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A REVIEW STUDY ON SEQUENTIAL ESSENCE USING GENETIC ALGORITHM AND FUZZY LOGIC APPROACH IN STOCK MARKET BASED ON NEURAL NETWORK

T. Saritha, (Research Scholar,
School of Sciences, Career Point University, Kota, Rajasthan)
Dr. M. Raghavender Sharma, Assistant Professor,
Department of Statistics, Osmania University, Hyderabad, Telangana

Abstract:

Since time is money, time optimization is the most important issue, so researchers develop a system to schedule in the best way by applying best solutions. Once you look at the production line of a factory or the number of classrooms and classrooms in a university, it can be seen that having a schedule in these places not only helps to regulate things, but it also helps to optimize the use of resources such as time and limitation. A significant financial topic that has drawn the interest of scientists for a long time is the stock return or stock market forecast. It is believed that historical history is publicly accessible in a manner indicative of potential stock returns. This statistics include economic factors such as interest and exchange rates, detailed details on manufacturing, such as factory output growth rates and market costs, and specific data from businesses, such as financial statement and dividend returns. Technical research shows a fresh, substantial knowledge of psychological variables that affect market markets in a proposal to predict future price and pattern. Technically speaking, it is a reflection of the psychology of mass that try to anticipate market fluctuations in the future on the basis that the psychology of the crowd shifts from hysteria, apprehension and pessimism, to trust, irrational confidence and avarice, on the other. This paper presents an application of Neural Network for stock market predictions and is very useful for predicting world stock markets.

Key Words: Stock market forecast, price and pattern, anticipate market fluctuations, hysteria, apprehension and pessimism.

Introduction:

There are as yet numerous issues with how to analyze and assess anticipating strategies. Most specialists either don't team up intimately with the product business and recent concerns, or they trust it's smarter to zero in on a substitution instead of improving the current strategies utilized by the business. In this manner, it is suggested that future examination work center around software improvement rather than proposing new substitution methods. It is acceptable to take note of that a few articles depend on datasets that are excessively old as portrayals for current or future undertakings.

Future exploration should zero in on understanding the connection between project attributes (dataset quality) and figure evaluation. Numerous articles assessed gauges utilizing verifiable datasets, yet a couple were determined by the full genuine circumstance. In this way, more investigations ought to be led on the strategies utilized, in actuality, circumstances.

It has been well noted that performing forecasting via effective predictor models is of prime concern in the growth of business sector. In this scenario, it is required to analyse and develop predictor models to carry out effective prediction of the considered application based on their data pertaining to the previous years. Thus, in this research certain neural network architectures hybridized with stochastic population based evolutionary algorithms are proposed to produce effective forecasting with a guarantee on training and prediction accuracy. "This research is based on the applicability of the proposed neural network architectures and evolutionary optimization algorithms which had proven its efficiency to perform prediction with

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better prediction rate. In precise, this research work contributes to prediction application by developing effective and scalable proposed approaches that are based on population based stochastic evolutionary algorithms and biological modelling of the human brain." The proposed predictor models are used to facilitate the prediction process based on the knowledge and experience of previous years with a complete guarantee on predictive solutions in a responsive and efficient way.

Neural Networks:

Neural Networks are universal and highly flexible function approximations first used in the fields of cognitive science and engineering. In recent years, neural network applications in finance for such tasks as pattern recognition, classification, and time series forecasting have dramatically increased. However, the large number of parameters that must be selected to develop a neural network forecasting model have meant that the design process still involves much trial and error. Neural Network is a challenging and daunting task to find out which is more effective and accurate method for stock rate prediction so that a buy or sell signal can be generated for given stocks. Predicting stock index with traditional time series analysis has proven to be difficult an Artificial Neural network may be suitable for the task. A Neural Network has the ability to extract useful information from large set of data.

