Proceedings of International Structural Engineering and Construction, 8(1), 2021
Interdisciplinary Civil and Construction Engineering Projects
Edited by El Baradei, S., Abodonya, A., Singh, A., and Yazdani, S.

ISSN: 2644-108X
www.doi.org/10.14455/ISEC.2021.8(1).CON-11

FINANCIAL RATIO ANALYSIS IN CONSTRUCTION INDUSTRY: AN INVESTIGATION USING MACHINE LEARNING

OSAMA SALAH[1], MAGED GEORGY[1,2], and ATEF RAGAB[3]

[1]*Structural Engineering Dept, Cairo University, Giza, Egypt*
[2]*School of Property, Construction and Project Management, RMIT University, Melbourne, Australia*
[3]*Civil Engineering Dept, Misr University for Science and Technology (MUST), 6th October City, Egypt*

Financial Ratio Analysis is considered one of the most fundamental ways of evaluating performance in companies. Analysis of major financial ratios of a company can help decision-makers take early business decisions/actions that could prevent, or at least alleviate, the potential hardships in the future. This paper reviews the literature and shows that various financial models have been developed in the past to evaluate an organization's financial performance. The paper further proposes to upgrade and extend the resources used for financial performance evaluation through employing advanced artificial intelligence (AI) techniques, with application onto Egyptian construction companies. Research methodology included the gathering of a large number of financial reports/data items from relevant companies. Six major financial ratios were determined over a number of years, based on the consolidated financial accounts and income statements. These ratios include Current Ratio, Quick Ratio, Return on Equity, and others. The use of Machine Learning (ML) techniques is then investigated to analyze those ratios and to develop a financial performance evaluation model. K-means, as an un-supervised ML technique, was utilized to cluster the collected data set into three major groups. Each group has its own unique financial characteristics. Finally, future study measures are discussed where case studies will be used to verify and explain the findings.

Keywords: Performance evaluation, Artificial intelligence, K-Means neighbor, Benchmarking, Clustering, Micro-economics, Un-supervised learning.

1 INTRODUCTION

Financial performance analysis is a technique to assess and track the business performance based on statistics and numbers taken from the companies' accounting statements. For owners, shareholders and funding agencies, this type of analysis is critical for understanding the financial performance and actions. In certain instances, researching each financial factor alone may be misleading. This research is aimed at updating and extending the resources available for financial analysis of construction contractors using Artificial Intelligence (AI) and Machine Learning (ML) methods. The research approach is further demonstrated in the Egyptian construction industry. This research creates a model of performance appraisal, where construction contractors can be grouped into clusters, each with its own financial characteristics. If the contractor is in a certain cluster, this could increase the interest of investors and other agencies, or vice versa.

Industry benchmarking data is sometimes outdated and may have been measured under different economic conditions. For instance, in Egypt, almost a decade had passed since up-to-date financial data were collected for the construction market. Hence, a significant number of more recent Egyptian contractors' balance sheets and income statements were compiled and analyzed. Financial ratios have been measured for the last decade. Industrial averages for many forms of financial ratios have been calculated and evaluated for the time period under review. K-Means was chosen as the ML technique for grouping and clustering the collected financial ratios. Details are presented in the remainder of this paper.

2 REVIEW OF RELEVANT PAST RESEARCH

Most of the studies concerning the financial performance of construction firms focused on methods for carrying out the financial analysis itself or means for the forecasting of companies' possible financial failure. Meanwhile, few of these studies addressed the non-financial aspects as well, for instance, the forecasting of a downturn in construction companies (Koksal and Arditi 2004), which takes into account not only the financial factors but some of the non-financial factors as well e.g. communication, standardization, self-performance, resource utilization, etc.

Kangari (1988) explored the influence of the macroeconomic factors on the failure of the construction industry and developed a model for analyzing and predicting these failures. Another quantitative model by Kangari *et al.* (1992) employed financial ratios to rank construction companies according to their financial performance and determine their potential for business survival. Ratios used to build Kangari *et al.*'s (1992) model included: current ratio, total liabilities to net worth, total assets to sales, revenues to networking resources, return on total assets, and return on net worth. Also, Abidali and Harris (1995) designed an operating system, incorporating financial ratios and a statistical methodology known as a linear discriminant analysis that distinguishes businesses at risk of failure. The product of this combination is a value called the Z score. Moreover, Elyamany *et al.* (2007) employed regression modelling to develop an index for evaluating the performance of Egyptian construction companies over nine consecutive years from 1992 to 2000. Meanwhile, Ibn-Homaid and Tijani (2015) investigated the concept of financial management in deciding the financial status of a construction company in Saudi Arabia. Their research provided a failure forecast model for the organization based on the previous business data available.

