

PREDICTING STOCK PRICES IN DUBAI FINANCIAL MARKET USING NEURAL NETWORKS AND POLYNOMIAL CLASSIFIERS

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ABSTRACT

Predicting stock prices has always been the aim of investors in stock markets around the globe and has been considered as one of the most challenging applications of modern Time Series Forecasting. Accordingly, there were many studies conducted in this area which addressed the prediction of stock prices. In broad terms, methods used in predicting market prices fall into three categories; fundamental analysis, technical analysis and time series forecasting.

Fundamental analysis concerns analyzing the company's operation and the market in which the company is operating in order to reasonably predict the stock prices. Technical Analysis deals with past stock prices and volume information in forecasting future prices, assuming certain trends and patterns in price movement

will be repeated in future. Time series forecasting is also applied to predict stock price movement, using techniques like multivariate regression, in which stock prices data can be modeled as non-linear functions.

Financial markets can be either emerging markets or mature markets. Emerging markets are newly established markets with few listed companies and limited number of buy/sell deals. Price movements in these markets are more volatile and often score radical changes. On the other hand, mature markets were established in much earlier stages, and currently have large number of listed companies with enormous daily trading deals. Accordingly, prices volatility is usually more rational and stable compared to the emerging markets.

This thesis is based on technical analysis of stock prices movement in an emerging market; Dubai Financial Market (DFM). The historical prices of three active companies were used as the data to the intelligent systems developed in this study, namely, neural networks and polynomial classifiers. In recent years, artificial neural networks have been used widely in predicting stock prices; due to their capability in capturing the non-linearity that exists in price movement. On the other hand, polynomial classifiers became very popular in the area of recognition and classification, in view of their superior capability in such applications compared to other techniques.

In the first part of this thesis, feed-forward back-propagation neural network was used to construct a prediction model based on stock historical prices. The model was tested on three leading stocks listed in Dubai Financial Market. In the second part, polynomial classifiers were used to develop a similar prediction model with first order and second order classifiers, and the model was also tested on the same three stocks. Results of both models were compared throughout the analysis.

The analysis was based on predicting the closing prices of the consecutive three trading days. The results showed that both prediction models scored high prediction accuracy and could achieve small prediction errors. Particularly, both models scored around 1.5 % average error on the first predicted day and around 2.5 % average error on the second day. Whilst the average prediction error on the third predicted day was almost 4 %. The performance of the two models was very close where polynomial classifiers performed slightly better than the neural network.

At the end of this study, some future improvements were suggested in order to enhance the current results and achieve better prediction accuracy.

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LIST OF ABBREVIATIONS

AI – Artificial Intelligence

ANN – Artificial Neural Networks

DFM – Dubai Financial Market

DIB – Dubai Islamic Bank

IS – Intelligent Systems

NN – Neural Networks

PC – Polynomial Classifiers

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