International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019

Forecasting of Commodity Future Index using a Hybrid Regression Model based on Support Vector Machine and Grey Wolf Optimization Algorithm

V. Veeramanikandan, M. Jeyakarthic

***Abstract**: The forecasting and investigation of finance time series data are hard, and are the most confounded works pertained with investor decision. In this paper, an economic derivative instrument for Multi Commodity Exchange (MCX) index of CRUDEOIL is estimated by utilizing forecasting models based on recently formulated artificial intelligence (AI) approaches. These approaches have been appeared to perform astoundingly well in different optimization problems. Specifically, a novel hybrid forecasting model is designed by combining the support vector machine (SVM) and grey wolf optimization (GWO) and it is named as hybrid SVM-GWO. The presented hybrid SVM-GWO model eliminates the user determined control parameter, which is needed for other AI techniques. The practicality and proficiency of the presented SVM-GWO regression method is evaluated by predicting the everyday close price of CRUDEOIL index traded in the MCX of India Limited. The exploratory outcomes depicts that the present hybrid SVM-GWO technique is viable and outperforms superior to the conventional SVM, hybrid SVM-TLBO and SVM-PSO regression models.*

***Keywords** : Support vector machine (SVM), Grey wolf optimization (GWO) Commodity futures contract Financial time series.*

I. INTRODUCTION

The dynamics of producer prices for crude oil has a significant impact on the financial and economic results of Indian market. Since crude oil is one of the sectors with a long investment cycle, a change in the level of prices for crude oil can lead to a significant increase or decrease in the payback period of large investment projects [1]. Under these conditions, forecasting the level of prices for crude oil is of great importance in determining the direction and development of the industry, and also making investment decisions by the management of refinery companies [2].

Revised Manuscript Received on December 30, 2019.
***** Correspondence Author
V. Veeramanikandan*, Assistant Professor, Department of CS, T.K. Govt. Arts College, Vridhachalam, India. Email: klmvmani@gmail.com
Dr. M. Jeyakarthic, Assistant Director , Tamil Virtual Academy, Chennai, India. Email: jeya_karthic@yahoo.com

The problem of forecasting the price of a good is one of the key in economic theory which affecting the interaction of supply and demand in the market. According to S Rosen, in any market, supply and demand are jointly determined by both the number of goods bought and sold, and their relative prices [3]. Similarly, demand and supply are operating in the same way on international trade as well as local and domestic markets [4]. Thus, the determination of supply and demand factors included in model calculations is importance when forecasting prices [5]. Pricing processes differ in different industry markets, as a result of which it is necessary both to determine the boundaries of the market under study and to identify specific pricing factors specific to a particular market. Consequently, generalized theoretical approaches to price forecasting should be specified using empirical facts characterizing the industry market under consideration [6].

Currently, there are many methods for predicting the prices of the multi commodity futures (COMDEX) index traded in the Multi Commodity Exchange (MCX) of India Limited that use multivariate (less often univariate) regression equations [7]. In [8], lots of factors were included in the model for forecasting prices of stainless steel such as the volume of deliveries of stainless steel sheets to the market (tons), the volume of production of passenger cars (units), the need for car plants in stainless steel sheets (tons), export prices for stainless sheet (USD/t) and money supply.

A model for forecasting world prices for crude oil has been developed, a factor such as the load factor of crude oil inventory was used; other factors were classified as insignificant from a statistical point of view [9]. In [10], a technique based on neural network model has been developed that combines Elman Recurrent Neural Networks (ERNN) and Multi-Layer Perception (MLP) with random time effective function. This approach has an enhanced the prediction accuracy of closing cost of crude oil. In [11], a teaching learning based optimization (TLBO) algorithm has been employed to find the best parameters for the Support Vector Machine (SVM) regression model for prediction of closing cost for COMDEX commodity futures index traded in MCX India.

Various prediction methods such as time series and multivariate analyses have been employed for forecasting models.

However, many authors have started to use artificial intelligence (AI) techniques to economic markets, due to the recent successful developments such as artificial neural networks (ANNs) [10], support vector machines (SVMs) [11], particle swarm optimization (PSO) with eagle strategy [12], and fuzzy controllers [13].

