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Optimization of the variance of attribute by hybrid swarm intelligence and option price predication by cascading neural network

Payal Shrivastava* and Chandan Kumar Verma

Department of Applied Mathematics, Maulana Azad National Institute of Technology, Bhopal, MP

ABSTRACT

The variation of attribute varies the prediction of option price in the stock market. The variation of attribute value creates uncertain behaviour in the stock market and increases the risk factors for buyers. For the minimization of risk and prediction accuracy used various neural network models and optimization algorithm. The optimization algorithm reduces the impact of variance and neural network increase the accuracy of prediction. In this paper proposed cascaded neural network-based classifier for the purification of data. For the optimization of attribute correlation used hybrid swarm intelligence algorithm. The hybrid swarm intelligence algorithm is a combination of plant grows optimization and ant colony optimization. The hybrid swarm intelligence algorithm reduces the variation of prices and proceeds the data for the prediction. For the validation of proposed algorithm used NSE stock banking data of recent years. The total settles price for the processing used 20871. For the evaluation of the performance used standard parameters such as MAE, MSE, RMSE and MI. The proposed algorithm implemented in MATLAB 14.0. the cascaded neural network classifier is the combination of SOM and RBF neural network model. The SOM neural network model basically proceeds the task of clustering and RBF neural network model used for prediction.

KEY WORDS: STOCK MARKET, OPTION PREDICTIONS, SWARM INTELLIGENCE, SOM, RBF, NSE

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INTRODUCTION

The forecasting of stock market implied the future of company assets and buyers of market. For the better forecasting and prediction of stock price used parametric and non-parametric model for option pricing. In option pricing, basically the role of variables is very high. The variation of variables changes the nature of prediction. For the better prediction, various authors and researcher used non-parametric model such as artificial neural network, deep learning, and optimization technique. The-attribute optimization process reduces the variance of variable value. The reduce variance implied the better prediction for the stock market. The impact of variance also impacts the performance of the prediction, (Andreou et al, 2008, Park et al, 2014; Verma et al, 2014; Hajizadeh et al, 2018, Liu et al, 2019).

In the process of prediction used various classifications and clustering technique such as neural network and support vector machine. In the process of prediction, the rate of option price prediction basically depends on the sampling of data. The process of sampling of data reduces the size of data and normalized the data. The-normalized data gives better prediction Liang et al, 2009 and Jang et al, 2019). In this paper proposed the cascaded based classifier for the prediction of option pricing.The cascaded classifier is a combination of SOM and RBF neural network models. Self-organized map (SOM) is basically used for the process of clustering of stock data. Radialbias function (RBF) is used here for the process of classification. The combination of two models plays a role of prototype classifier for the prediction of option pricing. For the optimization of attribute(variables) used the hybrid swarm intelligence. The hybrid swarm intelligence is a combination of plant grows optimization algorithm and ant colony optimization. The plant grows optimization algorithm work in three phase morphogen, branch and termination (Verma et al, 2016). The ant colony optimization algorithm basically works in the nature of real ants. The behaviours of real ants are finding shortest path source to the food (Chou et al, 2015; Barumik et al, 2016). In our optimization algorithm the ant colony optimization plays role of distance reduction of attribute. The reduce distance of attributes creates a new set of data in the process of prediction (Olatomiwa et al, 2015; Kang et al, 2014; Mitra et al, 2012, Jang et al, 2019).

The proposed classification algorithm compares with deep learning-based option pricing model. For the experimental analysis used NSE dataset of 20871 thousand of data of different settle price. The contribution of this paper is summarized as follows : Wang et al, 2013; Burkovska et al, 2015; Al et al, 2015 Fridrich et al, 2017, Hirsa et al, 2019).

1. Optimized the value of variance of attribute (variable)
2. Based on cascaded classifier enhanced the performance of option pricing
3. A design hybrid optimization process based on plant grow optimization and ant colony optimization.
4. Conduct experimental simulation of an NSE dataset of different sample data unit and measure their performance.

