Two-tier machine learning ensemble model for option price forecasting using salp swarm optimization

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Abstract:
Options and derivative products are complicated financial tools. Because of the risk involved in options trading, trade support systems are in high demand to help clients manage and mitigate their volatility. The major issue of option price forecasting is the non-linearity and non-stationarity of option characteristics. The key job in options trading is to calculate the realistic price option, which may be used to assess which options are now inexpensive and which are currently expensive. To address these issues in option price forecasting, a Two-Tier Machine Learning Ensemble model (TTMLE) using Salp Swarm Optimization (SSO) has been proposed. In the TTML model, Arbitrary Mode Disintegration (AMD) and Composition Search Algorithm (CSA) has been integrated into tier 1 and tier 2, respectively to forecast option pricing. The salp swarm optimization technique has been used to teach the TTMLE model and improve the weights of the model, resulting in the TTMLE-SSO model, which enhances forecasting accuracy. Other models such as the Non-linear Neural Network (NNN), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) network have been compared to the suggested model. The new approach beats previous methods, and predicting accuracy is substantially improved, according to empirical data.
Keywords: Option price forecasting, Machine Learning, Swarm Optimization, Ensemble model, Composition search algorithm.

1. Introduction

The use of machine learning (ML) and neural networks to generate forecasts and information analysis of a large database improves the options market stability. For investors and scholars, predicting option prices is always a difficult task [1, 2]. Different neural network and statistical models for option pricing prediction have been suggested in the recent decade. The viability of models is determined by the value of prediction [3]. In terms of prediction stability, the continual change of machine learning algorithms and mathematical models has to be achieved.

ML is a new approach in the prediction and information science platforms. The limitations of many traditional models of option price forecasting are solved by ML techniques. These prediction results are dependent on the fund's volatility factor [4]. Structural, analytical, and market feelings all influence the variety and volatility of option pricing. These elements have an impact on precision forecast, and managing these characteristics enhances option price forecasting. Support vector machine (SVM) neural networks, supervised learning, and numerous techniques relying on ensemble-based classification are examples of ML approaches. These approaches are now being employed in option price forecasting. The effectiveness of a machine-learning-based categorization model is determined by feature extraction and refinement [5, 6]. Various directed and unsupervised swarm intelligence techniques are used in the refinement and choice selection process.

Options trading necessitates a high level of subject expertise, making it difficult for traders to make an informed choice quickly. As a result, building a choice support system is critical. The system must be able to acquire data directly and generate predictions. The framework aims to relieve shareholders' burdens and assist them in maximising earnings [7].

The rest of the article has been arranged as follows: Section 2 analyses the associated works on machine learning and swarm intelligence for options price forecasting. The proposed TTMLE-SSO model by integrating AMD and CSA with SSO for better optimization has been described in section 3. Section 4 offers the simulation results and a detailed discussion. Finally, the inference and opportunity for future studies have been given in section 5.

2. Related works on machine learning and swarm intelligence for price forecasting

The financial market is expected to increase, according to the forecasts. Even more, academics are focusing on using artificial intelligence (AI) technology for stock market forecasting to better deal with the noisy room. The authors of [8] developed a unique algorithmic investment strategy based on deep convolutional neural networks (CNN) to forecast stock price by converting financial time data into 2-D visuals. Zhang et al. [9] suggested a forecasting model that combined support vector regression (SVR) with the firefly algorithm.

Due to their high computational power, several AI models currently produce good results for many regression challenges. Nevertheless, the majority of them take a long time. To address this problem, the authors of [10] created an exceptionally quick model known as the extreme learning machine (ELM). ELM is a unique quasi training approach in which the hidden weights of a single neural network are not adjusted by iterative learning.

