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ON PERFORMANCE OF ABC, FPA, BBO AND MVO ALGORITHMS IN ANFIS TRAINING FOR SHORT-TERM FORECASTING OF CRUDE OIL PRICE

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ABSTRACT

Crude oil is one of the most important assets that are used in the production of many industrial products in a wide variety of areas. The importance of crude oil has made it important to predict its future price. Therefore, it is possible to come across many studies in the literature in which the price of crude oil is estimated in the short or long term. In this study, innovative adaptive neuro-fuzzy inference systems (ANFIS) based approaches are proposed to estimate the daily minimum and maximum prices of crude oil. The used data was taken from the period between January 3, 2022, and December 29, 2023. A total of 516 different days of data were collected to create the dataset for analysis. For daily forecasting, time series data were transformed into a data set consisting of two inputs and one output. Moth-flame optimization algorithm (MFO), flower pollination algorithm (FPA), biogeography-based optimization (BBO) and artificial bee colony (ABC) were used in training ANFIS. The results obtained in the training and testing processes were compared. When the results obtained were compared, it was shown that the relevant algorithms were effective in the daily estimation of crude oil. It has been observed that effective results are also achieved at low evaluation numbers, especially thanks to the fast convergence feature of the MFO and BBO algorithms.

Keywords: Artificial intelligence, ANFIS, Crude oil, Metaheuristic algorithms, Time series analysis.

1 INTRODUCTION

Crude oil is one of the most important and even most strategically critical assets that is used in the production of many industrial products in a wide variety of areas, including fertilizers, pesticides, solvents, and plastics [1]. Furthermore, it is a source of several products, such as paraffin, asphalt, different fuels, and LPG [2]. In addition, it plays a leading role in meeting global energy demands, providing approximately one-third of worldwide energy consumption [3].

Therefore, it has an enormous effect on the economies of both producing and consuming countries as well as the global financial system [4, 5]. This demonstrates how vital it is to create price predictions. However, it is quite difficult to make an accurate prediction because there are numerous variables and events that affect the price, and as a result, the price fluctuates seriously [6]. These fluctuations have an impact on countries' inflation rates, economic growth, and investment decisions [7].

2 LITERATURE REVIEW

Many scientific approaches have been created and used in research to forecast crude oil prices. For example, Gupta and Nigam [8] used artificial neural networks (ANN) to reliably capture the shifting trends in crude oil prices. They demonstrate that identifying optimum time lags is a useful strategy for short-term price prediction.

Wu et al. [6] aimed to create an innovative hybrid approach for predicting crude oil prices. They eliminated outliers with the Hampel descriptor and reduced noise with the ensemble empirical mode decomposition approach. They proposed a modified water cyce algorithm to cover the deficient points of the traditional water cycle algorithm (WCA) in some conditions and used it to optimize the echo state network parameters. Finally, the efficacy of the model was tested and evaluated for daily and weekly crude oil price forecasts.

Chiroma et al. [9] proposed a hybrid technique for predicting West Texas Intermediate Oil (WTI) crude oil prices called GA-NN, which is based on the fundamentals of genetic algorithms and neural networks. This paper introduces a GA strategy to optimize the weights, biases, and topology of neural networks.

Mirmirani and Cheng [5]employed a VAR-based technique to predict US oil prices based on lagged data on oil prices, supply, and consumption. Additionally, the genetic algorithm-based ANN model makes predictions based on oil supply, energy use, and supply of cash.

Al-Qaness et al. [10] used the dendritic nerve regression (DNR) model, which is an artificial neural network that has excellent potential performance in time series forecasting due to its ability to deal with nonlinear characteristics found in historical data. Several metaheuristic algorithms like the whale optimization algorithm (WOA), particle swarm optimization algorithm (PSO), genetic algorithm (GA), sine-cosine algorithm (SCA), differential evolution (DE), and harmony search algorithm (HS) have been added to the estimation process in order to get around some restrictions associated with parameter configuration and training.

In their work, Sohrabi et al. [11] predict West Texas Intermediate Oil (WTI) prices using the whale optimization algorithm (WOA) and ANN; and compare the results with traditional ANN results.

In order to successfully predict the prices of crude oil futures, Hu et al. [12] employed three well-known neural network techniques: multilayer perceptron, Elman recurrent neural networks (ERNN), and recurrent fuzzy neural networks (RFNN).

Anshori et al. [2] applied the ANFIS technique to optimize the price of crude oil. This technique's initial settings are optimized using the Cuckoo Search approach.

