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Stock Price Prediction of Oil and Gas Corporation using Modified Genetic Algorithm Simulated Annealing Approach

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ABSTRACT

Background: Stock Market is amessy place for predicting since there are no significant rules to estimate or predict the price of shares in the stock market. Many methods like technical analysis, fundamental analysis, time series analysis and statistical analysis, etc. are all used to attempt to forecast the price in the stock market, but none of these methods are proven as a consistently acceptable prediction tool. **Objective:**In this paper, an artificial neural network based on Modified Genetic Algorithm-Simulated Annealing (MGASA) is used to predict the stock price index.In designing the model, the data of oil and gas company is taken from Bombay Stock Exchange (BSE) (2010-2014).**Result:** The network is trained by 60% of the experimental data. 30% of the essential information which had been acknowledged for testing the appropriateness has been fed into the model. The predicted values were compared with the experimental values for evaluating the performance. The result obtained by using MGASA are in astounding concurrence with the experimental results and has high execution in stock price prediction.**Conclusion:**It is observed that the proposed algorithm significantly outperforms resulting in more profits. Hence, it can be concluded that the proposed algorithm is well suited for prediction of the stock prices.

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INTRODUCTION

Stock market statistics play a vital role in hypothetical research, especially in the past decades. An important hypothesis related to the stock market, which has been debated and researched time and again is EMH (Efficient Market Hypothesis). According to the EMH, the stock market immediately reflects all of the information available publicly. But in reality, the stock market is not that efficient, so the prediction of stock market is possible.

Stock market prediction is an act of attempting to determine the upcoming value of a business stock traded on financial exchange. This would yield a considerable profit in business.

Many methods like technical analysis, fundamental analysis, and time series analysis are used to predict stock market price, where time series analysis seeks to determine the future price of a stock based only on the probable past price. Researchers analyzed and faced that the standard time series models have numerous drawbacks in precision and robustness. There is no experimental evidence of linearity in stock returns, various researchers and financial experts have focused on the nonlinear prediction methods.

The hybrid GS network as a potential stock market analysis tool, which is a combination of Neural Network and Genetic Algorithm, has been used by Robert Verner for stock market prediction, a field of Artificial Intelligence is capable of providing a better result in predicting the financial market to help finance practitioners to make qualitative decisions but it has an overhead of higher computational requirements and time.

This paper proposes Modified Genetic Algorithm and Simulated Annealing Network (MGSN) and applied to Oil and Gas Stock Price Prediction and produces higher quality solutions and overheads less computation time. The results obtained from these applications have proved that the MGSN has the ability of addressing large and complex problems and minimizing the MSE error value in training and testing period by improving an accuracy in Oil and Gas Stock Price Prediction and is a new promising prediction algorithm for stock market forecasting.

Related Works:

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Computers play a vital role in each and every field, especially in stock markets. Before the invention of computers, Shareholders and Financiers initially forecasted stocks based on their intuition. This helped financial practitioners to make decisions on price prediction on stock values. The vast improvement in trading stocks and shares force us to find a better mechanism, with the help of computers, to predict the stock price in a short period of time with more accuracy in order to upturn profits, thus diminish losses.

Several research efforts were carried out to observe the forecasted price in stock markets. Various techniques like fundamental analysis, technical analysis, and time series analysis, data mining techniques, machine learning algorithms, chaos theory and linear regression and machine learning algorithms have been used to predict stock market data. Researchers analyzed and faced that the above mentioned models have numerous shortcomings in precision and robustness of statistics.

The technical analysis and fundamental analysis take a long time to respond to a company about stock price. Time series analysis seeks to determine the future price of a stock based only on the probable past price. There is no experimental evidence of linearity in stock returns, various researchers and financial experts have focused on the nonlinear prediction methods. Hybridized approach, a data mining technique, improved approach of technical and fundamental analysis provides enhanced accuracy of stock prediction, which is not attempted to fix the critical effect of specific analysis variables.

