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ORIGINAL ARTICLE

A Flexible Approach Towards Multi-frequency Re-engineering of the Moving Average Convergence Divergence Indicator

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Abstract *The study develops an innovative and flexible methodology for re-defining the traditional convergence–divergence indicators in the light of multi frequency trading behaviour of the heterogeneous agents. The developed indicator is labelled as multi-resolution convergence divergence indicator (MRCD). In contrast to the traditional moving average convergence divergence (MACD), the MRCD is "flexible" as it reacts to fluctuations arising at any frequency interval and is thereby capable of adapting to a wide variety of future possibilities. The "innovative dimension" underpinning this methodology is the replacement of the traditional trend extractor (moving-average) with a more novel methodology—the multi-resolution analysis. The forecasting ability of this newly engineered indicator is examined by structuring a neural network based MRCD–NARX model. The performance of this model is bench-marked against that of a similar model developed using the traditional MACD indicator. Out-of-the sample mean square error and the Diebold–Mariano test are used to examine the statistical accuracy of the forecasts. The profitability of the indicator is ascertained using the correlation measure and the hit ratio. A "long-short trading rule" is developed and back-tested on the testing data-sample to validate the practical applicability and "reproducibility" of the methodology.*

Keywords Forecasting · Moving average convergence divergence · Neural networks · Technical analysis · Trading strategy · Wavelets

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Introduction

The underlying philosophy behind the popularity of technical analysis is that past information can be profitably used (*to certain extent*) to predict the future price movements (Lo and MacKinlay 2011).The school of thought originated from the series of articles published by Charles Dow at the Wall-Street Journal in the late 1800s (Kirkpatrick II and Dahlquist 2010). Though extensively used for centuries, the approach is still subjected to varied criticism from the academicians and practitioners (Lo et al. 2000). Several works had taken place on examining the predictive ability of technical analysis but the outcome is still inconclusive (Park and Irwin 2007). Park and Irwin (2007) categorized these empirical literature into two categories—*early* and *modern* based on the rigor and sophistication of the testing procedure used. On an average the *early* literature revealed that technical trading strategies are profitable in the foreign exchange and future markets and not in the stock markets. Among the 95 "modern" studies surveyed, 56 found positive results, 20 found negative results while the remaining 19 studies obtained mixed results. A survey, conducted by Taylor and Allen (1992) among the foreign exchange dealers based in London, revealed that at least 90 % of the respondents favour technical analysis while developing their views over the possible price movements over multiple horizons. For short horizon more weightage is bestowed on technical analysis as opposed to the fundamental analysis. The dominance of the technical analysis decreases as the investment horizon increases wherein fundamental analysis is given a higher importance. One thing is evident from their study that the *technical school of thought* is not *flexible* enough to *adjust* their system to *respond* quickly to the *changing* horizon of the investors. Investors trade at different frequency intervals and this behaviour results from different consumption requirements and risk-return trade-off utility of the investors (Lee et al. 1990). Even same information can be interpreted in a different ways by *different-horizon-investors* resulting in different trading outcomes. For example, a bad news may create a selling urge among the intra-day trader and a buying opportunity for the long term investors who believe that this bad news will have temporary impact. Thus the multi-frequency trading is contingent upon a wide variety of available information and most importantly on the way these are *interpreted* by the potential investors. Unless the dynamism of this entire spectrum of information and how they are interpreted is studied, accurate visibility of the future is not possible. What is required in this situation is to *re-engineer* the system so as to enable it *adopt* to the multi-frequency environment. Adaptability is driven by innovation and can be considered as a crucial dimension of flexibility. A flexible system is bimodal or ambidextrous by design and is inundated with multi-dimensional characteristics like adaptability, responsiveness, customization, localization and agility (Sushil 2012). It can be said that "*….to cope with business uncertainty and associated risk, a lot of innovation can be witnessed in modern organizations at the level of products/services, processes, management practices, and strategies. These innovations can be both proactive and reactive in nature and are intended to result in strategic renewal and transformation of a variety of organizations*" (Sushil 2012).

As computer science and mathematical theory evolved, sophisticated concepts like the fuzzy theory, artificial neural network, genetic algorithm and wavelet theory penetrated the realm of predictive analysis and were used to re-define the anatomy of the trading mechanism. Riding this wave of *innovation*, the current study intends to engineer a multi-resolution convergence divergence indicator (MRCD), which has its root in the multi frequency trading behaviour of the heterogeneous agents. The predictive accuracy and profitability of the developed indicator is bench-marked against that of the traditional moving average convergence divergence (MACD) indicator to answer the following questions as:

RQ1 Is this flexible indicator provides superior forecasting accuracy and is profitable in comparison to the traditional MACD indicators?

RQ2 Is the outcome reproducible in practice?

The rest of the paper is structured as follows. "Literature Review" section unearths the wisdoms from the related literature; "Conceptual Framework and Hypothesis Formulation" section develops the conceptual framework underpinning the MRCD indicator. "Research Methodology" section explains the methodology and "Findings and analysis" section reveals the findings. The conclusion and scope for further research are sketched in "Conclusion, Unique Contribution and Scope for Further Research" section.

Literature Review

The aim of literature review section is to set the path for the present study through critical review of extant literature published in reputable journals and books. The present study adopted systematic literature review as suggested by Tranfield et al. (2003). To begin with, the objective of the literature review has been clearly defined. Once the objective have been clearly specified, databases like Proquest, Science Direct, Springer, EBSCO, Emerald, Scopus, Web of Science and Compendex are searched meticulously to ascertain related articles using key words like technical analysis, MACD, flexible stock market prediction, multi resolution analysis etc. Initially we have identified 157 articles from varied sources as displayed in the references section. Out of 157 articles we have carried out review from 113 articles which are relevant to our research questions. We have divided this section into three subsections as follows.

Flexibility and Stock Market Trading

Flexibility has been defined in a wide variety of ways by researchers (e.g. Sushil 2000, 2001, 2005, 2007, 2013; Sharma et al. 2010).Two significant approaches toward flexibility which have close resemblance to the essence of this study are provided by Upton (1994) and Merkhofer (1977). Upton (1994) defines flexibility as the ability to react to the external changes in a quick and cost efficient way. Merkhofer (1977) introduces the concept of *decision flexibility* which asserts that the accuracy of a decision is contingent upon the availability of a wide variety of alternatives. Literature in the field of stock market flexibility are rare. Few of the literature which exist in this domain focus on *innovation* to comprehend the complex chaotic behaviour of the market (Chen et al. 2007) and *adaptability* by relaxing restrictive assumptions (Ledoit et al. 2003).