It's important to remember that utilising a solitary AI framework does not necessarily ensure incredible precision in all situations. Ensemble learning, an approach that combines findings gained by multiple scenarios, has been suggested to reduce the unpredictability of one-time forecast outcomes. In general, several recent research has shown that ensemble approaches outperform single predictors. Tang et al., for example, introduced a unique modal character trait-based decomposition ensemble method for nuclear energy utilization prediction [11], which demonstrated excellent forecasting abilities. The authors developed a sequential subdomain ensemble learning strategy for noisy data in [12], and the results of experiments demonstrated that the ensemble learning method outperformed several individual classifiers. Wang et al. devised an ensemble learning strategy for predicting energy consumption, demonstrating that the EL approach outperformed standalone methods [13].

Weng et al. created a financial specialist structure that typically consists of an AI platform and three ML ensemble approaches. The results of the experiments revealed that this market analyst system outperformed other standalone model prediction approaches [14]. Authors in [15] presented a hybrid technique for modern power system assessment based on certain EL models. The outcomes of the experiments showed that the hybrid method might yield better results than standalone AI techniques. Liu et al. proposed a novel layered ensemble approach for pollution monitoring and shown that it outperforms standalone approaches [16]. However, while EL is frequently utilised in classification techniques, few researchers gave credence to extending it to option price prediction. The goal of this research is to create a two-tier machine learning ensemble model that uses salp swarm optimization to reliably forecast option prices.

3. Proposed two-tier machine learning ensemble model (TTMLE) using salp swarm optimization (SSO)

Inspired by ensemble learning, the TTMLE model by integrating AMD and CSA has been proposed for option price prediction. In the first stage, the AMD based MLE model is employed for preliminary price prediction under different parameters. In the second stage, an improved CSA algorithm has been designed to obtain final predictions by integrating the prediction results obtained in the first stage.

3.1 Tier 1- Forecasting based on AMD

AMD model initially fragments a sequence of periods into a group of internal functions (IF). Let $d(t)$ be the sample of information (financial or stock or options). $c(t)$ denotes a duplicate copy of $d(t)$. The internal functions can be calculated using the following steps:

Step 1: Obtain regional limits of sample information $c(t)$

Step 2: Use a quadratic polynomial regression approach based on regional peaks and troughs to calculate the minimum and maximum boundaries.

Step 3: Calculate the mean value of the minimum and the maximum boundaries represented by $b(t)$. Update the period sequence as $g(t) = c(t) - b(t)$.

Step 4: Two criteria to be satisfied by $g(t)$: i) value of $b(t)$ should be zero. ii) Difference between regional peaks and troughs should be less than unity. If these conditions are satisfied, then $g(t)$ has been considered as i^{th} internal function of $e_j(t)$. If the above two conditions are not satisfied, update $c(t)$.

$$c(t) = \begin{cases} d(t) - \sum_{i<i+1} e_j(t)\,, if\ b(t) = 0\ and\ (peak - trough) < 1 \\ g(t), otherwise \end{cases} \quad (1)$$

Then, the actual information sample $d(t)$ is given as follows:

$$d(t) = \sum_{j=1}^{n} e_j(t) + c(t) \quad (2)$$

Where n is an arbitrary number and $c(t)$ is the enduring value that cannot be fragmented further. In tier 1, the AMD model has been used to obtain initial forecasted values defined by $F_{n,t}$, $t > n$. The input data with j elements at period $t-n$ is given by $C_{t-n} = \{c_{t-n,1}, c_{t-n,2}, \dots \dots, c_{t-n,j}\}$ using the AMD model and the output forecasting is given by F_{n-t}. Values of n are changed to obtain more forecasted values by considering different factors. Through appropriate treatment of F_{n-t}, mode fragmentation and IF are obtained.

3.2 Tier 2- Integrating initial forecasted values using the CSA algorithm

The CSA is a heuristic algorithm based on population. The technique of acoustic experimentation prompted a coherent search. The method replicates the technique by which a musician modifies different sounds to get the best tune by considering the significance of the variables in the set of vectors as a pure tone of a song.

