Development of Cycle Estimation Model of Construction Cost Index using Fractal Analysis

Seonghyeon Moon, blank54@snu.ac.kr
Seoul National University, Republic of South Korea

Duyon Kim, duyon.kim@gmail.com
Kyungil University, Republic of South Korea

Seokho Chi, shchi@snu.ac.kr
Seoul National University, Republic of South Korea

Minhyuk Jung, minstrl@gmail.com
Seoul National University, Republic of South Korea

Abstract
In the global market, the total amount of contracts of Korean construction companies has increased for about 10 years. However, the number of extreme cases of failures has been occur constantly. Many previous researches have indicated that a sudden change of the market is one of the most influential causes of the global construction market. Conventional methods that anlayze the construction market are commonly based on the regression approach, which assumes that there exist trends and statistical distributions in historical data, so that they have a limitation to predict a sudden change of the market. For those reasons, this research aims to develop an early warning system against a sudden change of the global construction market by focusing on Construction Cost Index (CCI). To achieve this objective, this research provides a brief overviews of previous researches to clarify the difference of the analysis concept of fractal analysis from others. The results of this analysis will have a contribution to supplement the deficiencies of the conventional methods and evolve construction market body of knowledge.

Keywords: Global construction market, construction cost index, early warning system, fractal analysis, cycle estimation.

1 Introduction

1.1 Research Background

Because of continuous decline in the domestic market, many construction companies in Korea have been trying to enter the global construction market such as South-East Asia or Middle East (ICAK 2016). The total amount of contracts of Korean contractors in the global market has increased for a decade, however, the number of the extreme cases of market failures has occurred continuously (Kim et al 2007). Figure 1 shows the trend of the contract amount of Korean contractors in the global construction markets and Figure 2 illustrated the profit rates with respect to time periods

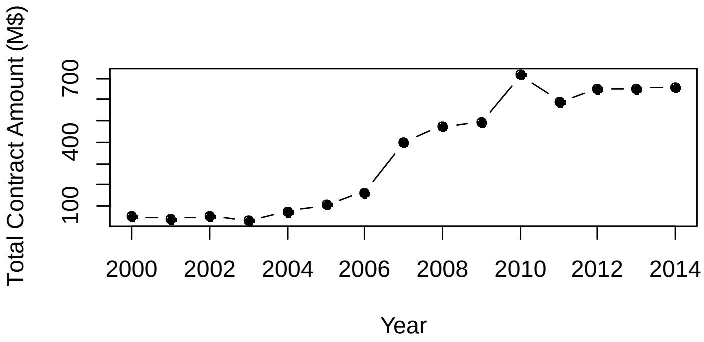

Figure 1 Contract amount of Korean contractors in global markets (ICAK 2016)

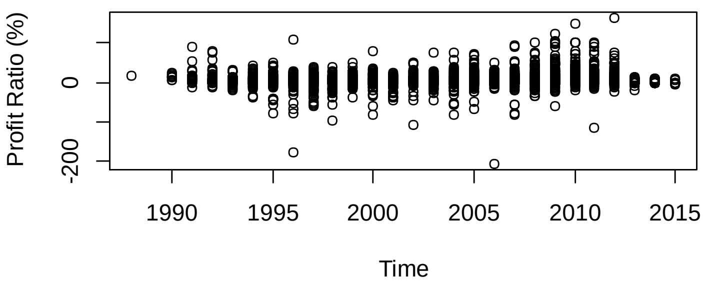

Figure 2 Profit rates with respect to time periods

Many researches revealed various causes of failures in the global construction markets. Han et al (2007) identified 64 influencing factors and suggested a hierarchical framework of a cause-and-effect relationship between the risk variables. Other studies established that a sudden change of market is one of the most significant causes of the global construction market failure (Griffis and Christodoulou 2000; Nasirzadeh et al 2008; Kim et al 2009).