Depending on the nature of the problem and how it will be solved, methods mentioned in this literature have different advantages or disadvantages. For example, GA, which is inspired by biological evolution methods, uses the solution population to reach the global optimum without being stuck in local optima. Without differentiation, it can be used for both continuous and discrete problems. It has the benefit of operating with its own rules without requiring the issue to be linearized, but it also has the drawback of defining the fitness function and calculating the parameters required for the algorithm. [13].

On the other hand, ANN works incredibly well with large and complex data. It can be effectively used to solve a variety of problems, including regression, classification, and time series forecasting. Despite these advantages, its primary disadvantage is the time-consuming training process and the need for large data. Additionally, insufficient data might lead to overfitting. [14].

ANFIS, which we applied in our study, is a technique that combines fuzzy logic structure and ANN. Thanks to this structure, it can be successfully applied to various subjects. Fuzzy logic principles make background processes easier to understand. The inability to properly set fuzzy logic rules and parameters is its primary limitation. Additionally, this adjustment process can be challenging and time-consuming [15].

When the literature is examined, it is seen that ANFIS-based methods are used in the estimation of crude oil. The training process is important in order to make effective estimations with ANFIS. Therefore, the optimization algorithms used in the training of ANFIS directly affect the result. In this study, for the first time, ANFIS training was performed with FPA, BBO, ABC and MFO algorithms for the estimation of daily price values of crude oil and their performances were compared.

3 MATERIAL AND METHOD

3.1 Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

The Neuro-Fuzzy is a unique architecture that combines neural networks and fuzzy systems, enabling supervised learning and the conversion of complex systems into if-then rules. Neuro-Fuzzy systems can be viewed as neural networks that embody distributed knowledge across their connection weights. Research has shown that Neuro-Fuzzy systems are effective in various applications, particularly in adapting knowledge expressed in fuzzy linguistic rules. An adaptive network is a key component of Neuro-Fuzzy systems, consisting of nodes and directed connections with modifiable parameters [16].

Although there are many Neuro-fuzzy models proposed in the literature, the most popular one is the ANFIS model [17]. ANFIS consists of two parts as seen in Figure 1. These sections are called premise and consequence. Both sections are connected to each other with the IF-THEN rule. The parameters in these sections are used in ANFIS training. An ANFIS model consists of five layers. Output values corresponding to inputs are calculated with the calculations performed in the layers [17, 18].

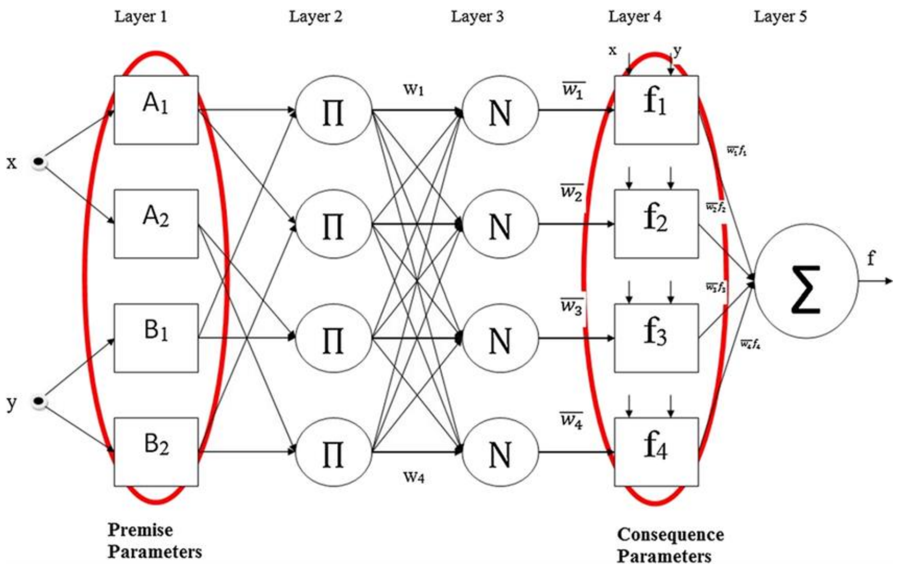


Figure 1. Display of parameters used in ANFIS training[18].