In this paper, the problem of daily closing prices forecasting for the CRUDEOIL commodity futures index by the SVM with grey wolf optimization (GWO) is proposed. The SVM technique has a fairly wide application such as pattern recognition, text and hypertext categorization, image segmentation and classification, Hand-written characters recognized and many more applications in biological and other sciences [14]. The GWO is a novel algorithm inspired by grey wolves (Canis lupus). The GWO technique mimes the hunt activity and leading hierarchy behaviors of grey wolf. Alpha, beta, delta, and omega are the four different types of grey wolves that have been implemented for miming the leading hierarchy behaviors of grey wolf in [14].

The remainder of this work is formulated as; a solution method for regression problem using SVM is presented in section 2. The GWO algorithm and the proposed hybrid SVM-GWO regression model for determining the optimal SVM parameters is presented in section 3. Section 4 presents the proposed method for forecasting the commodity futures index, followed by our results, comparisons, and analysis. Finally the conclusion of the presented work is shown in section 5.

II. SUPPORT VECTOR MACHINE

A. Solution for Regression Problem using SVM

It is necessary to solve the regression problem, the purpose of which is to estimate the function of the output variable taking a continuous range of numerical values from the matrix of input variable parameters. It was demonstrated by Vapnik in 1995 that the SVM approach has been employed to solve the regression problem [15]. Vapnik's approach is demonstrated as follows.

Given a training data sample S(x,y) can be defined as,

$$S(x,y)=\{(x_1,y_1),......,(x_l,y_l)\} \qquad \begin{matrix} x_i \in X \subset R^n \\ y_i \in Y \subset R \end{matrix} \tag{1}$$

where, X represents the input sample data and Y represents the corresponding target values, l denotes the training sample size.

Therefore the aim of problem of regression is to determine a function $f: R^n \rightarrow R$ that can be an approximate target for y even when x is not present in the training set.

Thus, estimating function f can be formulated as,

$$f(x)=\left(w^T\Phi(x)\right)+b, \tag{2}$$

where, $b \in R$ is the bias, $w \in R^m$ and Φ denotes a nonlinear function from R^n to high-dimensional space R^m ($m > n$).

The objective is to find w and b such that the value of $f(x)$ can be estimated by optimizing the risk R_{reg},

$$R_{reg}(f)=C\sum_{i=1}^{n}L_{\in}\left(y_i, f(x_i)\right)+\frac{1}{2}\|w\|^2 \tag{3}$$

where, $L_{\in}$ is the extension of the insensitive loss function originally proposed by Vapnik [15], which is computed as,

$$L_{\in}=\begin{Bmatrix} |y-z|=\in, & |y-z|\geq\in, \\ 0, & otherwise \end{Bmatrix}. \tag{4}$$

By adding the slack variables ζ_i and $\zeta_i^{'}$ in the risk R_{reg} equation, Eq. (3) can be rewritten as (P),

(P) = Minimize $C\left[\sum_{i=1}^{l}\left(\zeta_i+\zeta_i^{'}\right)\right]+\frac{1}{2}\|w\|^2$ subject to constraints,

$$\begin{aligned} & y_i-w^T\Phi(x_i)-b\leq\in+\zeta_i, \\ & w^T\Phi(x_i)+b-y_i\leq\in+\zeta_i^{'}, \\ & \zeta_i\geq 0, \\ & \zeta_i^{'}\geq 0, \end{aligned} \tag{5}$$

where, i = 1, . . . , l, and C is a user-specified constant known as regularization parameter.

To solve (P), primal dual method has been employed to obtain the following dual problem.

