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Oil Consumption Forecasting Using Optimized Adaptive Neuro-Fuzzy Inference System Based on Sine Cosine Algorithm

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ABSTRACT Oil consumption is one of the main factors that affect industry and economy. Therefore, it is very important to estimate and forecast the consumption of oil. This helps the governments to take the right decisions and avoid the wrong decisions that lead to negative outcomes. For that reason, there are several methods that have been applied to forecast the oil consumption, such as the adaptive neuro-fuzzy inference system (ANFIS) model. It is one of the most popular data mining methods used to perform the forecast. However, the ANFIS model may not be accurate (biased) in all data, since its parameters require to be determined and updated and this may lead to stuck in the local point and not convergence to the optimal value. To this end, this paper presents an alternative oil consumption forecasting method by improving the ANFIS using the sine–cosine algorithm (SCA). In the proposed method called SCA-ANFIS, the parameters of the ANFIS are optimized using the SCA. In order to assess the performance of the proposed SCA-ANFIS method, a real dataset of petroleum products' consumption of three countries, namely, Canada, Germany, and Japan, is used. This dataset is collected on the period between 2007 and 2017, which contains 120 records per month for each country. Moreover, the results of the proposed method are compared with variants of ANFIS models. The experimental results demonstrate that the proposed SCA-ANFIS method outperforms other algorithms.

INDEX TERMS Time-series, optimized ANFIS, sine-cosine algorithm, oil consumption forecasting.

I. INTRODUCTION

Energy is considered one of the most critical factors to devolve human civilization, primarily industrial and economic sectors since energy affects various industrial environments. However, it is worldwide required to increase the quantities of energy from different sources either from non-renewable sources such as oil, coal, and natural gas; or from the renewable sources such as solar, wind, and other [1].

Based on the statistical review proposed by British Petroleum (BP) [2] which proved that the energy consumption of the world from oil is increased from 9943.8 million tons oil equivalent (Mtoe) (with an average of the annual growth rate of 2.8%) to 12,730.4 Mtoe. This study also illustrated that energy consumption from oil is 32.9% and from coal is 27.7%. Whereas, from natural gas, nuclear, biofuels, hydro is 21.4%, 5.7%, 10%, and 2.3%, respectively. According to this study, oil is still the main energy source in many countries, however, the consumption of each country changes from one year to another. Besides, the forecasting process of the oil consumption is not exclusive problem for particular country. For example, in Saudi Arabia, the oil consumption is increased from 0.41 MB/d (million barrels per day) to 3.07 MB/d in past four decades, however, this consumption represents one quarter of oil production [2]. Additionally, the oil consumption in 2013 of the UK, France, and the US is about 1508, 1767, and 18900 thousand b/d, respectively. These statistics of the oil consumption for the three countries refers to the France and UK are importing small amount from the oil countries, in contrast, the US the largest oil consumption country and this can effect on the market price [3]. In addition, the economics of China growth more than the US and also, its growth rate of oil consumption is faster than the US. From the previous studies of oil consumption for different countries, it can be reached to the facts that the oil consumption has more effect on the social development and economic growth in countries. Therefore, this can be treat as national economic security; so, a suitable forecast model for the oil consumption is very important to take a right decision especially for the long-term planning of economic development and social welfare since the wrong decision leads to negative outcomes [4].

The forecasting oil consumption methods can be divided into two categories: 1) statistical methods; 2) data mining. The statistical methods contain many techniques, for example, the autoregressive integrated moving average (ARIMA) which needs the historical information of the target variable to forecast it. In addition, the regression analysis [5], and Markov [6] belong to the statistical methods. On the contrary, the data mining techniques, which include a support vector regression [7], artificial neural networks [8], and ANFIS are widely forecasting methods, and they provide a good performance. However, the ANFIS model has several advantages over all other methods since it can reduce the time of training, and it can benefit from the problem domain to initialize its parameters [5], [9], [10].

In the recent years, ANFIS has attracted much attention because it can be used in several applications such as Choi *et al.* [11] used the ANFIS to improve the energy management system (EMS) technology through saving the electric power consumption at home. Zhang and Mao [12] proposed a method based on the ANFIS model to find the relation between energy consumption and the growth of the economy. As for forecasting the load of electricity, Cheng and Wei [13] compared the ANFIS with ANN model, and the results illustrated that the ANFIS is better than ANN. Due to the ANFIS is a combination of a fuzzy inference system (FIS) and ANN; as well as, the FIS has a high ability to deal with reasoning which is approximate, unlike the ANN that only give a crisp logic. All of these properties of the ANFIS leads to improve the fault tolerance (see [14], for more details about using ANFIS in renewable energy). Jiang *et al.* [15] used the ANFIS to find the relation between design attributes of mobile phones and customer satisfaction. Moreover, the ANFIS is used in several kinds of literature as a prediction model of wastewater treatment such as in [16], the authors have predicted the effluent quality of paper mill to remove the chromium and arsenic from water [17]. The ANFIS is also used to predict the effluent from industrial [18], and hospital [19], wastewater treatment plant. In addition, the ANFIS can be used to determine the non-linear relationships between the input and the output in machining processes [20], [21].