Support Vector Machine (SVM) (Huang et al., 2005) and Reinforcement Learning, a Machine Learning Algorithms (Vatsal H. Shah), which are intended to accumulate data from numerous global financial markets makes the algorithm slower to calculate the imminent price of stock. Time Delay, Recurrent, and Probabilistic Neural Networks have certain disadvantages like execution complexity, shortage of memory and require much time for testing where each method is used to predict forthcoming value of a stock based on the history of day-to-day closing prices.

Artificial Neural Networks (ANNs) and Genetic Algorithms, a field of Artificial Intelligence is capable of providing a better result in predicting the financial market to help finance practitioners to make qualitative decision. There is a wide variety of research work on the applications of Neural Networks especially in finance and stock markets. Artificial neural networks are competent inaccurate predictions without any specific assumptions about variables and their effectiveness.

(Abdüsselam Altunkaynak ,2009) utilized a genetic algorithm for the forecasting of sediment load and discharge. Very few have attempted to utilize just genetic algorithms to foresee stock prices. Since the genetic algorithm can perform sensibly well by and large there must be an approach to anticipate stock price utilizing GA .

Shaikh A. Hamid and Zahid Iqbal present a preparation for utilizing neural networks for financial determining. They analyze instability estimates from neural networks with inferred unpredictability from S&p 500 Index future alternatives utilizing the Barone-Adesi and Whaley (BAW) American future alternatives estimating model. Gauges from neural networks beat intimated unpredictability gauges and are most certainly not discovered to be essentially unique in relation to acknowledged unpredictability (Shaikh, 2003). (David Enke and Suraphan Thawornwong,2005) Presents an information gain procedure utilized as a part of machine learning for information mining to assess the prescient connections of various finance related and investment variables. Neural system models for level estimation and grouping are then analyzed for their capability to give a compelling gauge of future qualities. (Zhang Yudong and Wu Lenan,2008) proposed an improved bacterial chemo taxis enhancement (IBCO), which is then incorporated into the back propagation (BP) artificial neural system to create an efficient anticipating model for expectation of different stock records. Experiments demonstrate to its better performance over other systems in taking in capacity and generalization. (E.L. de Faria and J.L. Gonzalez, 2009) performs a predictive investigation of the chief index of the Brazilian stock market through artificialneural networks and the versatile exponential smoothing strategy. The target is to compare the anticipating execution of both systems on this market record, also, specifically, to assess the exactness of both systems to predict the indication of the market returns. Additionally the impact on the outcomes of a few parameters associated with both systems is contemplated. Their effects demonstrate that both systems produce comparative outcomes in regards to the prediction of the record returns. On the opposite, the neural networks outperform the adjustable exponential smoothing strategy in the gauging of the market development, with relative hit rates like the ones found in other created markets. (E.L. de Faria and J.L. Gonzalez, 2009)Performs a prescient investigation of the principal index of the Brazilian stock exchange through artificial neural networks and the versatile exponential smoothing strategy. The target is to compare the anticipating execution of both routines on this business sector index, also, specifically, to assess the correctness of both techniques to anticipate the indication of the business returns. Likewise the impact on the outcomes of a few parameters chatted to both techniques is considered. Their effects demonstrate that both strategies produce comparative outcomes with respect to the prediction of the index returns. On the opposite, the neural networks beat the versatile exponential smoothing strategy in the determining of the business development, with relative hit rates like the ones found in other developed markets.

Financial forecasting is of respectable pragmatic investment furthermore, because of the artificial neural network's capability to mine profitable data from a mass history of information; its provisions for financial estimating have been extremely prominent in the course of the last few years (T. H. Roh, 2007). (Guresen, et al., 2011)Reported the legitimacy of ANNs in stock business index prediction.

