market conditions, the PPI of each of the four materials was collected from January 1985 to March 2023 from the US Census Bureau of Labor Statistics (2023). That being said, the input of each model has a total of 459 input points (i.e., PPI values from January 1985 to March 2023) to obtain an output of a PPI time-series.

Table 1. Construction material considered in this study

Construction Material	Material's Code	Material's Subtype(s)	Average PPI
Concrete products	WPU133	Ready-mixed concrete, precast concrete products, concrete blocks and bricks, concrete pipe, and prestressed concrete products	181.54
Concrete ingredients	WPU132	-	196.80
Paving mixtures and blocks	WPU1394	-	198.15
Iron and steel	WPU101	Steel pipe and tube, iron and steel scrap, steel mill products, and stainless and alloy steel scrap	172.98

Data Partitioning. To develop an accurate forecasting model and avoid overly optimistic estimates, the data was portioned into training and testing sets, where the training data is from January 1985 until March 2022 for all four construction materials models. The prediction period is for the 1-year period from April 2022 to March 2023.

DeepAR Implementation. The used algorithm in this paper is the DeepAR model which is a state-of-the-art probabilistic forecasting approach developed by Amazon and is based on autoregressive recurrent networks (Salinas et al. 2020). This algorithm is a stochastic forecasting model that estimates the probability distribution of future time series based on their previous trends. DeepAR uses a large time series data to train an autoregressive recurrent neural network model with an approach similar to long short-term memory (LSTM) neural networks. DeepAR has been proven as an efficient forecasting model that learns seasonal behaviors with minimal required manual intervention (Salinas et al. 2020).

The DeepAR algorithm models the future time series' conditional distribution based on past data. The process used for training and prediction using the DeepAR algorithm is represented in Figure 1.

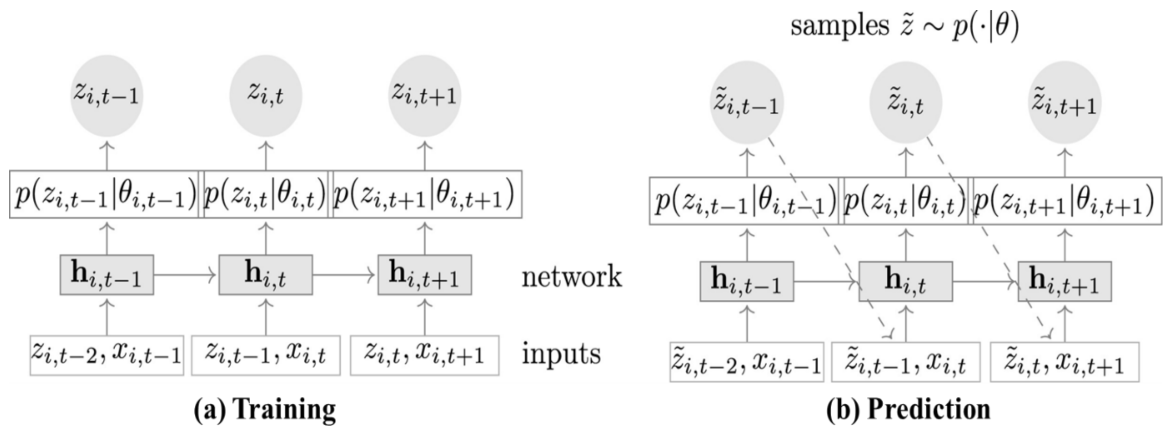

Figure 1. DeepAR training and prediction processes (adapted from Salinas et al. 2020)

Figure 1(a) shows the training process. Denoting *i* as the number of the timeseries and *t* as the time step, the model has the following input at each time point *t*: the covariate $x_{i,t}$, the target value at the previous time point $z_{i,t-1}$, and the previous network output $h_{i,t-1}$. The output of the network, $h_{i,t}= h(h_{i,t-1}, z_{i,t-1}, x_{i,t}, \Theta)$, is used to calculate the parameters θ of the likelihood distribution $p(z|\theta)$; where $\theta_{i,t}=\theta(h_{i,t}, \Theta)$. In the training process (see Figure 1a), the past value of the time series, $z_{i,t}$, are known and seen by the model; where Θ refers to the parameters of the model (e.g., the number of neurons, the number of layers, etc.) and θ refers to the parameters of the likelihood function (e.g., the mean and standard deviation for a Gaussian distribution). Moreover, Θ is learned by the model through maximizing the log-likelihood. For the prediction process (see Figure 1b), the past values, $z_{i,t}$, are not seen by the model, rather a sample $\tilde{z}_{i,t} \sim p(\cdot|\theta)$ is drawn by Monte-Carlo simulations and fed as inputs for the next point (Huang et al. 2021). In summary, the DeepAR models the conditional distribution according to Equation 1 (Jiang et al. 2021).