While the use of ML in the context of financial ratio analysis may be novel, the past decade has witnessed several studies that employed ML in various areas of construction management e.g. bid/no-bid decision making (Sonmez and Sözgen 2017), construction safety (Poh *et al.* 2018), and others. Clustering is a fundamental concept in ML. In particular, K-Means, as an unsupervised ML technique, can be used to identify the data set in clusters. These clusters share similar characteristics. Data clustering has been used in research concerning pattern recognition, image analysis and bioinformatics (Bataineh *et al.* 2011). Clustering techniques have been used in building related studies as well. For instance, Al-Qady and Kandil (2014) used a hybrid clustering method in the clustering of building project documents based on textual similarity. The Fuzzy Cluster-Based Genetic Algorithm approach was further used for time-cost-quality trade-off problem, where a case study of a highway construction project was demonstrated (Mungle 2013).

3 RESEARCH OVERVIEW AND METHODOLOGY

The research methodology adopted to meet research objectives is shown in Figure 1.

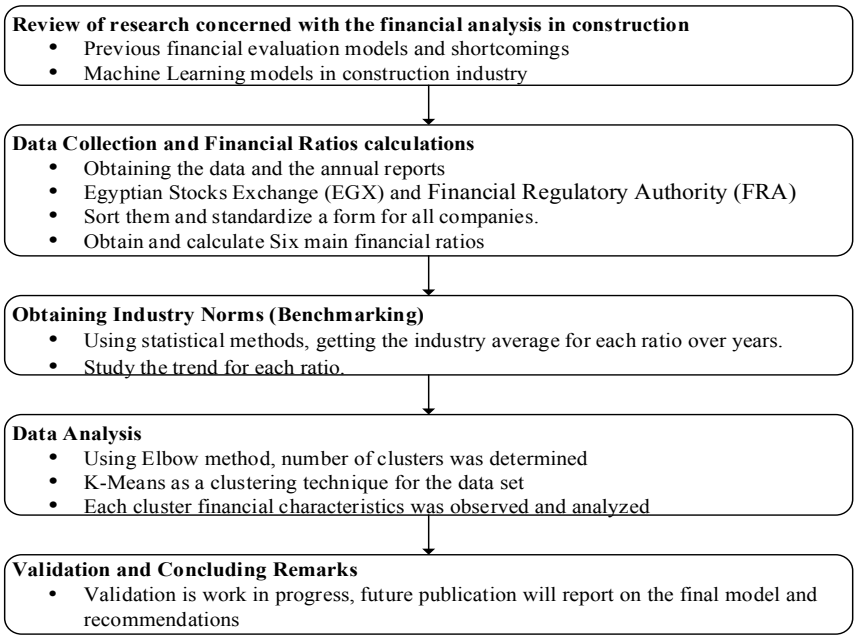

Figure 1. Research overview and methodology.

Financial reports/data items were collected for 23 tier-1 construction companies, as per the classification of the Egyptian Federation of Construction and Building Contractors (EFCBC). Six financial ratios were then considered in the model development, which are sufficient to indicate financial performance for a company according to Dun and Bradstreet (2001). The six ratios are:

1. Current Ratio (CR)
2. Total debt to Net Worth ratio (TD/NW)
3. Fixed Assets to Net Worth ratio (FA/ NW)
4. Revenue to Working Capital ratio (RV/WC)
5. Net Profit to Total Assets (NP/TA)
6. Net Profit to Net Worth (NP/NW)

Model development is still work in progress; future publications will report on the final ML model and the validation of that model via case studies. Meanwhile the current paper will report on the initial ML model for financial ratio analysis.

4 BENCHMARKING

Benchmarking is the process of assessing companies' performance against a peer group of organizations of comparable scale. Financial ratios were calculated and sorted, over the study period. This allows statistical analysis to be carried out for each ratio and to undertake a trend analysis over studied years. And the most important point is to evaluate the overall industry performance, enabling those companies to benchmark their performance. Next is a summary of the analysis conducted for two of the ratios in reference.

4.1 Current Ratio

This ratio indicates the relationship between current assets and current liabilities. From the data obtained, most of the construction companies in Egypt have fulfilled their own financial

obligations. Current ratio values typically increase in two instances; first, if the value of current assets increased, second, if the value of current liabilities decreased. As per the data obtained, the growth of the business normally resulted from the first instance, since this condition is more favorable for the industry. The more cash financed onto the market would allow the industry to expand and more opportunities for investors will arise. The opposite situation implies a contraction in the market by removing the cash from it, i.e. a recess in the industry. Perhaps not in the case of the Egyptian market; the trend analysis, in Figure 2, shows overall growth over the years.