Sheng-Hsun Hsu and JJ Po-An Hsieh study utilizes a two-stage design for better stock price prediction. Particularly, the self-organizing map (SOM) is initially used to deteriorate the entire information space in areas where information focuses with comparable factual circulations are gathered together, in order to hold and catch the non-stationary property of financial arrangement. In the wake of breaking down heterogeneous information focuses into a few homogenous districts, support vector regression (SVR) is connected to predict financial indices. The proposed system is experimentally tried utilizing stock price arrangement from seven significant financial markets(Sheng-Hsun Hsu and JJ Po-An Hsieh, 2008).

The main objective of this paper involves in attempting to predict the intrinsic value of Oil and Gas in Stock market. Following techniques forecast performance differences among different types of models and neural network.

We introduced a new model, combination of Genetic Algorithm (GA) and Simulated Annealing (SA), Modified G-S network for Oil and Gas Price Prediction, to improve on the existing approaches of forecasting the upcoming value of Oil and Gas. Genetic Algorithm is an experimental scrutiny which provides the best solution in specific time. Simulated Annealing is an effective technique to obtain a considerable future Oil and Gas stock price by a specified amount of pride. But it fails in providing optimal solution. While combining these two algorithms, we can be able to find a great solution to predict stock price value with minimal time for a specific period irrespective of increasing time period. This will improve the solution presented here.

The stock price is changed time to time in microseconds, where it is more important to predict accurate values of future price to get to profit in the stock exchange. This G-S Network allows contemplative analysis of small and large set of statistics, especially those that have the tendency to oscillate within a short of period of time.

The performance of this method is compared with other techniques. The Modified G-S Network would be a best approach rather than a time series analysis, current Neural Networks and other methods. However, the focus of this paper will improve accuracy in Oil and Gas Stock Price Prediction with a short period of time.

Basics of Genetic Algorithm and simulated annealing:

Genetic Algorithm:

Genetic algorithms (GA) are a particular kind of Evolutionary Algorithm (EA).The essential principles of Genetic Algorithms (GAs) were proposed by Holland in 1975 (Holland JH ,1975). GAs are optimization and search procedure that are based on the mechanics of biological evolution. They have been applied successfully to solve a variety of complex problems (Beasley, D, Bull, D R and Martin, R, 2008). In general genetic algorithm works as follows:

The general sketch of GA in pseudocode

Algorithm: GA(n, a,α):

i:=0; //Initialize generation
p_i=population of randomly selected individuals; //Initialize generation
compute fitness(x) for each x € p_i; //Evaluate P_i

do:

1.select:
Select(1-a) × n members from p_i and insert into p_{i+1};
2.crossover:
Select a × n members from p_i; pair them upon and produce offspring; insert them into into p_{i+1};
3.mutation:
Select α × n members from p_{i+1}, invert a randomly selected bit
4.Evauate p_{i+1};
Compute fitness(x);
incrementi=i+1
while fitness(i) not high enough;
return fittest individual from p_i

The algorithm starts with generating initial population randomly. Individuals from the population are selected for reproduction based on their fitness value. The selected chromosomes are recombined (crossover) and mutated to generate new population. The process is continued until a termination condition is met.

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Simulated Annealing:

Simulated annealing (SA) is a random-search technique [10] for combinatorial optimization problems to search for feasible solution and converge to an optimal solution. The idea of SA is based on thermodynamics, process of cooling metals (annealing). When you heat metal at a melting point and then gradually cooled, a large crystals will be formed. If the fluid is cooled quickly the crystal will contain blemishes (Kirkpatrick., 1983). The SA performs a random search on the range of values with metropolis criteria. The performance of SA is based on the annealing schedule.

Simulated annealing is a straightforward algorithm for a set of optimization heuristic that searches for an optimal neighborhood solution. The major benefit of SA over other traditional local search techniques is that its potential to escape from local minima. The basic principle of SA is as follows:

Generate initial solution S_p
Set initial temperature t_0
Set $0 < \beta < 1$

Loop:

Select neighboring solution x_i
Evaluate $f(x_i)$
Calculate $\delta f = f(x_i) - f(x_j)$
if($\delta f < 0$)
Then$x_j = x_i$
Else
if$\frac{1}{1+e^{\frac{-\delta f}{t}}} >$ random(0,1)
Then$x_j = x_i$
Else
$t(k+1) = \beta\, t(k)$
until termination condition is met.