3.2 Moth-Flame Optimization Algorithm (MFO)

In nature, over 160,000 different species of moths have been documented, characterized by a two-stage life cycle consisting of a larval stage and a pupal stage, followed by the transformation into an adult moth [19]. One of the most intriguing aspects of moths' lives is their navigation method at night. They have evolved to fly at night using moonlight and employ a mechanism called transverse orientation to navigate. This mechanism enables the moth to maintain a constant angle with respect to the moon, allowing it to traverse long distances in a straight line [20]. Figure 2 illustrates a conceptual model of transverse orientation. Since the moon is far away from the moth, this mechanism guarantees flight in a straight line. Humans can also use this navigation method. For example, if a person wants to walk east and keeps the moon on their left side, they can move in a straight line.

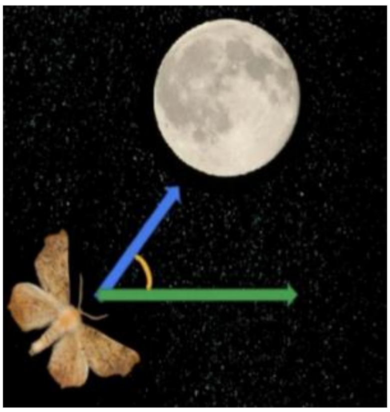


Figure 2. Moth’s transverse orientation [21].

Figure 3 shows that moths do not follow a straightforward path, but instead fly in a spiral pattern around light sources. This is because the transverse orientation method is only effective when the light source is very far away (moonlight). In the case of artificial light sources, moths attempt to maintain the same angle with respect to the light source, resulting in spiral motion around the light.

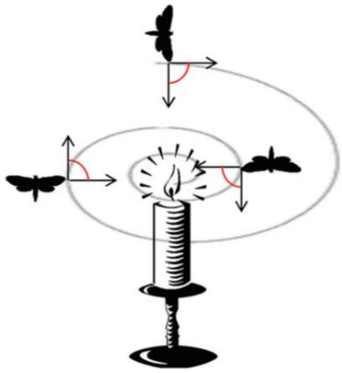


Figure 3. Moth's spiral flyingpath around a light source[21].

The Moth-Flame Optimization (MFO) algorithm was proposed by Mirjalili [22]. It is a population-based metaheuristic algorithm. MFO starts by generating a random population of moths in the solution space, followed by calculating the fitness value (i.e., position) of each moth and labeling the best position as a flame. Then, the moths' positions are updated using a spiral motion function to obtain better positions labeled by a flame, update the best individual positions, and repeat the previous steps until the termination criteria are met.

3.3 Flower Pollination Algorithm (FPA)

Prior to elucidating the intricacies of the Flower Pollination Algorithm (FPA), it is essential to delve into the fundamental principles governing the pollination behavior of plants. A dichotomy exists in the realm of pollination, as illustrated in Figure 4, which categorizes this phenomenon into two distinct forms.

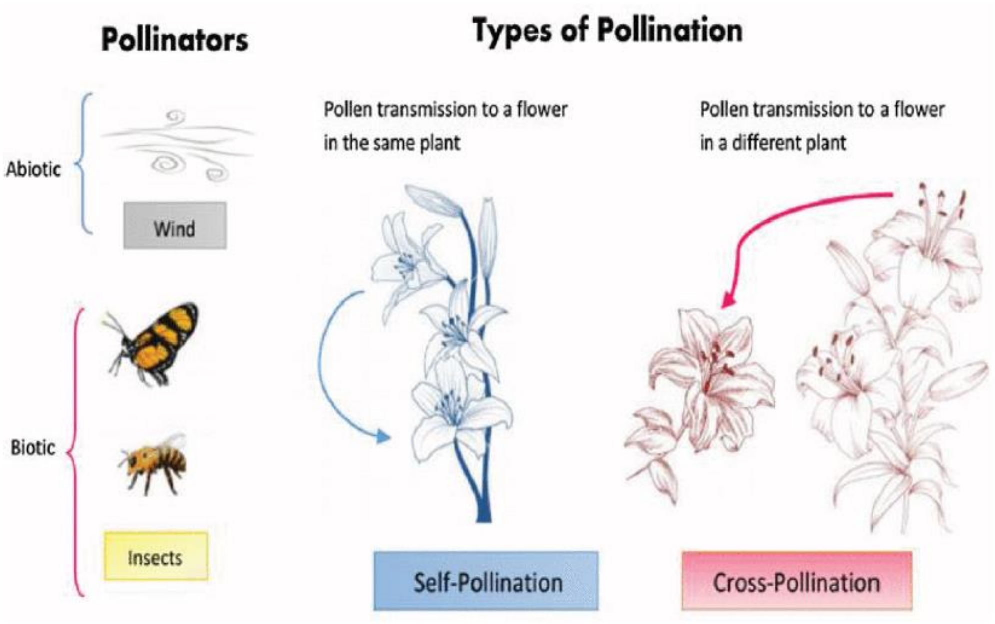


Figure4. The pollinators and pollination types[23].