Random Walk Hypothesis and Technical Analysis

For several years economist, finance-researchers and statisticians have been trying to de-mystify the process followed by stock price across time (Fama 1965). In one of his seminal paper, Samuelson (1965) conjectured that in a well informed and competitive-speculative market the intertemporal change in price is *random*. This entails that historical prices have no useful information that can empower an investor (*more precisely technical analyst*) to consistently outperform a buy-and-hold strategy. This inference was challenged from both behavioural and empirical fronts. For example, Grossman (1976) and Grossman and Stiglitz (1980) debated that it is impossible to achieve a perfectly informationally efficient market. If a market is highly efficient, there will be no reward from amassing information and this will deter agents from trading. If markets reach their highest level of efficiency, *investing* in those markets will be like *gambling in a casino* and this realization will destroy the very existence of those markets. Empirical evidence of the presence of autocorrelation in the stock return contradicted the notion of random walk (Lo and MacKinlay 1988; Darrat and Zhong 2000; Smith and Ryoo 2003). Several researchers investigated the effectiveness of technical indicator. If technical analysis is found to be profitable then the assumption of random walk can safely be ignored. The next section probes this issue.

Profitability of Technical Analysis

A large assortment of empirical literature exists on the examination of the predictive ability and profitability of different technical indicators. Some of the prominent studies are displayed in Table 1.

Table 1 Selective list of studies on technical indicators

Technical indicators (chart, patterns and indicators)	Literature references
Relative strength index	Abbey and Doukas (2012)
Candlestick patterns	Marshall et al. (2008)
Moving average convergence divergence and relative strength index	Chong and Ng (2008)
Point and figure charting	Anderson and Faff (2008)
Bollinger bands	Lento et al. (2007)
Combined signal approach	Lento and Gradojevic (2011)
Moving averages	LeBaron (2000)
Candlestick patterns	Caginalp and Laurent (1998)
Moving averages	Van Horne and Parker (1967)

Source Authors compilation

The outcomes of the studies are mixed (Park and Irwin 2007). When on the one hand some of the studies have found that the technical tool cannot be leveraged profitably (Marshall et al. 2006, 2008), other studies revealed the exact opposite (Caginalp and Constantine 1995; Chong and Ip 2009; Chong and Lam 2010, Chong et al. 2012), which is contrary to the weak-form market efficiency (Malkiel and Fama 1970). Marshall et al. (2008) revealed that candlestick charting, the oldest known form of technical analysis, was not profitable in the Japanese market over a sample of 30 year's period. Marshall et al. (2006) found the same results for the Dow Jones Industrial Average (DJIA) stocks. Gencay (1998) studied the profitability of technical trading rules using non-parametric models and evaluated the same against the buy and hold strategy. The predictive performances of competing rules are evaluated using the market timing tests of Henriksson–Merton and Pesaran–Timmermann to ascertain whether predictions have economic value. Their study revealed that technical strategies are profitable over the naïve buy and hold strategy. Lento et al. (2007) studied the profitability and the forecasting efficiency of the moving average crossover rules, filter rules, Bollinger bands and trading range break-out in both the currency and stock market. The technical trading rules revealed performance improvement over buy-and-hold strategy in the currency market but failed to outperform the naïve rule in the stock market. Anderson and Faff (2008) developed a methodology for the calculation of point and figure chart using high frequency data and assessed the forecasting power of the point and figure chart based trading rules. They got mixed results where some of the trading rules are found to significantly contribute toward profitability, while the rest are dominated by the naïve rule. Abbey and Doukas (2012) found that the use of technical indicator reduces the performances of the traders in the currency market. Chong and Ng (2008) critically examined the profitability of the MACD and the relative strength index (RSI) in the London Stock Exchange over a period of 60 years. The study revealed that the indicators outperformed the buy and hold strategy most of the time. Caginalp and Laurent (1998) studied the predictive ability of Candlestick patterns using the daily prices of the S&P 500 stocks over a period of 4 years (1992–1996). Statistical tests indicated that on an average the use of Candlestick patterns results in the abnormal gain of 1 % over 2 years of holding period. Tanaka-Yamawaki and Tokuoka (2007) probed into the intra-day forecasting ability of the commonly used technical indicators and found that an optimal combination of few indicators chosen using evolutional computation provides superior forecasting ability. Osler (2003), in his empirical paper found support of the fact that trends tends to reverse courses at the support and resistance level. Mills (1997) investigated the forecasting power of the commonly used technical indicators and found them to out-perform the buy-and hold strategy for a sample period (1935–1980). However analysis over the sample period (1980–1994) revealed the opposite. Wong et al. (2003) in their study on Singapore Stock Exchange found that the moving average indicators and the RSI can be profitably used to generate above-average return. The combination of machine learning and technical analysis in forecasting is not new in financial literature. Mizuno et al. (1998) developed a neural-network model for stock market prediction using the technical indicators as input variables. They calibrated the model for predicting the timing of buying and selling in the market and obtained superior performance in comparison to the linear models. Leigh et al. (2002) combined the wisdom from the traditional technical analysis and the contemporary machine learning systems like the neural network and genetic algorithm to generate a superior predictive model. Chavarnakul and Enke (2008) developed volume adjusted moving average (VAMA) and ease of movement (EMA) indicators from the equi-volume charting and probed the profitability of those indicator using a generalized regression neural network model (GRNN). Their result indicated that the stock forecasting model using the combination of neural network and the VAMA & EMV indicators generates superior outcome in comparison to the VAMA & EMV based trading without neural network support. Chang and Liu (2008) developed a Takagi–Sugeno-Kang (TSK) type fuzzy rule based system for stock price prediction. With the technical indicators as predictor-variable, the model was found to predict the price variation with an accuracy level of 97.6 and 98.08 % at the Taiwan Stock Exchange (TSE) and MediaTek respectively. There are also evidences from the recent literature where combination of wavelet technology and neural network approximation is used to generate superior results. For Example Ozun and Cifter (2010) studied the impact of exchange rates on interest rate using a *wavelet network* methodology, which is essentially a combination of wavelet and neural network. In the model the wavelet transformations of the input variables are used as input to the neural network Hsieh et al. (2011) developed an integrated framework where wavelet transformation and the RNN based on the artificial bee colony algorithm (ABC-RNN) are used for stock price forecasting. They used wavelet transformation on the raw return for noise reduction. The processed data was further used in the RNN prediction model as target variable. Several fundamental and technical indicators are chosen as input variable via stepwise regression–correlation selection (SRCS). Artificial Bee Colony algorithm was used for training the network. The model was tested on the simulation results of several international stock markets and was found to provide superior predictive accuracy.