The algorithm starts with an initial solution. It then selects the neighborhood solution and evaluates the objective function. The value of the objective function is better than the current solution, then it is accepted. It also accepts worse quality solutions based on some probability. The process continues until the termination condition is met (Roh, T.H., 2007).

Modified Genetic Algorithm and Simulated Annealing:

Genetic algorithms can save brilliant individuals for the following generation in the genetic operation process and assure the assorted qualities of the population. The simulated annealing algorithm has the strong local search capability and is equipped for getting away from local optimal solutions. Anyway GAs is prone to premature convergence and be trapped in local optimal solutions. Likewise, the SA requires more reckoning time. Thus, by the synthesis of the two algorithms, aModified Genetic Algorithm-Simulated Annealing algorithm is demonstrated in this area.

In general an allied methodology of GAs and the SA is to house the SA inside GAs. The SA enhances each individual from GAs populations with an iteration number that is obliged to achieve Markov chain length. Along these lines, the accepted GA-SA takes significantly more execution time than GAs or the SA. To defeat this inadequacy, this study enhances the customary GA-SA algorithm. The enhanced algorithm changes the optimal method of the SA to the GAs population, that is, the SA just enhances the optimal individual of GAs population, not all people. After the change, the algorithm can spare substantially more execution time than the customary GA-SA. Additionally, the MGASA is equipped for attaining better results than other improvement strategies.

MGASA Algorithm:

GA Phase:

Step 1: Initialize population and temperature.
Step 2: Evaluate the population
Step 3: Repeat
  Apply selection operator
  Apply crossover operator
  Apply mutation operator
  Evaluate population
  Until termination condition is met

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SA, Phase:
Step 4: Select best optimal solution from GA
Step 5: Evaluate the objective function.
Step 6: Repeat
Generate new neighbourhood solution
Estimate fitness function
Accept new neighbourhood based on metropolis criteria
Until **(** max solutions to be considered for each single iteration)
Step 7: Decrease the temperature using the annealing schedule.
Step 8: Repeat steps 6-7 until stopping criteria is met.

The MGASA algorithm comprises of two stages, the GA stage and the SA stage. In the IGA-SA algorithm, Initially GAs creates the initial population randomly. The GA then assesses the initialpopulation and works on the population utilizing three genetic operators to process new population. After every generation the GA sends the best individual to the SA in phase II for further change. Having completed the further change of the individual, the SA sends it to the GA for the following generation once more. This methodology proceeds until the termination condition of the algorithm is met.

Phase 1 Optimal genetic algorithm process:
The GA produces stochastically the initial population and afterward operates on the population utilizing three genetic operators to prepare new population. As per pseudo code of the genetic algorithm, a few parts in respect to GAs ought to be resolved, for example, the choice variables, the population estimate, the generation ofthe initial population, the assessment of population, the plans of encoding and interpreting for chromosomes, the determination of genetic operators and the termination condition.

Objective Function:
The objective is to decrease the forecasting error of oil and gas stock price. The objective function can be written as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(A-P)^2}{n}}$$

Where ‘n’ is the population size, A is the actual price and P is the predicted value.

Generate Initial Population:
The initial population is produced randomly. Each of Initial weights is randomly created between -1 and + 1.

Fitness Function:
GAs assesses the population dependent upon the fitness function. An individual with higher fitness rate has higher opportunity to be chosen into the following generation. Generally the fitness of a string is with respect to the target function**.**

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(A-P)^2}{n}}$$

Selection Procedure:
We utilize truncation selection for selecting the population. In truncation selection people are sorted as per their fitness. Just the best individuals are chosen for individuals. The truncation limit shows the extent of the population to be chosen as individuals. At that point we utilize a binary truncation selectionfor producing new offsprings by utilization of genetic operators. In truncation selection, two members of the population are chosen as arbitrary and their fitness contrasted and the best one concurring with fitness worth will be decided to one parent. Likewise an alternate parent chosen with the same technique.