Biotic or Cross-Pollination is precipitated by the agency of pollinators, including, but not limited to, avian and insect species. These pollinators traverse extensive distances, exhibiting varied velocities and speeds, thereby exemplifying a global pollination process characterized by Levy flight attributes [24-26]. Notably, a significant proportion of flowering plants (approximately 90%) on our planet conform to this pollination paradigm.

Abiotic or Self-Pollination occurs without the necessitation of external pollinators. A relatively smaller proportion of plants (approximately 10%) employ this pollination mechanism, wherein the distance traversed by pollinators, such as wind, is limited, resulting in a localized pollination process.

The flower pollination algorithm is shaped around four basic rules:

- Rule 1: Global Pollination Encompasses Biotic and Cross-Pollination via Levy Flight

Global pollination is characterized by the synergistic interplay between biotic and cross-pollination, mediated by pollinators exhibiting Levy flight patterns.

- Rule 2: Abiotic and Self-Pollination Induce Localized Pollination

Conversely, abiotic and self-pollination precipitate localized pollination, wherein the spatial scope of pollination is limited.

- Rule 3: Floral Similarity and Reproductive Probability

The similarity between two flowers is directly proportional to the probability of successful reproduction, a phenomenon referred to as flower constancy.

- Rule 4: Pollination Mode Selection via Switch Probability

The algorithm's pollination mode, whether local or global, can be modulated by adjusting the switch probability, a parameter bounded between 0 and 1.

3.4 Biogeography-Based Optimization (BBO)

Biogeography, a nebulous threshold beyond which a self-reinforcing paradigm of positive feedback is necessitated. This characteristic of biogeography bears a striking semblance to the principles of natural selection, wherein species, as they evolve to become increasingly adapted, augment their prospects for survival, thereby facilitating an enhanced capacity for dispersal and adaptation. Both natural selection and biogeography encompass this self-reinforcing attribute, wherein the iterative perpetuation of advantageous traits precipitates an incremental augmentation of fitness. However, the temporal scales at which these processes operate diverge significantly, with natural selection unfolding over an expansive timescale of millions and billions of years, whereas biogeography's timeframe is decidedly more compressed, spanning mere hundreds and thousands of years. This disparity in temporal scope suggests that, were we to invoke biogeography rather than natural selection as a motivating paradigm for an optimization algorithm (i.e., BBO as opposed to GAs), the prospect of achieving superior optimization outcomes is rendered more plausible. The supposition that biogeography optimizes habitats has, in turn, provided the impetus for the introduction of BBO as an optimization algorithm [27].

Biogeography-Based Optimization (BBO), developed by Dan Simon in 2008, is an evolutionary algorithm (EA) inspired by biogeography, the study of the distribution of biological species through time and space. Similar to other evolutionary algorithms, BBO aims to optimize a problem by maintaining a population of candidate solutions [27].

Each solution is comprised of a constellation of attributes or independent variables. A superior solution corresponds to a biological habitat that is optimally conducive to sustenance, whereas a suboptimal solution is tantamount to a habitat that is inimical to existence. Solutions with elevated degrees of fitness exhibit a propensity to share their attributes with other solutions; that is to say, attributes tend to migrate from solutions with high fitness to those with lower fitness, and vice versa. Conversely, solutions with diminished fitness exhibit a predilection for accepting attributes shared by other solutions. Like other EAs, Biogeography-Based Optimization (BBO) encompasses two distinct phases: information sharing and mutation. In the context of BBO, information sharing is effectuated through the mechanism of migration.

3.5 Artificial Bee Colony (ABC)

In the year 2007, Karaboğa introduced the Artificial Bee Colony (ABC) algorithm, a novel optimization technique predicated on swarm intelligence, which simulates the intriguing foraging behavior exhibited by honey bees [28]. Within the hierarchical structure of a bee colony, the bees are delineated into three distinct species [29], each with their unique roles and responsibilities:

I. Employed bees (forager bees): These diligent bees engage in an exhaustive search for sustenance sources, and upon their return to the hive, they disseminate pertinent information regarding the location of these sources to the onlooker bees, thereby facilitating a collective understanding of the environment.