Find the Lagrange multiplier α_i and α_i^* that maximizes the fitness function.

$$\begin{aligned} Q(\alpha_i,\alpha_i^*) = & \sum_{i=1}^{l}y_i(\alpha_i,\alpha_i^*)-\in\sum_{i=1}^{l}(\alpha_i,\alpha_i^*) \\ & -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i,\alpha_i^*)(\alpha_j,\alpha_i^*)K(x_i,x_j), \end{aligned} \tag{6}$$

subject to constraints,

$$\sum_{i=1}^{l}(\alpha_i,\alpha_i^*)=0, \tag{7}$$

$$0\leq\alpha_i\leq C, 0\leq\alpha_i^*\leq C. \tag{8}$$

where, i = 1, . . . , l, and K : X x X → R is the Mercer kernel denoted by,

$$K(x,z)=\Phi(x^T)\Phi(z) \tag{9}$$

The solution of the primal dual approach results,

$$w=\sum_{i=1}^{l}(\alpha_j-\alpha_i^*)\Phi(x_i), \tag{10}$$

where b is calculated using the Karush–Kuhn–Tucker conditions. That is,

$$\alpha_i\left(\varepsilon+\zeta_i-y_i+w^T\Phi\left(x_i\right)+b\right)=0, \quad (11)$$

$$\alpha_i^*\left(\varepsilon+\zeta_i+y_i-w^T\Phi\left(x_i\right)-b\right)=0,$$

$$\left(C-\alpha_i\right)\zeta_i=0 \quad and \quad \left(C-\alpha_i^*\right)\zeta_i^*=0, \quad where \quad i=1,..., \quad (12)$$

Since $\alpha_i \cdot \alpha_i^* = 0$ both α_i and α_i^* cannot be simultaneously non-zero, there exists some i for which either $\alpha_i \in (0,C)$ or $\alpha_i^* \in (0,C)$ and hence b can be estimated as follows,

$$b=y_i-\sum_{j=1}^{l}\left(\alpha_j-\alpha_j^*\right)K\left(x_j,x_i\right)-\varepsilon \; for \quad 0<\alpha_i<C, \quad (13)$$

$$b=y_i-\sum_{j=1}^{l}\left(\alpha_j-\alpha_j^*\right)K\left(x_j,x_i\right)+\varepsilon \; for \quad 0<\alpha_i^*<C.$$

The x_i corresponding to $0<\alpha_i<C$ and $0<\alpha_i^*<C$ are termed as SVM vectors.

Using the equations for w and b in Eqs. (10) and (13), f(x) can be calculated as follows,

$$f\left(x\right)=\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)\left(\Phi\left(x_i\right)^T\Phi\left(x\right)\right)+b, \quad (14)$$

$$=\sum_{i=1}^{l}\left(\alpha_i-\alpha_i^*\right)K\left(x_i,x\right)+b.$$

Note that function U is not required to calculate f(x), which is an advent of using the kernel.

III. PROPOSED METHODOLOGY

The forecasting task is to determine or estimate future event outcome which uses information from the previous events, combined with recent trends. Usually such previous event's data is a vector in n-dimensional real space. The coordinates of the vector describe the individual attributes of the event data. In this paper, a hybrid SVM-GWO technique is proposed to solve the problem of daily closing price forecasting in the COMDEX commodity futures index.

A. Grey Wolf Optimization (GWO) Algorithm

The GWO algorithm was first developed by Mirjalili and his coworkers in 2014 inspired from the behavior of grey wolf (Canis lupus) [14]. The GWO technique mimes the hunt activity and leading hierarchy behaviors of grey wolf. Alpha, beta, delta, and omega are the four different types of grey wolves that have been implemented for miming the leading hierarchy behaviors of grey wolf in [14].

B. GWO Algorithmic Steps

The algorithmic steps of GWO technique is discussed as follows,

Step 1: Initialize the GWO parameters such as grey wolf hunt agent (Gs), pack size i.,e dimensional of the problem (Gd), GWO vectors a, A, C and maximum iteration count ($iter_{max}$).

$$\vec{A}=2\vec{a}.rand_1-\vec{a} \quad (15)$$

$$\vec{C}=2.rand_2 \quad (16)$$

The values of a is linearly decreased from 2 to 0 for consecutive iteration.