Genetic Operators:
Here, we utilize two-point crossover and one-point mutation as genetic operators.

Replacement:
The present population has been replaced by the recently produced offsprings, which structures the next generation.

Termination Criteria:
If the number of generation equivalents the maximum generation number then stop.

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Phase 2 Optimal Simulated Annealing Process:

In the methodology of the MGASA, the GA will send its best individual to the SA for enhancement. After the optimal individual of the GA being enhanced, the SA passes it to the GA for the subsequent generation. This methodology proceeds until the termination condition is met.

Initial Temperature:

The SA accepts new states dependent upon Metropolis criterion which is a stochastic procedure . The criterion is given by P(e)= min{1, exp(−δe/t)}, where δe =f(s_i)−f(s_j) is the difference of the objective function values of the new state s_i and the present state s_j, and t is the present temperature. Assuming that δe is not exactly zero, then the new state is held and the present state is discarded. Overall, the new state may be held if the Boltzmann likelihood,P_b=exp(−δe/t), is greater than an arbitrary number within the range 0 to 1. At a high temperature, the SA can accept another state that has a higher value than that of the past unified with a substantial likelihood. As cooling proceeds, the state may be accepted by the SA with a less likelihood.

Cooling Rate:

The performance of the SA is relative with respect to the cooling rate. So as to enhance the consistency and the search effectiveness of the SA, an enormous cooling rate ought to be maintained. In the event that the cooling rate of each temperature change counter is excessively low, the SA will cost reckoning time expenditure. On alternate hands, if a faster cooling rate is utilized, the likelihood of getting trapped into a local minimum is higher. In general, the value of cooling rate may be controlled by its sensitivity analysis. The cooling schedule is given as follows:

$$T_k = \gamma \, T_{k-1}$$

Where $T_k$and T_{k-1} are temperatures at time k and k-1; γ is the cooling rate between 0 and 1.

Number of Transitions at a Temperature:

In a search methodology of the SA, the state move at every temperature change counter is just dependent on the new states and current status. Hence, the search procedure of SA could be acknowledged as a Markov chain, whose length is characterized by the amount of moves permitted at the current temperature. The amount of moves at each temperature is characterized as:

$$R_t = \alpha t$$

R is the maximum number of repetitions at a particular temperature, α is a constant variable.

Generation of neighbourhood structure:

The focus of neighbourhood structure generation is to change arbitrarily the present state to an feasible range of its current value. There are numerous diverse approaches to generate the neighborhood structure. In the present work, the non-uniform transformation approach in the GA is received with some adjustment for generation methodology. In the event that a uniform arbitrary number distributed in the range [0,1] is less than the mutation Pm, the present choice variable is permitted to transform its value randomly. Otherwise, the present decision variable is not permitted to do that.

Termination Condition:

The algorithm runs until the last generation or when the low RMSE value is reached.

Simulation Study:

Experimental Data:

The research information utilized within this study is BSE oil and gas stock index from 1 January 2010 to 31 December 2014. We gather a sample of 48 trading months; we pick 60% for training phase and 30% for the testing phase.

Numerous past stock market investigations have utilized technical indicators as characteristics. Technical indicators are components that forecast the future performance of stocks in a given set of economic situations. By and large technical indicators are utilized for short – term designs. They are regularly dependent upon scientific estimations which take into consideration the current relationship between the stock price and the general development of the market where the stock is exchanged. These indicators are ascertained dependent upon fundamental qualities: closing price, opening price, high price, low price , all these prices speak to the stock quality throughout the trading session.

In this research, we utilize the technical indicators as input variables. We pick seven technical indicators to constrictionthe set of variables. These are calculated from the raw data as demonstrated (RitanjaliMajhi et al., 2008).

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Performance Evaluation:

Training of the forecasting models utilize MGASA algorithm.Then, utilizing these weights the same anticipating models are again utilized for the testing reason. The assessment is done to test the execution of the model for forecasting the close price of the index.