MATERIAL AND METHODS:

Hybrid Swarm Optimization: In this section describe the process of hybrid swarm intelligence. The hybrid swarm intelligence is a combination of plant grows optimization algorithm and ant colony optimization. The plant grows optimization algorithm follow the nature of natural plant grows under sunlight. And ant colony optimization follows the real ant behaviors in environments (Heaton et al, 2017; Feuerriegel et al, 2015; Xiong et al, 2015; Yang et al, 2014).

The development of plants divided into three sections as describe below

1. Morphogen. In the case of morphogen check the status of plants for growing.
2. Branching. In the case of branching check the section condition of new leaf policy
3. Termination. Termination is the final process of plant theory. The termination process gives the optimal solution of given problems

The following parameter is used for the process of attribute, x_1, x_2,..............,x_n is the attribute of NSE data for option pricing. W is the Wight factor for the attribute, is the value of a morphogen, C_1 and C_2 is the contour value of attribute.

Step1. Define the value of attribute-set $S_1\{x_1, x_2, \ldots\ldots\ldots\ldots, x_n\}$ with population

Assign the value of the contour and weight of attribute C_1=0, C_2=0 and W=0

a. Morphogen selection of plant function

$$F(s) = \frac{(Ffd - Fpf)}{Fd * fp}, wi\epsilon S(x_1, x_2 \ldots\ldots x_n) \tag{1}$$

Here F_{fd} is initial attribute and F_{pf} is final attribute of the plant and w is set of attribute variable of sum sets

The attribute variables set the value of branch F = $\{f_{a1}\ldots\ldots\ldots\ldots\ldots_{an}\}$. Thesebranchvalues proceed for theestimation Competition condition of local leaf.

$$Fcom = \begin{cases} \dfrac{(T_i)^\alpha \left(LI_i^{S_j}\right)^\beta}{\sum_{g\notin S_j}(\tau_g)^\alpha \left(LI_g^{S_j}\right)^\beta} if \quad i \notin S_j \\ 0 \qquad\qquad otherwise \end{cases} \tag{2}$$

Here T is the target value of attribute, and LI is the value of attribute difference.

Step 2. Branching condition

Input the selected attribute for the **Competition**

1. Calculate the value of relative attribute of C_1 and C_2 $Rf = \frac{LSI}{Wd}$ Here Lsi the difference of attribute set.
2. The PGO estimate the final attribute for selection.

$$FS = \begin{cases} \frac{\max \ (RF) \ -F(s)}{\max_{h=1:} (WS)} & if \ s_i \in f_j \\ 0 & otherwise \end{cases} \tag{3}$$

3. Create the relative FS difference value of attribute

$$R_d = \sum_{fd=1}^{n} \sum_{pf=1}^{m} (x_i - fs) \tag{4}$$

4. if the value of Rd is zero the attribute termination condition is call

Step 3. Termination

Where Rd is the relative difference of $T(i)$; f_z is the fitness value; standard deviation S_z and local density D_z are defined in formula (5):

$$\begin{cases} R_d = \sqrt{\frac{\sum_{i=1}^{n} (z(i) - E(z))^2}{(n-1)}} \\ f_z = \sum_{i=1}^{n} \sum_{j=1}^{n} (R - r(i,j)) \, u(R - r(i,j)) \end{cases} \tag{5}$$

Defining $D(z(k),z(h))$ as the absolute distance between the two-optimal attributes

$$d(z(k), z(h)) = \sqrt{(z(k) - z(h))(z(k) - z(h))} = \sqrt{(z(k) - z(h))^2}$$

k =1, 2,... ... ., N; h = 1, 2,... ... ., N and finally, the attribute is terminated.

5. The optimal features attributes set the value of ants F = $\{f_{a1} \dots \dots \dots \dots_{an}\}$. These ants value proceed for the estimation of variance, define an ant selection function as

$$Ants = \begin{cases} \frac{(\tau_i)^\alpha \left(LI_i^{S_j}\right)^\beta}{\sum_{g \notin s_j} (\tau_g)^\alpha \left(LI_g^{S_j}\right)^\beta} if i \notin S_j \\ 0 \qquad otherwise \end{cases} \tag{6}$$

Here τ_i is phenomenal value of ants and LI is value of the least interface of ants.