However, ANFIS has some limitations because it is influenced by the approach used to learn its parameters. There are two sets of adjustable parameters in ANFIS, the consequent and the premise parameters. These parameters are determined by using several methods, for example, the least square method (LSM), however, is not accurate and can get stuck at the local optimal point. Therefore, the hybrid between the back-propagation (BP) algorithm and the LSM is used to overcome these drawbacks, and it consists of two phases. In the first phase, if the premise parameters are steady, the functional signals will propagate to layer four, where the LSM specifies the consequent parameters. In the second phase, the consequent parameters will be kept fixed and the premise parameters are determined.

The adaptation methods of the fuzziest inference systems rely on the back-propagation algorithm that is applied to deal with parameter optimization in general. This traditional optimization techniques such as gradient descent approaches are popular algorithms that are used to learn the parameters of ANFIS. However, the gradient is computed at each iteration and it can get stuck at a local point and therefore no global solution can be determined [22]. To solve these drawbacks, the meta-heuristics like genetic algorithms (GAs) [20], particle swarm optimization (PSO) [22], [23] and Krill-herd optimization [24] are used. However, GAs are slow convergence speed, whereas PSO is sensitive to neighborhood topology. So, the Sine-Cosine algorithm (SCA) is used to solve this problem. SCA is a new metaheuristic algorithm that uses the two mathematics functions called sine and cosine to find the solution of the given problems [25].

The SCA has been applied to different applications, and its performance is established providing good results in comparison with other metaheuristic algorithms. It also has fewer operators and fewer parameters to adjust, and it is easy to implement [25]–[27]. For example, in [25], the SCA is used to solve a set of global optimization problems and another real application that is called the design of airfoil. Also, it is used in image processing applications such as in [28] as a threshold method and apply it to a handwritten Arabic text to enhance the historical Arabic documents. Moreover, Aziz *et al.* [29] apply the binary version of SCA as a feature method to detect the type of galaxy image. In addition, the SCA is applied to energy field as in [30], which is used to solve the unit commitment problem in energy production.

This paper aims to propose an alternative oil consumption forecasting method by enhancing the performance of the ANFIS model using SCA. The use of SCA is to determine the optimal parameters of the ANFIS model, where two types of parameters exist: consequent and premise. This combination improves the ANFIS performance in preserving the good regression ability of the ANFIS model. The proposed SCA-ANFIS model has been experimentally tested over an extensive set of real oil consumption dataset. Moreover, the proposed method is compared with other similar ANFIS methods, and the comparison results illustrate that the SCA-ANFIS can provide better results in term of performance measures than other algorithms such as traditional ANFIS, modified versions of ANFIS using Particle swarm optimization (PSO-ANFIS), Genetic algorithm (GA-ANFIS), grey wolf optimization (GWO-ANFIS), and whale optimization algorithm (WOA-ANFIS).

The rest of the paper is organized as follows: Section II introduces Preliminaries over, the traditional ANFIS model and the SCA. The proposed SCA-ANFIS method is presented in Section III. Meanwhile, Section IV presents

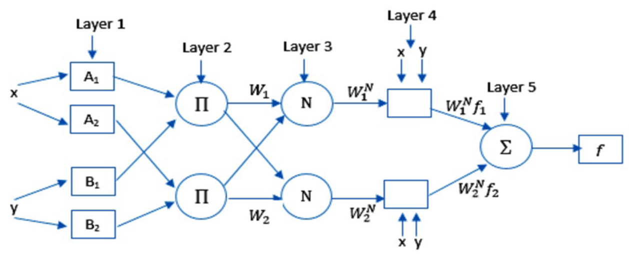

FIGURE 1. The structure of the ANFIS model [22].

experiments and comparisons. Finally Section V presents the conclusions.

II. PRELIMINARIES

A. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

In this section, the basic concepts of the Adaptive Neuro-Fuzzy Inference System (ANFIS) are presented [22]. The ANFIS is the model that combines the neural networks (NN) and the fuzzy logic. Also, it uses the fuzzy IF-THEN rules to generate a nonlinear mapping between the input and the output. This is also known as the Takagi–Sugeno inference model (see Figure 1). In this figure, x and y are the crisp inputs to the first layer's node and O_{1i} is the output of this node computed as:

$$O_{1i} = \mu_{A_i}(x), \quad i = 1, 2, \; O_{1i} = \mu_{B_{i-2}}(y), \; i = 3, 4 \tag{1}$$

where μ represents the generalized Gaussian membership functions, and it is computed as:

$$\mu(x) = e^{-(\frac{x-\rho_i}{\alpha_i})^2}, \tag{2}$$

where A_i, B_i (in Eq.(1)) represent the membership values of μ, also ρ_i and α_i are the premise parameters set. The output of the node in the second layer of ANFIS (which is called the firing strength of a rule) is computed as:

$$O_{2i} = \mu_{A_i}(x) \times \mu_{B_{i-2}}(y) \tag{3}$$

Meanwhile, the output of the node in the third layer (which is called the normalized firing strength) is computed as:

$$O_{3i} = \overline{w}_i = \frac{\omega_i}{\sum_{(i=1)}^{2} \omega_i}, \tag{4}$$