FUZZY LOGIC:

Fuzzy logic is a form of logic where a truth value x is not binary but continuous in the interval x€[0, 1]. In many formal logic systems, a statement is either true or false and nothing else. However, it can often be hard for humans to represent their knowledge in such a way that every statement is either 100% true or 100% false. Fuzzy logic is an answer to vagueness naturally occurring for us which makes it easier to represent an expert's knowledge in a computer system. For instance, when asking people about the temperature, one person might answer that it is hot, another that it is very hot. It is not common for a human to answer with an exact number. Such a situation is an example where the relevant information better can be represented with fuzzy logic than two-valued logic.

GENETIC ALGORITHMS:

A Genetic Algorithms (GA) is a population-based optimization algorithm. The candidate solutions that make up the population are the chromosomes in the algorithm. These chromosomes turn into solution candidates that represent better results through various evolutionary processes such as selection, crossover and mutation....

Genetic Algorithms (GAs) are a type of algorithms belonging to a larger family of algorithms called Evolutionary Algorithms. The idea is to mimic nature in a simulated evolutionary process for coming up with a suitable solution from a predefined space of solutions. When it comes to Genetic Algorithms, the space of solutions often consists of variations of function parameters. The process is made up of a series of steps where the first step is to randomly create a start population (sometimes this population is consciously chosen in areas where an optimal solution is expected to be, called seeding). The instances in the population are then selected through a stochastic process where their fitness is evaluated and a new generation is generated through crossover and mutation. The process continues until a fixed set of generations have been reached or a particular fitness value has been achieved.

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GENETIC PROGRAMMING:

GAs are stochastic search techniques that can search large and complicated spaces on the ideas from natural genetics and evolutionary principle. They have been demonstrated to be effective and robust in searching very large spaces in a wide range of applications. GAs are particularly suitable for multi-parameter optimization problems with an objective function subject to numerous hard and soft constraints. The financial application of GAs has been

Genetic Programming (GP) is also a type of algorithm belonging to the superclass Evolutionary Algorithms. The difference from GAs where (usually) function parameters are optimized is that entire programs are evolved in Genetic Programming. Genetic Programming can, however, be implemented with Genetic Algorithms where the solution space consists of programs relevant to the problem.

Forecasting financial markets has long been a fascination in the minds of equity investors. Technical analysis [1] provides a framework for studying investor behavior and usually focuses only on price and volume data. Technical analysis using this approach has short-term investment horizons and only access to price and exchange data. The advent of powerful computers has brought much attention to this field. Equity market prices depend on many factors. The main factors influencing future equity prices can be divided into quantitative and qualitative types. Primary quantitative factors include the open rate, high rate, low rate, close rate, and volume for individual equities. Qualitative factors include socio-economic, political, international, regional and performance factors to name but a few.

Review of Literature:

The forecast of Stock market have a vital role since they can considerably impact the global economy. Due to its well-designed magnitude, analysing stock market unpredictability has become a key research issue in various areas, including finance, statistics, and mathematics. On the other hand, most stock index behaves very on the contrary to a random walk, because the financial time series data is quiet and non-stationary in nature. Undoubtedly, it is very difficult to calculate the stock market, since the unpredictability is too large to be captured in a model. In spite of these technical hitches, there has been a invariable wish to develop a reliable stock market prediction model. Quite a lot of approaches, in recent decades, have been made to forecast stock markets using statistics and soft computing skills. Mainly near the beginning the studies tend to occupy statistical methods, but these approaches have margins when applied to complex real-world financial data, unpaid to many statistical assumptions, such as linearity and normality. For that reason, various machine learning(ML) techniques, together with artificial neural networks (ANN) and support vector machines (SVM), that can reproduce nonlinearity and multifaceted characteristics of financial time series, have started being applied to stock market prediction. These approaches have provided well-known skills in predicting the incompetent environments of stock markets by capturing their nonlinear and unstructured nature.