II. Onlooker bees (observer bees): These unemployed bees, awaiting their cue to initiate the search process, are informed by the employed bees about the locations of the sustenance sources, which they subsequently utilize as a starting point for their own exploration.

III. Scout bees: These intrepid bees, tasked with the responsibility of abandoning depleted sources, embark upon an exploration of novel sustenance sources, conducting meticulous reconnaissance searches to identify potential alternatives.

In the ABC algorithm, the location of the source is metaphorically regarded as the solution to the problem at hand, while the quantity of source present is analogously considered as the fitness or quality of the solution. Each employed bee is assigned to a specific sustenance source, with the number of employed bees being commensurate with the number of solutions.

4 SIMULATIONS RESULTS AND DISCUSSION

In this study, ANFIS training was performed using ABC, FPA, BBO, and MFO metaheuristic optimization algorithms for short-term forecasting of crude oil. The data used is for the period between January 3, 2022, and December 29, 2023. Generally, the data excludes or does not account for weekends and public holidays. A total of 516 different days of data were collected to create the dataset for analysis.

Daily data is very important in modeling to understand sudden fluctuations or short-term trend changes. The point to be considered here is whether the data fluctuates significantly within the chosen time period. In our study, daily data for a two-year period was taken to obtain meaningful results and to ensure smooth operation of ANFIS. Normally, daily data is affected by seasonal factors and uncertainties such as short-term trends. Sometimes political events on a local or global scale affect the oil price. We took the data set for two years, allowing ANFIS to handle these impacts and learn the pattern. In addition, since we receive data for a long time, the system will be able to tolerate any deficiencies in the data. Taking the daily lowest and highest data is crucial to gain a better knowledge of the fluctuation in daily data and for ANFIS to understand and manage this pattern. In addition, these low and high values contain important information to determine the direction of the trend and the turning points.

The data set was created separately for the daily lowest and highest values. In other words, analyses were carried out to estimate the daily minimum and daily maximum values of crude oil. 80% of the dataset was used for the training process, while the rest was allocated to the testing process. Mean squared error (MSE) was utilized to calculate errors for both training and testing errors. For metaheuristic algorithms, the colony size was taken as 20. The maximum generation number was chosen as 2500.

The data obtained for the relevant prediction were transformed into data sets consisting of input and output in order to integrate it into the structure of ANFIS. In other words, time series data were transformed into a data set consisting of two inputs and one output. While the inputs represent the values of the previous two days, the output gives the value of the day to be estimated. The generalized Bell function (gbellf) was used in the structure of ANFIS. The network structure of ANFIS has a big impact on how well the algorithm performs. Therefore, the results were obtained by using 2, 3 and 4 membership functions for each input. In this way, the effect of the number of membership functions on performance was also analyzed.

Table 1 and Table 2 provides the mean error, best error, and standard deviation values for the training and test data acquired using these four metaheuristic methods for daily lowest and highest crude oil price respectively. BBO produced the most effective mean error and best error results, even though optimization algorithms for training data gave close results for the lowest price prediction. As is well known, a lower standard deviation denotes consistency between the results of different algorithm runs, while a higher standard deviation indicates greater variability. In the train phase, standard deviation values are around E-5, indicating that the optimization techniques provide consistent results across various runs. However, the FPA method produced the best standard deviation value. Furthermore, the findings were better with 4 gbellf in the BBO algorithm, although it was usually found that different gbellf had no obvious impact on the results.

Table 1. Results found with ABC, FPA, BBO and MFO algorithms for daily lowest price prediction.

Algorithm	The Number of MF	The Results					
		Train			Test		
		Mean	Best	Standard Deviation	Mean	Best	Standard Deviation
ABC	2	0.00154249	0.00140645	4.55721e-05	0.00132585	0.00125505	6.79725e-05
	3	0.00154616	0.00146477	3.29384e-05	0.00170155	0.00121331	0.00190897
	4	0.00153333	0.00148998	2.2437e-05	0.00132764	0.00116903	0.000134089
FPA	2	0.00153183	0.00150383	1.44265e-05	0.00131314	0.0011937	6.2601e-05
	3	0.00153748	0.00149388	2.15828e-05	0.00133359	0.00116378	0.000174327
	4	0.0015400	0.00148619	1.83605e-05	0.00134992	0.00122503	0.000104509
BBO	2	0.00147139	0.00140182	3.81338e-05	0.00135345	0.0012658	5.60871e-05
	3	0.00145527	0.00137498	3.81314e-05	0.00135535	0.00126513	5.35977e-05
	4	0.00143279	0.00132934	4.97694e-05	0.00138747	0.00127159	7.49651e-05
MFO	2	0.00150257	0.0014053	4.33461e-05	0.00134791	0.00128429	6.01915e-05
	3	0.0014741	0.0013621	5.28765e-05	0.00134216	0.0012741	6.08687e-05
	4	0.00146622	0.0013492	4.84771e-05	0.00135517	0.00125383	5.14631e-05