1.2 Literature Review

Akintoye et al (1998) mentioned that the understanding of future trends in construction price is likely to influence the stakeholders of construction projects, and found out the relationship between macro-economic leading indicators of construction contract prices. These days, there are lots of previous research about Construction Cost Index (CCI), a typical market factor representing the U.S. construction market measured by a famous Indexing company – Engineering News-Record (ENR). Predicting CCI is very important, since construction players consider it for cost estimation, bid preparation, and investment planning on the global construction market (Williams 1994; Kim et al 2008; Hwang 2011; Lesniak 2013; Jiang et al 2013; Shahandashti and Ashuri 2013).

There exist two big concepts to analyze construction market based on CCI: Time-series analysis and Data-mining. Time-series means a sequenced data observed over a uniform time interval, hence the data is affected by the time (Cho and Son 2009; Shmueli et al 2012). Hwang (2011) estimated CCI using Autoregressive-Moving Average (ARMA) and Vector-Autoregressive Model (VARM). Other researches used Vector Error-Correction Model (VECM) to overcome the technical limitation of ARMA and VARM that require the stationarity of time-series data. (Wong and Ng 2010; Jiang et al 2013; Shahandashti and Ashuri 2013).

The other concept is data-mining techniques. Williams (1994) developed a back-propagation neural network model on the change of percentage of CCI. Lesniak (2013) and Wang et al (2013) developed an artificial neural network (ANN) and Support Vector Machine (SVM) model on project-level variables (type of works, project complexity, duration, etc.) to predict cost and schedule of construction project.

1.3 Problem Statement & Research Objective

The problem is that those conventional analysis methods are commonly based on the regression approach that assumes trends and distributions of historical data to be exist. The prediction results of conventional models depend on the past observations, which is limited to predict the sudden change of market. For this reason, construction companies have a difficulty in risk management in the global market.

This research aims to develop an early warning system against a sudden change of the global construction market. As a part of the objective, the research introduces a different analysis concept using fractal analysis that estimates every cycles of the market. The results will supplement the deficiencies of the conventional methods and evolve construction market body of knowledge. Furthermore, it is considered to achieve a progressed body of knowledge that supports decision making on the global construction market.

2 Methodology

2.1 Fractal Theory

A market fluctuates because of the result from the integration of some periodic or non-periodic cycles. To develop a cycle estimation model, the research studied Fractal theory. Fractal is a geometric phenomenon and mathematical set that has characteristics of self-similarity and recursiveness. The definitions of the fractal characteristics are following in table 1. Self-similarity is a characteristic that a special tendency or pattern is found at various resolutions of the system. Recursiveness is similar to repetitiveness, meaning that the tendency or pattern is found in the various regions of the system. Fractal analysis means identifying these fractal characteristics of a system (Peters 1994).

Table 1 Definition of Fractal Characteristics

Characteristic	Explanation
Self-similarity	A tendency of the system to be similar to parts of itself
Recursiveness	A parts of the system appear in the entire area

Fractal theory is known to explain the real world better than the classical model because it rarely assumes distribution of data (Mandelbrot 1985; Alvarez-Ramirez et al 2008; Kumar and Manchanda 2009; Sánchez-Granero et al 2012; Anderson and Noss 2013; Yin 2013; Abdulhadi 2015). Hence it is used in various fields of researches. Mandelbrot (1985) designed the fractal concept to forecast the amount of rain. In a statistic field, the fractal theory is used for detecting outliers (Mohammadi 2010). Topper and Lagadec (2013) introduced a new crisis management approach based on the fractal theory. Recently, fractal theory is widely used in economic researches, such as estimating the stock market behavior (Alvarez-Ramirez et al 2008; Kumar and Manchanda 2009; Sánchez-Granero et al 2012; Anderson and Noss 2013; Yin 2013; Abdulhadi 2015).

