

# **A Quantitative Neural Network (QNN) Model for Stock Trading Decisions**

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## ***Abstract:***

Trading activities are based on technical analysis, market sentiment (asymmetric information, rumours, noise trading) and imitative behaviour. This leads to unjustified biasness in decision making. To remove such subjectivity, this paper suggests a neural network model for the investors to decide whether buy or sell the shares. The model consists two wings – one, based on technical analysis and the other, on fundamental analysis. The integral part of this model is the existence of a hidden layer between the input layer and output layer. To remain away from the subjectivity, this model does not consider the behavioural factors in modeling.

## **1. INTRODUCTION**

General decisions for stock trading include whether to hold, buy or sell set of stock. The key to a better decision-making lies in obtaining relevant, accurate and timely information and using the cognitive capacity of individual, then translating information into knowledge and decision-making (Wilson 1995). Decisions are programmed to the extent that they are repetitive and routine, to the extent that a definite procedure has been worked out for handling them so that they do not have to be treated as new each time they occur. Decisions are non-programmed or heuristic to the extent that they are novel, unstructured, and consequential (Simon 1960). Decision for stock trading may fall in between these two extremes. Decision making is considered to be a difficult task in stock trading as it involves innumerable combinations of complexities and uncertainties. Different structural, psychological, physical and environmental factors coupled with organizational and environmental pressures on the decision maker turn decision making in stock trading a confusing task. When the individual or the institutional decision maker takes decision regarding buy or sell of stocks, subjective judgment plays a significant role. Presence of subjectivity creates variations between or among the decision makers; also it may create

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decision errors. Some, not all, part of the trading decision can be automated for better optimization of investment through a quantitative model. This paper tries to suggest a model, which could provide buy or sell decisions in stock trading. These decisions would be objective. This objective model is based on neural network. The use of neural network model in forecasting is not new. A comprehensive review of the fundamental concepts and principals of the artificial neural network (ANN) can be found in Rumelhart and McClelland (1986) and Caudill and Butler (1993). Moreover, Hawley, Johnson, and Raina (1990) and Medsker, Turban and Trippi (1993) provide an overview of the neural network models in the fields of finance and investment. Specht (1988, 1990) proposes probabilistic neural network (PNN). Chattopadhyay (1997), in his paper, proposes a new methodology for predicting country risk ratings in evaluating global portfolio investment decisions. Chen, Daouk, Leung (2001) suggest a forecasting model using the neural network for Taiwan Stock Index.

Our paper differs from the aforesaid works in two aspects. First, we tried to develop a theoretical foundation to our model. Both technical and fundamental analyses have been accommodated in our model. No empirical attempt to prove this model has been taken. Second, we tried to avoid subjective variables as much as possible. The main objective of this model is to help the investors taking buy or sell decisions using objective parameters. Another motivation for this study is to confirm whether we can extend some basic notions of traditional financial forecasting modeling. This paper is arranged in the following way. Section two, at first, discusses the foundation of behavioural aspect of human and decision making process; and then explains the departure of our neural network model from the behavioural factors. Section three explains in detail the quantitative neural network model, and the last section, Section four, concludes the paper.

## **2. HUMAN BEHAVIOUR AND DECISION MAKING**

### **Statistical Man**

Sometimes the question arises: Does the trader conceive a statistical model in the mind and base its decision on it? Is that the human being i.e. the stock member or the decision maker on behalf of the member is calculating every time and trading each time? Peterson and Beach (1967) tried to co-relate statistics and human being. They developed a normative model, i.e., the correct answer in line with probability theory and statistics. Then they tested the population with the result of a statistical test. They concluded that participants performed

quite well. The researchers find out some discrepancies between participants' behavior and normative model, however, the general idea was that, though normative models might need some adjustment, they nonetheless capture human behavior in a fundamental way. According to the result of the test it could be concluded that traders use statistical models in their judgments for trading related decisions.