Step 2: Randomly generate grey wolves based on pack size. The structure of wolves can be formulated as,

$$Wolves=\begin{bmatrix} G_1^1 & G_2^1 & . & . & G_{Gd-1}^1 & G_{Gd}^1 \\ G_1^2 & G_2^2 & . & . & G_{Gd-1}^2 & G_{Gd-1}^2 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ G_1^{Gs} & G_2^{Gs} & . & . & G_{Gd-1}^{Gs} & G_{Gd-1}^{Gs} \end{bmatrix} \quad (17)$$

where, G_i^j is the randomly generated value of the j^{th} pack of the i^{th} grey wolf search agent.

Step 3: Calculate the objective value of each grey wolf agents using below Eqs. (18) and (19).

$$\vec{D}=\left|\vec{C}.\vec{Gp}(t)-\vec{G}(t)\right| \quad (18)$$

$$\vec{G}(t+1)=\vec{Gp}(t)-\vec{A}.\vec{D} \quad (19)$$

Step 4: Find the first optimal grey wolf hunt agent (G_α), the second optimal grey wolf hunt agent (G_β) and the third optimal grey wolf hunt agent (G_δ) using Eqs. (20) to (25).

$$\vec{D}_\alpha=\left|\vec{C}_1.\vec{G}_\alpha-\vec{G}\right| \quad (20)$$

$$\vec{D}_\beta=\left|\vec{C}_2.\vec{G}_\beta-\vec{G}\right| \quad (21)$$

$$\vec{D}_\delta=\left|\vec{C}_3.\vec{G}_\delta-\vec{G}\right| \quad (22)$$

$$\vec{G}_1=\vec{G}_\alpha-\vec{A}_1.(\vec{D}_\alpha) \quad (23)$$

$$\vec{G}_2=\vec{G}_\beta-\vec{A}_2.(\vec{D}_\beta) \quad (24)$$

$$\vec{G}_3=\vec{G}_\delta-\vec{A}_3.(\vec{D}_\delta) \quad (25)$$

Step 5: Modify the new position of the current grey wolves hunt agent using below equation,

$$\vec{G}(t+1)=\frac{\vec{G}_1+\vec{G}_2+\vec{G}_3}{3} \quad (26)$$

Step 6: Calculate the objective value of all grey wolves search hunts.

Step 7: Amend the value of Gα ,Gβ and Gδ.

Step 8: Whether iteration count (Iter) reaches maximum number of iterations ($Iter_{max}$), if yes, stopping criteria reached and display the optimal grey wolf hunt agent, unless go to step 5and repeat the process until stopping criteria achieved.

C. GWO Algorithm - Pseudo code

1: Initialize grey wolves as search agents G_i (i=1, 2,…., n)

2: Initialize the vector's of each grey wolves i.e., a, A and C

3: Compute the fitness value of each grey wolves

The first optimal grey wolf as Gα

The second optimal grey wolf as Gβ

The third optimal grey wolf as Gδ

4: Initialize Iter = 0

5: Set Iter = Iter + 1

Retrieval Number: B7207129219//2019©BEIESP
DOI: 10.35940/ijitee.B7207.129219
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

6: for i=1: Gs
Calculate the new position of the current grey wolf using Eq. (26).
End for
7: Estimate the fitness value of newly computed current grey wolves
8: Amend the value of Gα, Gβ, Gδ
9: Amend the grey wolves vectors a, A and C
10: Is Iter >= $Iter_{max}$, if yes, stopping criteria reached and go to step 11, unless go to step 5and repeat the process until stopping criteria achieved.
11: output G

D. SVM–GWO Hybrid Regression Model

In this paper, a hybrid SVM-GWO regression model for MCX crudeoil price forecasting is presented that employs GWO technique for deciding the parameters of SVM and SVM for price forecasting. Generally, SVM may utilize any one of the core kernels, such as Gaussian, wavelet, sigmoid, polynomial and linear kernels. In this work, the Gaussian kernel (radial basis) function is employed as the kernel for SVM. This creates better time series predictions, since the information are nonlinear and complex [16,17].

The proposed SVM uses Gaussian kernel that has three parameters such as e (radius of insensitive loss function), r (width of kernel) and C (regularization) which are need to be optimized by using GWO algorithm. Since the parameter e is kept constant at an affordable value (i.e., 0.0001), the proposed hybrid SVM–GWO regression model is modeled to operate in a solution space with two dimensions, i.e., to optimize r and C only. The reason for the value of e kept constant is because of the number of SVM vectors decreases when e increases i.e., when e is higher than 0.01 [17].