The node in the fourth layer (which is called an adaptive node) receives the output of the third layer O_{3i} and then computes the output as:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{5}$$

where p_i, q_i and r_i represent the consequent parameters of the node i. There exits only one node in the last layer of the ANFIS model, and the output of this node is computed as:

$$O_5 = \sum_i \overline{w}_i f_i \tag{6}$$

Algorithm 1 Sine Cosine Algorithm

Generate a random population X
repeat
  Compute the objective function for each solution.
  Find the the best solution ($Best$).
  Update r_1, r_2, r_3, and r_4.
  Update the solutions of X using Eq. (9).
until (Stop conditions met)
Return the P.

B. SINE COSINE ALGORITHM

Mirjalili [25] presents a new metaheuristic algorithm called sine cosine algorithm (SCA). This algorithm uses the sine and cosine functions to update the population as in the following two equations:

$$X_i = X_i + r_1 \times sin(r_2) \times |r_3 Best - X_i| \tag{7}$$

$$X_i = X_i + r_1 \times cos(r_2) \times |r_3 Best - X_i| \tag{8}$$

However, the above two equations are combined together as in the following equation [25]:

$$X_i = \begin{cases} X_i + r_1 \times sin(r_2) \times |r_3 Best - X_i| & if \; r_4 < 0.5 \\ X_i + r_1 \times cos(r_2) \times |r_3 Best - X_i| & if \; r_4 \geq 0.5 \end{cases} \tag{9}$$

where $Best$ and X_i represent the best solution and the current solution, respectively. Also, the $|.|$ represents the absolute value; and r_1 is a random variable that is responsible for specifying the search space of the next solution. This space may be either outside space between X_i and $Best$ or inside them. This parameter is updated using the following equation to make a balance between the exploration and exploitation.

$$r_1 = a - t\frac{a}{t_{max}} \tag{10}$$

where a, t and t_{max} represent a constant, the current iteration, and the maximum number of iterations, respectively.

The r_2 is a random variable that is used to determine the movement direction of the next solution (i.e., if it moves towards or outwards $Best$). Also, the r_3 represents a random variable that assigns a random weight for the best solution to stochastically emphasize ($r_3 > 1$) or deemphasize ($r_3 < 1$) the effect of desalination in defining the distance. The r_4 is used to determine if the current solution will be updated using the sine and cosine functions as in Eq. (9).

III. THE PROPOSED METHOD

The proposed algorithm that called SCA-ANFIS is explained in this section which is a time series process for forecasting oil consumption. The SCA-ANFIS hybrids between the SCA and ANFIS, which the parameters of the ANFIS are determined using the SCA algorithm.

The proposed method consists of five layers similar to the classic ANFIS model. The nodes at Layer 1 represent input variables (i.e., historical oil's consumption). Meanwhile, the nodes at Layer 2 are the membership functions of the input variables; whereas, Layer 3 represents the fuzzy logic rules. The nodes of Layer 4 apply the consequent part of the Takagi-Sugeno-Kang model. The output of layer 5 is the oil consumption. In the learning stage, the SCA is applied to determine the best values of the weights between Layer 4 and Layer 5.

The proposed algorithm begins by preparing the input variables (the historical time series of oil); it applies the auto-correlation function (ACF) to prepare these variables. After analyzing the results of ACF it is recommended that the variables greater than 0.2 are more suitable for forecasting, as shown in Figure 6. Thus, the variables with ACF greater than 0.2 are considered. Therefore, these variables have been reduced to 3-lags response and the delays are set to 3. Consequently, the dataset is divided into 75% training set and 25% test set. The fuzzy c-mean (FCM) is applied to define the number of clustering (the number of membership functions). The next step is constructing the ANFIS using FCM output. The ANFIS parameters are updated using the SCA algorithm, where the SCA explores different regions of the search space that has many local minima and then reduces the domain of search to the area containing the global solution. In the training phase, the error information between the actual output and the corresponding predict values is used to update the parameters (weights between Layer 4 and Layer 5 as well as the parameters of Gaussian membership function).

The error between the actual oil consumption (T) and the prediction value (P) is used as a fitness function, and it is defined as:

$$objective\ function = \| T - P \|_2^2 \tag{11}$$

where $||.||_2$ represents the l_2-norm, so this objective function is quadratic loss function and it is more suitable during the training stage. Due to the gradient of it is high for larger error values, also, its value is decreased with decreasing the error value.

The SCA starts by building the population of the solutions (X), then the fitness function of each solution is computed. The best solution is determined and used to update the other solutions using Equation (9). The updated process is performed until stop conditions are met, and the best solution is returned. The ANFIS puts the values of the best solution to its parameters and computes the output.