### **Cognitive Limitation and Uncertainty**

The statistical models for decision making in stock trading require considerable amount of statistical analysis with historical data. Research by Miller (1956) pointed out cognitive limitations of human being. He finds that at any given moment, a human being is limited to the manipulation of between five and nine distinct pieces of information. Miller introduced the term chunk to describe an "organized unit of information" stored in the working memory. Another thing that has to be considered along with cognitive limitation is the uncertainty associated with the states of the decision matrix. Total certainty implies that a total knowledge of the problem domain is understood and the outcome is predictable. However, stock trading is not the case. So even if the decision maker intuitively develops quantitative model of the problem, the outcome of the decision can be faulty because of the cognitive limitation and uncertainty.

### **Heuristics and Biases**

Decision under uncertainty can be divided into two sub-categories: 1) uncertainty due to inadequate information, and 2) uncertainty due to inaccurate information. According to the paper published by Kahneman and Tversky (1970), human beings employ three heuristic principles in an effort to reduce the complexity of the decision making. These principles are: 1) representativeness, 2) availability, and 3) adjustment and anchoring.

'Heuristic' is a term used by psychologists to denote general problem solving procedures involving everyday solution of problems. It is a rule-of-thumb, a guideline for coming up with a solution (Best, 1989). Skitmore et al. (1989) mentioned that cognitive heuristics or principles are systematic rules that operate instead of a detailed analysis of the available information thus conserving mental effort.

Representativeness relates to categorization problems and relies on the estimation of similarity. This states that the probability that event A is related to event B is evaluated by the

degree to which A resembles B. This involves search and compare strategies (Chi and Fan, 1997). The availability of heuristic states that instances of large classes are usually recalled better and faster than instances of less frequent classes. The third heuristic, anchoring and adjustment, states that people estimate an uncertain value by starting from some obvious value (anchor) and adjusting in the desired direction. Heuristics, therefore, define how a member of a stock exchange is making decision in case of imperfect information.

### **Functional Fixedness and Mental Model**

Baron (1989) defined 'Functional Fixedness' as another way of doing work. The decision-maker tends to develop a device in a way they used in the past and repeating the same thing in similar circumstances. This is the outcome of the past experience used in the present problem solving. People in this case try to retain the successful methods and use those in the future.

Best (1989) describes mental models as internal representations of problems that are formed over a period of time by various experiences of a similar nature. These representations are defined as cognitive maps (Tolman, 1948). Barlett (1932) proposed that memory is guided by a schema. This schema is nothing but a mental structure. This schema always changes with experiences.

### **The Consequences and Departure from Behavioural Factors**

Whatever the case is in decision making, i.e., heuristics, functional fixedness or mental models, the consequences are something not desirable. These create biases in the decision making. BSV model by Barberis, Shleifer, and Vishny (1996, 1998), and DHS model by Daniel, Hirshleifer and Subramanyam (1998) pointed out that these biases can produce over-reaction and under-reaction to others. BSV model is based on judgmental bias, i.e., representativeness bias of Kahneman and Tversky (1982), which expresses: People give too much weight to recent patterns in the data and too little to the properties of the population that generates the data. Both the over- and under-reaction creates anomalies in the market. This anomaly is being identified and is now the topics of behavioral finance.

Behavioral finance is a study of investor market behavior that derives from psychological principles of decision making, to explain why people buy or sell the stocks they do. Behavioral finance focuses upon how investors interpret and act on information to make

informed investment decisions. Investors do not always behave in a rational, predictable and an unbiased manner indicated by the quantitative models. Behavioral finance places an emphasis upon investor behavior leading to various market anomalies. Financial economists have been aware for a long time that in laboratory settings, humans often make systematic mistakes and choices that cannot be explained by traditional models of choice under uncertainty. For example, many portfolio managers herd around their benchmark portfolio (Scharfstein and Stein, 1990; Lakonishok et al. 1994). Many of the financial economists accept the notion that some of the behavioral phenomena uncovered in laboratory settings may affect pricing in financial markets.

There are different outcomes of investors' behavioural pattern in stock trading. One significant anomaly is trading is biased according to weekdays. Miller (1988) and Lakonishok and Maberly's (1990) hypothesis is that although it is costly for all investors to gather and process information, it is particularly costly for individuals to do so during weekday trading hours when these people are typically employed in other activities. For individual investors, weekends provide a convenient, low-cost opportunity to reach investment decisions. Thus, when markets reopen following weekends, individual investors might be expected to be more active traders. Individual trading behaviour is skewed toward selling early in the week and, second, liquidity in general is lower during the earliest part of the week.