Sudarsana RaoH., Vaishali G. Ghorpade, A. Mukherjee (2006), are concluded in their study, 'A genetic algorithm based back propagation network for simulation of stress–strain response of ceramic-matrix-composites', that A micromechanical finite element analysis has been synthesized into a GA/BPN model. The stress-strain response of whisker reinforced Al_2O_3/SiC CMC has been simulated by training a feed forward form of neural architecture using a genetic algorithm to derive weights. From the training examples provided, the network model automatically captures the stress-strain behavior of the composite. This relationship is automatically incorporated into the network model in an implicit manner during the training process. Further, during the training process, the degree of non-linearity present in the problem is also automatically established. A novel approach for simulation of stress-strain response of

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CMCs using genetic algorithm based back propagation neural network has been demonstrated. Isoperimetric interface elements have been used in finite element analysis to model the whisker/matrix interface in CMCs. The results obtained from this finite element model have been useful in understanding the effect of interface strength on the stress-strain response of CMCs. After its successful training, the network is able to predict the stress-strain response to the new interface strength of the CMC. The reliability of the GA/BPN network is thus established for its practical use in the design of CMCs. The advantages of the network model presented here illustrate that neural networks provide a tool for conducting sensitivity studies of CMCs to obtain their optimal property profiles. This will enable the designer to come up with CMCs with desired mechanical properties. GA based neural networks provide a very fast and computationally efficient economic analysis tool for analyzing CMC considering interface strength effects on stress-strain response. There is future scope for using neural networks to arrive at guidelines for designing CMCs with desired mechanical properties.

Pater, Lukasz (2006),has concluded in his study “Application of artificial neural networks and genetic algorithms for crude fractional distillation process modeling”, that Artificial neural networks, whose weights and structures are optimized by genetic algorithms, have proven that they can be successfully used for modeling complex relationships using raw process data. Genetic algorithms can also operate on large parameter chromosomes, set by the amount of crossing-over and mutation operations. The presented techniques have great potential not only in the crude oil refining industry but also in general model estimation as well as global optimization problems.

The study done by **Asif Ullah Khan, Bandopadhyaya T.K. and Sudhir Sharma (2008)** on ‘Genetic Algorithm Based Backpropagation Neural Network Performs betterthan Backpropagation Neural Network in Stock Rates Prediction’ and observed that This system has been developed and tested on Windows XP operating system.We have used Visual Basic and Microsoft Access as Front End and Back End tools. Normalization is a key part of data pre-processing for neural networks and should enable more accurate predicted rates. Normalized data is used to train backpropagation neural network and genetic algorithm-based backpropagation neural network. The researchers were normalizing the input so that the input values were between 0 and 1. The simulation data was obtained from the Indian National Stock Exchange (NSE). The input attributes must be chosen carefully to keep the dimensions of the input vectors relatively small. They know that close rates and volume are the primary quantitative factors for individual equities, and that quantitative factors can derive key qualitative factors of market sentiment.So, the researcher used the stock's close rate and volume as our targets for backpropagation neural network and genetic algorithm-based backpropagation neural network and further stock rate training network. BPNN and GA-BPNN are trained on the Maruti data set for the years January 2004 to December 2006, followed by training and testing on the Maruti stock data set from January 2, 2007 to March 30, 2007. GA-BPNN and BPNN performance are compared with Maruti's stock price for a specific period. GA based BPNN system showed better performance than BPNN on stock prices of Maruti for a specific time period. Based on the comparison it is found that GA's BPNN system can predict the stock price movement of Maruti with 98.31% accuracy, while BPNN's performance is 93.22%.