The objective function is defined by $OF(.)$. The choice parameters are defined as $C = \{c_1, c_2, \dots \dots \dots, c_N\}$, where $c_j, j = \{1,2, \dots \dots ., N\}$. CSA has been implemented using the following steps:

Step 1: Initialization of parameters required for pre-processing.

Step 2: Initialize the value of Composition Memory (CM). Identify the finest C_{fine} and poorest C_{poor} composition values.

Step 3: Find a novel composition represented as C_{novel}.

Step 4: If $C_{novel} > C_{poor}$, update C_{novel} value in the CM. Else, repeat step 3.

Step 5: Repeat the process until the final value is stored in CM or until termination criteria have been satisfied.

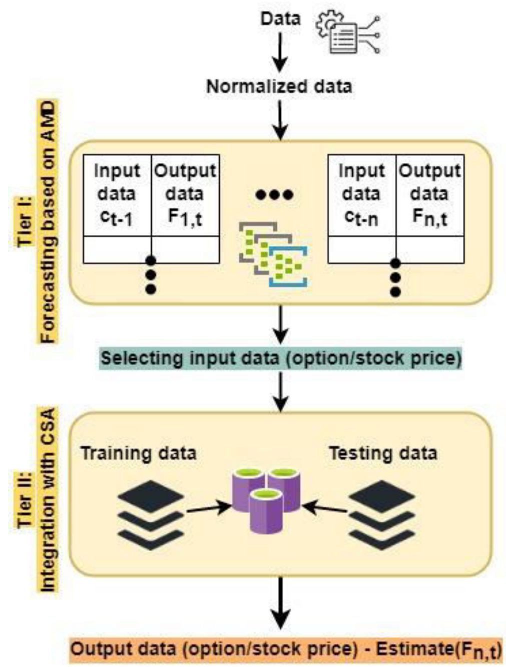

Fig. 1 Two-tier machine learning ensemble model for option price forecasting

A two-tier machine learning ensemble model for option price forecasting has been depicted in Fig. 1. Input stock or options trading data has been normalized to remove redundancies. F_t is the option price at period t. $Estimate(F_t)$ is the final forecasted option price based on the TTMLE model. In tier 1, initial forecasting using the AMD model has been done to obtain $F_{n,t}$, for different values of n. In tier 2, initial forecasted values $F_{n,t}$ are integrated using CSA and $Estimate(F_t)$ values are obtained.

3.3 Enhancing the forecasting accuracy using SSO

The TTMLE model has been trained using the SSO method. The SSO method has been used to improve the weights of the TTMLE model that focuses on salp densities and their navigation and feeding activities, to achieve greater performance with minimal errors.