Timing is another important factor in trading, especially for those investors, who focus much on short term gain. An electronic order book provides an important flow of information about the state of the market: prices on each side, volumes, past trades (purchases and sells), spreads (nature of adverse selection), proposed, cancelled and matched orders (Glosten, 1994). Thus, time is seen to be a particular variable, which has a direct influence on trading (Barneto). As Goodhart and O'Hara (1997) suggested, time is endogenous and consequently raises problems. Recent studies on microstructure and high frequency data have emphasized the role of time and duration between two trade prices (Easley and O'Hara, 1992; Engle, 1996).

Intraday trading variability is another important aspect. Both informed and liquidity traders concentrate trading at the open and close. Specialists and limit order book markets exhibit concentration of volume and volatility at the open and close of the trading day, while spreads

are widest at these times (Ahn and Cheung (1999), Andersen et al. (2000), Brockman and Chung (1998 & 1999), Chung et al. (1999), Ding and Lau (2001), Foster and Viswanathan (1993), Ke et al. (2004), Madhavan et al. (1997), and Comerton-Forde et al. (2005)). In contrast, dealer markets exhibit a decreasing spread through the trading day with concentrated volume and volatility at the open and close [Chan et al. (1995), Chung and Van Ness (2001), Levin and Wright (1999), Reiss and Werner (1995), and Werner and Kleidon (1996)].

Liquidity need and rebalancing of portfolio or dynamic hedging may also be considered as important reasons for stock trading. Several researchers have reported that buy recommendations by the brokerage community outnumber sell recommendations by wide margins. Groth et al. (1979) report that of 6,000 recommendations from analysts, 77 percent suggested purchase while only 13 percent recommended sales. Diefenbach (1972) reports the ratio of purchases to sales recommendations to be even further skewed. This implies the sell-decision may not be a well-thought decision in many times as the buy-decisions are. From the above and several other discussions, we can summarize some key factors to address in stock trading such as: liquidity position, expected portfolio composition, opening and closing trading pattern, biasness towards specific type of firms or portfolios, timing of trading, selling or buying skewness, etc.

We believe that price is the reflection of aggregate behaviour of the investors. So, instead of considering each and every behavioural issue, which is in fact not unanimous at every level, we rather prefer to use the price – which is universally accepted – as one of the important input in our model. Our QNN model is based on the following assumptions:

- (1) Investors are objective in choosing shares.
- (2) The investors do not have liquidity crisis. This ensures absence of unjustified selling decisions of shares.
- (3) Intraday timing of trading is not important, as this model uses daily data.

By incorporating these assumptions we are departing from the behavioural finance in the sense that we are not incorporating any specific behavioural factors in our model. However, this model also assumes that the investors are independent in constructing the portfolio or

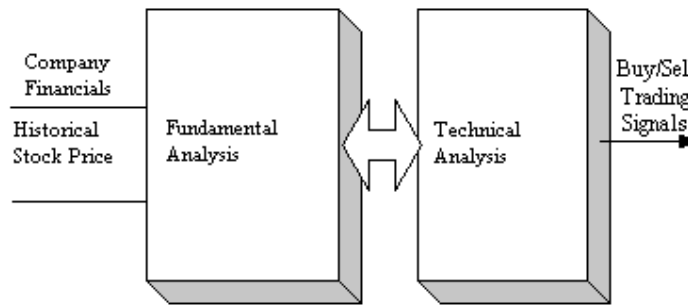
choosing a stock to or not to buy or sell. The chief objective of this model is to provide objective signal to buy or sell; implementation of the decision rests upon the investors.