In order to evaluate the output of the training stage, the testing set is used with the same values of the best solution (parameter values), and the output is computed. By comparing the output from the testing set with the actual value, we can assess the accuracy of the proposed SCA-ANFIS model.

The final stage of the proposed model is the forecasting process, in which the model predicts the value of the oil consumption in the next months. The stages of the proposed model are given in Figure 2.

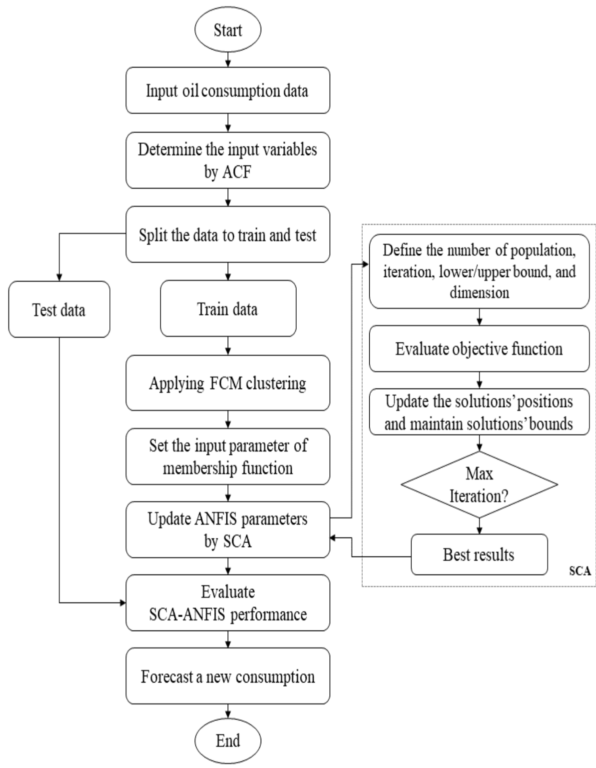

FIGURE 2. The proposed SCA-ANFIS method.

IV. EXPERIMENTS

In this section, the performance of the proposed SCA-ANFIS model is evaluated using a set of real oil consumption data for three countries. Also, the results of the proposed model are compared with variant versions of the ANFIS model. The outline of this section is given in section IV-A, the description of the dataset is given. The performance measures that are used to assess the quality of the results are illustrated in IV-B. Meanwhile, the parameters setting of each algorithm and the experimental environment are presented in IV-C. Also, the results and Discussion are given in IV-D.

A. DATASET DESCRIPTION

The experiment uses a real dataset of petroleum products' consumption of three countries namely Canada, Germany, and Japan. The data is collected from [31], it consists of 120 records/months (12 records per year) of the period between September 2007 and August 2017. Each record contains the consumption number of barrels per day (in thousands). The distribution of these data over the months are shown in Figures 3, 4, and 5. This consumption is varying from one country to another. In Canada, it varies between 2100 and 2600 thousand barrels per day, while in Germany it varies between 2100 and 2800, whereas in Japan, it varies between 3500 and 5700. The standard deviation of these countries are 93, 130, and 504 for Canada, Germany, and Japan, respectively.

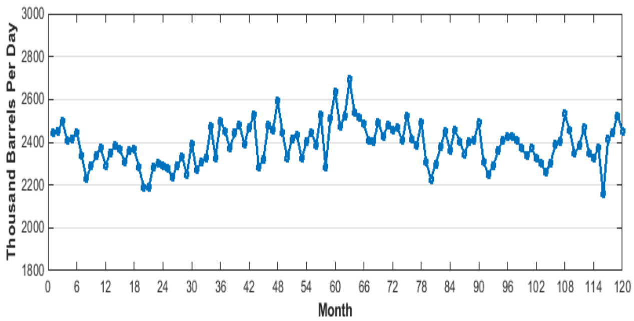

FIGURE 3. The consumption of Canada oil during Sep. 2007 to Aug. 2017.

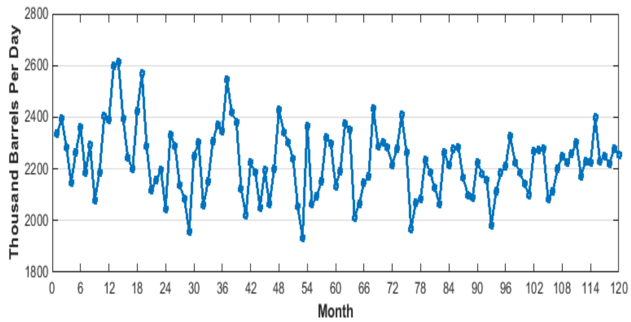

FIGURE 4. The consumption of Germany oil during Sep. 2007 to Aug. 2017.

