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TIME SERIES ANALYSIS OF CONSTRUCTION COST INDEX USING WAVELET TRANSFORMATION AND A NEURAL NETWORK

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ABSTRACT

Construction Cost Index (CCI) is widely used to analyze the construction cost variation in time. It can convert the present construction cost to the future or to the past. The current practice of the future cost estimation is simply an extrapolation of the past CCI, which often leads to the inaccurate estimation of future construction cost. This paper presents a new CCI forecasting model using wavelet transformation and an artificial neural network. Preliminary tests showed that the proposed method produced the short-term range of a future CCI with a greater accuracy as well as a higher reliability compared to existing methods.

KEYWORDS

Construction Cost Index, Forecasting, Time Series Analysis, Wavelet Transform, Neural Network

1. INTRODUCTION

In cost estimating practices, careful consideration should be given to predicting the cost change of a construction project. Labor, material and equipment cost tend to rise over time, so a proper adjustment needs to be made to the initially estimated construction cost. Construction Cost Index (CCI) is a kind of price index for the construction industry. It is widely used for its ability and simplicity to convert the present construction cost to the future or the past. Major cost items are monitored and weighted, then processed to a CCI. Thus, a CCI is representative of general construction cost changes in a region.

A range of efforts have been made to produce and forecast a CCI. Each country or region has their own CCI different from those of other regions. The local social and economic situations are reflected in the different CCIs. The current practice of a CCI prediction, however, is largely based on a simple extrapolation of the past CCI. This simple extrapolation approach often leads to the inaccurate estimation of future construction cost. Thus, a strong need exists to develop a more accurate cost prediction method for CCI. A back-propagation neural-network model was developed to predict the change in the ENR construction cost index for one month and six months ahead (Trefor, 1994). However, the prediction accuracy of the neural network model was not superior to either exponential smoothing or linear regression methods.

The objective of this study is to suggest a new CCI forecasting model that can produce the better accuracy compared to existing methods. When it is possible to accurately predict the future CCI, there exists a better chance to get accurate estimation of future construction costs. To this end, wavelet transformation and artificial neural networks constitute the proposed methodology. Wavelet transformation is used to get rid of unnecessary noisy data from the past construction cost indices, while an artificial neural network is used to forecast the future construction cost index based on the refined past index data.

2. TIME SERIES ANALYSIS OF CONSTRUCTION COST INDEX

2.1 Construction Cost Index Variations

This study used the CCI data published in Korea. The official CCI data have been published since February 2004 by the Korea Institute of Construction Technology (KICT). This CCI is a analytic statistics data, based on a Korea Producer Price Index and an Inter-industry Relation Table. However, the authors extended time range to 1995 using the KICT methodology to secure sufficient amount of data for prediction model development. Figure 1 shows the monthly change in CCI for 140 months from January 1995 to July 2006.

As shown in Figure 1, the CCI increases over time, however it shows many small fluctuations in short intervals such as several months. For 84.9% of the data, monthly change ranges between 0 to 1%, however some cases differs by over 3% reflecting the economic situations at that particular times. For example, the leap increase around 1998 was the result of critical changes due to the financial meltdown that severely attacked Asian countries. As shown, construction costs can vary over time with changes in demand, economic conditions, prices and etc. (Trefor, 1994).

2.2 Data De-noising

Wavelet transformation is a "method that analyses time-frequency localization with fixed window size and with changeable time-windows and frequency-windows" (Meyer, 1993). By using wavelet analysis, longer time windows can be used to detect low frequency information, while shorter time windows are used to detect high frequency information. Wavelet transformed signal is decomposed into components that different scales. This offers a "method for a local outlook of the signal, a multi-scale outlook, and a time-scale analysis" (Misiti et al., 1996). Thus it can be used as a tool for performing a wide range of tasks which include: detecting discontinuities in signals, detecting trends, analyze time-frequency, de-noising and compression of signals (Khaled and A. Ramachandra, 2000).

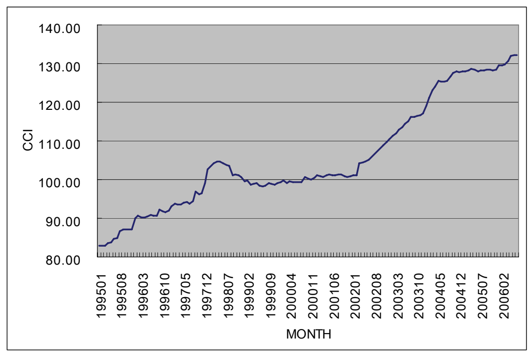

Figure 1 Construction Cost Index (KOREA)

As stated, CCI varies with many factors; some factors have influenced on the CCI for a longer time of period, some for only short time period. The latter particularly results in noisy data in the process of predicting the future CCI, which disallows accurate prediction. In this study, wavelet transform is used to de-noise raw CCI data. The raw data was first de-noised by fixed form thresholding in the wavelet domain. Figure 2 shows the de-noised data compared with origin data. This processing was conducted using a MATLAB 7.1 wavelet toolbox. Monthly difference of de-noised CCI data was used as input data for a back-propagation neural network model.