### **3. QUANTITATIVE NEURAL NETWORK (QNN) MODEL**

Neural network, a kind of an expert system, is a powerful modeling tool that is able to capture and represent complex relationships among relevant variables. It can compare existing stock-trading patterns with previous situations, analyze all kind of indicators and eventually "learn" what works and what does not as the program digests more data. The true power and advantage of neural networks lies in their ability to digest a huge amount of data, find both linear and non-linear relationships from trading patterns, and make deep analytics that can never be accomplished by human analysts at the same time. Efficient Market Hypothesis claims that financial market reflects a set of random time series. Most of the technical analysis that tested the hypothesis relied on linear time series modeling (Black & Scholes, 1973). These linear models focus on historical data. The nature and complexities embedded into the stock market makes it really difficult to forecast a particular market by using a linear relationship. These linear relationships are not capable of identifying dynamic or non linear relationship in the historical data. The proper relationship can be derived by using some expert system. An expert system is a sophisticated computer program that can make intelligent or best possible decisions by taking many related variables or measurements into account. An expert system gets its intelligence from two sources: (a) knowledge from human experts or tested rules, which are programmed to the system, and (b) dynamic learning via neural network technology and statistical analysis on historical data.

In this section we describe our suggested quantitative neural network (QNN) model. This model consists of two parts. Both parts show buy or sell decisions; one using the technical analysis, and the other using the fundamental analysis. The investor is independent to accept any result derived from the both parts. The whole system can work as follows depicted in Figure 1. Using the historic stock prices and other company financials, the model will provide buy or sell signal objectively with the help of technical and fundamental analysis.

**Figure 1: Trading Model using Fundamental and Technical Analysis**



The use of technical analysis has always posed an interesting question for the efficient market hypothesis (EMH) as later implies that such methods could not be successful. In particular, the weak form of the efficient market hypothesis maintains that prices incorporate all historic information so that an analysis of price pattern cannot produce any profit. On the contrary, the basic objective of technical analysis is to identify the price pattern to make profit in the short run. So, there is a close link between the validity of technical analysis and the inefficiency of the market. As the foundation of this model is technical and fundamental analysis, the question may come whether we are departing from the concept of efficient market hypothesis. Studies show that capital market misprices assets. Evidence is there that plenty of technical analyses could produce abnormal profits. However, among many different technical analyses, not all could help to reap profit. Brock et al. (1992) test the hypothesis of moving average trading rule that consists of a buy signal when price moves above a particular moving average and a sell signal when the price crosses below the average. Using the data set of the Dow Jones average for several decades, they found almost no net gain for using either the buy or sell signal. However, Neely et al. (1997), and LeBaron (1999) found profitability for exchange rates using moving average rules. White (1993) analyzed neural networks on 1000 closing prices of IBM stock that was used to make predictions on the next 500. White's procedure involved simply finding the optimal fit for the past three days of closing prices and utilizing it to predict the next day. The procedure failed to produce a profitable trading strategy. However, Blume et al. (1994) conclude that sequences of volume and price can be informative and argue that traders who use information contained in the market statistics attain a competitive advantage. A different approach, adopted by Caginalp and Laurent (1998) involves testing of short term patterns, called Japanese Candlesticks, believed to have predictive power. Morris (1992) found significant predictive power using 265,000-day data set. Antoniou et al. (1997) worked on moving average and found that price trend integrated



with volume yield some predictability in the emerging market of Istanbul. Similarly, Bessembinder and Chan (1998) included dividends in the returns and found some positive return. Chang and Osler (1999) found that the head and shoulders pattern was predictive in some cases and not in others. Chan et al. (2000) found that momentum strategies (particularly if augmented by volume considerations) have some significant positive returns for international stock indexes for holding periods less than four weeks.

There are further evidences that capital market misprices assets. Analysts can pick the mispriced assets through fundamental analysis. Asquith and Meulbroek (1996) provide evidence that short-sellers, as a group, successfully identify securities that subsequently underperform the market. A large body of evidence demonstrates that ratios of measures of fundamental value to market value systematically predict future stock returns. These ratios compare estimates of “intrinsic” value based on accounting data to observed market prices. They range from simple ratios such as earnings-to-price and book-to-market to ratios based on more sophisticated valuation models such as Ohlson (1995). Basu (1983), Lakonishok et al. (1994), and Sloan (1996) show that various measures of cash flows scaled by price are positively related to future stock returns. Basu (1983) and Fama and French (1992) show that earnings-to-price ratios are positively related to future returns. Stattman (1980), Rosenberg et al. (1985), and Fama and French (1992) show that book-to-market ratios are positively related to future returns. Edwards and Bell (1961) and Ohlson (1995) described firm value as sum of the book value of common equity plus the present value of future abnormal earnings.