Fig. 1 depicts the flowchart of the hybrid SVM-GWO regression model for closing price forecasting of MCX CRUDEOIL. Table I and II show the GWO and SVM parameters used in the proposed work respectively.

Table-I: GWO parameters

GWO parameter	Parameter value
Population size (hunt agent)	10
Maximum iteration, $Iter_{max}$	100
Optimization category	Minimum

Table-II: SVM parameters

SVM Parameters	Parameter Value
C (regularization parameter)	0.01 to 35,000
σ^2 (bandwidth)	0.0001 to 32
ε	0.0001 (Fixed)
Kernel type	Radial basis (Gaussian)

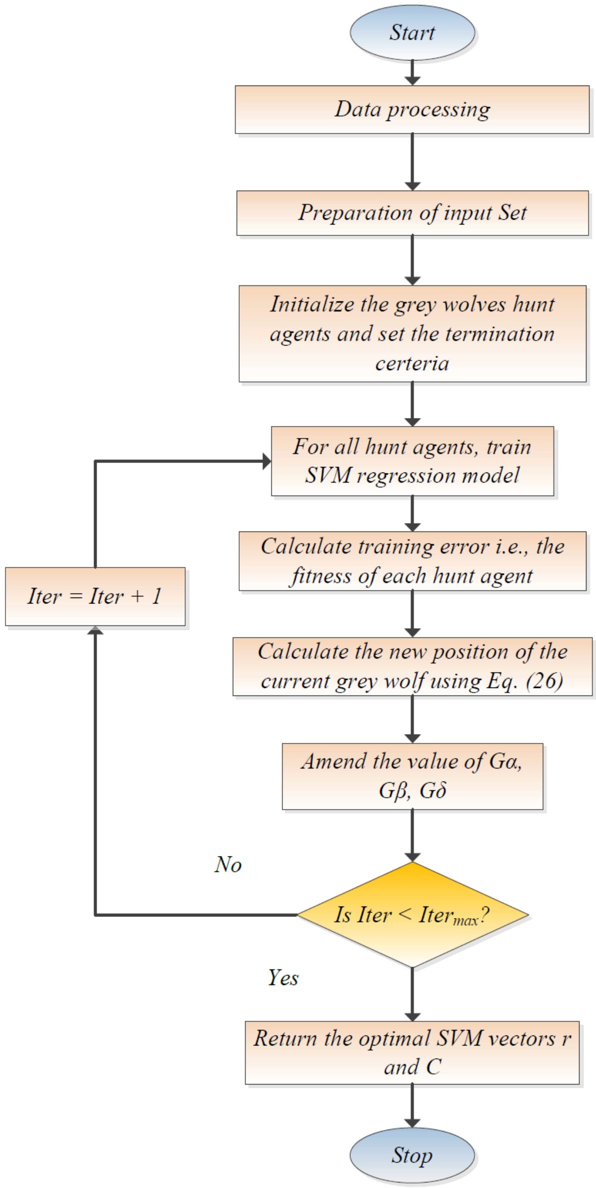

Fig. 1.Flowchart of the proposed hybrid SVM-GWO regression model for price forecasting of MCX CRUDEOIL

IV. RESULTS AND DISCUSSION

A. Database

The proposed hybrid SVM-GWO forecasting model is applied to real MCX CRUDEOIL DEC2018 index and its sample data are collected from the MCX website (http://www.mcxindia.com). Table-III portrays the informational collection as far as the low and high price, mean, median and standard deviation of closing price for 45 days span of MCX CRUDEOIL DEC2018 index.

Forty five day by day trade information are gathered from the MCX website for MCX CRUDEOIL DEC2018 index from 17th October 2018, to 18th Dec 2018. The time series information comprise of trade date, every day open and close prices, high and low prices. These day by day price values are utilized as the inputs to ascertain the finance technical pointers.

This time length covers numerous importance and noteworthy financial occasions, which is believed as suitable to train the SVM regression models.