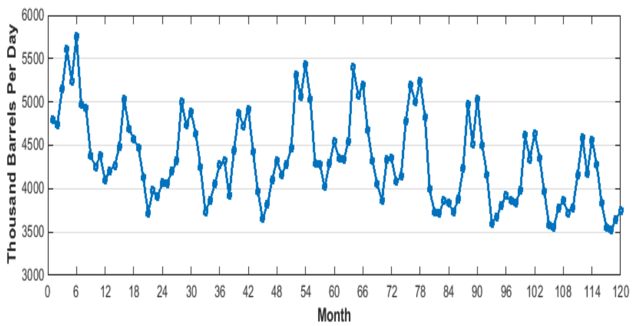

FIGURE 5. The consumption of Japan oil during Sep. 2007 to Aug. 2017.

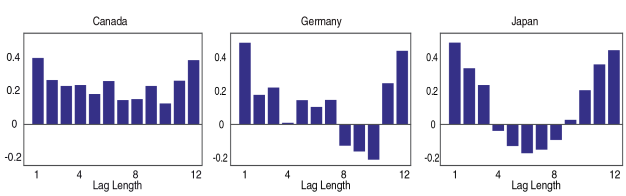

FIGURE 6. ACF analysis of the countries.

B. PERFORMANCE MEASURES

There is a set of performance measures used in this paper to test the performance of the proposed algorithm overall experiments. These are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Relative Error (RMSRE). The definitions of these measures are given in details as follows:

1) Root Mean Square Error (RMSE): It is the computed error between predicted and original values; the lowest RMSE value indicates the most accurate of the predictions. It is defined as follows:

$$RMSE = \sqrt{\frac{1}{N_s}\sum_{i=1}^{N_s}(P_i - T_i)^2} \tag{12}$$

2) Mean Absolute Error (MAE): It is compute the difference between the predict variable (P) and its target T. This measure is used since it is robust to outliers in the oil consumption and it is defined as:

$$MAE = \frac{1}{N_s}\sum_{i=1}^{N_s}|P_i - T_i| \tag{13}$$

3) Mean Absolute Percentage Error (MAPE): It is one of the most popular measures used to evaluate the accuracy of the forecasting model. The MAPE puts more weight on dates with higher oil consumptions and it can be defined as the following:

$$MAPE = \frac{1}{N_s}\sum_{i=1}^{N_s}|\frac{P_i - T_i}{P_i}| \tag{14}$$

4) Root Mean Squared Relative Error (RMSRE): It is one of the relative error measures that can be used when the

$$RMSRE = \sqrt{\frac{1}{N_s}\sum_{i=1}^{N_s}(\frac{P_i - T_i}{P_i})^2} \tag{15}$$

where P is the produced value (predicted) from an algorithm, T is the original (target) values, and N_s represents the sample size of the oil consumption.

C. PARAMETER SETTINGS

In this study, the performance of the proposed algorithm is compared with other five ANIFS models namely, ANFIS, PSO-ANFIS, GA-ANFIS, GWO-ANFIS, and WOA-ANFIS. Table 3 shows the parameters setting of all algorithms that are used in this paper. The value of the parameter a in SCA algorithm is selected based on a sensitivity analysis; the values 1, 2, 3, and 4 are evaluated over 10 independent runs and the best one is selected (i.e., 2) as shown in Table 2.

The environmental settings of the experiment are: the population size = 25, iterations number = 100, and the lower and upper bounds are set to 5 and −5, respectively. These parameters are selected because they showed good results in some previous studies performed by Ahmed *et al.* [24], Ewees *et al.* [32], and Aziz *et al.* [33]–[35].

D. RESULTS AND DISCUSSION

Table 3 shows the results of the performance measures of the test phase. From this table, we can conclude that the proposed algorithm (SCA-ANFIS) outperforms all other algorithms in

TABLE 1. The parameters setting of all algorithms.

Algorithm	Parameters setting
ANFIS	$Max.\ epochs = 100, Error\ goal = 0,$ $Initial\ step = 0.01, Decrease\ rate = 0.9,$ $Increase\ rate = 1.1$
PSO-ANFIS	$wMax = 0.9,\ wMin = 0.2,\ C1 = 2,\ C2 = 2$
GA-ANFIS	$Crossover\ type = 1,$ $crossover\ probability = 1,$ $mutation\ probability = 0.01$
GWO-ANFIS	$\alpha = [2, 0], r_1 = [0, 1], r_2 = [0, 1]$
WOA-ANFIS	$a = 2, l = 1$
SCA-ANFIS	$a = 2$
ARIMA	$Seasonality = 12,\ SMALags = 3,\ SARLags = 3,\ TolCon = 1e^{-9}$

TABLE 2. Sensitivity analysis to tune SCA parameter *a*.