Lev and Thiagarajan (1993) introduces a collection of “fundamental signals” that reflect relations in current accounting data that are purported to predict future earnings changes. Abarbanell and Bushee (1997a) present evidence that many of the fundamental signals are associated with subsequent actual earnings changes. Abarbanell and Bushee (1997b) show that an average 12-month cumulative size-adjusted abnormal return of 13.2 percent is earned on hedge portfolios formed on the basis of the decile ranks of the fundamental signals over the sample period 1974-1988.

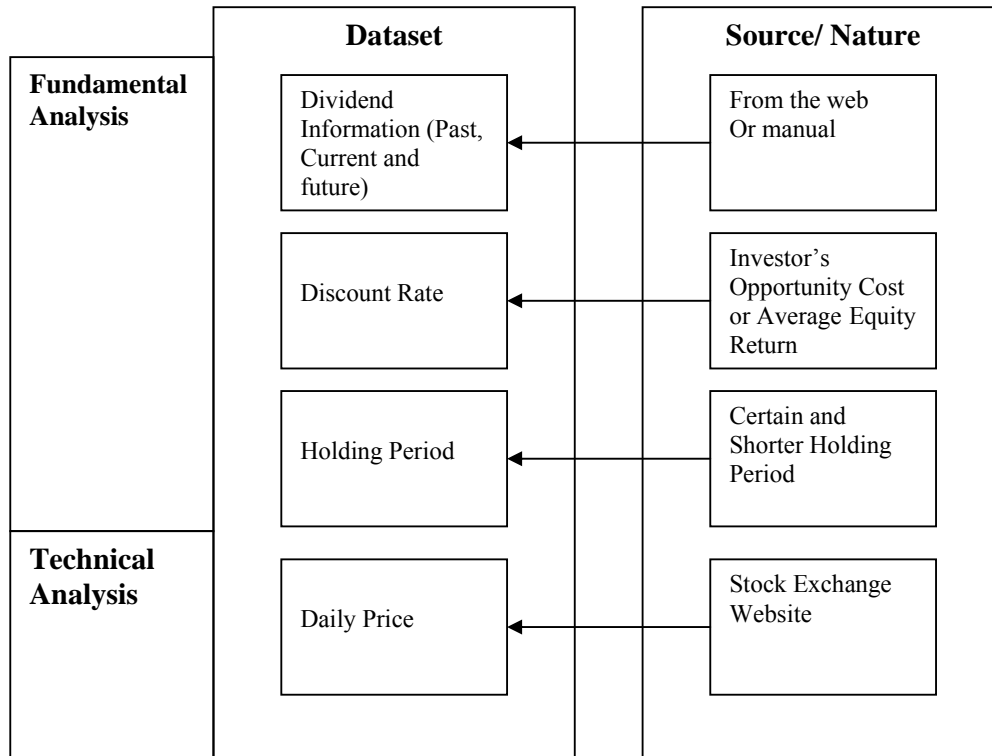
To keep this study brief, we avoid the discussion of “January Effect”, “Monday Effect” and others anomalies. The point is, we suggest one model, which helps the investors in buy or sell without any bias regarding human behaviour or other anomalies. We assume the market temporarily underuses the information about future economic variables.

The second part of our neural network model is based on fundamental analysis. This is a challenging task to integrate both technical analysis and fundamental analysis under the same decision rule. That is why our neural model includes a separate module for the fundamental analysis. The basic objective of fundamental analysis is valuation. Several common valuation models in practice are: dividend discount model, operating free cash flow model, and free cash flows to equity model. All these models apply a basic computation technique – forecast the future cash flow, assume a discount rate, and discount the cash flows of the years. Myers (1984) stated that discounted cash flow is not helpful in valuing companies with significant growth opportunities. He mentioned four chief problems applying the DCF technique as estimation of discount rate, estimation of project's future cash flow, estimation of project's impact on the firm's other cash flows, and estimation of the project's impact on the firm's future investment opportunities. To trim down these problems we adopt the suggestions by Penman (2001). These are: to use finite, especially shorter time horizon to forecast; to be able to forecast observable; and to keep the pieces of information fewer.