Research Gaps

However, till date, none of the literature were found to addresses how the multifaceted interpretation driven by information complexity and cognitive prejudice (*resulting from trading behaviour of the heterogeneous horizon investors*) can be leveraged profitability. The current study made a humble attempt to address these dimensions. The next section develops these concepts.

Conceptual Framework and Hypothesis Formulation

Market witnesses agents trading at different frequencies, ranging from every second to more than a year (Candelon et al. 2008). The trading philosophies of these multi-horizon investors are different—for example the short term traders rely primarily on the short term market information. Any relevant information which can create a price adjustment even in the short term is relevant for them. On the other side of the spectrum lies the long term investors like the pension funds and the government. They design their investment strategies based on the projection of the overall macroeconomic condition over the long run and weigh the systematic risk more than the idiosyncratic noise. Intraday traders on the other hand do not always hold a well-diversified portfolio and thereby weighs the total risk of an asset including the firm specific idiosyncratic risk. Thus agents consider information which is relevant to their investment horizons while making a trading decision. Each of these multi-horizon trading activities impacts the price and hence the returns. The stock returns thus exhibit multi-scale behaviour where the fluctuation at each scale indicates the trading activity of the investors operating in those respective scales (Ramsey 2002). If the weak form of market efficiency does not holds, the relevant information guiding the long (short) scale investors should be reflected in the fluctuation of the stock price in the long (short) scale. This intuition is behind the popularity of the “Moving Average Convergence Divergence (MACD)” stochastic oscillator. Developed by Gerald Appel in the late 1970s, MACD indicator is used to gauge the shifting trend of the short term moving average of the prices over the long term moving average. An increasing trend of the short term moving average over the long term moving average indicates a buying trend and if the momentum continues in the future more buy will follow (Appel 2003). This momentum impact is further supported by the quantitative finance community who defines this effect using an autoregressive model and buttresses that if a stock return shows persistence (statistically significant auto correlation for the first few lags) then conditional prediction of the future returns is feasible within a certain confidence interval (Marcellino et al. 2006).

Traditionally practitioners rely on the following configuration to define the MACD indicator.

$$\text{MACD Line} = 12_{\text{days}}\text{EMA} - 26_{\text{days}}\text{EMA} \tag{1}$$

$$\text{Signal Line} = 9_{\text{days}}\text{EMA of MACD Line} \tag{2}$$

$$\text{MACD Histogram} = \text{MACD Line} - \text{Signal Line} \tag{3}$$

Exponential moving averages (EMA) are similar to the simple moving averages except that more weights are bestowed upon latest data and as a result the indicator reacts fast to the price change as opposed to the simple moving average based construct. The degree of divergence, as measured by the MACD Histogram, signals the profit booking opportunity. A rigorous methodology for quantifying the divergence was not available (*until recently*) apart from the traditional "moving average". Further what time interval can be defined as "short term" and "long term" is not clear and the technical analyst uses adhoc intervals (12 and 26 days respectively) that work best for them. This restriction deprives the system from the movements happening in the other frequency intervals and thereby induces sub-optimality. Advent of wavelet technology enables the extraction of different frequency components from the stock price process without compromising on the time property (Percival and Walden 2000). These frequency components can be individually brought back to the time domain using inverse wavelet transformation (Mallat 1989) and then can be compared across frequency levels to detect divergences. This inter-frequency comparison results in the development of MRCD oscillator. The theoretical framework underpinning the MRCD indicator can be derived from the principle of muti-resolution analysis (MRA), wherein, using the recursive pyramid algorithm of Mallat (1989) any finite energy time series can be represented as a linear combination of the father and mother wavelets as follows

$$R_t^S = \sum_{k=1}^{N} \tilde{\vartheta}_{J,k}\varphi_{J,k}(t) + \sum_{j=1}^{J}\sum_{k=1}^{N} \tilde{w}_{j,k}\psi_{j,k}(t) \tag{4}$$

where, $\tilde{w}_{j,k}$ and $\tilde{\vartheta}_{J,k}$ are the wavelet and scaling coefficients respectively. j and k are the dilation and translation parameters. J is the maximum number of scales considered in the decomposition. $\varphi_{J,k}(t)$ and $\psi_{j,k}(t)$ are the dilated and translated versions of the discrete father and mother wavelets. The decomposition is energy preserving as the norm of the original series can be represented as a summation of the norms of the individual coefficients.

$$\sum_{t=1}^{N} |R_t^S|^2 = \sum_{k=1}^{N} |\tilde{\vartheta}_{J,k}|^2 + \sum_{j=1}^{J}\sum_{k=1}^{N} |\tilde{w}_{j,k}|^2 \tag{5}$$

Equation 4 can be represented in additive decomposition form as

$$R_t^S = S_J + D_J + D_{J-1} + D_{J-2} + \ldots D_j + \ldots D_1 \tag{6}$$

where,

$$\boldsymbol{S_J} = \sum_{k=1}^{N} \tilde{\vartheta}_{J,k}\varphi_{J,k}(t)$$

$$\boldsymbol{D_j} = \sum_{k=1}^{N} \tilde{w}_{j,k}\psi_{j,k}(t) \quad \boldsymbol{for\, j} = 1, 2, \ldots .\boldsymbol{J}$$

D_j represents the zero-mean fluctuations at scale j (also called the detail component) and S_J represents the overall trend in the time series at the highest scale J (also called the smooth component). The decomposition (as given in Eq. 6) is recursive in nature (Mallat 1989) and can be represented in a step-wise decomposition layout as follows.

$$R_t^S = S_1 + D_1 \tag{7}$$

$$R_t^S = S_2 + D_2 + D_1 \tag{8}$$

$$R_t^S = S_3 + D_3 + D_2 + D_1 \tag{9}$$

$$R_t^S = S_J + D_J + D_{J-1} + D_{J-2} + \ldots D_j + \ldots D_1 \tag{10}$$

Subtracting Eq. (7) from Eq. (8) results

$$D_2 = S_1 - S_2 \tag{11}$$

The detail coefficient (D_2) represents the divergence of the 2–4 days smooth coefficient (S_1) from the 4–8 days smooth coefficient(S_2). Its value will increase when a buying pressure increase among the high frequency traders resulting from the positive news incidence, which has not been reflected into the trading activity of the low frequency (4–8 days) traders. On the similar ground subtracting Eq. (8) from Eq. (9) provides the divergence indicator between the 4–8 days smooth coefficient (S_2) and the 8–16 days smooth coefficient (S_3).

$$D_3 = S_2 - S_3 \tag{12}$$

Arguing along the similar line it can be said that the entire assortment of the detail coefficients $(D_1 \ldots\ldots D_J \;\; \textit{for a particular}\; J)$ represents the convergence-divergence indicator across dyadic frequency intervals. These are categorized as MRCD indicators in this paper. The stock return series is decomposed into 8 scales using multi-resolution analysis. The scale components along with the captured trading horizon are displayed in Table 2.

