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Modeling the trend of construction materials industry with NARNETs

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Abstract

The price of materials is dependent on different factors such as raw material costs, production costs, and cost of logistics. The construction industry professionals face difficulties in times when there are fluctuations in material prices. This study aimed to model the expectancy of trends in material prices through a time series analysis, as the expectancy of trend is a time dependent dataset. . In this context, the study is focused on utilization of a special type of ANN (and special type of RNN) architecture known as Nonlinear Autoregressive Neural Network (NARNET). Ten different NARNET configurations were implemented in MATLAB and their performance were tested in the study. The results have shown that NARNETs are able to model the expectancy of trend accurately.

Introduction

The cost of a construction is dependent on several factors, including the direct costs such as the cost of labour, the cost of machinery and equipment, material cost, and other indirect costs such as site mobilization. The price of materials is one of the components of the direct costs and is dependent on different factors such as raw material costs, production costs, and the cost of logistics. The construction industry professionals, especially contractors face difficulties in times when there are fluctuations in material prices. These fluctuations make it difficult to foresee the material prices, which then lead to uncertainties in decision making in the procurement processes. Unexpected price changes can cause cost overruns in the project budgets, which would then cause difficulties both for the owner and the contractor. There are several indicators developed in different countries that provide insights to industry professionals regarding material prices. In Turkey, IMSAD (The Association of Turkish Construction Material Producers) provides an economical indicator that can be defined as (the expectancy of) trends in material prices. This indicator provides insights to professionals in Turkish Construction Industry regarding the trends of the material prices. This study aimed to model (the expectancy of) trends in material prices through a time series analysis, as the expectancy of trend indicator provided by IMSAD is a time dependent dataset.

Time series analysis is used for different purposes in construction industry. Time series estimation methods such as ARIMA, ANN, Hybrid ARIMA-ANN were implemented for different purposes. For example, [1] aimed to estimate the production level of the construction industry in China and investigated whether the forecasting performance can be improved by using neural network (ANN) models for short-term forecasting. [2] aimed to develop a model to estimate the early design construction costs of building projects using an Artificial Neural Network (ANN) model. 169 case studies from the construction industry were collected to develop the ANN model and identify key parameters for building project costs. In order to estimate the Construction Cost Index, [3] used Linear Regression and Autoregressive Time Series (ARIMA), Artificial Neural Networks (ANN) methods. In this study we concentrate on the use of special type of ANNs (i.e., NARNET) for estimation of the (expectancy of) material price trend indicator. The following sections will elaborate on the dataset, the NARNET modelling method used in this study, and later will present the configurations and accuracy metrics of the tested models.

Material and Method

In this study we statistically model "General Trend in Construction Materials Industry" indicator of the Trust Index of IMSAD, which is indicating the expectancy of the trend in material prices. The indicator value is determined as a response to the question "How has your view of the general trend in the construction materials industry in which you operate this month change compared to your view in the previous month?". The base value for the index (and all indicators) is 100, which is equal to the indicator value of August 2013 (base year/month). The dataset is obtained through digitization of reports in İMSAD web site and covers the indicator values between 08.2013-03.2021. The dataset consists of a single variable, and is in form of a univariate time series. In the first stage, we have checked the ACF and PACF plots of the dataset, at level and the plots indicated significant autocorrelations until Lag22. In contrast, both ACF and PACF plots of first difference of the series tend to degrade into the confidence interval quickly in Lag2 (Fig 1.). In order to use a stationary time series, we decided to use the first difference of the series in our estimation.