$$P\left(z_{i,t_0:T}\middle|z_{i,1:t_0-1}, x_{i,1:T}\right) = \prod_{t=t_o}^{T} P\left(z_{i,t}\middle|z_{i,1:t-1}\,, x_{i,1:T}\right) = \prod_{t=t_o}^{T} P\left(z_{i,t}\middle|\theta(h_{i,t}, \Theta)\right) \qquad (1)$$

Where t_0 is the start of the prediction time, the range 1 to t_0 - 1 is the conditioning range, and the range t_0 to T is the prediction range.

By following this approach, the DeepAR model was implemented for each of the four construction materials considered in this paper (see Table 1). Finally, it is worth mentioning that no covariates were used in the developed DeepAR model.

DeepAR Evaluation. To assess the prediction accuracy of the developed stochastic model, the model performance was evaluated using the following metrics: the root mean square error

(RMSE), MAPE, and normalized deviation (ND) as presented in Equations 2-4 (Jiang et al. 2021, Salinas et al. 2020).

$$RMSE = \sqrt{\frac{1}{T} \times \sum_{t=1}^{T} (\hat{z}_t - z_t)^2} \tag{2}$$

$$MAPE = \frac{1}{T} \times \sum_{t=1}^{T} \left| \frac{\hat{z}_t - z_t}{z_t} \right| \times 100\% \tag{3}$$

$$ND = \frac{\sum_t |z_t - \hat{z}_t|}{\sum_t |z_t|} \tag{4}$$

Where, z_t is the actual ground truth value at time *t*, $\hat{z}_t$ is the predicted value at time *t*, and *T* is the number of samples used in the testing set.

Moreover, to ensure the development of the optimal model, tuning of the hyperparameters was performed. In relation to that, the tuned hyperparameters in this paper include: the number of layers, number of cells, and the context length. The number of layers is equal to the number of layers in the recurrent neural network, the number of cells is that used in each layer in the recurrent neural network, and the context length is the number of time-points that are seen by the model prior to prediction or those that are used for the prediction. These three hyperparameters were tuned to ensure a minimal RMSE, MAPE, and ND for each prediction model of the four studied ingredients using the 5-fold cross validation grid search method.

RESULTS

As explained in the Methodology section, the DeepAR algorithm was implemented for the following 4 construction materials: Concrete products, Concrete ingredients, Paving, and Iron and steel. The obtained optimal hyperparameters for the different material are presented in Table 2.

Table 2. Optimal hyperparameters of the DeepAR model for the different material

Material	Optimal Number of Layers	Optimal Number of Cells	Optimal Context Length
Concrete products	12	32	3
Concrete Ingredients	12	32	3
Paving mixtures and blocks	7	29	3
Steel and iron	9	35	17

Using the obtained optimal hyperparameters (see Table 2), the 4 DeepAR models were implemented to forecast the PPI of the associated construction material. Furthermore, since DeepAR is a probabilistic forecasting method, it provides prediction intervals and median predictions rather than point predictions. A prediction interval is defined as the interval that has a lower and upper bound with coverage probability to show its accuracy (Kavousi-Fard 2016). For instance, a 90%-prediction interval means that it is 90% certain that the actual target value falls between the upper and lower bound of the interval (Jørgensen and Sjoeberg 2003).

Figure 2 presents the actual observations or values for the PPI of concrete products, the median prediction of the last year (obtained from the developed DeepAR model), the 90% prediction interval of the last year (obtained from the developed DeepAR model), and the 50% prediction interval of the last year (obtained from the developed DeepAR model).