This approach uses a wide range of scale intervals (2, 4, 8, 16, 32, 64, 128, 256, 512 days) for the computation of the convergence divergence (CD) oscillators as opposed to 12–26 days adhoc selection. The practical utility of this

Table 2 Breakup of the investor's horizon intervals used in the study

Scale	Captured trading horizon
1	2–4 days
2	4–8 days (1 week approx.)
3	8–16 days (1–2 weeks approx.)
4	16–32 days (½ to 1 month approx.)
5	32–64 days (1–2 months approx.)
6	64–128 days (2–4 months approx.)
7	128–256 days (½ to 1 year approx.)
8	256–512 days (1–2 years approx.)

Source Authors analysis

adaptation can be explained as follows. Financial market fluctuation across multiple scales is contingent upon the complex interpretation of a wide variety of information. While at one end of the spectrum the interpretation of macroeconomic and fundamental news drives the low frequency (long term) price movement, on the other end the high frequency movements are driven by high frequency (short term) idiosyncratic news. Even a particular piece of information can be interpreted differently by the different groups of investors. These varied and complex interpretations results in a wide variety of reactions which drives the price. This entire breadth of these reactions is indispensible for conditional forecasting of the financial asset price. The detail coefficients, derived from the multiresolution decomposition, capture this broad spectrum and thereby reflect the best possible raw-material for visualizing the future movement. This system is *flexible* as it reacts to fluctuations arising at any frequency interval and is therefore capable of adapting to a wide variety of future possibilities.

This newly defined indicator is benchmarked against the traditional MACD for examining its forecasting capability.

The following alternative hypothesis is tested in the study

H_A The predictive accuracy of MRCD based forecasting model of stock return is higher than that of the MACD based forecasting model

Research Methodology

The research methodology is delineated sequentially through the following sub-sections.

Resolving Debates Between Positivism and Interpretivism Philosophy

A critical portrayal of research philosophy is precursor to the description of the research approach and design. This is instrumental behind the resolution of conflict between the perception of the researchers and the expectation of the readers. There are three principal ways of thinking about research philosophy—epistemology, ontology and axiology (Saunders et al. 2011). Epistemology has three approaches—*positivism, interpretivism and realism.* Positivist believes that there exist universal truths which can be visualized by analyzing observable data. They rely on existing theories to generate hypothesis and uses evident data to comment on the same. *Positivism* is a philosophy of simplifying the complexities of nature to deduce tangible outcome. In reality the social environment is more complex than what it seems. For example, in the stock market, the prices are driven not only by the fundamental and short term news but also by the way these news are interpreted by the potential investors. Coming back to the previously cited example, a bad news may create a selling urge among the intra-day trader and a buying opportunity for the long term investors. This difference of action arises from the way human-beings interpret complex information. This notion give rise to the *interpretivism* philosophy, which urges that human error/biasness/view in decision making cannot and "should-not" be removed in order to understand the reality. Failing to do so will result in a gap between what is visible and what is reality. This leads to the *realism* way of thinking. For the purpose of stock market prediction, it is more vital to analyze what investors believe rather than focusing only on the content and type market information. The different interpretation of the same information by the heterogeneous investors creates a tangible impact on the way they trade and hence on the price movement. This is the place where the *positivism and interpretivism* ways of thinking *converges.* The behavioural differences, arising from varied interpretation, can be captured by extracting the fluctuation of the price across several frequency intervals. This is the underlying philosophy behind the development of the "MRCD indicator". The research approach is *deductive* as the theory is first conceptualized and then it is validated through hypothesis development and testing.

Data Collection

To evaluate the predictive ability of the MRCD indicator, the daily adjusted closing prices of CNX Nifty index are collected for a period from 1st January, 2004 to 1st November, 2013 from the website of the National Stock Exchange if India Ltd. (www.nseindia.com). CNX Nifty is a well-diversified index of 50 free floating market capitalization weighted Indian stocks which traces the overall market conditions. This wider representation makes it viable for an extensive variety of financial market research including studies on market forecasting. A reasonable sample size of *2,453 closing prices* (*which generated 2,452 daily return data*), nullifies the estimation error.

Research Design

The research process is "*explanatory*" in nature as the relationship between the technical indicators and the future stock return has been studied. Using the construct as discussed in section-3 the MRCD and MACD oscillators are developed over the following intervals—(2–4 days), (4–8 days), (8–16 days), (16–32 days), (32–64 days), (64–128 days), (128–264 days), and (264–512 days). The technical indicators, thus developed, are used for conditional one-step ahead forecasting of the CNX-Nifty return. There have been traditionally two major types of forecasting methodology—model driven parametric forecasting and the data driven non-parametric forecasting (Smith et al. 2002). While the ARIMA, ARFIMA, Regime Switching etc. are the example of the former class, neural network models are the popular variant of the latter type. Historical literature buttresses the data driven prediction as opposed to the model driven ones. For example Kanas and Yannopoulos (2001) found that the RMSE of the neural network based forecasts is significantly lower than that of the parametric model based forecasts. He used the Diebold–Mariano test for comparing the predictive accuracy of the two competing models. Zhang (2003) found that investment strategies developed using the time delay neural network (TDNN) and RNN based prediction are more profitable as compared to the strategy developed using ARIMA based forecasting. Their works is further supported by the findings of several researchers (Kohzadi et al. 1996; Yao and Tan 2000; Matilla-García and Argüello 2005; El-Hammady and Abo-Rizka 2011; Fernandez-Rodrıguez et al. 2000; Gencay 1999; Chang et al. 2009). The reason for this popularity can be attributed to a series of unique traits like fault tolerance, adaptability and regularization (Emin 2011; Medsker et al. 1993). As the model is data driven, it is not contingent upon model specification (Desai and Bharati 1998), and is often labeled by several researchers as universal approximator (Hornik et al. 1989; Cybenko 1989; Hornik et al. 1990). Neural network models have the ability to approximate, from the set of input and output variables, any complex functional form whose exact specification is not known (Hill et al. 1994). The model is robust in the field of time series analysis as the assumption of stationarity is not required. Given these findings the paper uses the non-linear auto regressive with exogenous input (NARX) neural network model for conditional forecasting with the competing indicators as the input variables. NARX is a form of advanced RNN model where the network's output is passed back with certain number of delay units to the hidden layer in parallel with the inputs (Menezes and Barreto 2008). The model out-performs it's contemporaries in modeling dynamic non-linear time series (Diaconescu 2008). The NARX framework can be can be depicted as follows