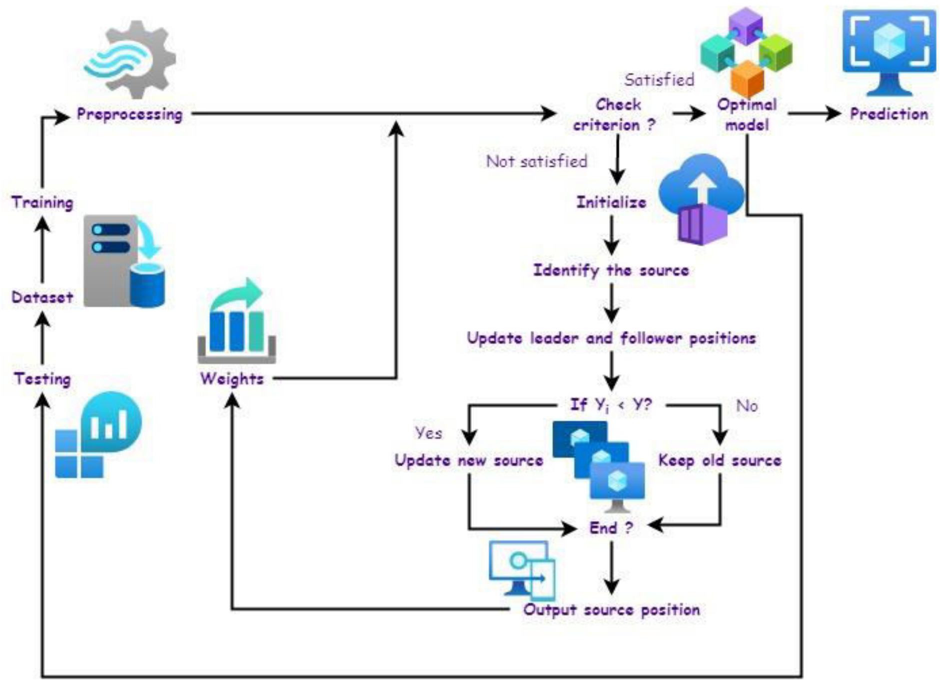

Fig. 2 Salp Swarm Optimization framework to obtain accurate option price.

Fig. 2 depicts the Salp Swarm Optimization (SSO) framework to obtain an accurate option price. Input data used for the SSO model is the output forecasted data obtained from the TTMLE model. The prediction models have been used to estimate option prices in the testing dataset once they were matched and well-developed on the whole training examples. It is indeed important to mention that the testing sample was not used for the training set, thus it is technically a fresh sample (or unused dataset). The samples are preprocessed and given to convolution layers. The weight criterion has been checked and if it is not satisfied, then the accuracy of data can be improved using SSO. SSO is based on the movement of salps in the ocean as a chain. These salps always update their position and follow the leading salp to search for their food. After parameter initialization, salp identifies the food source and it becomes the leader. The leader now updates their position and other followers also update their positions. If the current weight y_i is less than the previous weight y, it updates the source information. Else, the old weight is kept as such. The obtained weight is again given to the training phase and once the weight criterion is satisfied, optimal weights and hence the final predicted values are obtained.

4. Results and discussion of the TTMLE-SSO model

The proposed TTMLE-SSO model has been compared with other models like NNN, SVR and LSTM to analyse their performance for trading choices and gains. The dataset considered is the Indian stock data from National Stock Exchange (NSE) [17]. The parameters used for analysis are: Mean Square Error (MSE) and Mean Absolute Fraction Error (MAFE). MSE and MAFE are calculated as follows:

$$MSE = \frac{1}{t}\sum_{t=1}^{n}[estimate(F_{t,n}) - F_{t,n}]^2 \quad (3)$$

$$MAFE = \frac{1}{t}\sum_{t=1}^{n}\left|\frac{estimate(F_{t,n})-F_{t,n}}{F_{t,n}}\right| \quad (4)$$

$F_{t,n}$ is the initial forecast values obtained as a result of the AMD model. $Estimate(F_{t,n})$ has been obtained after integrating $F_{t,n}$ using CSA in tier 2.