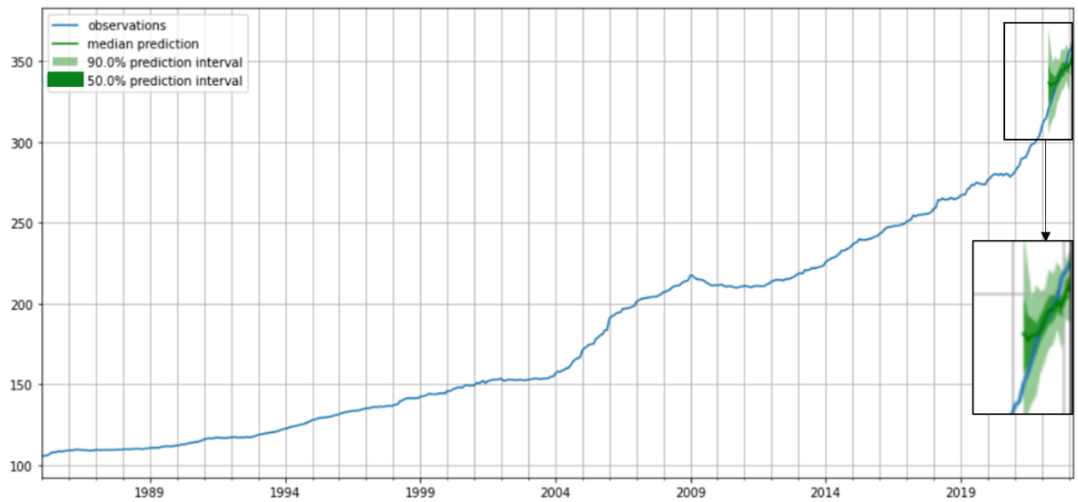

Figure 2. Concrete products PPI observations and predictions

Figure 2 shows a great increase in the PPI of concrete products around year 2021 (which is the year where the COVID-19 outbreak reached its peak). Moreover, using a context length of 3 months, the DeepAR was efficiently capable of predicting the PPI values of concrete products with a median value very close to the actual observed values. That being said, the last 3 months prior to the prediction were enough to capture the variation of the PPI of concrete products.

Similarly, Figure 3 presents the actual observations and predicted values of the PPI of the concrete ingredients.

Figure 3 shows that the concrete ingredients have witnessed continuous increases in the PPI both pre- and post-COVID-19 conditions. Also, the developed DeepAR was capable of capturing this increase and accurately predicting the PPI.

Furthermore, Figure 4 presents the actual observations and predicted values of the PPI of the paving mixtures and blocks.

Figure 4 indicates that the PPI of paving mixtures and blocks have witnessed some increases and decreases in the PPI. Despite the continuous and random changes in the PPI, the developed DeepAR was still capable of predicting PPI that are very near to the actual observations for the last 12 months.

Finally, Figure 5 presents the actual observations and predicted values of the PPI of the iron and steel materials.

Figure 5 shows that the iron and steel materials are affected by high uncertainties, where the PPI values changes dramatically over the years with several ups and downs. The PPI reached a peak between 2021 and 2022, then it decreased. As shown in Figure 5, the developed DeepAR model was capable of accurately predicting the values of the PPI corresponding to the last 12 months.