In the test phase for the lowest price prediction, the better and mean error values were found with the FPA algorithm. At this stage, the algorithms also returned results that were similar to each other. While the standard deviation statistics are consistent, the ABC algorithm's value for 3 gbellf is slightly higher.

In daily highest price prediction, the BBO algorithm outperformed others for a mean error value with 4 gbellf in the training phase. In addition, the best test error value was achieved as 0.00107589 with BBO. The other algorithms also performed well and provided results that were quite similar to BBO. In addition, consistent standard deviation values around E-5 were observed in both train and test phases.

Table 2. Results found with ABC, FPA, BBO and MFO algorithms for daily highest price prediction.

Algorithm	The Number of MF	The Results					
		Train			Test		
		Mean	Best	Standard Deviation	Mean	Best	Standard Deviation
ABC	2	0.00117105	0.00110336	4.61632e-05	0.00130587	0.00113348	8.39413e-05
	3	0.00115298	0.00110503	2.58662e-05	0.00126585	0.00112633	7.19967e-05
	4	0.00113414	0.00105515	2.4414e-05	0.00123768	0.0010982	7.02308e-05
FPA	2	0.00112432	0.00106925	1.41747e-05	0.00126797	0.00115898	5.6367e-05
	3	0.00114205	0.0011134	1.5816e-05	0.00129328	0.00114006	8.20375e-05
	4	0.00114664	0.00111429	1.58977e-05	0.00128786	0.00115503	8.81623e-05
BBO	2	0.00109202	0.000977377	3.54083e-05	0.00125036	0.00107589	5.69311e-05
	3	0.00107727	0.000885529	4.9627e-05	0.00125655	0.00117072	3.87653e-05
	4	0.00105926	0.000919088	5.70019e-05	0.0012569	0.001119	5.44527e-05
MFO	2	0.00111429	0.00094193	3.2932e-05	0.00127759	0.00122568	4.4203e-05
	3	0.0011035	0.00098341	2.93164e-05	0.00124368	0.00116902	2.94704e-05
	4	0.00108048	0.00097419	5.01938e-05	0.00125194	0.00118246	3.57427e-05