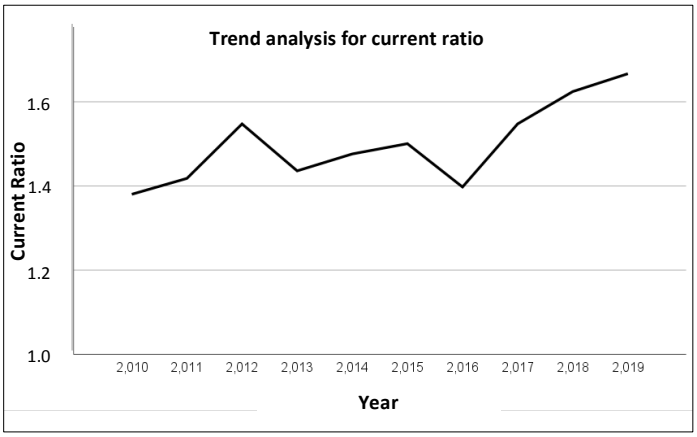

Figure 2. Trend analysis for current ratio.

4.2 Net Profit to Total Assets

This ratio equals the profit after taxes to total assets. It shows the efficiency of assets management, and return comes from the total invested money in the market. The higher the ratio, the better a company performs. As per the collected date, Net Profit to Total Assets ratio median ranged from 0.014 to 0.04 with overall median of 0.02; Figure 3 shows the ratio histogram.

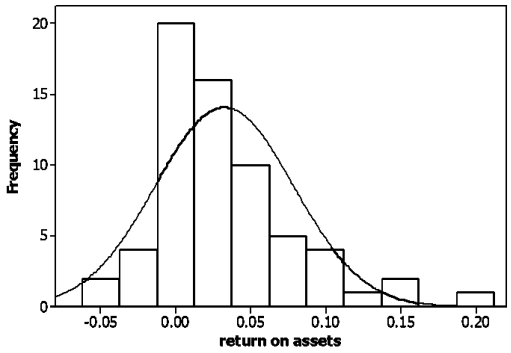

Figure 3. Return on assets histogram.

In some cases, the ratio decreases over years. If it decreased due to declined profits, it's an indication of the company's poor performance. If decreased from increasing the invested money in new assets, which resulted in reducing the whole profit or part of it, then better performance may follow. This shows an increase in equities which is a favorable situation for investors.

5 PERFORMANCE EVALUATION MODEL USING MACHINE LEARNING

The research model can help in evaluating the financial performance of companies working in the Egyptian construction industry. Six financial ratios have been selected depending on their importance as chosen by Elyamany *et al.* (2007). They also match five of the ratios chosen by Kangari *et al.* (1992). The six ratios are: CR, TD/NW, FA/ NW, RV/WC, NP/TA, NP/NW.

As noted, some ratios, such as those represented via percentages or times, have values that vary greatly while others vary within a narrow range. If all are combined -*as is*- in a financial performance index/formula, some will be over weighted. In line with the advice by Kangari *et al.* (1992), normalization coefficients are utilized for each ratio to give near equal weights.

The three main types of learning problems in ML are: Supervised Learning, Unsupervised Learning, and Reinforcement Learning. The current research adopts unsupervised learning, since the data set is not labelled. Unsupervised Learning algorithms help to recognize patterns in data based on the determined optimal number of clusters, *k*. This study particularly employs the Elbow Method, which is one of the most popular methods to determine the optimal number of clusters, *k*, while running k-means clustering on the dataset for a range of *k* from 1 to 10. For each value of *k*, Sum of Squared Errors (SSE) is calculated. SSE tends to decrease as *k* increases. By plotting a line chart of the SSE, which represents the distortion of the data set against the value of *k*, appropriate number of clusters could be chosen, as shown in Figure 4.

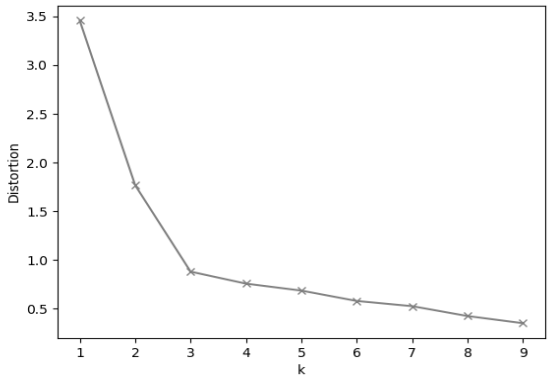

Figure 4. Elbow method.