The everyday close price plot of MCX CRUDEOIL DEC2018 index for forty four days is given in Fig. 2. The information portrayal in Table III and the closing price data diagram in Fig. 2 plainly show that the information is well spread. In this way, a SVM trained with the forty four days data ought to be a well-generalized model.

Table-III Description of MCX CRUDEOIL DEC2018 data for last 45 days

Parameter (for 45 days span)	Price
High	5316
Low	3346
Mean	4217.4444
Standard deviation	565.1206
Median	4104

B. Performance Index

The performance of the presented model using standard statistical metrics such as mean absolute error (MAE) and root mean square error (RMSE) has been evaluated. Detailed descriptions and definitions of these performance criteria are given as follows,

$$MAE = \frac{1}{n}\sum_{i=1}^{n}| y_i - p_i | \quad (27)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - p_i)^2} \quad (28)$$

C. Comparative Analysis

The RMSE value of the SVM forecasting model in the training and testing stages, and the optimal estimations of r and C are exhibited in Table IV for one day ahead forecasting. The outcomes for the presented hybrid SVM-GWO forecasting technique and its optimal estimations of r and C are depicted in Table IV.

Table-IV Model performance and final parameter settings using the conventional SVM and hybrid SVM-GWO regression models

Regression Model	Final value		Training error RMSE	Testing error RMSE
	C	σ^2		
SVM	100	0.01	0.0781	0.1087
SVM-GWO	2017.142	1.841	0.0514	0.0879

Table-V Comparison of MAE and RMSE

Performance Index	Svm	Svm+Pso	Svm+Tlbo	Svm+Gwo
Mae	0.0985	0.069	0.053	0.039
Rmse	0.0941	0.052	0.048	0.024