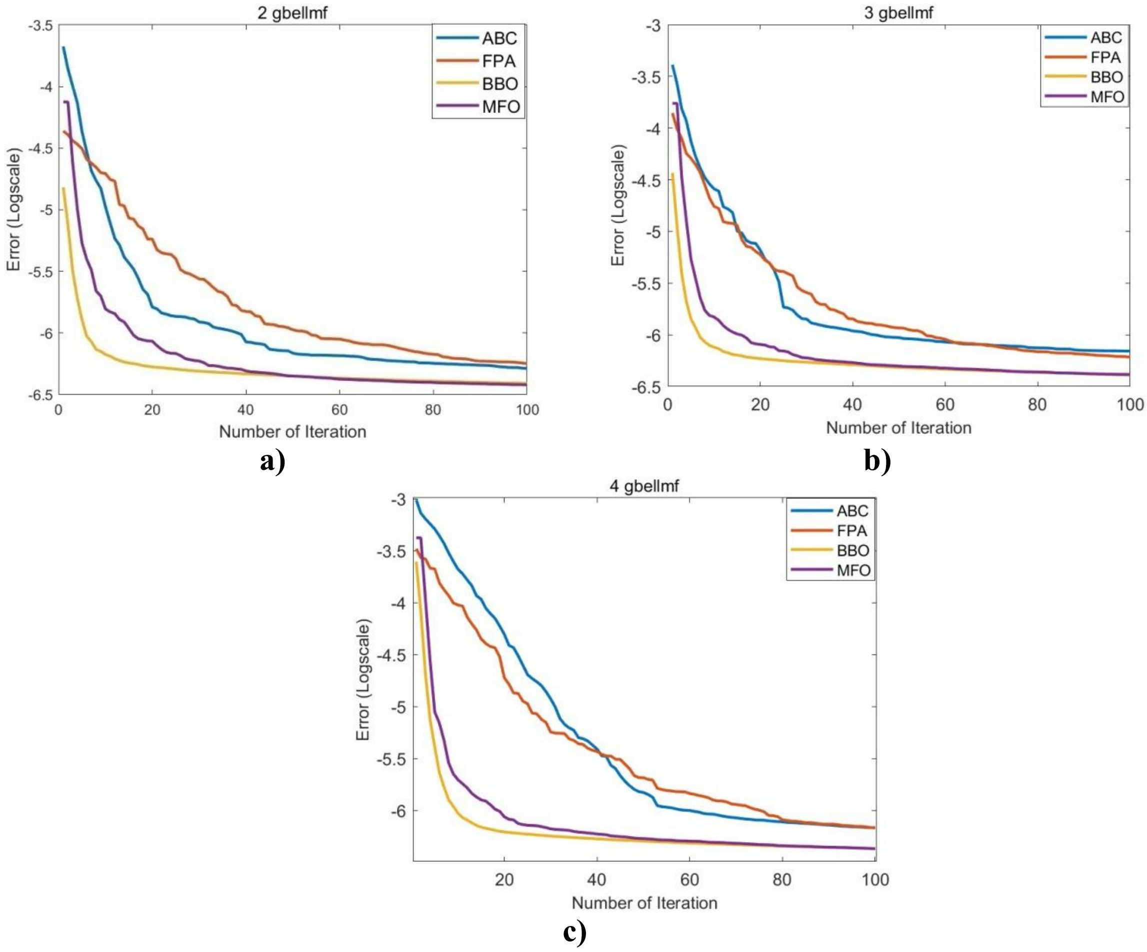
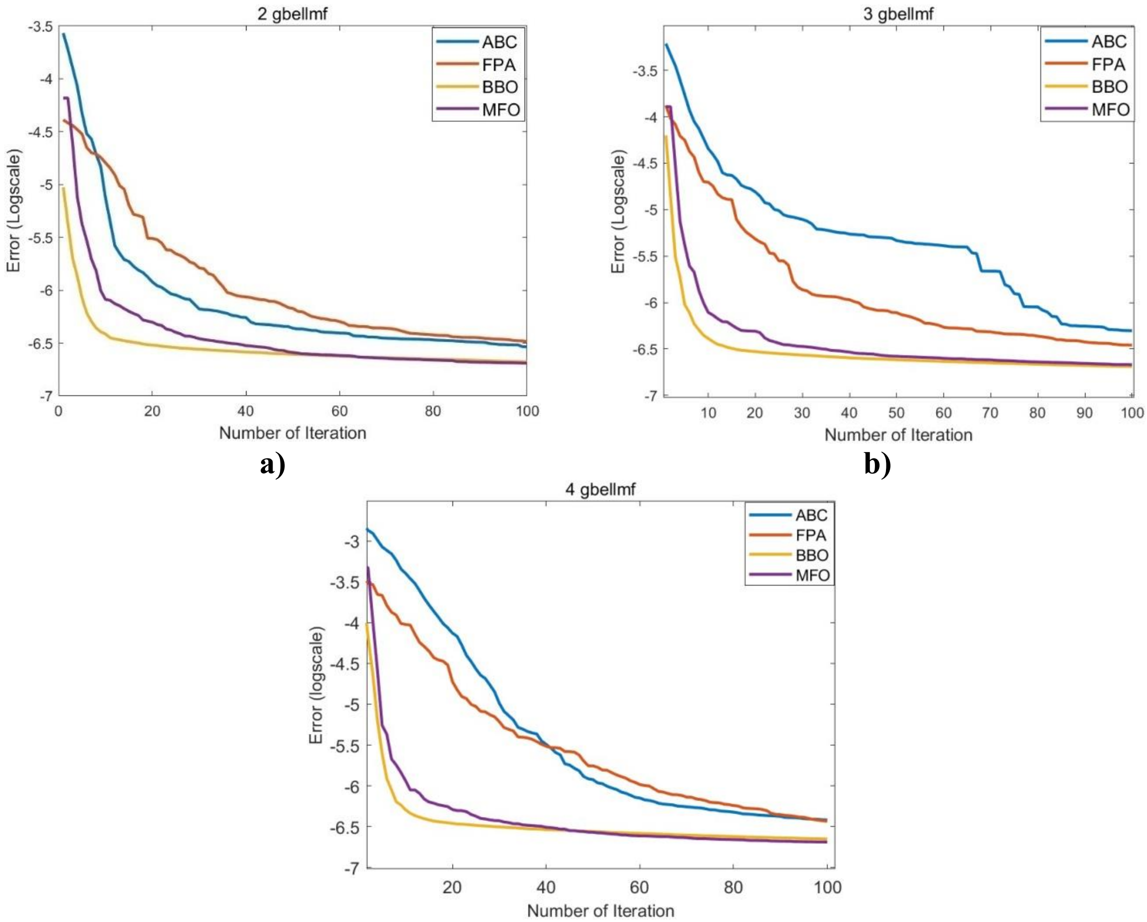