6. The selected ants value proceeds for the process of classification.

Cascaded Classifier for Prediction: Cascading is a new area of neural network hybridization. In the process of cascading encapsulate two different neural network models based on requirement of the classification process. In option price prediction used two neural network models one is a SOM neural network and other is a RBF neural network model. In the process of cascading the SOM neural network model creates the clusters for the processing of RBF pattern. The RBF pattern is finally prediction value of option prices. The selection of settle price proceeds through the process of plant grows optimization. The RBF neural network model is a single hidden layer classifier and the process of classification is very fast and accurate. And other side used SOM network, it is self-organized map neural network and property of this network is unsupervised. Due to this property training process of the network is not required. In SOM network, optimal attribute which has been selected by selector passes to this network and create two different attribute vector one is winner attribute vector, and another is a successor attribute vector. The successor attributes vector passes through the RBF neural network in the process of training and pattern classification. The attributes vector passes through SOM acts as a clustering mechanism that projects N-dimensional attributes from the attribute matrix into an M-dimensional attribute space. The resulting vectors are fed into a SOM that categorizes them into one of the relearned optimal attributes. The transformed attribute vectors are fed into the SOM, which classifies them. We call the attribute space generated from the attribute selector function output as the primary attribute space and M-dimensional attribute space for SOM output as a secondary attribute space. The secondary attribute space passes through as vector input of RBF function.

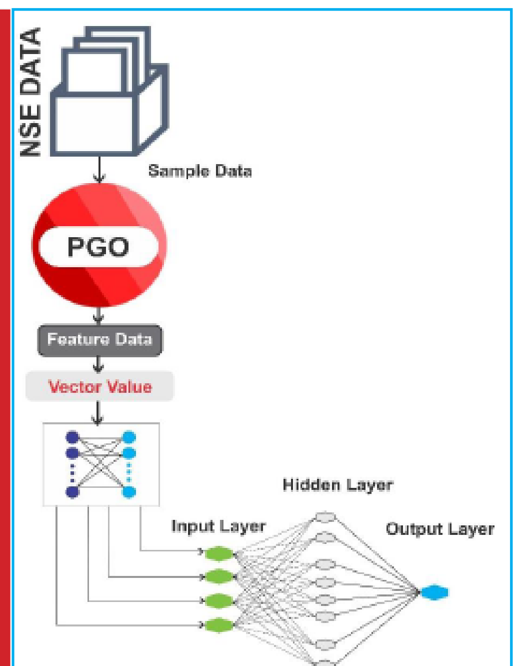

FIGURE 1. Process block diagram of attribute optimization and price prediction

The output of optimal data of the PGO map as $X = [x_1, x_2, \ldots, x_{N_l}, x_{N_l+1}, \ldots, x_N] \in R^{D \times N}$ that is corresponding to a cascaded, where each $x_i \in R^D$ represents the i^th^ index of vector, D is the number of data samples and $N = (N_l + N_u)$ is the number of training samples. The first N_l samples $X_l = [X_1^l, X_2^l, \ldots\ldots X_{N_l}^l]$ are labeled with the corresponding labels $Y_l = \{y_i\}_{i=1}^{N_l}$ the remaining N_u samples $X_u = [X_{N_l+1}^u, \ldots\ldots\ldots, X_N^u]$.