Our objective in this neural network model is to reduce the subjective judgments. That is why, in fundamental analysis model also, our objective is to keep it as much objective as possible. Among the different valuation models we choose dividend discount model in our QNN model. The reason behind not choosing the other two models is the possibility of high forecasting error due to computational biasness and uncertainty of variables involved. To compute free cash flow and free cash flow to equity, computational bias is evident with the choice of depreciation and other accounting methods. Another issue is uncertainty in determining cash flows due to company's growth prospect. On the contrary, dividend discount model may have low forecast error. Lintner (1956) said firms have long-run target dividend payout ratios. As managers "smooth" dividends, thus, transitory earnings changes are unlikely to affect dividend payouts. So, a forecasted dividend may have less subjectivity. The holding period for the valuation model will be determined by the user of the QNN model. Our suggestion would be to keep the holding period shorter to minimize the computational error. As we are adopting the dividend for the valuation, it is better forecastable for a shorter time horizon. The larger the assumed holding period the greater would be the error in dividend forecast. Lastly, the discount rate would be the average equity return or the opportunity cost of the respective investor. This is unwise to make this 'variable' uniform to all the investors. So, in this model, instead of using average equity return, the

investor can apply his/her own judgment to determine the discount rate. Figure 2 shows the data required and the source of data for the QNN model.

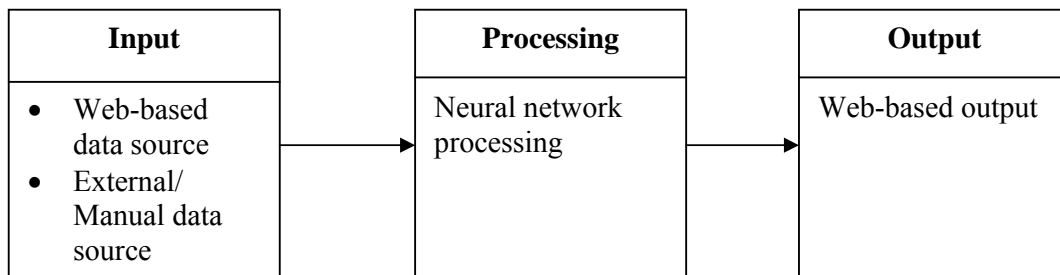
**Figure 2: Dataset and Sources of Data for the QNN Model**



**Physical Architecture of QNN Model**

Architecture defines the way the neural network will be working. The architecture deals with both the legacy data and current data. The legacy, that is historical data, will be imported from external sources while the daily data will be captured from the web site. This data will then be stored in database. Data from the database will then be retrieved to be incorporated into the neural network. The decision from the neural network regarding the stock decision will be conveyed to the users through another web-based technology (Figure 3).

**Figure 3: Neural Network Model**



On the server-side, the system employs an *n-tier* architecture consisting of web-server, database server and business object server. This approach allows the separation of business rules from data storage. As a result, business rules can evolve over time without necessitating changes at the underlying data layer. The architecture will be developed in such a way that it becomes platform-independent, code-independent and data-independent. Platform and code independence are facilitated through JAVA technologies, platform independence by virtue of the Java Virtual Machine (JVM), and code-independence, through Java Servlet/JS and Java Database Connectivity. The final objective of data-independence is facilitated by the Extensible Markup Language (XML) and its derivatives. The derivative that is considered in this case is Simple Object Access Protocol (SOAP). The rules regarding the neural network will be employed as business objects and will be stored in the business object server.

**Neural Network Process (NNP)**

The neural network process may be described as follows. Consider that  $x_i$  represents today’s price and  $y_i$  represents price after ten days. If the price of the stock is predicted after ten days then there should be a functional mapping from  $x_i$  to  $y_i$  where  $y_i = f_i(x_i)$ . Using all  $(x_i, y_i)$  pairs of historical data, a general function  $f()$ , which consists of  $f_i()$  could be obtained, that is  $y = f(x)$ . That is  $x$ , which consists of more information in today’s price could be used in function  $f()$ . This function can be simulated in a neural network. This trained network is then used to predict the movement of the future.