The optimal number of clusters was determined to be three (3), which corresponds to the elbow in Figure 4. Process for obtaining the k-means centroids starts with an initial random assumption for centroids positions, and then performs iterative calculations to optimize the positions of these centroids. Summation of Euclidian distance between data points and all centroids is then computed. Accordingly, each data point is assigned to the closest cluster. Each point in a given cluster shares unique financial performance characteristics with the other data points in that cluster, in comparison to the other clusters.

As shown in Figure 5, most of the contractors in Egypt are having similar financial characteristics. Around 72% of all studied contractors belong to the same cluster, C1; satisfying their own liabilities. A sudden bankruptcy or financial failure in short term isn't a likely occurrence for most companies in cluster C1. C2 has greater values for Current Ratio, which reflects having current assets to cover the cost of current liabilities. In addition, they possess a higher Net Profit to Total Assets ratio, which could indicate an efficient utilization of their assets. C3 is unique for having lower Revenue to Working Capital ratio, which may indicate that a business is investing in too many accounts receivable to support its sales.

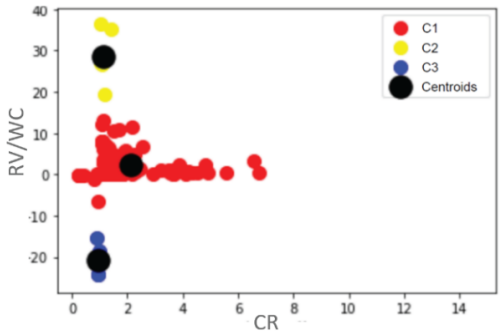

Figure 5. K-Means three clusters.

6 CONCLUDING REMARKS

Analyzing each financial ratio solely may not be sufficient for financial performance evaluation. K-means clustering, as a ML technique, was used in the current study to group companies –from a financial performance point of view– into clusters. Each cluster has its own financial characteristics. Most of the studied contractors belong to one cluster, C1, having current assets higher than their current liabilities; which means they are less likely to struggle in paying their debts. Cluster C2 exhibits higher CR as well as higher NP/TA ratio, which indicates an efficient utilization of the companies' assets. C3 indicates lower revenues compared to working capital.

The study of using ML and k-means, in addition to analyzing each cluster's unique financial characteristics, is still in progress. Study will now focus on increasing the model maturity.

References

Abidali, A., and Harris, F., *A Methodology for Predicting Company Failure in Construction Industry,* Journal of Construction Management and Economics, 13, pp 189-196, 1995.

Al-Qady, M. and Kandil, A., *Automatic Clustering of Construction Project Documents Based on Textual Similarity*, Automation in Construction, 42, pp. 36–49, 2014.

Bataineh, K., Naji, M., and Saqer, M., *A Comparison Study Between Various Fuzzy Clustering Algorithms,* Jordan Journal of Mechanical and Industrial Engineering. 5, pp. 335-343, 2011.

Dun and Bradstreet, *Fourteen Key Business Ratios Used by D&B*, 2011. Retrieved from https://www.dnb.com/product/contract/ratiosP.htm.

Elyamany, A., Basha, I., and Zayed, T., *Performance Evaluation Model for Construction Companies: Egyptian Case Study*, Journal of Construction Engineering and Management, 133(8), pp. 574-581, 2007.

Ibn-Homaid N. T., and Tijani I. A., *Financial Analysis of a Construction Company in Saudi Arabia*, International Journal of Construction Engineering and Management, 4(3), pp. 80-86, 2015.

Kangari R., *Business Failure in Construction Industry*, Journal of Construction Engineering and Management, 114(2), pp 172-191, 1988.

Kangari R., Farid F., and Elgharib H., *Financial Performance Analysis for Construction Industry*, Journal of Construction Engineering and Management, 118(2), pp 349-361, 1992.

Koksal, A., and Arditi, D. *Predicting Construction Company Decline*, Journal of Construction Engineering and Management, 130(6), pp 799-807, 2004.

Mungle, S., *A Fuzzy Clustering-Based Genetic Algorithm Approach for Time–Cost–Quality Trade-Off Problems: A Case Study of Highway Construction Project,* Engineering Applications of Artificial Intelligence, 26, pp. 1953–1966, 2013.

Poh, C., Ubeynarayana, C., and Goh, Y., *Safety Leading Indicators for Construction Sites: A Machine Learning Approach,* Automation in Construction, 93, 375-386, 2018.

Sonmez, R., and Sözgen, B., *A Support Vector Machine Method for Bid/No Bid Decision Making,* Journal of Civil Engineering and Management, 23(5), 641-649, 2017.