Country	Measures	$a = 1$	$a = 2$	$a = 3$	$a = 4$
Canada	RMSE	79.85	**75.45**	85.49	78.42
	MAE	56.73	**54.06**	61.89	54.40
	MAPE	2.407	2.292	2.636	**2.291**
	RMSRE	0.034	**0.032**	0.037	0.033
Germany	RMSE	66.50	**64.35**	66.51	69.17
	MAE	49.43	**46.98**	47.98	47.84
	MAPE	2.045	**1.944**	1.993	1.997
	RMSRE	0.028	**0.027**	0.028	0.029
Japan	RMSE	274.4	**267.9**	289.5	287.1
	MAE	**214.6**	215.2	234.1	239.8
	MAPE	**5.265**	5.278	5.732	5.917
	RMSRE	0.068	**0.066**	0.071	0.071

TABLE 3. Results of SCA-ANFIS and other algorithms.

Country	Measures	ARIMA	ANFIS	PSO-ANFIS	GA-ANFIS	GWO-ANFIS	WOA-ANFIS	SCA-ANFIS
Canada	RMSE	133.0	143.32	81.39	75.08	81.05	82.56	**74.60**
	MAE	63.72	87.72	53.76	52.46	56.66	56.13	**51.82**
	MAPE	2.660	3.924	2.260	2.208	2.410	2.400	**2.187**
	RMSRE	0.044	0.069	0.034	0.032	0.035	0.036	**0.031**
Germany	RMSE	179.7	80.46	64.48	**63.16**	68.53	67.94	64.76
	MAE	104.1	58.93	46.56	43.51	49.51	45.01	**42.56**
	MAPE	4.260	2.409	1.917	1.790	2.057	1.878	**1.772**
	RMSRE	0.070	0.033	0.026	**0.026**	0.029	0.029	0.027
Japan	RMSE	480.1	562.4	307.5	270.1	286.2	470.5	**268.6**
	MAE	213.3	363.5	235.8	215.4	227.7	378.6	**212.7**
	MAPE	13.92	9.375	5.697	5.302	5.657	9.405	**5.185**
	RMSRE	0.890	0.163	0.073	0.067	0.072	0.118	**0.066**

* The boldface indicates the best value.

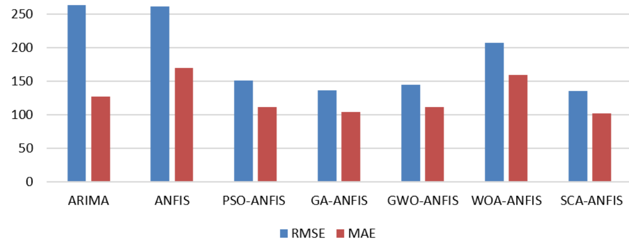

FIGURE 7. Results of RMSE and MAE for all algorithms overall experiments.

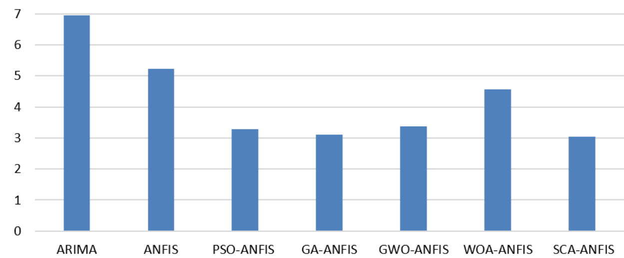

FIGURE 8. Results of MAPE for all algorithms overall experiments.

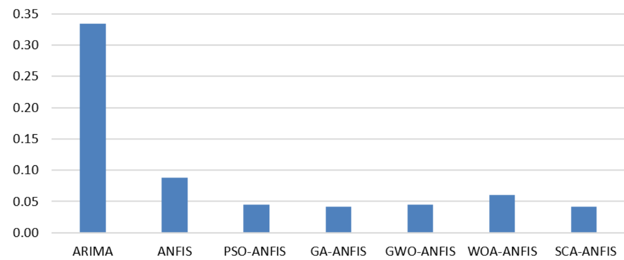

FIGURE 9. Results of RMSRE for all algorithms overall experiments.

TABLE 4. Differences between SCA-ANFIS and the other ANFIS's methods in term of AIC results.

Country	ANFIS	PSO-ANFIS	GA-ANFIS	GWO-ANFIS	WOA-ANFIS
Canada	0.0507	0.0417	0.0461	0.0190	0.0402
Germany	0.0567	0.0257	0.0282	0.0250	0.0060
Japan	0.0380	0.0092	0.0101	0.0254	0.0168

forecasting the oil consumption of Canada and Japan in terms of all performance measures. Whereas, in the oil consumption of Germany, SCA-ANFIS reaches the best values in MAE and MAPE, where GA-ANFIS achieves the best values in RMSE and RMSRE. In addition, SCA-ANFIS improves the performance of the classic ANFIS significantly, from Table 3 we can see the difference between the results of SCA-ANFIS and ANFIS (e.g., in Canada, the RMSE values of them are 82.56 and 143.32, respectively).

In general, as shown in Figures 7, 8, and 9, SCA-ANFIS outperforms all other algorithms in RMSE, MAE, MAPE, and RMSRE overall experiments. In details, in terms of RMSE and MAE, GA-ANFIS achieves the second rank whereas, GWO-ANFIS comes in the third rank followed by PSO-ANFIS, WOA-ANFIS, ARIMA, and ANFIS, respectively.