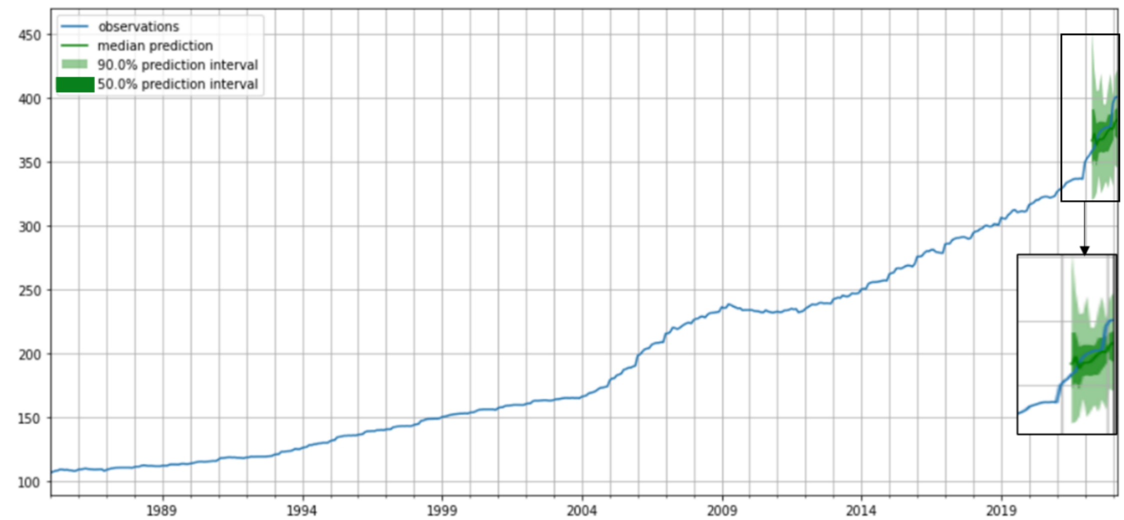

Figure 3. Concrete ingredients PPI observations and predictions

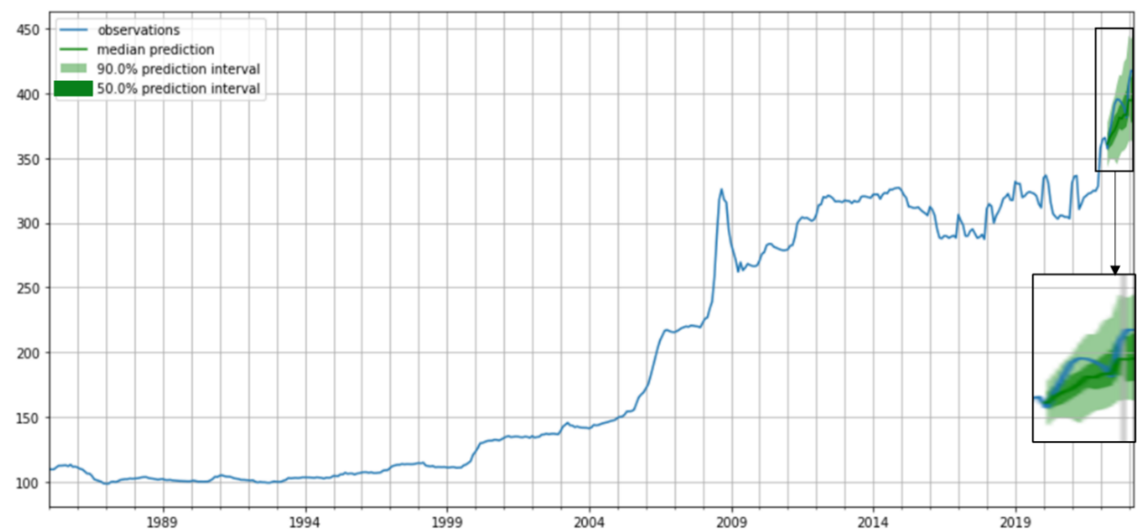

Figure 4. Paving mixtures and blocks PPI observations and predictions

To quantitatively assess the accuracy of the proposed stochastic models, the evaluation metrics on the testing set were obtained as shown in Table 3.

Table 3 shows that the RMSE of the four developed DeepAR models are considered low, the MAPE of the four models is less than 5% and thus the models are considered accurate forecasting models (Swanson 2015), and all the ND are less than 10%. Thus, the four stochastic models developed and proposed in this study are considered accurate prediction models to estimate or predict the prices of the construction materials.