Zuchang Gao, Cheng Siong Chin, Wai Lok Woo, Junbo Jia and Wei Da Toh (2015) are concluded in their study ‘Genetic Algorithm Based Back-Propagation Neural Network Approachfor Fault Diagnosis in Lithium-ion Battery System’ that A genetic algorithm based back-propagation neural network approach is proposed for fault diagnosis in lithium-ion battery systems. Models of BPNN and GABPNN based fault diagnosis systems are built and experiment data are imported into both models to evaluate the performance. From the comparison, the proposed GA-BPNN model performs higher value and lower error range in this fault diagnosis system. Therefore, compared to the traditional BP neural network, the GA-

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BPNN model provides better fault diagnosis performance in battery power systems. In the future, the GA-BPNN fault diagnosis model will be integrated into the lithium-ion battery model, real-time battery information will be shared among different modules, to achieve online diagnosis and control of the battery power system.

Loye Rayand Henry Felch(2006) has concluded in his study 'Challenges to Multi-Layer Feed Forward Neural Networks in Intrusion Detection', that the problem can be solved by using a multi-layer feed forward neural network intrusion detection system. Using a hybrid algorithm based on back propagation and genetic algorithm can overcome the weaknesses of these individual algorithms. It was found that optimizing the multi-layer feed forward neural network intrusion detection system architecture to process multiple types of intrusions can improve the detection of known, unknown and new intrusions. However, intrusion detection system architecture needs to balance convergence and performance rates to avoid missing attacks. Amer and Hamilton 2009 support this claim and explain that an intrusion detection system must be carefully designed to be effective. Otherwise, the performance of the multi-layer feed forward neural network intrusion detection system will be degraded. Also, the use of a composite data sample of real and simulated data can eliminate the pitfalls of using the KDD 99 dataset. However, there is no quantitative data to support these claims.

Hetty Rohayani, TugaMauritsius, Spit WarnarsHarco Leslie H. and EdiAbdurrachman (2019), concluded in their study 'Evaluation Performance Neural Network GeneticAlgorithm' that the optimization of artificial neural networks, genetic algorithms are used to obtain the structure of neurons in the hidden layer that is optimal. If all the neurons in the hidden layer provide a high objective contribution value, the NN will be recognized with a high predictive value. The function of FFNN training using genetic algorithm for prediction is to build network architecture on FFNN, then network architecture. The next step is to find weight estimates or parameters using Genetic Algorithm (AG). AG as a training method on FFNN is processed by initializing the population, then decoding the chromosomes, evaluating the individuals, and classification. If the maximum generation is not achieved then linear fitness ranking (LFR), selection, crossover, mutation, population replacement, then individual evaluation and selection are performed until the specified maximum generation is reached. Genetic algorithms can be used to optimize the performance of ANNs. Design of neurons in the hidden layer to obtain the best model measured by the obtained RMSE value. Splitting the data groups into training data and testing data gives relatively different results.

Bing Li, AnxieTuo,Hanyue Kong, Sujiao Liuand Jia Chen (2021) concluded in their study 'Application of Multilayer Perceptron Genetic Algorithm NeuralNetwork in Chinese-English Parallel Corpus Noise Processing' that the gradient algorithm, combined with category separation criterion theory, has built a genetic algorithm-based multilayer feedforward neural network classifier model that studies on the CWMT2018 training set. Experimental results show that the English-Chinese machine translation model with the help of subword vector initialization parameters can increase the accuracy value by 1.79% more than the baseline model; The English-Chinese neural network machine translation model based on reinforcement learning can increase the accuracy value by 0.6% compared to the baseline model. Without raising any theoretical difficulties, rolling optimization can easily handle a variety of problems. It can be applied to large delay, non-minimum phase and nonlinear systems and can achieve good control effect. With data enhancement technology, the translation quality of English-Chinese neural network machine translation improves accuracy by 1.1% compared to baseline results. Experiments prove that the convergence of GA neural network is better than simple neural network and the network is more stable. A comparative analysis of the human behavior recognition rate of the two is also performed and the GA neural network can achieve satisfactory recognition results. The feature selection method proposed in this paper uses the model based on genetic operation and interclass distance criteria theory to effectively reduce the feature error, thus not only focusing on strong computing power and high accuracy of multilayer feedforward neural network features, but also improving the overall classification efficiency.