2.2 Fractal Analysis in Time-series

the characteristics of fractal (i.e., self-similarity and recursiveness) are found in time-series data in the form of different period of cycles. Figure 3 shows an example of time-series integrated by 4 different periods of cycles and amplitudes. The large peak between index 4 and 8 is shaped very similar to the small peak ranged between index 2 and 4; self-similarity. A small peak ranged between index 2 and 4 looks similar to the other small peak ranged between index 8 and 10; recursiveness. Figure 4 shows the component cycles of the example in figure 3. Fractal analysis in time-series is to identify every cycle and estimate each period of cycles like figure 4. If every cycle of the system is identified, a sudden change of the system would be explained better by re-integrating the decomposed cycles.

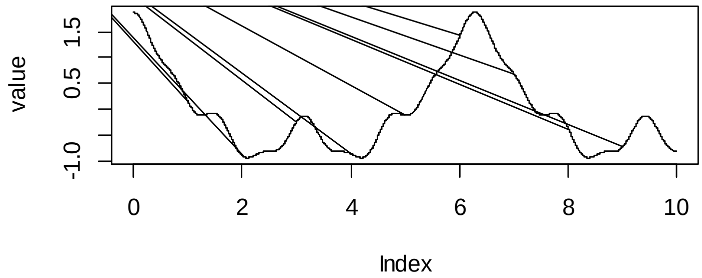

Figure 3 Example of Fractal in Time-series

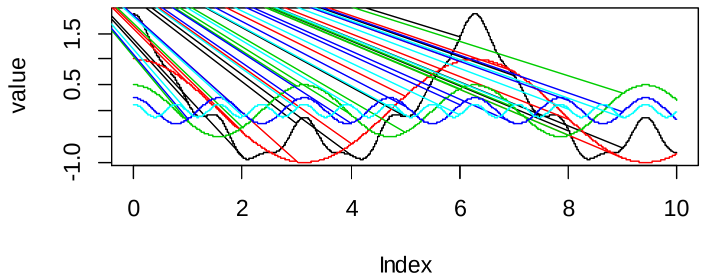

Figure 4 Example of Fractal in Time-series (Decomposed Version)

2.3 R/S Analysis

Rescaled range (Range/Scale; R/S) analysis is the most general concept of the fractal analysis for time-series data (Peters 1994; Kumar and Manchanda 2009; Yin et al 2013; Abdulhadi et al 2015). The basic logic of the R/S analysis is that a range of the cycle never grows bigger than the amplitude.

The process of calculating R/S is following. First, rescale or "normalize" the time-series data x_t to the adjusted range R_n, as provided in equation (1) to (3)

$$Z_r = x_r - \bar{x}\ (\mathrm{r} = 1, \dots, \mathrm{n}) \qquad (1)$$

$$Y_i = \sum_{r=1}^{i} Z_r \ \ (i = 1, \dots, n) \qquad (2)$$

$$R_n = \max(Y_1, \dots, Y_n) - \min(Y_1, \dots, Y_n) \qquad (3)$$

where n is the length of the sub section from the whole data points, that is a resolution of the time-series data, namely, the scale. Second, the adjusted range R_n divided by S_n, standard deviation of the sub section with length n, is the rescaled range R/S_n (Peters 1994). When n grows, the R/S_n value would also grow usually and converge to a threshold when the maximum range is covered.

2.4 V Statistics

As mentioned above, the range of the time-series data never grows bigger than the amplitude. In other words, the R/S_n value stops growing when the range reaches to the amplitude, and when n reached to the length of a cycle. To represent the break point more clearly, a simple statistic – V statistic – is measured (Peters 1994). V statistic is defined as the equation (4)

$$V_n = (R/S)_n/\sqrt{n} \qquad (4)$$

By plotting V statistics on the X axis and $\log(\mathrm{n})$ on the Y axis, the break points would occur when a cycle of time-series is over. In this way, the research can identify the period length of each cycle in time-series.

3 Results

3.1 Variable Description

This research used Construction Cost Index (CCI) as a variable to develop the cycle estimation model for the early warning system. CCI is a cost index from 20-cities of U.S. published monthly by Engineering News Record (ENR), covering four important cost factors of construction projects – labor rates, steel price, cement price, and lumber price. Table 2 describes the detailed definition of each cost.