$$Y_t = F\left(Y_{t-1}, Y_{t-2}, Y_{t-3}, \ldots, Y_{t-p}, \ldots\ldots X_{t-1}, X_{t-2}, \ldots, X_{t-p}\right) + \varepsilon_t \tag{13}$$

where, Y_t is the target variable and X_t is the predictor series. NARX is basically a nonlinear representation of the ARX (p) model where the function F() mapping the input to the output is approximated from the data itself. The structure of a neural network depends upon the number of neuron in each layer and the type of transfer function. The number of input and output neurons is contingent upon the number of input and output variables. For the purpose of the study, a two-layer NARX network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer is considered. Levenberg–Marquardt algorithm is used for training the network. The Levenberg–Marquardt (LM) algorithm is the most widely used optimization algorithm and it outperforms simple gradient descent and other conjugate gradient methods in a wide variety of neural network problems (Ngia and Sjoberg 2000). Before proceeding further it is crucial to discuss certain issues related to the prediction modeling.

Data Partition and Network Generalization

There has always been a danger that network training may leads to model over-fitting (Cawley and Talbot 2010). The problem is more acute when many free parameters exist in the model. Over-fitting is detrimental because the network will not only learn to capture the dynamic relationship within the data but will also trace the inherent noise embedded within the data (Zhang 2004). The over-fitted network will start making better prediction for the in-sample data while performing poorly on the out-sample. Several literature exist on model over fitting (Hu et al. 1999; Weigend et al. 1991; Hassibi et al. 1993; MacKay 1992, Prechelt 1998a, b; Peterson et al. 1995, Larose 2005). To avert model over-fitting using *early stopping approach* (Sarle 1995; Yao et al. 2007) the sample of 2,452 daily CNX-Nifty return-data is divided into three sets—*Training, Validation and Testing* (Demuth et al. 2008) in the 70 %–15 %–15 % ratio (Hasan et al. 2014; Shi et al. 2013). In accordance to this rule, the first 1,716 days data points (70 %) are included in the *training set*, the next 368 days data (15 %) are considered for *validation set* and the last 368 days data (15 %) are included in *testing set*. The *validation set* is used to decide when the training should be stopped. The *testing set* is kept un-touched during the training and configuration procedure to prevent *data-snooping* (White 2000). Once the training stops the final configuration is used to predict the data from the *testing set*.

Network Configuration

The number of neurons in the hidden layer and the number of lags of the output in the feedback loops has to be determined before the training begins. For ascertaining the parameters in neural network architecture trial and error procedure is required (Murphy et al. 1997). Several researchers have revealed that minimization of the prediction errors over the training sample is asymptotically equivalent to minimizing the information criteria like AIC and BIC (Wei 1992; Inoue and Kilian 2006; Ing 2007). In the light of these findings a pilot survey is conducted where several combinations of parameters (*number of lags of the target and the number of neurons in the hidden layer*) are used to train the network and the mean square errors of the *validation set* (*out-of-the-sample MSE*) are recorded against each trial. *Validation set* is considered for configuration as opposed to the *testing set* to prevent *data snooping* (White 2000).Out-of-the-sample MSE is selected as opposed to the in-sample MSE to restrict *over-fitting* (Prechelt 1998a, b). Finally the specification that minimizes the validation set prediction error is selected for the final run of prediction on the *testing set*. Table 3 displays the configuration procedure. The "3-20" configuration is found to provide the lowest MSE for both the competing models.

Predictive Accuracy

The widely used measures of time series forecasting accuracy are—mean square error (MSE), mean absolute percentage error (MAPE), mean square prediction error (MSPE), normalized mean square errors (NMES), root mean squared error (RMSE), and prediction standard deviation (PSD). Although the above measures are convenient to gauge the statistical accuracy of the forecast, they fail measurably in evaluating the profitability-dimension of forecasting. There has been strong consensus among the researcher that the statistical measures of predictive accuracy are not correlated with the profitability of using the forecast (Pesaran and Timmermann 1995). The forecasting performance based on the direction measure i.e. the number of times the forecast correctly predict the direction of the actual movement is believed to closely match with the profit booking opportunity (Leitch and Tanner 1991). However, there is a problem with the directional measure (hit ratio). Consider a situation where the forecast correctly predicts the direction of the price movement for most of the time but fails in limited states when the magnitude of the movement is large. In such a case the profitability of using the forecast cannot be truly measured by the directional measure alone. What is needed is a measure which pools the impact of direction and magnitude of the movement. The correlation coefficient between the forecasts and the actual returns fulfills this gap. The paper uses "correlation coefficient" along with the other measures to evaluate the profitability of the forecast.

Diebold–Mariano Test

The Diebold–Mariano (DM) test is a robust test of statistical significance of the difference between the predictive accuracy of two competing forecasting model (Diebold and Mariano 2002). It has been extensively used to compare the predictive ability of different models through (pseudo-)out-of-sample forecasting. (Kanas 2001; Cao et al. 2005; Constantinou et al. 2006). The current study uses this test to compare the predictive ability of MRCD–NARX and MACD–NARX models. The statistic uses the normalized mean of the loss-differentials (d) from the two competing forecasts as shown in Eq. 14.

Table 3 Network configuration

MRCD –NARX model			MACD NARX model		
No. of lags of the target	No. of neurons in the hidden layer	MSE (validation set prediction)	No. of lags of the target	No. of neurons in the hidden layer	MSE (validation set prediction)
2	10	1.32931e−5	2	10	2.91360e−4
2	20	1.32869e−5	2	20	3.05291e−4
3	10	1.27831e−5	3	10	3.07984e−4
3	**20**	**1.23783*e−5**	**3**	**20**	**2.73886e−4***
4	10	1.60496e−5	4	10	3.76411e−4
4	20	1.87069e−5	4	20	2.93629e−4
5	10	1.34130e−5	5	10	3.36531e−4
5	20	1.46465e−5	5	20	2.94026e−4

Source Author's analysis

The line in bold highlights the configuration which provides lowest *Validation Set Prediction MSE*

$$\bar{d} = \frac{1}{N}\sum_{t=1}^{N} \mathcal{L}(e_{it}) - \mathcal{L}(e_{jt}) \tag{14}$$

where, e_{it} and e_{jt} are the (pseudo-)out-of-sample forecast errors from the competing models MRCD and MACD model respectively, and $\mathcal{L}()$ is the loss function used. The DM statistic is represented by Eq. 15.

$$DM = \frac{\bar{d}}{\sqrt{\widehat{LRV}(\bar{d})/T}} \tag{15}$$

$\widehat{LRV}(\bar{d})$ is a consistent estimate of the asymptotic variance of $\sqrt{T}\bar{d}$. The long-run variance is used because the sample of loss differentials $\{\mathcal{L}(e_{it}) - \mathcal{L}(e_{jt})\}$ are found to be serially correlated when the power of the loss function is greater that one. The statistic is well behaved, normally distributed with mean of zero and standard deviation of 1 for a wide variety of loss function. The following research hypothesis is tested

H_A The predictive accuracy of MRCD based model is statistically greater than the predictive accuracy of the MACD based predictive model.