A general regression analysis with neural network can be represented as follows:

$$y = \sum_i w_i x_i + \Theta \dots\dots\dots(1)$$

Here, input to the network is  $x_i$  or, in other word,  $x_i$  to be defined as input node of the neural network. Each input is multiplied by a random weight  $w_i$  and the products are summed together with a constant  $\Theta$ . The summation is an operation that is hidden at the hidden node. Since the weights and the constants are chosen at random, the value of the output will not match with experimental data. The weights are systematically changed until a best fit description of the output is obtained as a function of the inputs. This whole operation of matching the input with the output is called as “training the network”.

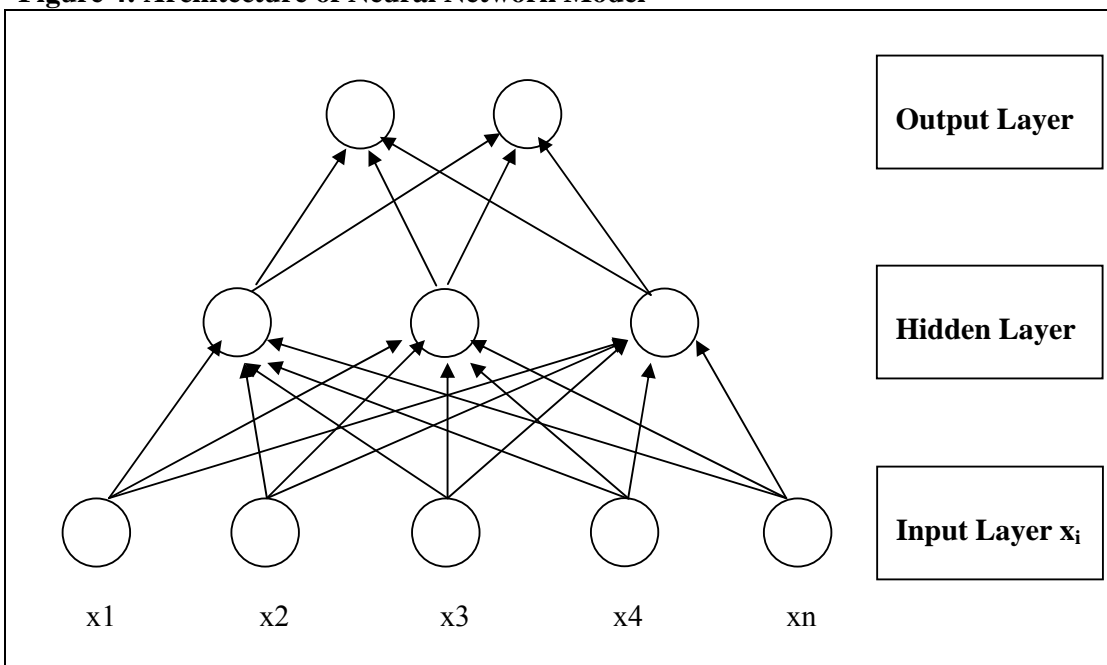
However, equation (1) is a linear neural regression model. This regression model can be changed towards a non-linear neural model by making a hyperbolic tangent function as follows:

$$h = \tanh (\sum_j w_j x_j + \Theta) \dots\dots\dots(2)$$

$$y = wh + \Theta \dots\dots\dots(3)$$

Again the input data  $x_j$  is multiplied by weights  $w_j$ . But the equation (2) represents a hyperbolic tangent function. The strength of the function is determined by the weight  $w_j$ . This makes the output  $y$  as the non-linear function of  $x$ . The hidden layer can be shown as in Figure 4.

**Figure 4: Architecture of Neural Network Model**



Further, degrees of non-linearity can be introduced by combining several of the hyperbolic tangents. By this way the neural network can capture as much of the non linear relationship. The function with  $l$  number of hidden units can be represented as follows:

$$y = \sum_i w_i h_i + \Theta \dots\dots\dots(4) \text{ and } h_i \text{ becomes}$$

$$h_i = \tanh (\sum_j w_{ij} x_j + \Theta_i) \dots\dots\dots(5)$$

Beale and Jackson (1990) portrayed that a network with one hidden layer can model any continuous function. However, more than one layer can be taken for better output. A model (Virili and Freisleben, 2000) regarding the number of hidden layers can be shown as follows:

$$\text{Number of hidden nodes} = (k * n) - 1 \dots (6)$$

Where  $n$  is the number of inputs and  $k$  is the multiple of  $n$ .