Table 2 Description of Construction Cost Index

Cost	Description
Labor rate	200 hours of common labor at the 20-city average of common labor rates
Steel price	25 cwt of standard structural steel shapes at the mill price prior to 1996 and the fabricated 20-city price from 1996
Cement price	1.128 tons of Portland cement at the 20-city price
Lumber price	1,088 board-ft of 2 x 4 lumber at the 20-city price

This research gathered CCI data from JAN 1990 to JAN 2015, 301 observations in a monthly period. As Peters (1994) and other researchers mentioned, R/S analysis functions well with the logarithmic ratio of the original data. For that reason, the research used the logarithmic ratio of CCI (i.e., returns of CCI) as a variable of the model (Peters 1994; Kumar and Manchanda 2009; Yin et al 2013; Abdulhadi et al 2015). Figure 5 represents the original CCI and Figure 6 represents logarithmic ratio of CCI, 1-mth returns.

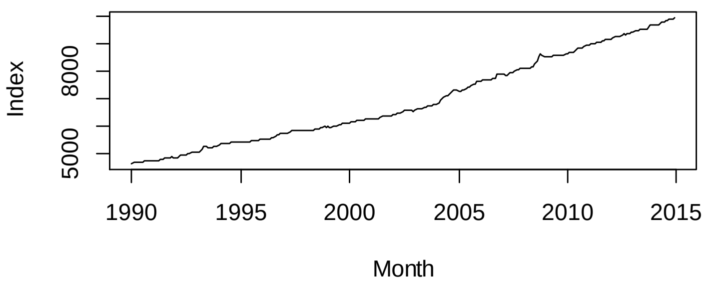

Figure 5 Construction Cost Index

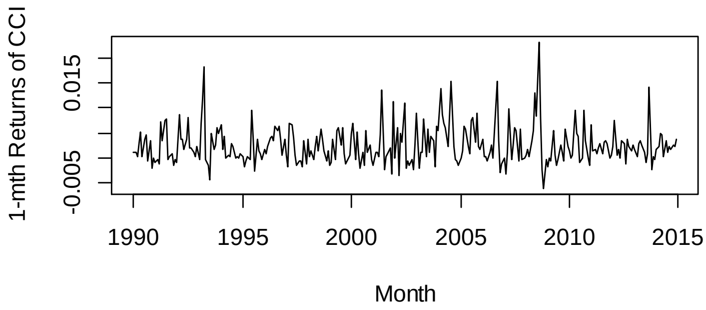

Figure 6 Logarithmic Ratio of Construction Cost Index (1-mth Returns)

3.2 Results of R/S Analysis

The V statistics stop growing and reach a break point when the range of the time-series data covers the amplitude of the cycle; the number of observation covers the period of a cycle. After the break point, the V statistics grow again heading towards the amplitude of the next cycle. Figure 7 shows the growing trend and arrival at the break point of the V statistics on the CCI data. The X axis represents the number of observations in the log and the Y axis represents the V statistics. The results show three break points at 12, 30, and 75 observations, which means there exist cycles of the period in 12, 30, and 75 months. The V statistics, then, grow again after the 75-mth break point and don't stop until the maximum scale of the observation, which means there exists the longer period of the cycles than that of the maximum data points, 300 months.