Since it is a right tailed hypothesis test, by design, the DM statistic should be greater than 1.645 to validate the hypothesis at 5 % level of significance ($p < 0.05$). The wide acceptance of DM test for the purpose of model selection has been recently criticized by Costantini and Kunst (2011) and Diebold (2012). The two major arguments were put forward. First, for small sample (data points <100), the DM test is biased toward the null hypothesis and second, if the selection of the competing models are based on information criteria (AIC & BIC), the DM test may sometime prefer simpler model. The paper uses a large data set (*2,452 with 368 out-of-the sample data points*) and hence the small-sample bias is not applicable. Secondly, the competing models are selected based on the underlying theory behind the construction and suitability of MRCD and MACD indicators as input variables and thereby the second argument is not applicable in this case. To gauge the practical applicability of the forecast, the paper further uses the correlation measure, HIT ratio and the outcome of a forecast based trading rule.

Forecast Based Trading Strategy

To address the issue of reproducibility of the methodology (*research question 2*), the out-of-the-sample forecasts are used to devise a long-short trading strategy, which is back-tested on a daily basis over the 368 days (15 % of 2,452 days) of the testing data set. The trading rule is explained as follows. Given the historical returns and the MRCD/MACD indicators on any date (t) the one-day ahead (t + 1) return is forecasted. If the forecast shows positive return, go long on the stock as soon as the market opens and if the forecast shows negative return go short. All open positions are covered before the market closes on the respective days. For simplicity, transaction cost is not taken into consideration.

Findings and Analysis

Before the trained MRCD–NARX and MACD–NARX models can be used for forecasting, it is essential to check the residuals for possible signs of auto-correlations and non-normality. Figures 1 and 2 reveals no sign of auto-correlation at 95 % confidence level. Figures 3 and 4 reveals that the errors are normally distributed. A white noise residual validates the model construction and provides clearance for forecasting evaluation.

Table 4 displays the predictive ability of MRCD and MACD based models. The out-of-the sample forecast of the MRCD–NARX model reveals lower MSE (1.24516e−5) in comparison to that of the MACD–NARX model (2.46130e−4). This buttresses the argument that MRCD provides statistically better prediction than MACD. To explore whether this statistical efficiency can be leveraged financially, the correlation coefficient between the target and forecasted values are measured over the testing set. A high correlation (0.933333) between the target and the forecast is establish for the MRCD based model while the corresponding correlation coefficient for the MACD based forecast is found to be significantly low (0.00108074). Figure 5 and 6 displays the correlation coefficients for the different sample sets. It is further revealed that the MRCD based model predicts the sign of the return correctly for 94.29 % of the cases while the MACD based model provided correct sign prediction for only 53.37 % cases. The long-short trading rule is applied on a daily basis over the *testing set* using forecasts from both the models. The payoff-multiple for each strategy is defined as the ratio between the final wealth and the initial wealth. It is taken as the measure of profitability. Figure 7 sketches the movement of the initial wealth (which is normalized to one) for both the strategies. For the trading rule that uses MRCD based forecast the wealth increases by 15.37 times within a period of 368 days (*testing period*). The corresponding payoff-multiple for the MACD forecast based trading rule is 1.082. This finding address the practical usability and reproducibility of the research (RQ: 2).

To address the research question (RQ: 1)—"*whether the predictive accuracy of MRCD based model is significantly greater than that of the MACD based model*?" the Diebold–Mariano (DM) test is conducted. The following competing hypotheses are evaluated.

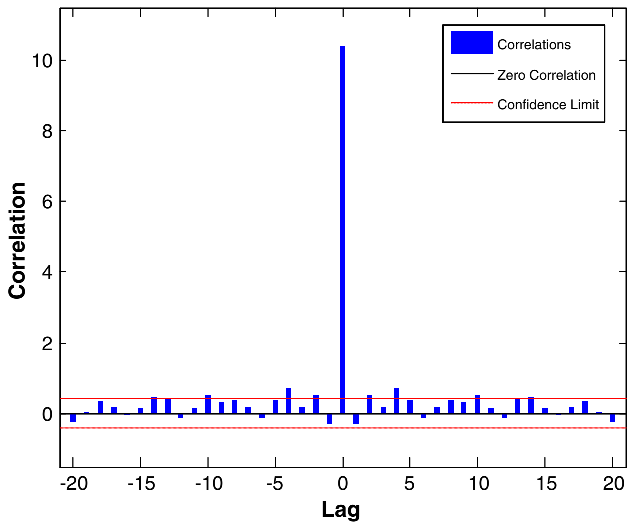

Fig. 1 Auto correlation among the errors of the MRCD based model

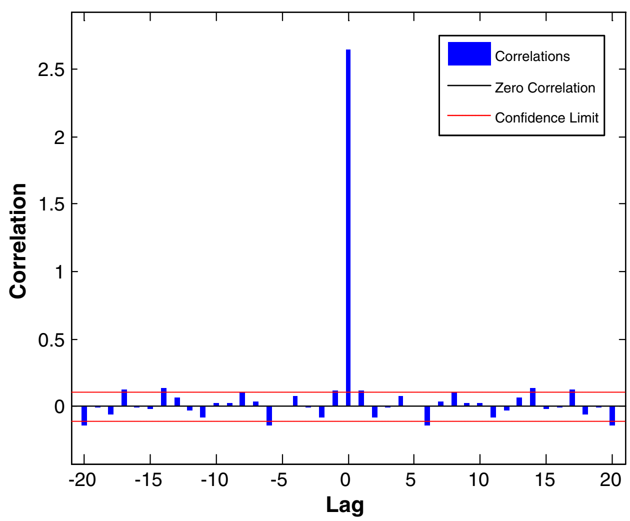

Fig. 2 Auto correlation among the errors of the MACD based model

H0 The predictive accuracy of the MRCD–NARX model is less than or equal to the predictive accuracy of the MACD–NARX model

against

HA The predictive accuracy of the MRCD–NARX model is greater than the predictive accuracy of the MACD–NARX model

The results of the right-tailed hypothesis test using the quadratic and linear loss function are displayed in Table 5. For both the loss functions the null hypothesis is rejected at 5 % level of significance. Hence at 95 % confidence level it can be concluded that the predictive ability of the MRCD indicator is superior to that of the MACD indicator.