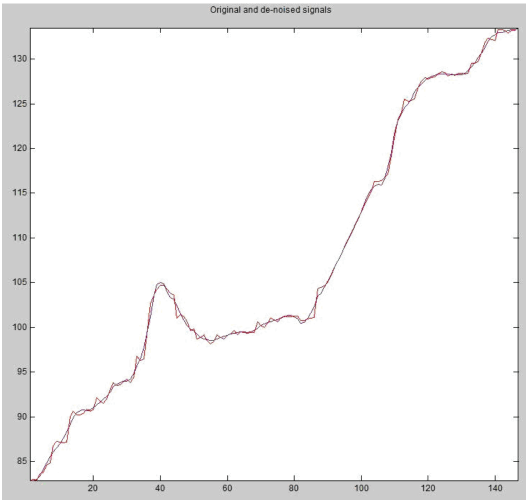

Figure 2 Original and De-Noised CCI
(X axis: Month, Y axis: CCI)

2.3 Prediction Using Neural Network

Artificial Neural Networks is a model that mimics human nerve system. In this study, the Back-Propagation Network is used for forecasting future CCI. As previously mentioned, de-noised CCI data's monthly difference were used for the neural network. The number of hidden layer is set to be 2, and the mean square error is used as a performance function for error evaluation.

A total of 147 months of CCI data were used for neural network training and testing (January 1995 to March 2007). Based on the de-noised CCI data, a total of 130 training sets and seven testing sets were prepared as follows:

- CCIs for month 1 to 10 are used as input data, and the 11th CCI is used for output data; the total of 11 monthly CCIs constitute a training set.
- CCIs for month 2 to 11 are used as input data, and the 12th CCI is used for output data; the total of 11 monthly CCIs constitute a training set.
- In this way, a total of 130 training sets are prepared and used to train the back propagation neural network.
- CCIs for month 131 to 140 are used as input data, and the 141st CCI is used for output data; the total of 11 monthly CCIs constitute the first testing set.
- CCIs for month 132 to 141 (the 141st CCI is the one calculated from the trained neural network) are used as input data, and the 142nd CCI is used for output data; the total of 11 monthly CCIs constitute the first testing set.
- CCIs for month 133 to 142 (the 141st and 142nd CCI are the ones calculated from the trained neural network) are used as input data, and the 143rd CCI is used for output data; the total of 11 monthly CCIs constitute the second testing set.
- In this way, a total of 7 testing sets are prepared to test the trained neural network.

Table 1 shows that comparison of predicted CCI and actual CCI of the seven test sets.

Table 1 CCI Comparison

Month	Actual CCI	Predicted CCI	Difference
Sep.2006	133.3	133.4	0.1
Oct.2006	133.3	133.6	0.3
Nov.2006	133.2	132.9	-0.3
Dec.2006	132.9	133.1	0.2
Jan.2007	133.2	133.4	0.2
Feb.2007	133.2	133.7	0.5
Mar.2007	133.5	134.0	0.5

2.4 Comparison With Other Forecasting Techniques

To check the usefulness of the suggested model, the results were compared with those of three other forecasting techniques: a moving average method, an exponential smoothing and a neural network without de-noise processing. A moving average method and an exponential smoothing are widely used due to its simplicity, computational efficiency and reasonable accuracy (Montgomery and Johnson, 1976). Prediction results were obtained using the four models for the same test period (7 months) with the same input data.

Figure 3 shows the comparison graphs of actual CCI, the proposed model, a moving average method, an exponential smoothing and a neural network without de-noise processing. Table 2 shows the sum of the squares of errors (SSE, Eq.1) of each model.

$$SSE = \sum_{i=1}^{n} (P - A)^2 \qquad (1)$$

(P= Predicted CCI by each model, A= Actual CCI)

The proposed model cannot produce as accurate predictions as actual data (Table. 2), however it gives the most accurate results among the four prediction models. It is noticeable to note that the neural network without denoising process produced the worst results. Wavelet-based denoising process is a powerful tool to increase the CCI prediction accuracy.

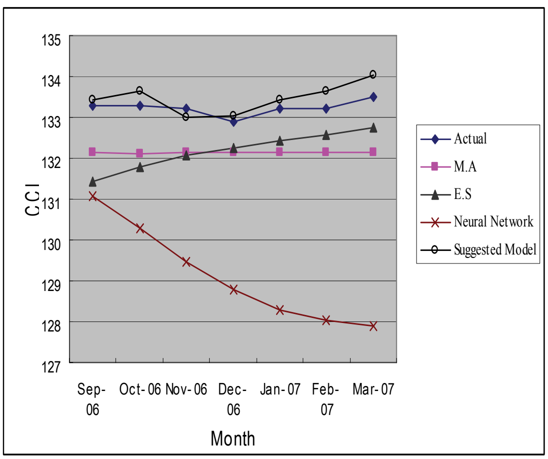

Figure 3 Comparison Graph

Table 2 SSE Comparison

Forecasting technique	SSE
Moving Average (2months)	8.6
Exponential Smoothing	9.1
Neural Network	127.04
Neural Network with De-noise	0.72

3. CONCLUSION

The objective of this study is to suggest a new model for accurately predicting a future CCI. In construction, the ability to predict trends in prices is very important for more accurate bids and reliable planning. Although the back-propagation neural network is a powerful tool to recognize patterns, it was inferior at CCI prediction due to the complex patterns and noisy signals of the periodic CCI data. The proposed model relied on the back-propagation neural network to predict a future CCI, but input CCI data is equipped with the pre-processing stage to get rid of unnecessary noisy data. The wavelet-based denoising process produced a much better chance of making more accurate prediction of future CCIs.

In this study, the new model was applied only for the prediction of seven CCIs. Further studies are required to verify and improve the model. The more training and testing sets will be used to produce a viable model that can predict the future CCIs in an accurate, reliable, and efficient way.

4. ACKNOWLEDGMENT

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