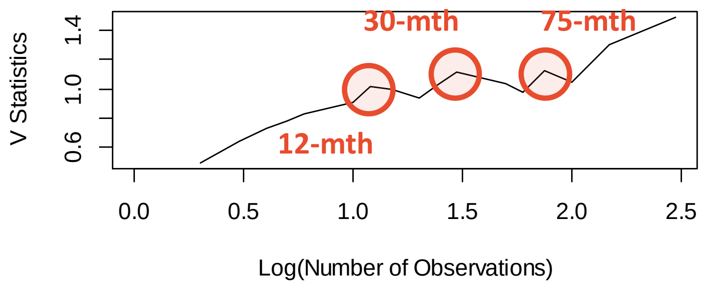

Figure 7 V Statistics of Construction Cost Index

3.3 Verification & Validation

The research estimated the cycles of CCI in different scales (i.e., the returns in different time lag) to verify the cycle estimation model based on the fractal analysis. Because the total length of the observations is only 300 data points, which is too small size that could mislead the results of the model, the research used the 2-mth, 3-mth, and 6-mth returns with 150, 100, and 50 data points for verification. The results are shown in figure 8 to 10. The 60-mth cycle in Figure 8 & 9 and 30-mth cycle in Figure 10 verify the 30-mth cycle of the original result of R/S analysis, as the 30-mth cycle supposed to derive the 60-mth cycle. Similarly, 150-mth cycle in Figure 8 verify the 75-mth cycle of the original result. The original results show that CCI also has 12-mth cycle, which is obvious to say, as many macroeconomic factors have 12-mth (1 year) cycle.

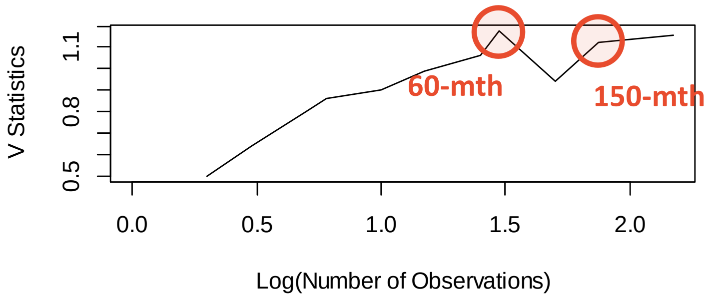

Figure 8 V Statistics of Construction Cost Index (2-mth Returns)

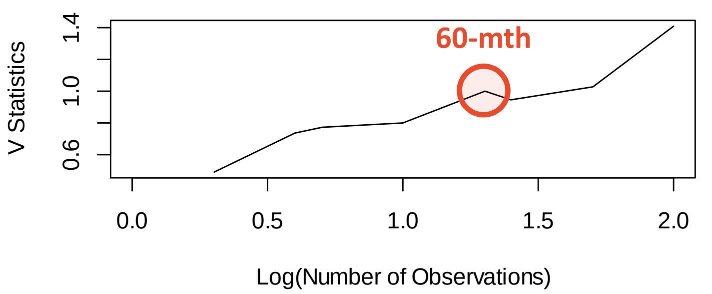

Figure 9 V Statistics of Construction Cost Index (3-mth Returns)

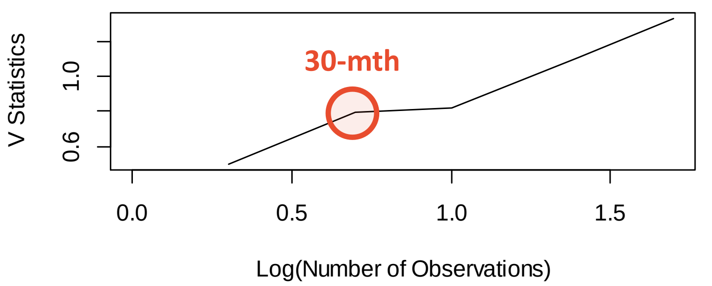

Figure 8 V Statistics of Construction Cost Index (6-mth Returns)

This research estimated cycles of other factors of the construction market, which are related to CCI. The model could be validated by estimating the other market factors because the relationship would share some cycles in the same period. Four variables are selected as CCI-related factors through the judgement of professionals, literature reviews of previous researched and cross-correlation function (Han et al 2007; Kim et al 2009; Deng and Low 2013; Jiang et al 2013). The variables are market factors representing the U.S. construction market, in detail, Crude Oil Price (COP) from western Texas, Gross Domestic Product (GDP), Construction Industrial Production (CIP), and Total Construction Spending (TCS). Among them, only COP is used for validation because other variables are quarterly data, thus, the number of observations is insufficient to proceed R/S analysis. The result is following with Figure 11. COP, one of the construction market factors related to CCI, have the cycles with the 30-mth and 60-mth periods, similar results to CCI.