The data that will be used for the prediction purpose can be divided into two factors such as: (a) training data and (b) test data. The model is developed using the training data. The test data is used to check with the target whether the model behaves well when presented with the previously unseen data. The input data will comprise of the data that are used for technical analysis. There are several indicators that are used for technical analysis. These are (a) stochastic indicator (SI), (b) relative strength index (RSI), and (c) moving average (MA).

Stochastic is a momentum indicator that indicates the overbought and oversold conditions. The formula for calculating momentum indicator is:

$$\%K = ((CP - LP) / (HP - LP)) * 100$$

$$\%D = 3 \text{ day simple moving average of } K$$

Where CP = Current closing price

LP = Low price of period

HP = High price of period

The numbers calculated can range between 0 and 100. The time period can vary from 1 to 200 days. This indicator is used to help customer buy low and sell high or vice versa.

Relative strength index (RSI) is widely used for chart interpretation. The RSI can be shown as follows:

$$RSI = 100 - 100 / (1 + RS)$$

$$RS = \text{Average of } N \text{ day's close up} / \text{average of } n \text{ day's close down}$$

The variable  $n$  can range between 1 and 30. RSI is used as indicator of early warning signal.

Moving average (MA) is calculated with the historical prices. There are two sets of moving average i.e. short term moving average and long term moving average. The trend is rising when the short term is above the longer term and vice versa. The formula for calculating the moving average can be shown as follows:

Simple moving average = Sum of n day's closing price / n, ( $1 \leq n \leq 200$ )

$$\text{Exponential moving average} = \sum_{k=0}^{n-1} (\text{Closing Price}) / ((\beta - \beta^k) / (1 - \beta))$$

$\beta \rightarrow 1.00$  makes the exponential MA to a simple MA.

Apart from the above mentioned data as input data, the network will take  $I_{t-1}$  and  $I_t$  as input data.  $I_t$  refers to the index at the  $t$ -th period.  $I_{t+1}$  is the output and  $I_{t-1}$  refers to the delayed time series.

For fundamental analysis, this model will initiate the forecasting of stock valuation with the help of past dividend information, discount rate and expected holding periods. After selecting the test data set, the next phase is to check the performance of the model. We will see what kind of input dataset is representing the process. The performance of the model can be increased by training the model. Error estimation is required for training the network. Back propagation is commonly used in various neural network analyses. This algorithm has been considered to be standard because it is easy to implement and find a satisfactory solution. The training dataset will develop the pattern of the model. Back propagation algorithm then helps compare the output of the processing elements of the output layer to target or desired output for the particular input pattern developed. The error is then calculated as the squared difference between the actual and desired output. This is done for all the output elements. The error is then propagated backward through the processing elements to modify the connection weight. The attempt is made in order to derive a smaller error measure after the subsequent representation of the training pattern. The neural network systematically and continuously corrects the weight of the model through this back and forward propagation.

The algorithm then becomes as follows:

Initialize the input layer

REPEAT until done  
    Propagate activity forward (for  $x = i$  to  $j$ )  
    Calculate the error in the output layer  
    Back propagate the error (for  $x = j$  to  $i$ )  
    Update weights and biases  
End

End

The algorithm terminates when the program reaches the minimum of the error function.

The model will have two different sets of buy and sell decisions; one, on the basis of technical analysis, and the other, on the basis of fundamental analysis. The investor may choose any one (or both) depending on the expected holding period.

#### **4. CONCLUSION**

The basic foundation of this model is that the capital market misprices assets, and different factors insist human being taking unjustified buy or sell decisions. Thus, an objective buy-sell signaling model is suggested here. The basic of this model is to use back propagation with the help of neural network. This back propagation will help to minimize the estimation error as the time goes on, because the neural network will learn from the earlier error and will correct its next possible estimation. The technical analysis part of this model ensures the best possible objectivity as this analysis uses only the historic price. But the fundamental analysis part may have some subjectivity due to unlike holding periods and discount rates by different investors. In future, further discussion is possible to minimize this subjectivity. In this paper, the model has been introduced and explained. A scope of empirical test of this model has been left to the future.

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