In the process of cascaded classifier, the value of matrix W map SOM output in RBF input vector and minimized the attribute variance value as

$$W_p = arg_w \min(\sum_{s=1}^{N} \sum_{t=1}^{k_s} \|W_{x_a} - W_{x_b}\|^2 rf) \tag{7}$$

Where X_b is the neighbor of X_a and k_s is the number of neighbors of X_s. rf is the relative feature difference values of sample X_a and X_b, A mapping of each sample $X_i^l (i = 1, 2, \ldots, N_l)$ can be as vector $a_i \in R^{N_l \times 1}$ under a sample of data $X_l = [X_1^l, X_2^l, \ldots\ldots X_{N_l}^l] \in R^{N_l \times 1}$ that is composed as

$$\min_{a_i} \|a_i\|_1, s.t. \frac{1}{2}\|X_i^l - X_l a_i\|^2 < MAR \tag{8}$$

where MAR is the mean absolute error define the value of w_{dif}^i as the distance between the winner X_i^l and its successor data

$$w_{dif}^i = \sum_{k=1}^{k_{s2}} \|X_i^l - X_{ik}^l\|^2 \tag{9}$$

Where X_{ik}^l are the successor data of points X_i^l and k_{s2} is the number of selected winners?

The learning rate in should be time varying. This requirement can be satisfied by choosing an exponential decay for $n(t)$.

$$\eta(t) = \eta o exp\left(-\frac{t}{w1}\right), t = 0,1,2 \tag{10}$$

The update matrix value process after learning

$$updateWij = \sum_{k=1}^{k_{s2}} \|WX_i^l - WX_{ik}^l\|^2 - \sum_{j=1}^{k_{s1}} \|WX_i^l - WX_{ij}^l\|^2 \tag{11}$$

The updated winner's matrix data passes through the RBF interconnected input layers

$$\begin{aligned} Rfb &= \sum_{i=1}^{N_l} updateWij, \\ &= \sum_{i=1}^{N_l} \sum_{k=1}^{k_{s2}} \|WX_i^l - WX_{ik}^l\|^2 - \sum_{i=1}^{N_l} \sum_{j=1}^{k_{s1}} \|WX_i^l - WX_{ij}^l\|^2. \end{aligned} \tag{12}$$

Calculating the deviation value of sample data points to measure the error rate

$$MSE = \frac{1}{n} \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{m} (Rfbij - yij)^2} \tag{13}$$

RESULTS AND DISCUSSION

In this section discuss the process of result analysis of proposed algorithm and optimization of swarm intelli-

Table 1. Input Data taken from National Stock Exchange of India (NSE) Stock option of Andhra Bank

Symbol	Strike Price	Settle Price	Underlying Value
AXIXBANK	75	0.05	49.85
AXIXBANK	75	0.05	50.65
AXIXBANK	75	0.1	51.05
AXIXBANK	75	0.05	51.5
AXIXBANK	75	0.05	51.85
AXIXBANK	70	0.05	49.5
AXIXBANK	67.5	0.1	47.85
AXIXBANK	75	0.05	53.2
AXIXBANK	70	0.05	49.85
AXIXBANK	75	0.05	53.95
AXIXBANK	70	0.05	50.65
AXIXBANK	75	1.5	54.35
AXIXBANK	67.5	0.05	49.5
AXIXBANK	67.5	1.4	49.6

Table 2. Input Data taken from National Stock Exchange of India (NSE) Stock option of ICICI Bank

Symbol	Strike Price	Settle Price	Underlying Value
ICICIBANK	310	0.2	190.75
ICICIBANK	300	0.05	192
ICICIBANK	310	0.05	198.45
ICICIBANK	300	0.05	193.55
ICICIBANK	310	0.35	204.05
ICICIBANK	300	0.15	199.25
ICICIBANK	280	0.05	187
ICICIBANK	270	0.05	183
ICICIBANK	300	0.25	203.5
ICICIBANK	270	0.2	184.8
ICICIBANK	280	0.05	192
ICICIBANK	300	0.15	207.25
ICICIBANK	280	0.05	193.55
ICICIBANK	280	0.1	196.6
ICICIBANK	260	0.3	183
ICICIBANK	270	0.15	190.05
ICICIBANK	280	0.05	198.45
ICICIBANK	280	0.05	198.8

Table 3. Input Data taken from National Stock Exchange of India (NSE) Stock option of RBL Bank