The Mean Squared Error(MSE), Root Mean Squared Error(RMSE), R-Squared(R^2), Adjusted R-squared(R_A^2), Hannan-Quinn Information Criterion (HQ) are used to gauge the performance of the trained forecasting model for the test data(Table 1).

Table 1: Performance Criteria and the related formula.

Performance Criteria	Formula
Mean Squared Error	$MSE = \sum_{i=1}^{n}(y_1 - y_2)^2$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_1 - y_2)^2}{n}}$
R-Squared(R^2)	$R^2 = \frac{\sum_{i=1}^{n}(y_1 - y_2)^2}{\sum_{i=1}^{n}(y - y_2)^2}$ y = real value, y_1= estimated value, y_2= mean value
Adjusted R-Squared(R_A^2)	$R_A^2 = 1 - (1 - R^2)\frac{T-1}{T-n}$
Hannan-Quinn Information Criterion (HQ)	$HQ = \ln\frac{SSR}{n} + \frac{k\ln[\ln(n)]}{n}$ SSR = $\sum_{i=1}^{n}(y - y_1)^2$

Results:

In this paper data from 01-01-2010 to 31-12-2011 are utilized for training purpose and then predict the stock close price of the year 2013 i.e, from January 2013 to December 201 and compare it with the closing data of that year.

Table 2: Actual and predicted price using modified genetic algorithm simulated annealing.

Period(2013)	Actual	Predicted
January	93.59	94.19
February	86.48	87.93
March	83.26	83.38
April	87.11	87.97
May	86.54	86.89
June	89	89.95
July	85.78	87.11
August	81.49	82.33
September	82.16	82.98
October	89.36	90.12
November	86.50	87.02
December	88.34	88.57

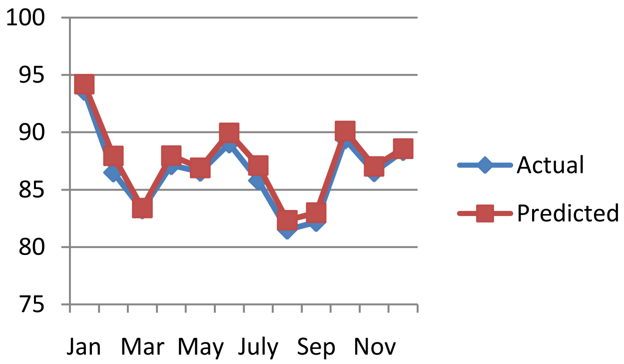

Fig. 1: Actual and predicted price using modified genetic algorithm simulated annealing.

Table 2 represents the actual value and the predicted value of the proposed approach. Fig 1 represents the test results by plotting the actual value against the value predicted by using the proposed algorithm.

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Table 3: Error rate of the proposed algorithm using various test criteria.

Test Criteria	Error Rate(%)
Mean Squared Error	3.45
Root Mean Squared Error (RMSE)	5.48
R-Squared(R^2)	0.17
Adjusted R-Squared(R_A^2)	1.15
Hannan-Quinn Information Criterion (HQ)	-5.03

Table 3 Shows the error rate of the proposed technique by using various methods. The proposed algorithm performed the prediction better than the other investigated model.

Conclusion:

Now-a-days Oil and Gas corporation because of the increase in infrastructure investment, is an attractive market for investment. Thus modelling a framework for stock price prediction in oil and gas corporation is vital for all traders and financial consultants to decrease their risk and increase the benefit of the shareholders.

In this research, a Modified Genetic Algorithm-Simulated Annealing is used to predict the stock price of Oil and Gas Corporation taken from Bombay Stock Exchange. The stock prices are estimated by the proposed MGASA algorithm and the effectiveness of the proposed algorithm was validated on the original data. It is observed that the proposed algorithm significantly outperforms resulting in more profits. Hence, it can be concluded that the proposed algorithm is well suited for prediction of the stock prices.

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