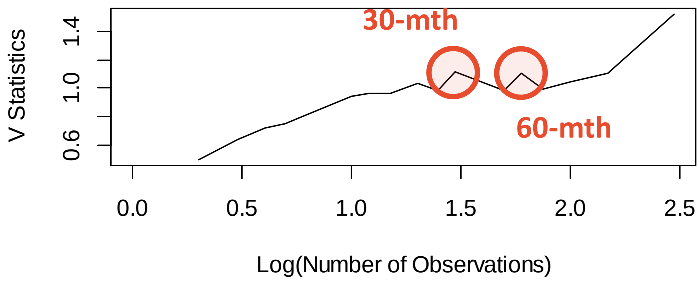

Figure 9 V Statistics of Crude Oil Price (1-mth Returns)

4 Conclusion

4.1 Summary

Many Korean construction companies have attempted to enter the global construction market. However, the failure cases still occur due to a sudden change in the market. Previous researches revealed risk factors, and tried to predict the market fluctuation using time-series analysis and data-mining. The problem is that these conventional methods are based on the concept of regression that assumes trends and distributions of the data to be exist, thus, a sudden change of market might be hardly predicted. The research aims to develop the early warning system against a sudden change of the construction market, focusing on the estimation of cycles of the global construction market factor, Construction Cost Index. This research performed the cycle estimation on CCI using R/S analysis, which adopts the fractal theory. The R/S analysis is used to identify the characteristics of fractal of time-series data (i.e., self-similarity & recursiveness). The V statistic, a result of R/S analysis, is used to estimate the length of a cycle. The results of the analysis showed that CCI has some cycles whose lengths of period are the 30-mth and 60-mth. The verification with different time lags and validation with other market factors were performed in a qualitative manner.

4.2 Contribution

The research introduced the fractal analysis in the construction domain in order to estimate cycle of market factors. For a practical contribution, the research estimated the cycles of Construction Cost Index, and made the basis of the development of the early warning system against sudden change of the global construction market.

4.3 Limitation

One limitation of this research is the insufficiency of observation data. Since the cycle estimation depends on the change of the rescaled range upon time scale, it is difficult to identify the cycles whose length of period is larger than the number of observation data. The other limitation is that the verification and validation were performed only in a qualitative manner, hence it is ambiguous to insist the existence of cycle.

4.4 Future Research

Future research will perform a process such as quantitative verification and validation in order to propose an objective criteria of cycle estimation. The results would converge with conventional time-series model to predict a sudden change of the global construction market and support decision makers with early warning system.

Acknowledgements

This research was supported by a grant (16CTAP-B080352-03) from the Infrastructure and Transportation Technology Promotion Program funded by the Ministry of Land, Infrastructure and Transport of the Korean government, Promising-Pioneering Researcher Program through Seoul National University(SNU) in 2015, and the National Research Foundation of Korea (NRF) Grant (No.2015R1A5A7037372) funded by the Korean Government (MSIP).

Reference

International Contractors Association of Korea (2016). International Construction Information Service. <http://www.icak.or.kr/sta/sta_0101.php>

Peters, E. (1994). *Fractal Market Analysis: Applying Chaos Theory to Investment and Economics.* John Wiley & Sons. New York, U. S.

Shmueli, G., Patel, N. R. & Bruce, P. C. (2012). *Data Mining for Business Intelligence.* John Wiley & Sons. Hoboken, U. S.

Cho, S. & Son, Y. (2009). *Time Series Analysis.* Yulgokbook publishing. Seoul, Korea.

Abdulhadia, D. A., Shetty, S. & Alshamali, M. (2015) Stock market behavior: A Fractal analysis of Saudi stock exchange. *International Journal of Business.* 20 (1).

Akintoye, A., Bowen, P. & Hardcastle, C. (1998) Macro-economic leading indicators of construction contract prices. *Construction Management and Economics*. 16 (2). pp. 159-175.