Symbol	Strike Price	Settle Price	Underlying Value
RBLBANK	620	0.05	505.85
RBLBANK	600	0.75	490.3
RBLBANK	600	0.8	490.35
RBLBANK	620	2.3	508.15
RBLBANK	620	0.05	508.95
RBLBANK	620	1.75	509.5
RBLBANK	620	0.15	511.7
RBLBANK	600	0.9	497.2
RBLBANK	620	0.65	516.35
RBLBANK	620	3	516.55
RBLBANK	620	0.45	518.1
RBLBANK	600	0.45	501.65
RBLBANK	600	3.3	501.65
RBLBANK	600	0.05	505.35
RBLBANK	600	0.2	505.85

gence. The proposed algorithm implemented in MATLAB 14.0. For the process of analysis used NSE dataset. For the evaluation used standard parameters NMSE, RMSE, MAE and MI. The proposed result compares with Deep learning algorithms.

In Figure 2, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for the Andhra Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of RMSE is optimized

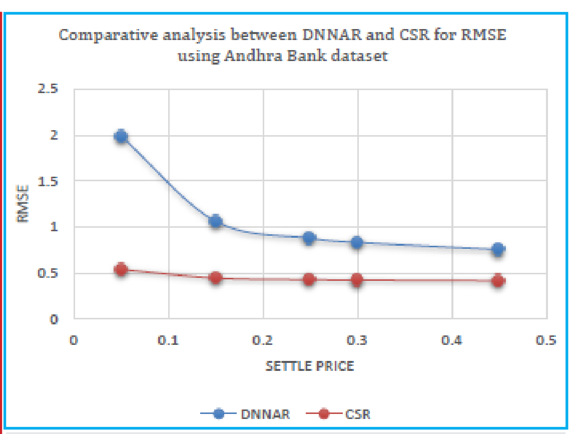

FIGURE 2. Comparison DNNAR and CSR for RMSE using Andhra Bank dataset

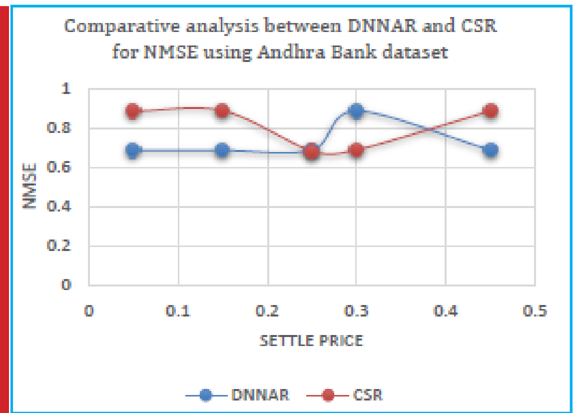

FIGURE 3. Comparison DNNAR and CSR for NMSE using Andhra Bank dataset

due to the process of optimization and better prediction of cascaded classifier. According to the settle price (0.05, 0.15, 0.25, 0.30 and 0.45) sequentially deep neural network method RMSE values are 1.988, 1.0627, 0.8776, 0.8313 and 0.7542 and similarly proposed cascaded algorithm RMSE values are 0.5388, 0.44627, 0.42776, 0.42313 and 0.41542.

In Figure 3, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for the Andhra Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of NMSE is optimized due to the process of optimization and better prediction of cascaded classifier. According to the settle price (0.05, 0.15, 0.25, 0.30 and 0.45) sequentially deep neural network method NMSE values are 0.68428, 0.68549, 0.68763, 0.88549 and 0.68756 and similarly proposed cascaded algorithm NMSE values are 0.88521, 0.88791, 0.68194, 0.68756 and 0.88634.

In Figure 4, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for the Andhra Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of MI is optimized due to the process of optimization and better prediction of cascaded classifier. According to the settle price (0.05, 0.15, 0.25, 0.30 and 0.45) sequentially deep neural network method MI values are 1.988, 1.0627, 0.8776, 0.8313 and 0.7542 and similarly proposed cascaded algorithm MI values are 1.0388, 0.94627, 0.92776, 0.92313 and 0.91542.