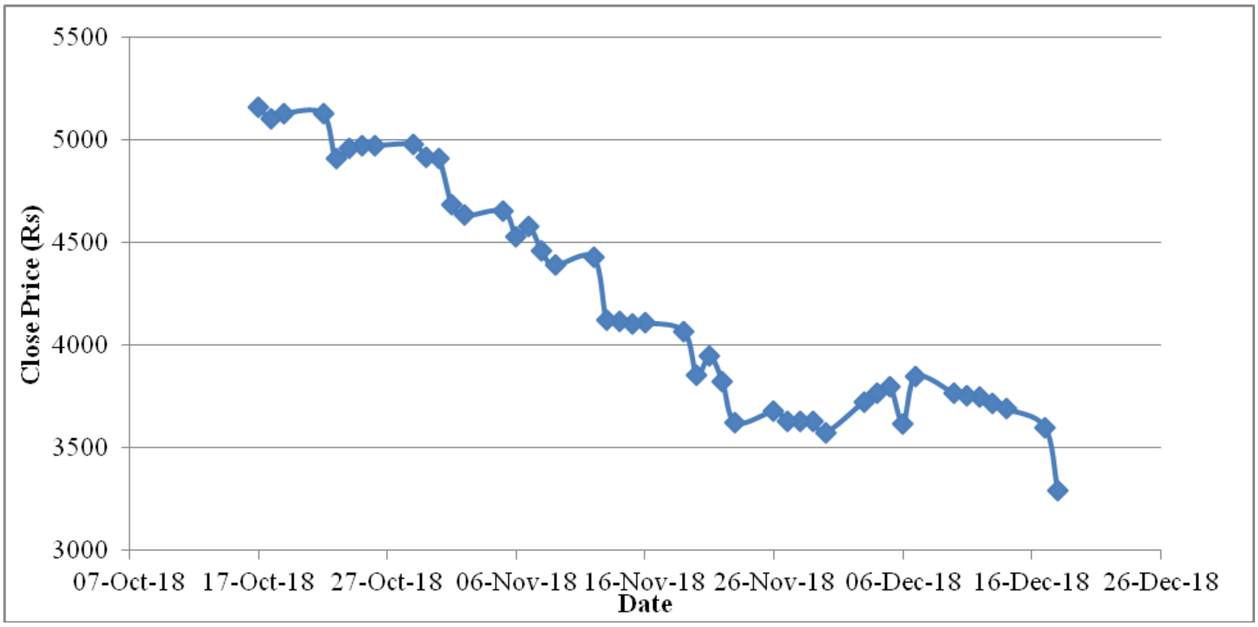

Fig. 2.Closing prices of MCX CRUDEOIL DEC2018 for last 45 days

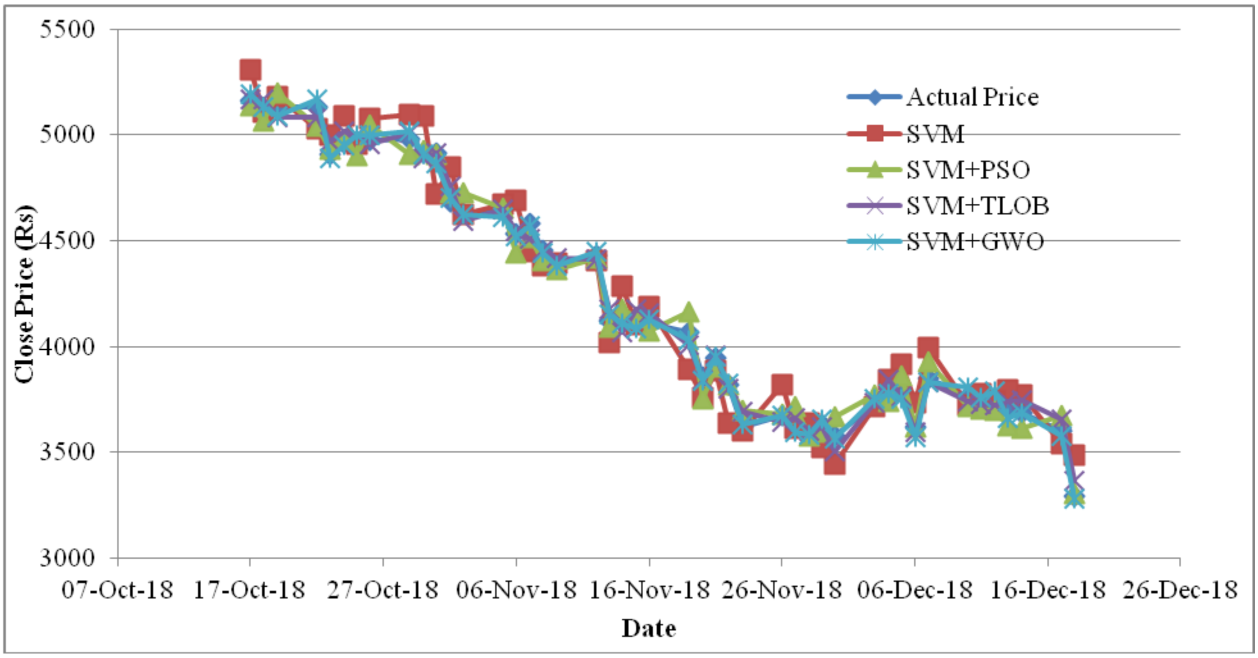

Fig. 3.Actual and predicted futures index prices using the SVM, SVM-PSO, SVM-TLBO and proposed hybrid SVM-GWO forecasting model

The values of MAE and RMSE are displayed in Table V depicts that the hybrid SVM-GWO forecasting technique beat the conventional SVM forecasting technique, hybrid SVM-PSO and hybrid SVM-TLBO methods for one day ahead forecasting. Concerning the execution metric, hybrid SVM-GWO outperformed superior to the conventional SVM, hybrid SVM-TLBO and SVM-PSO techniques methods for one day ahead forecasting. Money related market professionals assess the prediction model utilizing both directional exactness and minimal forecast error.

Fig. 3 depicts the actual futures index prices, and the price anticipated utilizing the conventional SVM, hybrid SVM-TLBO, hybrid SVM-PSO and the proposed SVM-GWO regression model for one day ahead forecasting.