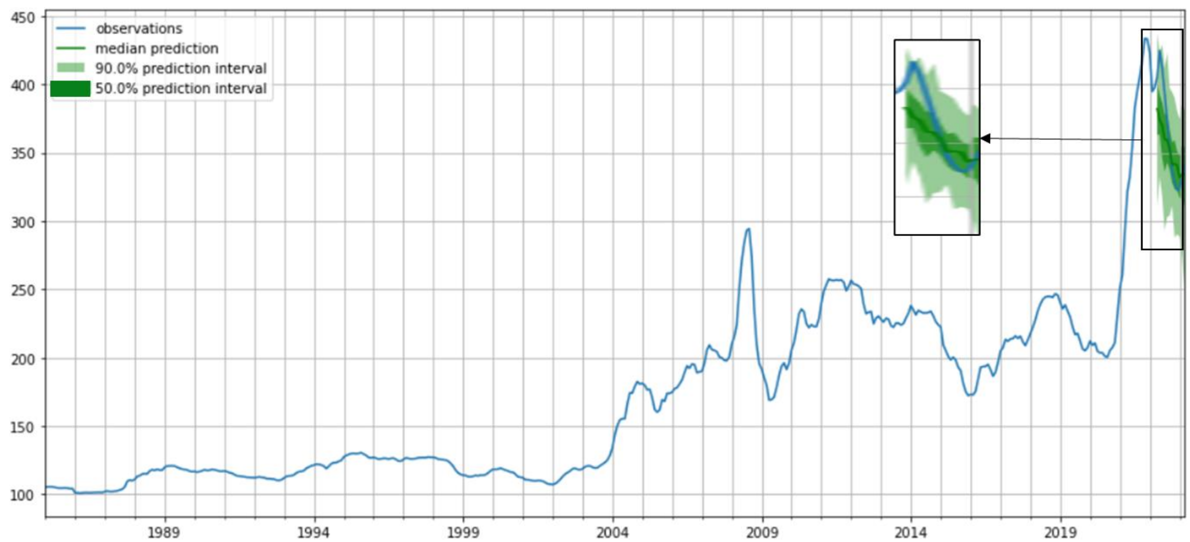

Figure 5. Iron and steel PPI observations and predictions

Table 3. Performance evaluation metrics for the different material

Material	RMSE	MAPE	ND
Concrete products	7.23	0.01	0.01
Concrete Ingredients	13.90	0.02	0.02
Paving mixtures and blocks	12.95	0.03	0.03
Steel and iron	24.66	0.04	0.05

CONTRIBUTIONS

This paper provides many contributions to the body of knowledge and has various practical implications. First, in contrast to traditional deep learning or machine learning method (such as artificial feed-forward neural networks, LSTM networks, etc.), the proposed stochastic model in this paper works by estimating the parameters of a probability distribution (rather than simply computing the predictions themselves), and then the probability distribution is sampled to produce probabilistic predictions of future material prices. In other words, the proposed stochastic model does not estimate the time series' future values but their future probability distribution. Second, compared to existing, traditional cost estimation models, the proposed approach in this paper makes probabilistic forecasts in the form of Monte Carlo samples that can be used to compute consistent quantile estimates in the prediction horizon (such as the median values, the 50% confidence intervals, and the 90% confidence intervals), which offers project stakeholders a better understanding of the potential risks in price fluctuations of their construction material. These probabilistic estimates help all project parties in having more realistic expectations and estimates for current and future material prices. This ultimately contributes to having more accurate estimation of project costs and thus leading to lower project cost overruns, minimal disputes between project parties, and consequently to improved project performance. Third, the proposed approach in this paper proves that it can predict the trends and fluctuations in different construction materials under uncertain market conditions by producing accurate probabilistic forecasts. While the proposed approach in this paper was applied to the following 4 construction materials: concrete products, concrete ingredients, paving mixtures and blocks, and steel and iron, future research studies are recommended to expand the proposed stochastic models to other construction materials that are frequently used in the construction industry. This will ultimately help in showing the capabilities of the proposed approach in modeling different construction material and their associated trends and price uncertainties.

CONCLUSION

One of the main hurdles faced in the construction industry is project cost overruns due to market uncertainty and price escalations. Such cost overruns could impact the overall performance of the project as well as its schedule. Thus, having accurate cost or budget estimation is critical for ensuring the success of any construction project. However, due to the constant change in construction material prices and their associated high uncertainties due to different market conditions (such as the steel tariffs, the COVID-19 outbreak, and the Ukraine-Russian conflict), most projects are being inefficiently budgeted. So, an accurate estimation of the prices of construction material is needed to hedge against prices changes. To that extent, this paper proposed a stochastic model that estimates the PPI of four main construction materials: concrete products, concrete ingredients, paving mixtures and blocks, and iron and steel using a probabilistic forecasting approach based on autoregressive recurrent networks using the state-of-the-art DeepAR algorithm. To optimize the developed models, the hyperparameters were tuned to minimize the RMSE of each model. The optimal hyperparameters for each model along with its evaluation metrics (the RMSE, MAPE, and ND) are presented. The results show that each construction material requires distinct model parameters and that materials that are associated with great cost uncertainties and changes, such as the iron and steel, requires to see more timesteps to accurately predict future values compared to materials with less changes. Finally, the findings of this study provide decision-makers with an accurate model that predicts the prices of different construction material to ensure an adequate budgeting for their projects and hedge over price changes and inflation. Moreover, the developed model is capable of capturing costs risks through predicting the probability distribution of the price of construction materials rather than just a point probability. Also, the significance of forecasting prediction intervals lies in presenting the uncertainty in the forecasts. Thus decision-makers are equipped with a method that not only predict the cost of construction material, but rather provide them with 50% and 90% confidence that the value will fall in the predicted intervals. Such forecasting is significant in risk analysis specifically in determining the risk of a project for falling out of budget. Finally, future work could aim to integrate sensitivity analysis with the developed model to identify features that affect the prediction model the most.