In Figure 5, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for the ICICI Bank dataset. The result of variation distributed in different

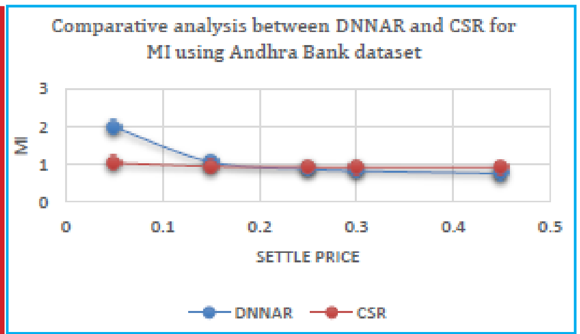

FIGURE 4. Comparison DNNAR and CSR for MI using Andhra Bank dataset

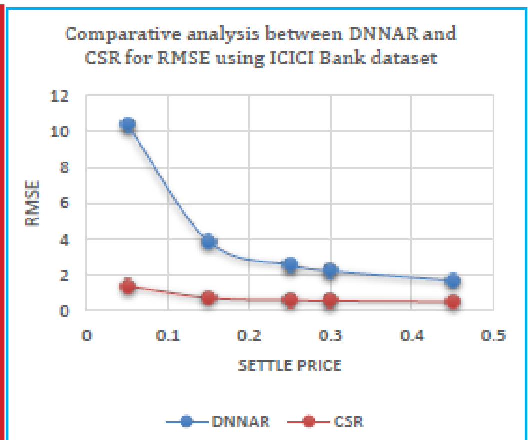

FIGURE 5. Comparison DNNAR and CSR for RMSE using ICICI Bank dataset

settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of RMSE is optimized due to the process of optimization and better predictionof cascaded classifier. According to the settle price (0.05, 0.15, 0.25, 0.30 and 0.45) sequentially deep neural network method RMSE values are 10.358, 3.8527, 2.5516, 2.2263 and 1.6842 and similarly proposed cascaded algorithm RMSE values are 1.3758, 0.72527, 0.59516, 0.56263 and 0.50842.

In Figure 6, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for the ICICI Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of NMSE is optimized due to the process of optimization and better prediction of cascaded classifier.

According to the settle price (0.05, 0.15, 0.25, 0.30 and 0.45) sequentially deep neural network method NMSE values are 0.58403, 0.5906, 0.61145, 0.61555 and 0.61272 and similarly proposed cascaded algorithm NMSE values are 0.81272, 0.75999, 0.81555, 0.7906 and 0.81438.

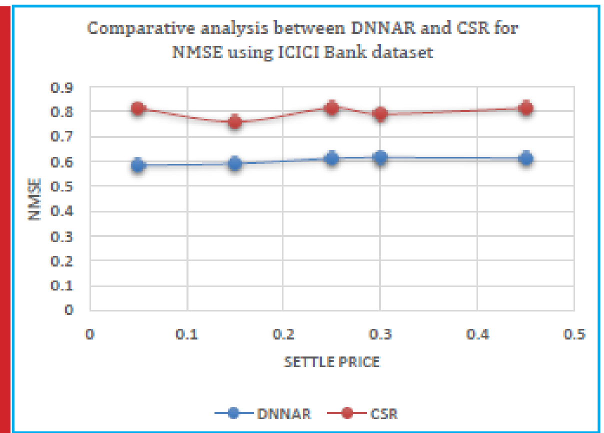

FIGURE 6. Comparison DNNAR and CSR for NMSE using ICICI Bank dataset

In Figure 7, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for the RBL Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of NMSE is optimized due to the process of optimization and better predictionof cascaded classifier. According to the settle price (0.05, 0.15, 0.25, 0.30 and 0.45) sequentially deep neural network method NMSE values are 0.67728, 0.68376, 0.68195, 0.68393 and 0.68393 and similarly proposed cascaded algorithm NMSE values are 0.88311, 0.8824, 0.88025, 0.88325 and 0.87926.