Alvarez-Ramirez, J., Alvarez, J., Rodriguez, E. & Fernandez-Anaya, G. (2008) Time-varying Hurst exponent for US stock markets. *Physica A: Statistical Mechanics and its Applications*. 387 (24). pp. 6159-6169.

Anderson, N. & Noss, J. (2013) The Fractal market hypothesis and its implications for the stability of financial markets. *Bank of England Financial Stability Paper*. 23.

Deng, X. & Low, S. P. (2013) Exploring critical variables that affect political risk level in international construction projects: case study from Chinese contractors. *Journal of Professional Issues in Engineering Education and Practice*. 140 (1).

Griffis, F. H. & Christodoulou, S. (2000) Construction risk analysis tool for determining liquidated damages insurance premiums: case study. *Journal of Construction Engineering and Management*. 126 (6). pp. 407-413.

Han, S. H., Park, S. H., Kim, D. Y., Kim, H. & Kang, Y. W. (2007) Causes of bad profit in overseas construction projects. *Journal of Construction Engineering and Management*. 133 (12). pp. 932-943.

Hwang, S. (2011) Time series models for forecasting construction costs using time series indexes. *Journal of Construction Engineering and Management-Asce*. 137 (9). pp. 656-662.

Jiang, H., Xu, Y. Q. & Liu, C. L. (2013) Construction price prediction using vector error correction models. *Journal of Construction Engineering and Management*. 139 (11).

Kim, D. Y., Han, S. H. & Kim, H. (2008) Discriminant analysis for predicting ranges of cost variance in international construction projects. *Journal of Construction Engineering and Management-Asce*. 134 (6). pp. 398-410.

Kim, D. Y., Han, S. H., Kim, H. & Park, H. (2009) Structuring the prediction model of project performance for international construction projects: A comparative analysis. *Expert Systems with Applications*. 36 (2). pp. 1961-1971.

Kumar, J. & Manchanda, P. (2009) Estimation of Hurst exponent for the financial time series. *AIP Conference Proceedings*. 1146 (1). pp. 272-283.

Leśniak, A. (2013) The Application of artificial neural networks in indirect cost estimation. *AIP Conference Proceedings*. 1558 (1). pp. 1312-1315.

Lovejoy, S. & Mandelbrot, B. B. (1985) Fractal properties of rain and a fractal model. *Tellus, Series A-Dynamic Meteorology and Oceanography*. 37. pp. 209-232.

Mohammadi, S. (2011) Effect of outliers on the fractal dimension estimation. *Fractals*. 19 (2). pp. 233-241.

Nasirzadeh, F., Afshar, A. & Khanzadi, M. (2008) Dynamic risk analysis in construction projects. *Canadian Journal of Civil Engineering*. 35 (8). pp. 820-831.

Sánchez-Granero, M. J., Fernández-Martínez, M. & Trinidad-Segovia, J. E. (2012) Introducing fractal dimension algorithms to calculate the Hurst exponent of financial time series. *The European Physical Journal B*. 85 (86).

Shahandashti, S. M. & Ashuri, B. (2013) Forecasting Engineering News-Record construction cost index using multivariate time series models. *Journal of Construction Engineering and Management*. 139 (9). pp. 1237-1243.

Topper, B. & Lagadec, P. (2013) Fractal crises - A New path for crisis theory and management. *Journal of Contingencies and Crisis Management*. 21 (1). pp. 4-16.

Williams, T. P. (1994) Predicting changes in construction cost indexes using neural networks. *Journal of Construction Engineering and Management*. 120 (2). pp. 306-320.

Wong, J. M. W. & Ng, S. T. (2010) Forecasting construction tender price index in Hong Kong using vector error correction model. *Construction Management and Economics*. 28 (12). pp. 1255-1268.

Yin, K., Zhang, H., Zhang, W. & Wei, Q. (2013) Fractal analysis of the gold market in China. *Journal for Economic Forecasting*. 3. pp. 144-163.