V. CONCLUSIONS

The practicality of implementing the recently created new GWO technique to find ideal parameters for a SVM forecasting model of finance time series data has been presented in this paper. The future index data of MCX CRUDEOIL has been gathered from MCX website and utilized for analysis. Our exploratory outcomes depicts that the presented hybrid SVM-GWO forecasting model adequately found the ideal parameters of SVM, and created preferable forecasts over the conventional SVM technique. The presented forecasting model enhanced the RMSE value by 74.495 % for the one day ahead forecast while comparing with conventional SVM method. Additionally, the presented hybrid forecasting model enhanced MAE value by 60.406 % for the one day ahead forecast while comparing with conventional SVM technique. There are comparative enhancements as far as RMSE and MAE while comparing the presented hybrid SVM-GWO forecasting strategy with existing methods such as hybrid SVM-PSO and hybrid SVM-TLBO regression models. Additionally, our investigations exhibit that the presented hybrid SVM-GWO forecasting technique is more effective than the standard SVM, hybrid SVM-PSO and hybrid SVM-TLBO regression models for finance time series prediction. The presented hybrid SVM-GWO model eliminates the user determined control parameter, which is needed while utilizing optimization techniques, for example, GAs, ACO, TLBO and PSO.

REFERENCES

1. Samanta SK, Zadeh AH. Co-movements of oil, gold, the US dollar, and stocks. Modern Economy. 2012 Jan 5;3(01):111.
2. Alizadeh A, Mafinezhad K. Monthly Brent oil price forecasting using artificial neural networks and a crisis index. In2010 International Conference on Electronics and Information Engineering 2010 Aug 1 (Vol. 2, pp. V2-465). IEEE.
3. Rosen S. Hedonic prices and implicit markets: product differentiation in pure competition. Journal of political economy. 1974 Jan 1;82(1):34-55.
4. Arrow KJ. The potentials and limits of the market in resource allocation. InIssues in contemporary microeconomics and welfare 1985 (pp. 107-124). Palgrave Macmillan, London.
5. Westcott PC, Hoffman LA. Price determination for corn and wheat: the role of market factors and government programs. 1999.
6. V. Veeramanikandan, M. Jeyakarthic. An ensemble model of outlier detection with random tree data classification for financial credit scoring prediction system. International Journal of Recent Technology and Engineering (IJRTE). (Vol.8, Issue.3, pp. 7108-7114), September 2019.
7. Bose S. Commodity futures market in India: A study of trends in the notional multi-commodity indices. Money & Finance, ICRA Bulletin. 2007 Sep 3;3(3).
8. Ilmark S. Market Forecast for Stainless Steel. Metallurgist. 2013 Mar 1;56(11-12):883-7.
9. Naser H. Estimating and forecasting the real prices of crude oil: A data rich model using a dynamic model averaging (DMA) approach. Energy Economics. 2016 May 1;56:75-87.
10. Alizadeh A, Mafinezhad K. Monthly Brent oil price forecasting using artificial neural networks and a crisis index. In2010 International Conference on Electronics and Information Engineering 2010 Aug 1 (Vol. 2, pp. V2-465). IEEE.
11. Das SP, Padhy S. A novel hybrid model using teaching–learning-based optimization and a support vector machine for commodity futures index forecasting. International Journal of Machine Learning and Cybernetics. 2018 Jan 1;9(1):97-111.

12. Santhosh K, Neela R. Optimal placement of distribution generation in micro-grid using eagle strategy with particle swarm optimizer. International Journal of Pure and Applied Mathematics. 2018;118(18):3819-25.
13. Lai RK, Fan CY, Huang WH, Chang PC. Evolving and clustering fuzzy decision tree for financial time series data forecasting. Expert Systems with Applications. 2009 Mar 1;36(2):3761-73.
14. Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. Advances in engineering software. 2014 Mar 1;69:46-61.
15. Vapnik V. The nature of statistical learning theory springer new york google scholar.
16. Tay FE, Cao LJ. Modified support vector machines in financial time series forecasting. Neurocomputing. 2002 Oct 1;48(1-4):847-61.
17. Cao LJ, Tay FE. Support vector machine with adaptive parameters in financial time series forecasting. IEEE Transactions on neural networks. 2003 Nov;14(6):1506-18.