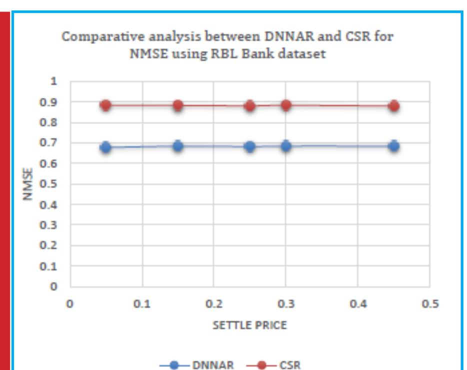

FIGURE 7. Comparison DNNAR and CSR for NMSE using RBL Bank dataset

In Figure 8, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for Andhra Bank, ICICI Bank and RBL Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of

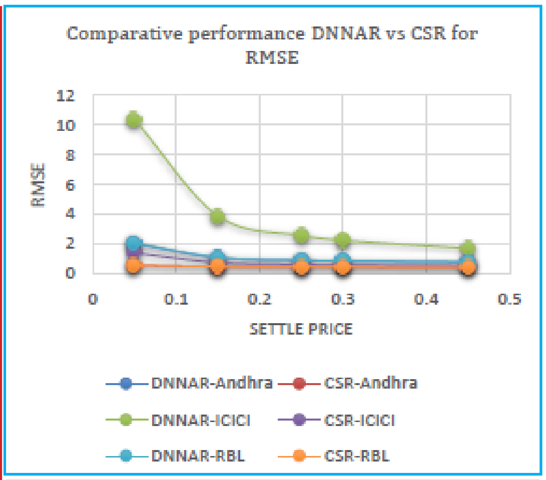

FIGURE 8. Comparison DNNAR vs CSR for RMSE

RMSE is optimized due to the process of optimization and better predictionof cascaded classifier.

In Figure 9, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for Andhra Bank, ICICI Bank and RBL Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of NMSE is optimized due to the process of optimization and better prediction of cascaded classifier.

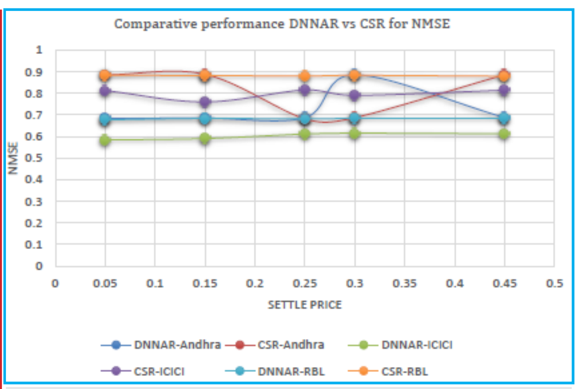

FIGURE 9. Comparison DNNAR vs CSR for NMSE

In Figure 10, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for Andhra Bank, ICICI Bank and RBL Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30, 0.45 the variation indicates the value of MAE is optimized due to the process of optimization and better predictionof cascaded classifier.

In Figure 11, indicates the variation of normalized mean square error between deep neural network methods and proposed cascaded algorithm for Andhra Bank, ICICI Bank and RBL Bank dataset. The result of variation distributed in different settle price such as 0.05, 0.15, 0.25, 0.30 and 0.45 the variation indicates the value of MI is optimized due to the process of optimization and better prediction of cascaded classifier.

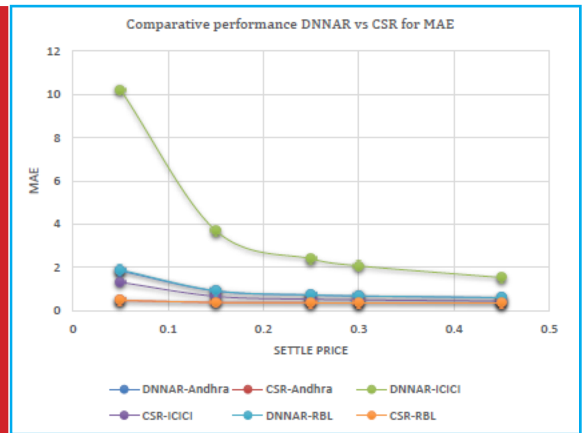

FIGURE 10. Comparison DNNAR vs CSR for MAE.