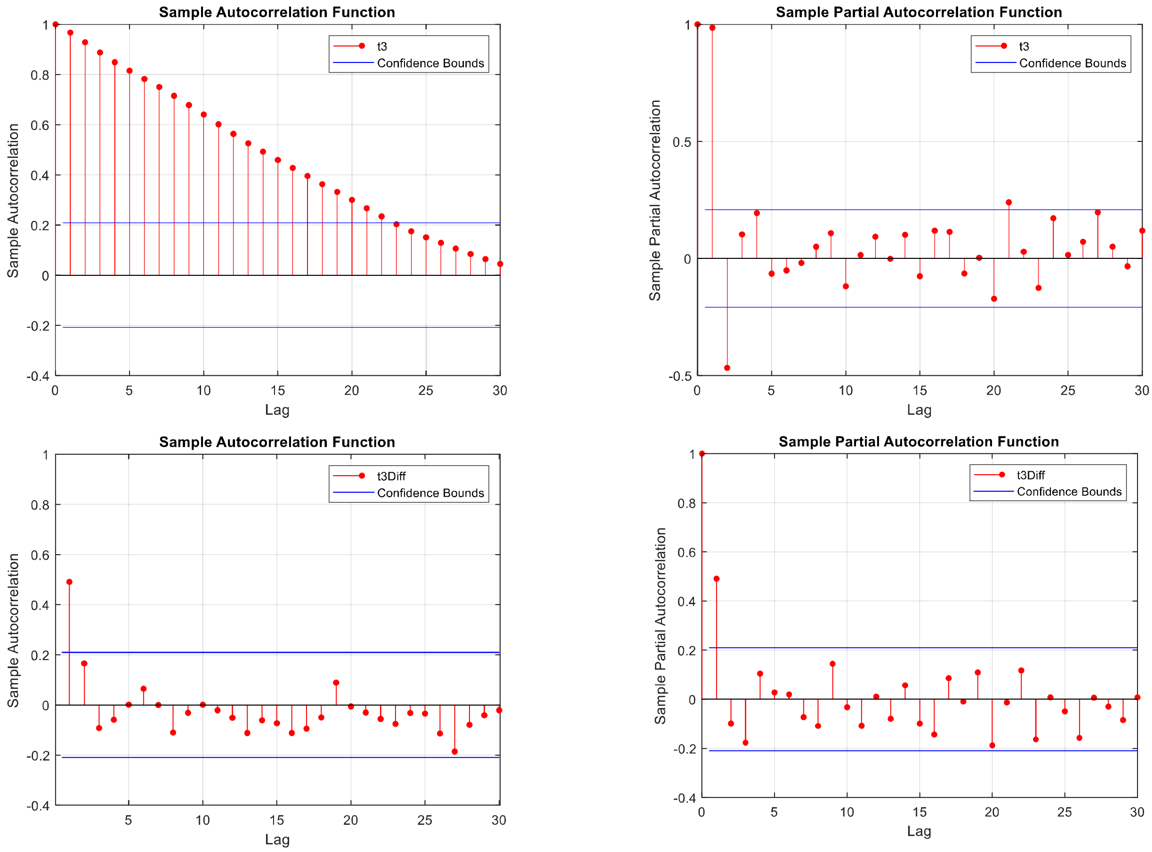

Figure 1. ACF and PACF graphs of the dataset at level(up) and at first difference(down)

As mention earlier, in this study, we have implemented a NARNET architecture to estimate the (expectancy of) Trend in Construction Materials Industry. The Nonlinear Autoregressive Neural Network (NARNET) is a Recurrent Neural Network (RNN) which can be written in the following form:

$$Y_t = h(Y_{t-1}, Y_{t-2}, \ldots\ldots Y_{t-p}) + \varepsilon_t$$

The function h(.) is unknown in advance, and the training of the neural network is aimed at fitting the function by means of the optimization of the weights of the network and bias of neurons. In a NAR network, the network is trained as an open-loop network with feeding in the real values of the target variable as the response variable and after the training the network performs a one-step ahead prediction. In order to perform a multi-step ahead (out-of-sample) predictions a closed-loop network need to be configured [4-5].

In this study we have tested a series of NARNET architectures through modification of a code generated by Neural Network Time Series App of the MATLAB software. 10 different NARNET configurations have been tested by considering 5 different layer sizes [1,2,2,3,5] and 2 different Feedback Delays types [1, 1:12], for one-step-ahead prediction. The train-test split approach is used for validation, where 60/10/30 % of the data is used for training, validation, and testing. The training set covered 55 values, validation set covered 9 values and the test set included 27 values. Each architecture has been trained 500 times and the best (minimum) Root Mean Square Error (RMSE) scores calculated for the Test Set has been used as the performance metric of the tests. The code and dataset used in the tests is available at [6].

Results

The NARNET configuration tested included an input layer, a single hidden layer, and an output layer. As illustrated in Table 1., the accuracy of the estimation changes slightly depending on the number of neurons used in the hidden layer (referred to as Layer Size). In addition, the number of Feedback Delays has either minor(negative) or insignificant impact on estimation accuracy.

Table 1. Accuracy metrics of different NARNET configurations

Layer Size	Feedback Delays	Mean RMSE Test Set	Feedback Delays	Mean RMSE Test Set
1	1	1.2716	1:12	1.2716
2	1	1.2651	1:12	1.2716
3	1	1.1995	1:12	1.2148
4	1	1.1580	1:12	1.1718
5	1	1.1580	1:12	1.1597

The best among the best RMSE scores of each configuration was achieved with NARNETs having 4/5 neurons in the hidden layer at the configurations with single Feedback Delay as an input (RMSE:1.1580). The worst performance among best RMSE scores of each configuration was identified at configurations having 1 neuron on the hidden layer with single Feedback Delay as an input (RMSE:1.12716), and at configurations having 1/2 neuron(s) on the hidden layer with 1:12 Feedback Delays as input.

Discussion & Conclusion

This study focused on modeling the expectancy of trends in material prices with a time series analysis. The literature in the field indicates the use of several different methods for time series analysis, ranging from ARIMA, Hybrid ARIMA to ANN. In this research, we focused on utilization of a special type of ANN (and special type of RNN) architecture known as Nonlinear Autoregressive Neural Network (NARNET). We have implemented 10 different NARNET configurations in MATLAB and tested their performance in terms of best RMSE scores that can be achieved in 500 train/test rounds. The search approach implemented for discovering the best RMSE scores for each NARNET configuration was a brute-force/uniformed search. The median of the search time was 12 seconds on a desktop computer with i5-9600K CPU. The accuracy metrics of different NARNET configurations indicate that increasing the number of neurons would help in achieving better accuracies, but when optimum number of neurons is reached it is advisable that the principal of parsimony needs to be considered, and the number of neurons should not need to be increased when targeting for better accuracies, especially in small datasets like the one in this study. The ACF and PACF graphs of the first difference of the series (i.e., trained/tested with NARNETs) shows signs of first order Autoregressive Model/Moving Average Model. In this situation, it can be proposed that for a NARNET trained as an open-loop network (where feedback delays = real values of the target variable), the lagged values of the series other than Lag1, would not have a significant contribution to accuracy of the series. This proposal is reinforced with accuracies achieved by the training/testing of the configuration with 1:12 Feedback Delays, where we seek the possible impact of seasonality or any other effect (which would most probably be eliminated through differencing), along with the autoregressive nature of the series. The results of the tests have shown that adding more Feedback Delays would have minor inverse effect on the accuracy. In terms of number of Feedback Delays that would be input into NARNET architectures, the principal of parsimony should also be considered especially when working with differenced series.

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