In terms of MAPE and RMSRE, GA-ANFIS also achieves the second rank while, PSO-ANFIS comes in the third rank followed by GWO-ANFIS, WOA-ANFIS, ANFIS, and ARIMA, respectively.

Moreover, for showing the performance of the proposed method against the other optimized-ANFIS methods, the Akaike's Information Criterion (AIC) is calculated and the differences between SCA-ANFIS's result and the other methods are presented in Table 4. From this table we can conclude that, the proposed method is better than the other methods whereas, it obtained the minimum value of AIC.

Whereas SCA-ANFIS has the best results overall experiments in forecasting the 12 months' oil consumption, Table 5 presents these results for Canada, Germany, and Japan. Moreover, Figures 10-12 show the curve of forecasted results along with the original oil consumption data for all countries and the

TABLE 5. Results of SCA-ANFIS of forecasting oil consumption in 12 months (thousand barrels per day).

Month/Year	Canada	Germany	Japan
September 2017	2439.57	2474.52	3894.74
October 2017	2483.95	2437.32	3948.55
November 2017	2439.57	2397.71	4200.14
December 2017	2440.14	2419.47	4199.76
January 2018	2439.57	2412.47	4082.23
February 2018	2420.93	2420.15	4296.68
March 2018	2417.25	2424.36	4296.01
April 2018	2439.57	2433.51	4456.03
May 2018	2406.87	2410.43	4559.80
June 2018	2384.98	2377.00	4534.93
July 2018	2439.57	2391.63	4534.22
August 2018	2400.13	2401.69	4463.94

green area in these figures contains only the forecasted data of 12 months.

E. STATISTICAL ANALYSIS

In this section, the Wilcoxon's non-parametric statistical test is used to check if there is a significant difference between the proposed model and other models. It is applied on RMSE and MAPE measures at a significant level equal to 0.05; if $p-value < 0.05$ that means the proposed method has a significant difference and the alternative hypothesis is accepted.

TABLE 6. Results of Wilcoxon's test between SCA-ANFIS and the other methods.

Country	Measures	ARIMA	ANFIS	PSO-ANFIS	GA-ANFIS	GWO-ANFIS	WOA-ANFIS
Canada	RMSE	0.000	0.000	0.000	0.361	0.023	0.648
	MAPE	0.000	0.000	0.000	0.038	0.431	0.590
Germany	RMSE	0.000	0.000	0.000	0.213	0.009	0.590
	MAPE	0.000	0.000	0.000	0.042	0.000	0.038
Japan	RMSE	0.000	0.000	0.000	0.031	0.384	0.000
	MAPE	0.000	0.000	0.000	0.245	0.263	0.000

As shown in Table 6 the results of the Wilcoxon's test denote that, in the results of Canada and Germany, in terms of RMSE, SCA-ANFIS outperforms ARIMA, ANFIS, PSO-ANFIS, and GWO-ANFIS; whereas, in terms of MAPE, SCA-ANFIS has significant differences from all algorithms in Canada except for GWO-ANFIS and WOA-ANFIS in Germany.

In the forecasted results of Japan, in terms of RMSE, SCA-ANFIS outperforms all algorithms except for GWO-ANFIS; whereas, in terms of MAPE, SCA-ANFIS has significant differences with ARIMA, ANFIS, PSO-ANFIS, and WOA-ANFIS.

In general, the optimized ANFIS is much better than the classic ANFIS in forecasting the oil consumption, due to the use of a metaheuristic algorithm called SCA to determine

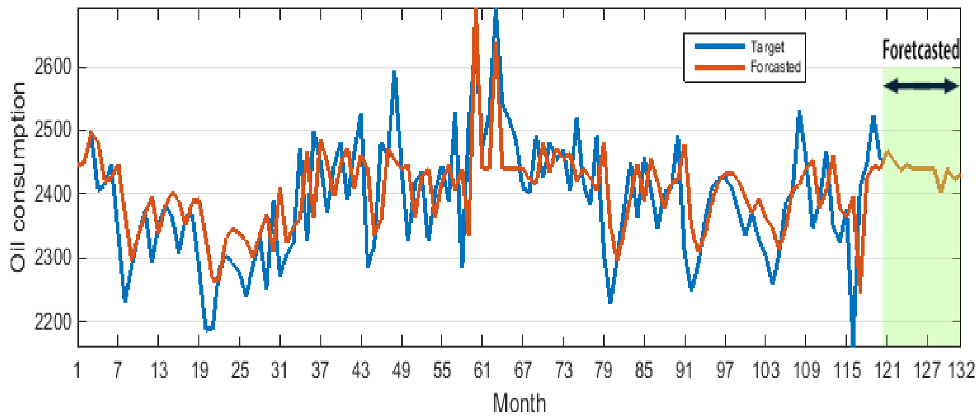

FIGURE 10. The real data against forecasted oil consumptions of Canada.