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Priti Bansal,Rishabh Lamba, Vaibhav Jain,Tanmay Jain, Sanchit Shokeen,Sumit Kumar, Pradeep Kumar Singhand Baseem Khan (2022) are concluded in their study 'GGA-MLP: A Greedy Genetic Algorithm to Optimize Weights andBiases in Multilayer Perceptron' that the use of domain-specific knowledge enables the creation of a good quality initial population. Mean-based crossover and greedy mutation help the algorithm to reach global optima by fully exploring the search space. Datasets of varying complexity are used to evaluate the performance of GGA-MLP and compare it with existing state-of-the-art algorithms as well as existing classifiers such as Na¨ıve Bayes, decision trees, logistic regression, and MLP. B.P. *E results show that although GGA-MLP takes more time to converge than other metaheuristic algorithms, the performance of GGA-MLP is better than or comparable to existing techniques for dataset classification, especially for large datasets, GGA-MLP searches. Solving the space properly by striking a balance between exploration and exploitation.

Objectives of the Research work:

1. To deliberate Neural Networks, Fuzzy Logic, and Genetic Algorithms in brief.
2. Research about the Genetic Algorithm backpropagation (BP) based models like GA-based BP, GA-based MFNN (Multi-layer feed-forward neural network and GA based Fuzzy BP adopt Sequential Genetic Algorithms (SGA), as opposed to Parallel Genetic Algorithms (PGA) for their weight determination.
3. To develop proposed predictors with certain neural network architectures hybridized with stochastic populations to produce effective and efficient.
4. To know about the applicability of the proposed neural network architectures and evolutionary optimization algorithms.
5. To analyze the neural network modelling and evolutionary optimization algorithm.

PROBLEM STATEMENT:

From the above extensive literature study on various prediction approaches in business applications employing computational intelligent techniques over the past decades, it has been noted that the following problems are observed when performing prediction process for the considered business applications – foreign exchange rate prediction, stock market price prediction. Originally, numerous statistical approaches and other machine learning approaches with higher computational complexity were adopted to carry out the prediction process in business applications for various areas with samples from previous experiences. It was observed during the progress of prediction operation that several of these approaches were vulnerable to get trapped in local and global optima, premature convergence, stagnation and more computational burden. To overcome these lacunae, this research work focused on developing predictor models based on artificial neural network models and stochastic population based evolutionary algorithms.

CONCLUSION:

Early studies of stock market prediction tended to use statistical techniques. However, studies using only classical statistical techniques for prediction reach their limits in applications with non-linearities in the data set. Compared with statistical methods, an artificial neural network (ANN) has an advantage in handling non-linear problems by using the hidden layer. Among ANN algorithms, the back-propagation neural network (BPN) is the most popular method in many applications such as classification, forecasting and pattern recognition. A major limitation of BPN, however, is that it can learn only an input–output mapping of static (or spatial) patterns that are independent of time. To overcome this limitation, two methods applying the time property are proposed: the first is use of recurrent links; the second is use of time-delayed links.

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To investigate the effectiveness of the integrated approach for building a neural network model for a time series property, we set GAs to search the optimal set of the number of time delays and network architectural factors simultaneously in ATNN and TDNN. To reduce the impact of random variation in GAs search processes, we replicate the experiment several times and suggest the best networks found in each model. The optimized GA–ATNN and GA–TDNN models are compared with the standard ATNN, TDNN, and RNN with the predefined number of time delays and the time lag, respectively. These predefined values of the standard ATNN, TDNN, and RNN are independently obtained by estimating the slope of the curve of the logarithm of the correlation integral. The embedding dimension can be chosen as 6, which indicates that we have to train on five successive stock price indices for predicting the sixth value. To compare the enhancement of GA–ATNN and GA–TDNN with the standard ATNN, TDNN, and RNN, the mean square error, which is the metric used in this experiment, of each network is calculated between the predicted and actual neural outputs.

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