Figure 5. Comparison of convergence graphs of ABC, FPA, BBO and MFO algorithms for daily lowest price prediction when a) 2 gbellmf b) 3 gbellmf c) 4 gbellmf are used.

Figures 5 and 6 show that a similar scenario exists in both the test and training data. When the figures were analyzed for convergence to the intended value based on the number of iterations, we discovered that the BBO and MFO algorithms converged swiftly. However, the ABC and FPA algorithms converged at a slightly slower rate. After 100 iterations, BBO and MFO values converged to the same value, and ABC and FPA converged to a different value very close to this value, with BBO and MFO doing somewhat better.



a) **b)**

c)

Figure 6. Comparison of convergence graphs of ABC, FPA, BBO and MFO algorithms for daily highest price prediction when a) 2 gbellmf b) 3 gbellmf c) 4 gbellmf are used.

It is seen that effective solutions are obtained with metaheuristic algorithms in solving the relevant problem. In both the estimation of the smallest value and the estimation of the largest value, all algorithms have reached e-03 level training and test error values. Namely, effective results were obtained in both the training and testing processes. Although the training algorithms started with random initial populations, they reached the most effective results they could find and supported them with low standard deviation values. It is important that the algorithms have the feature of repeating the same results. The training and testing performances of the relevant algorithms are parallel to each other. In other words, they have shown the success in the both processes. Convergence is an important feature to examine the performance of training algorithms. Although the results of all algorithms are close to each other, we see that the convergence range to effective results is different. In other words, in cases where the maximum number of iterations is not important, all algorithms can be used in general. On the other hand, if it is necessary to reach a fast result, the algorithm with a high convergence speed is the reason for preference. When we look at this problem specifically, the convergence of BBO and MFO is better than other algorithms.

5 CONCLUSION

In this study, the performance of an ANFIS-based approach to estimate the daily minimum and maximum value of crude oil was investigated. The performances of ABC, FPA, BBO, and MFO algorithms were evaluated for the optimization of the parameters of ANFIS. In addition, the structure of ANFIS and the number of membership functions used directly affect the result. Therefore, the effect of different membership function numbers on the performance was also investigated. As a result of the study, the following general conclusions were reached:

• All algorithms performed well in daily crude oil prediction, as evidenced by their mean best error values.

• When doing a general evaluation, BBO often gives better results in the training process in general.

• While MFO and BBO have faster convergence in a small number of iterations, there is no meaningful difference between the algorithms in large numbers of iterations.

• The training and test outcomes of each algorithm were very similar in both the highest and lowest price data. This demonstrates that the learning process was carried out satisfactorily.

This study was developed for crude oil daily price prediction based on metaheuristic algorithm. It is a guiding study for future research to predict the prices of other goods with the same or different optimization algorithms.

There are some limitations in this study. Especially the population size and maximum generation number directly affect the result. It is possible to reach effective results by experimenting with different values of these control parameters. Another limitation is the number of inputs. In the scope of the study, time series data belonging to crude oil were converted into a data set that ANFIS can understand. There are two inputs and one output in this data set. Changing the number of inputs can change the performance of the system. The results to be obtained for different input number can be analyzed. In addition, the performance of only four meta-heuristic algorithms was examined for the solution of the relevant problem. It is possible to evaluate the performance of different meta-heuristic algorithms.

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Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

Contributions of the Authors

Ebubekir Kaya: Conceptualization, methodology, validation, software, review and editing, original draft preparation, supervision; Ahmet Kaya: Methodology, software, data curation, original draft preparation; Eyüp Sıramkaya: Data curation, example analysis, original draft preparation; Ceren Baştemur Kaya: Data curation, example analysis, visualization.

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