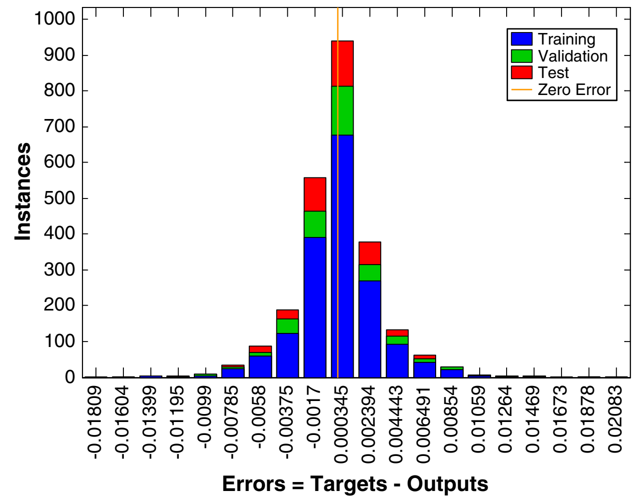

Fig. 3 Error histograms with 20 bins for MRCD based prediction model

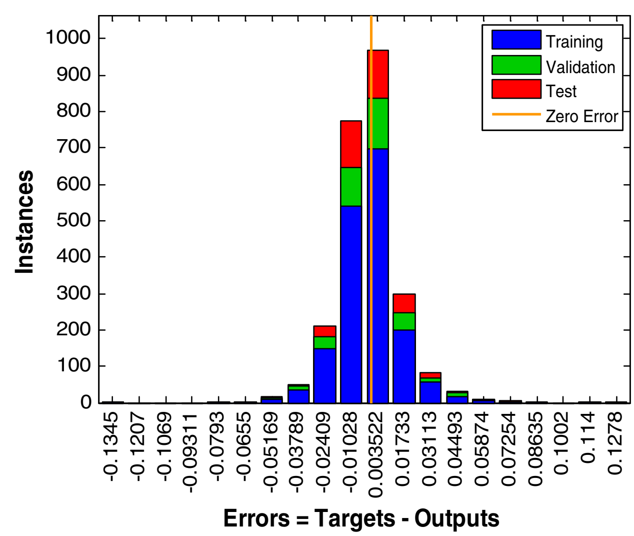

Fig. 4 Error histograms with 20 bins for MACD based prediction model

Conclusion, Unique Contribution and Scope for Further Research

The study buttresses the philosophy that it is not only information but the complex interpretation of the information that drives the stock price. This is also the *unique contribution* of the paper. The cumulative understanding of different information and its realization through *trading* is a complex process. The intricacy results primarily because of *cognitive prejudice* and *information complexity* across traders.

Table 4 Out-of-the sample performance evaluation

Predictive models	Measure of statistical accuracy	Measures of economic significance (results are from the testing sample)		
	MSE	Correlation measure	HIT ratio (in %)	Long–short trading rule payoff multiple
MRCD-NARX	1.24516e−5	0.933333	94.29	15.37
MACD-NARX	2.46130e−4	0.00108074	53.36	1.082

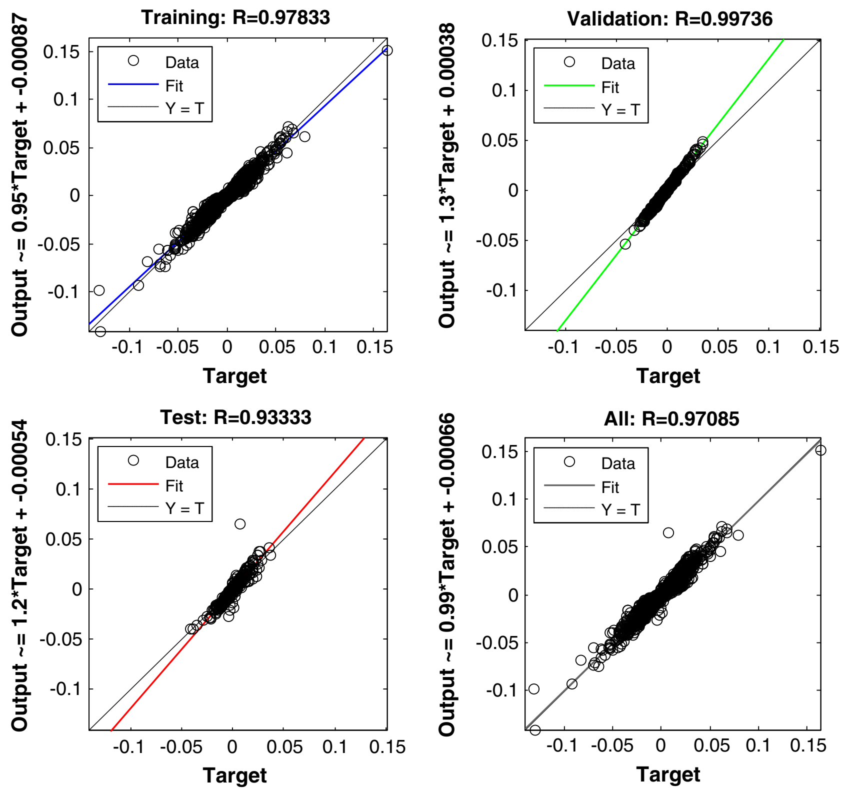

Fig. 5 Correlation measure (MRCD)

Addressing Cognitive Prejudice

Often the decision making process is guided by irrational elucidation of the environment that can arise either because of lack of awareness or because of human biasness toward a desirable outcome. It is required to appreciate that these irrational trading behaviours are equally important to predict the future outcomes. However, unlike the market information, the human irrationality is not measurable. What can be recorded is the price fluctuation which is the direct outcome of the way information is interpreted by the agents in the market. As investors, trading at different scales, view information in a different ways, it seemed reasonable to extract multiple frequency components from the stock return process to account for this variability. The MRCD indicator (*developed in this study*) displays divergence (convergence) when the buying pressure increase (decrease) among the high frequency traders resulting from the positive (negative) news incidence and which has not been reflected into the trading activity of the low frequency traders. The superior forecasting ability and realizable profitability of the indicator validates the principal argument of this study.