The cascaded classifier reduces the variation of price and enhances the process of prediction. For the validation and analysis of algorithm used NSE dataset in recent years. The total data instance is 20871. The total data are distributed into different settle prices for the measuring the variation of real value and predicated value. For the evaluation used 4 non-parametric parameters such as normalized mean square error, root mean square error, mean absolute error and mutual information. The value of mutual information indicates the independency of a variable during the process of cascaded classifier. In Figure 2, shows the variation value of NMSE (normalized mean square error), in case of CSR (cascaded classifier) the value of variation is decreased. In case of the deep

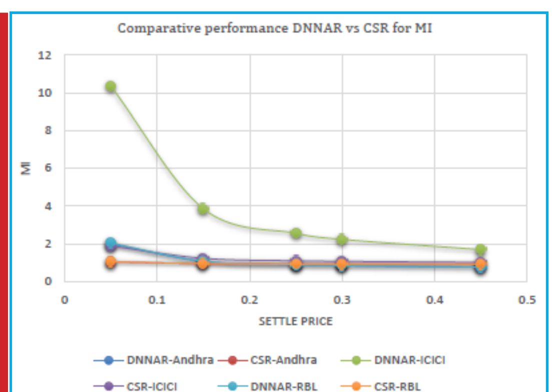

FIGURE 11. Comparison DNNAR vs CSR for MI

learning algorithm, the variation of error is increased in all distributed points for the selection of settle price.

The reduce value of NMSE increase the value of option price prediction. The enhance value of price also shows the best performance of the optimization of attribute selection and processing of data in the process of classification. In Figure 3, shows the value of RMSE (root mean square error). The variation value of RMSE is also decreasing in case of CSR. Due to the better selection and optimization of attribute according to the plant grow optimization algorithm, the deviation of attribute value is reduced. The reduced value of deviation indicates the minimum value of MSER. In Figure 4, describe the performance of mean absolute error, in case of CSR instead of DNNAR the value of MAE is down due to optimized patterns of price attribute of the RBF function. The processing of RBF function reduces the variation of attribute and enhance the predictionvalue of price and reduces the value of MAE. In Figure 5, describe the independency of price in the attribute selection process during the cascaded classifier. The target value of predictionis increase and value of error is decreasing, increase the value of MI shows that the better prediction ratio of classifier instead of DNNAR. In Figure 6 and 7, describe the process performance of individual algorithms satisfying the all parameters for the distribution of all settle prices. The interval ratio of settle price indicates that the variation in case of CSR is minimized instead of DNARR.

CONCLUSION

In this paper analyzed the performance of option price prediction using two algorithms. The used algorithms are a combination of optimization algorithm and cascaded neural network-based classification. The optimization algorithm reduces the variation of attribute selection in the process of classification. The optimization algorithm is called plant grow optimization. The plant grows optimization algorithm work in three phases. In a first phase basically dynamic define the population in the form of data loading for the process of optimization. In the second phase process used branch selection process for the new population, in this phase basically reduces the attribute variation relation of two distinct attributes. And finally measure the value of computation, for the final selection of the optimal value of the price of the input processing of cascaded classifier. The cascaded classifier is a combination of two neural network models. RBF and SOM neural network, here the SOM neural network model used for the process of clustering of input data by the optimization algorithms.

The rate of learning used 0.6 probability value and group data in good manners. The group of clusters passes through the RBF function, the RBF function generates the trained patterns and predict the value of option prices. For the validation and analysis of the optimization and cascaded classifier used NSE India dataset. The data interval is last 6 years. In all data instances used selected numbers of attributes. For the analysis of performance used 4 standard parameters NMSE, RMSE, MAE and MI. The values indicate better performance of cascaded classifier instead of deep neural network-based classifier. The deep neural network-based classifier suffers from the selection of feature attributes of price variation. The plant grow optimization algorithm reduces the variation of attributes and increase the value of option pricing.

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