REFERENCES

Assaad, R., El-Adaway, I. H., and Abotaleb, I. S. (2020). Predicting project performance in the construction industry. *Journal of Construction Engineering and Management*, 146(5), 04020030.

Assaad, R., and El-adaway, I. H. (2021). Guidelines for responding to COVID-19 pandemic: Best practices, impacts, and future research directions. *Journal of management in engineering*, 37(3), 06021001.

Assaf, G., and Assaad, R. H. (2023). Key Decision-Making Factors Influencing Bundling Strategies: Analysis of Bundled Infrastructure Projects. *Journal of Infrastructure Systems*, 29(2), 04023006.
Dharwadkar, N. V., and Arage, S. S. (2018). Prediction and estimation of civil construction cost using linear regression and neural network. *International Journal of Intelligent Systems Design and Computing*, 2(1), 28-44.
Elfahham, Y. (2019). Estimation and prediction of construction cost index using neural networks, time series, and regression. *Alexandria Engineering Journal*, 58(2), 499-506.
Faghih, S. A. M., and Kashani, H. (2018). Forecasting construction material prices using vector error correction model. *J. construction engineering and management*, 144(8), 04018075.
Huang, J., Huang, Y., Hassan, S. G., Xu, L., and Liu, S. (2021). Dissolved oxygen content interval prediction based on auto regression recurrent neural network. *Journal of Ambient Intelligence and Humanized Computing*, 1-10.
Jiang, F., Awaitey, J., and Xie, H. (2022). Analysis of construction cost and investment planning using time series data. *Sustainability*, 14(3), 1703.
Jiang, F., Han, X., Zhang, W., and Chen, G. (2021). Atmospheric PM2. 5 Prediction Using DeepAR Optimized by Sparrow Search Algorithm with Opposition-Based and Fitness-Based Learning. *Atmosphere*, 12(7), 894.
Jiang, H., Xu, Y., and Liu, C. (2013). Construction price prediction using vector error correction models. *Journal of Construction Engineering and Management*, 139(11), 04013022.
Jørgensen, M., and Sjoeberg, D. I. K. (2003). An effort prediction interval approach based on the empirical distribution of previous estimation accuracy. *Information and software Technology*, 45(3), 123-136.
Kavousi-Fard, A. (2016). Modeling uncertainty in tidal current forecast using prediction interval-based SVR. *IEEE Transactions on Sustainable Energy*, 8(2), 708-715.
Oshodi, O. S., Ejohwomu, O. A., Famakin, I. O., and Cortez, P. (2017). Comparing univariate techniques for tender price index forecasting: Box-Jenkins and neural network model. *Construction Economics and Building*, 17(3), 109-123.
Pewdum, W., Rujirayanyong, T., and Sooksatra, V. (2009). Forecasting final budget and duration of highway construction projects. *Eng., Construction and Architectural Management*.
Salinas, D., Flunkert, V., Gasthaus, J., and Januschowski, T. (2020). DeepAR: Probabilistic Neural networks model for prediction of construction material prices in Egypt using macroeconomic indicators. *Journal of Construction Engineering and Management*, 146(3), 04020010forecasting with autoregressive recurrent networks. International Journal of Forecasting, 36(3), 1181-1191.
Shiha, A., Dorra, E. M., and Nassar, K. (2020).
Steel Time International. (2022). Steel Times International March 2022. Accessed April 30, 2023. https://issuu.com/quartzbusinessmedia/docs/steel_times_international_march_2022.
Swanson, D. A. (2015). On the relationship among values of the same summary measure of error when used across multiple characteristics at the same point in time: an examination of MALPE and MAPE. *Review of Economics and Finance*, 5(1).
US Bureau of Labor Statistics. (2023). Producer Price Indexes. Accessed April 20, 2023. https://www.bls.gov/ppi/.