Addressing Information Complexity

Information does not come free. Even if one can afford to purchase the same, there is always a time-delay between the revelations of information and when the same is made available to the traders. Hence market generally takes time to react to the incident information. This generates *momentum* in the price movement. For example, positive (negative) news is found to create buying (selling) pressure for successive time periods. Significant news with market wide long lasting impact results in the realization of *trend*. Technical analyst relies on this underlying principle when they analyses past information to predict the future. Concurrent information is not considered as it is yet to be

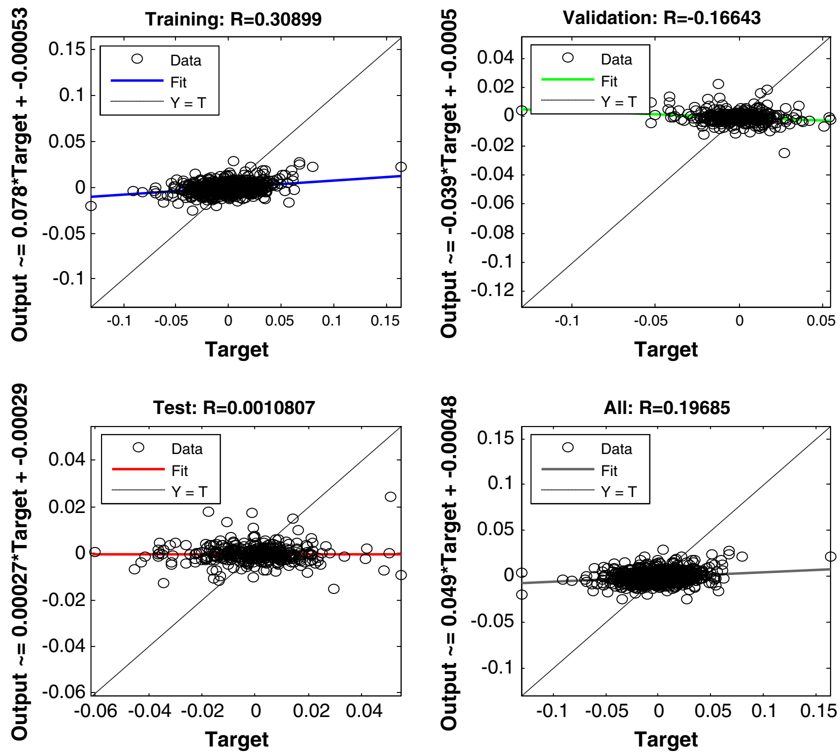

Fig. 6 Correlation measure (MACD)

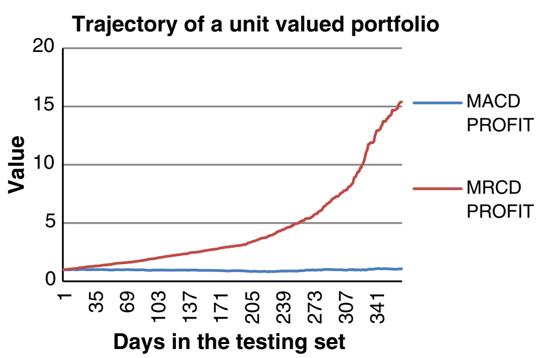

Fig. 7 Results from back-testing the long-short trading rule using the forecasts from the competing models

reflected in the price. With the advent of technology this information gap (*time-delay*) is narrowing at an increasing rate. *Real time information streaming* (through service providers like *Bloomberg, Thomson Reuters* etc.), *on-line & algorithmic trading* and advancement in *data & text analytics* enables agents to capture information early. When on the one hand this increases the market efficiency, on the other hand it adds to the volatility and uncertainty. In this era of high-frequency trading, charting tools and techniques seemed no longer sustainable. When, on the one hand, the wide spread use of technical indicators is threatening its effectiveness, on the other hand the unceasing metamorphosis of the system by the research community is refurbishing its competitive edge. Researchers have been reacting to the threat by developing sophisticated non-linear models to capture the *ordered chaotic reality* from the apparent random process. The domain has witnessed a colossal shift from charting tools to quantitative modeling, which has been initiated through the convergence of different expertise like statistics, econometrics, operation research, neuro-science, machine learning, genetic algorithm, fuzzy theory etc. The present study contributes to this *evolution*.

Table 5 Diebold–Mariano test results

Loss function type	DM statistic	Critical value	*p* value
Quadratic	2.1309	1.645	0.03319
Linear	4.6611	1.645	0.000003314

Source Author's analysis

Limitations and Further Research Directions

Like all studies, this current work has its own limitations and future studies are expected to be abetted if some limitations of the present study are examined. These are delineated through the following sections as follows:

Multi-frequency Re-engineering of the Fundamental Indicators

The current study ignored the role of fundamental analysis in stock market prediction. The school of fundamental analyst believe that macro-economic indicators (*like GDP growth rate, inflation, money supply* etc.) and firm specific fundamental indicators (*like dividend & earning announcements, price-to-earnings ratio, price-to-book-value ratio* etc.) plays a substantial role in predicting future movements (Dechow et al. 2001; Beneish et al. 2001; Ou and Penman 1989). While technical indicators capture information with a time delay, the fundamental indicator provides recent information that is likely to impact the price. Practitioners often combine wisdom from *fundamental and technical analysis* in generating efficient forecasts (Lam 2004; Atsalakis and Valavanis 2009). It is highly recommended to examine the fundamental indicators using the newly developed methodology of "*multi-frequency re-engineering*". Research along this line, in the future, can leads to a more comprehensive and robust forecasting methodology.

Study Using High Frequency Data

The methodology can be applied to high-frequency data in order to examine its performance on a minute-by-minute prediction. Behind the apparent *randomness* of the intraday stock price movement lays a nonlinear deterministic process called *chaos* (Hsieh 1991). It will be interesting to examine how the *multi-frequency re-engineering* performs in this environment.

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Key Questions

Reflecting Applicability in Real Life

i. How apposite synergy between *behavioural finance* and *financial engineering* can augment stock market predictability?
ii. Can the newly envisaged "*multi-frequency re-engineering*" be able to capture *market irrationality* in formulating a *flexible prediction paradigm*?
iii. How the developed system can be *reproduced* in the industry?

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