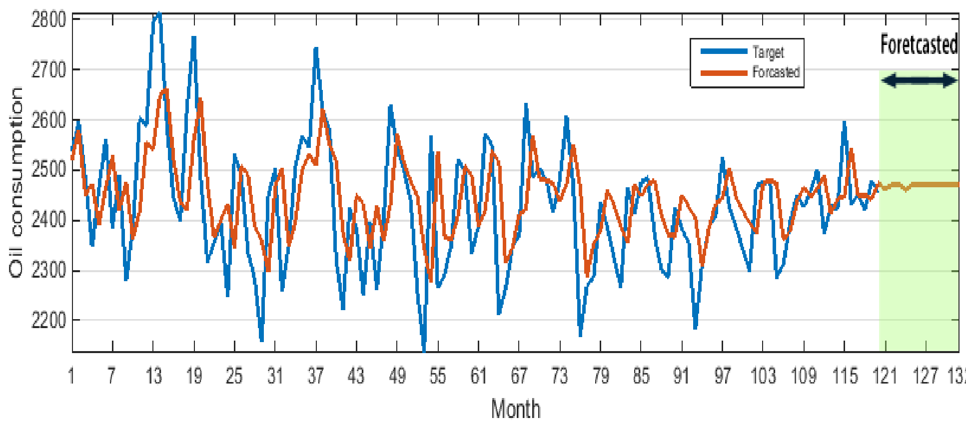

FIGURE 11. The real data against forecasted oil consumptions of Germany.

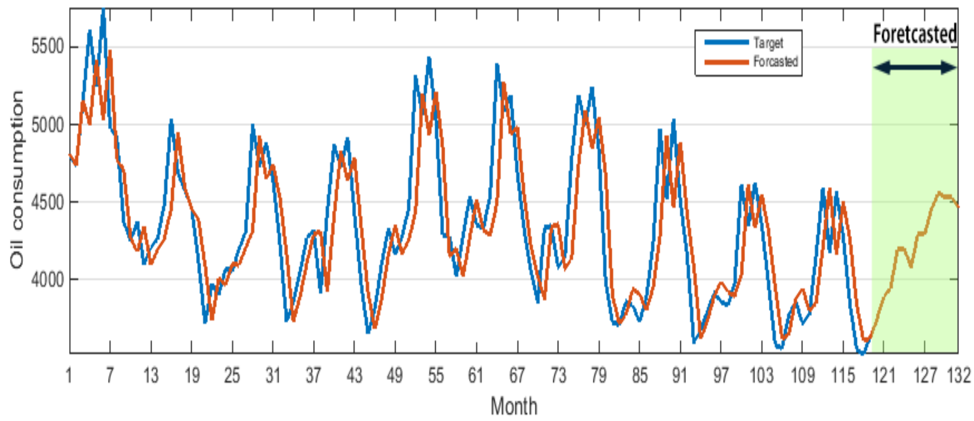

FIGURE 12. The real data against forecasted oil consumptions of Japan.

the optimal parameters of it. Also, the SCA has several advantages not found in metaheuristic algorithms such as it avoids the local point and leads to an improvement of the convergence curve, however, the GA and PSO suffer from slow convergence. Also, the SCA has a small number of parameters that need to be defined not as the GWO and the WOA which have a number of parameters greater than SCA. In addition, the SCA has good exploration, and exploitation abilities compared with the other metaheuristic algorithms. However, during the experiment, it is found that the exploration ability of SCA is better than its exploitation ability.

V. CONCLUSION AND FUTURE WORKS

Energy plays a significant role in managing and governing any country; meanwhile, oil consumption has more attention because oil is considered the main source of energy. Therefore, providing a more accurate method and avoiding the drawbacks of other existing methods for forecasting oil consumption are important trends. So, this paper concentrates on forecasting oil consumption in three countries (Canada, Germany, and Japan) based on improved adaptive neuro-fuzzy inference system (ANFIS) with the sine-cosine algorithm (SCA). For this purpose, the oil consumption in these countries is studied and analyzed to forecast oil consumption for 12 months. The experiment's dataset contains the oil consumption of 120 months from September 2007 to August 2017. The proposed method starts by determining the input variables using auto-correlation function (ACF) and the variables with ACF greater than 0.2 are considered. Improved ANFIS (SCA-ANFIS) is applied to forecast the future oil consumption. In this context, the classic ANFIS is improved by updating its parameters using SCA. The performance of SCA-ANFIS is evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Relative Error (RMSRE). Moreover, the efficiency of the proposed method is examined against the classic ANFIS and four versions of improved ANFIS. The results of all experiments prove that SCA-ANFIS is a competitive method while it outperforms all other methods in overall datasets and achieves the best values in most performance measures.

Based on the promising results of the proposed SCA-ANFIS model to predict oil consumption in the future, it can be applied to other kinds of applications such as Forecasting 1) the Electricity Consumption. 2) Agricultural output. 3) Wind speed. 4) Solar radiation. 5) Solar Activity.

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