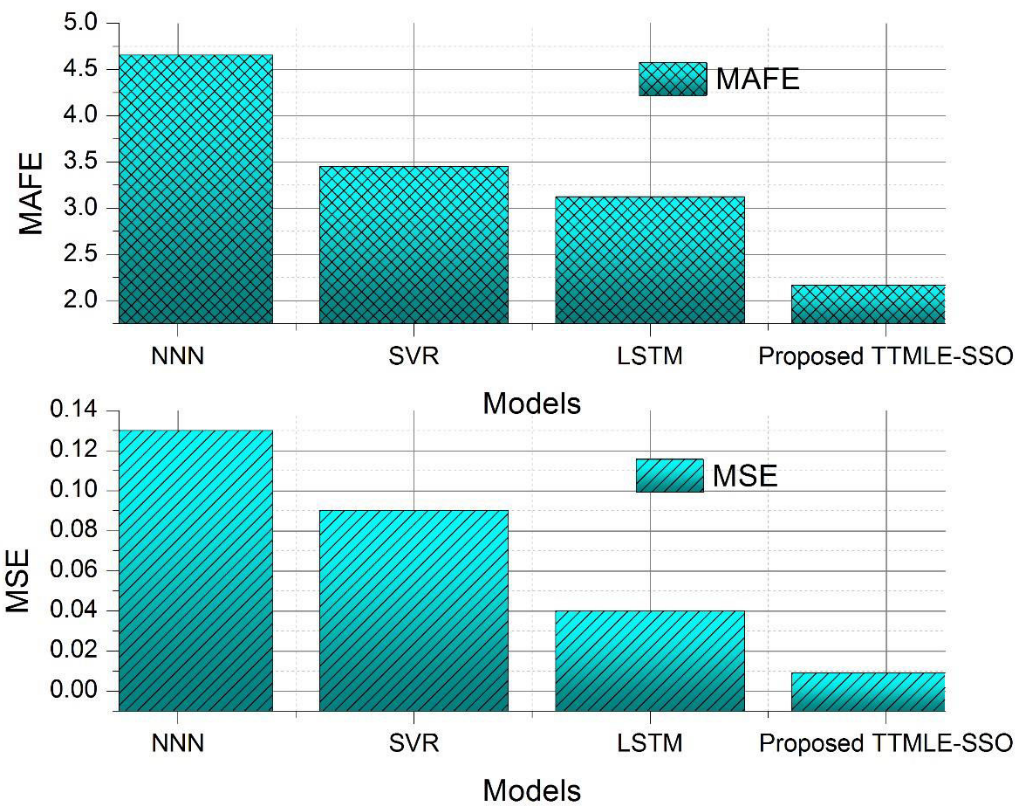

Fig. 3 MSE and MAFE values for NNN, SVR, LSTM and the proposed TTMLE-SSO models.

MSE and MAFE values for NNN, SVR, LSTM and the proposed TTMLE-SSO models have been shown in Fig. 3. To show the forecasting ability of the proposed TTMLE-SSO model, MSE and MAPE parameters have been compared with other regression models. The results have shown that the MSE and MAFE of the proposed TTMLE-SSO are very low than other models, thereby enhancing their forecasting accuracy. This is attributed to the fact that the proposed model is enhanced using two tiers of prediction, along with SSO which finds the optimal weights for prediction. NNN method gave a poor performance with high values of MSE and MAFE. SVR and LSTM gave moderate prediction accuracy with moderate values of MSE and MAFE.

Table 1: Stability analysis of the proposed TTMLE-SSO with other models

Model	Peak of MAFE	Trough of MAFE	Mean MAFE
NNN	3.766	2.465	3.1155
SVR	4.065	3.598	3.8315
LSTM	5.096	4.789	4.9425
Proposed TTMLE-SSO	2.764	2.764	2.764

Table 1 shows the constancy analysis of the proposed TTMLE-SSO with other models. It has been inferred from the table that the proposed TTMLE-SSO model has steady performance with a mean value of 2.764 and a standard deviation of zero. The NNN model has poor stability with high standard deviation value than SVR and LSTM models. SVR and LSTM models achieve moderate stability.

5. Conclusion

A two-tier machine learning ensemble model (TTMLE) using salp swarm optimization (SSO) has been proposed to address the issues in option price forecasting. The TTMLE model, which integrates AMD and CSA and is inspired by ensemble learning, has been presented for option price forecasting. The AMD-based MLE model is used for initial pricing under various parameters at the introductory level. An enhanced CSA algorithm has been created for the second step to produce final forecasts by combining the prediction results acquired in the first phase. The SSO approach was used to train the TTMLE model. To generate higher performance with fewer mistakes, the SSO approach was utilised to increase the weights of the TTMLE model, which focuses on salp densities and their navigation and feeding activities. To show the forecasting ability of the proposed TTMLE-SSO model, MSE and MAPE parameters have been compared with other regression models. The results have shown that the MSE and MAFE of the proposed TTMLE-SSO are very low than other models, thereby enhancing their forecasting accuracy. The proposed TTMLE-SSO model also has steady performance with a mean value of 2.764 and a standard deviation of zero.

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