Long-term prediction of the crude oil price using a new particle swarm optimization algorithm

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Oil is one of the most precious source of energy for the world and has an important role in the global economy. Therefore, the long-term prediction of the crude oil price is an important issue in economy and industry especially in recent years. The purpose of this paper is introducing a new Particle Swarm Optimization (PSO) algorithm to forecast the oil prices. Indeed, the PSO is a population-based optimization method inspired by the flocking behavior of birds. Its original version suffers from tripping in local minima. Here, the PSO is enhanced utilizing a convergence operator, an adaptive inertia weight and linear acceleration coefficients. The numerical results of mathematical test functions, obtained by the proposed algorithm and other variants of the PSO elucidate that this new approach operates competently in terms of the convergence speed, global optimality and solution accuracy. Furthermore, the effective variables on the long-term crude oil price are regarded and utilized as input data to the algorithm. The objective function of the optimization process considered in this research study is the summation of the square of the difference between the actual and the predicted oil prices. Finally, the long-term crude oil prices are accurately forecasted by the proposed strategy which proves its reliability and competence. © 2020 Journal of Energy Management and Technology

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1. INTRODUCTION

For many years, oil has been playing a crucial role in people's lives, and today, increasing and decreasing of its price has considerable effects on the economy of both developed and developing countries. Increasing the oil price is desirable for the economy of oil exporting countries and its decreasing will cause deficient budgetary problems for them [1]. Hence, the prediction of the oil price has been considered to be a popular topic in this century. Generally, the prediction is used as a guidance for public and private policies, because decision making is not possible without proper knowledge of future. Gathering some valuable data, which affect the oil price, and applying strong algorithms for the forecasting of the oil price would help the researchers to achieve the essential technical knowledge.

The PSO as is known as one of the most modern, strong and straightforward heuristic algorithms introduced by Kennedy and Eberhart [2]. It was developed through the simulation of simplified social systems and is a robust method for solving nonlinear optimization problems [3]. In this algorithm, each particle has a memory that saves the best individual location and updates its location using the best global location until it reaches an optimal solution [4–6].

Due to the profound intelligence, background and simple algorithm structure, the PSO has been broadly implemented in many scientific fields, especially in the forecasting and prediction topics. For instance, Junyou proposed a PSO based selective neural network ensemble algorithm analysis and prediction of the for Nasdaq Stock Market [7]. Abolhassani and Yaghobbi considered a machine learning system based on particle swarm optimization and support vector machines for stock market forecasting a variety of indicators and introduced as input features [8]. Furthermore, a PSO-based time series model for the gold price forecasting was proposed by Hadavandi et al. They also evaluated the capability of the proposed model by applying it on the daily observation of the gold price and compared the outcomes with previous methods using mean absolute error. y [9]. Assareh et al. employed the particle swarm optimization and genetic algorithm techniques to estimate oil demand in Iran, based on socio-economic indicators and using exponential and linear models [10]. Bi and Qiu utilized an exhaustive and extendable intelligent process to predict the crude price and employed a novel hybrid genetic algorithm-particle swarm optimization method to present a support vector machine model [11]. Han and Bian proposed a hybrid particle swarm optimization - support vector machine -based model to predict oil with regard to the permeability, well spacing density, ratio of oil and water wells, porosity, effective thickness and viscosity of crude oil [12]. A hybrid intelligent model based on the feasibility of support vector regression was developed to predict the maximum depth of pitting corrosion in oil and gas pipelines, whereas the performance of well-known meta-heuristic optimization techniques, such as genetic algorithm, particle swarm optimization and firefly algorithm, were considered to select optimal support vector regression hyper-parameters by Ben Seghier et al. [13]. Gong et al. proposed a virtual sample generation approach based on the Monte carlo and particle swarm optimization algorithms to improve the accuracy of the energy efficiency analysis on small data set problems [14]. A mathematical model based on adaptive neuro-fuzzy inference systems was designed and developed by Ejraei Bakyani et al. for accurate prediction of carbon dioxide diffusivity in oils at elevated temperature and pressures [15]. Akande et al. investigated the performance of the particle swarm optimization technique for optimal selection of support vector machine regression hyper-parameters in modelling and characterization of hydrocarbon reservoirs [16]. Zhou et al. predicted the favorable reservoirs in Niuzhuang area of Dongying, assisted geological exploration personnel quickly delineate favorable areas and avoided waste of resources caused by empty wells [17]. An approach based on the wavelet technique and the least square support vector machine was suggested by Zhang et al. for forecasting dissolved gases in oil-immersed transformers [18]. However, the most of these researchers have not paid any attention to use these techniques for the long-term prediction, and in fact, they predicted the daily or monthly oil price. The long-term prediction of crude oil price is a big risk for researchers because it encounters unreliable periods.

On the other hand, the artificial intelligent algorithms suffer from being trapped in local minima. Therefore, in this paper, a novel PSO algorithm is proposed to augment the accuracy and speed in order to escape from the local minima. The performance of this algorithm is compared with that of four well known algorithms, namely, Fully Informed Particle Swarm (FIPS) [19], Dynamic Multi-Swarm Particle Swarm Optimizer (DMS-PSO) [20], Comprehensive Learning Particle Swarm Optimizer (CLPSO) [21] and Adaptive Particle Swarm Optimization (APSO) [22], on four benchmark functions. It is illustrated that the proposed version of the PSO has the best accuracy and speed among other famous algorithms. Besides, this approach is employed to predict the long-term crude oil price, and the numerical results are displayed to prove its effectiveness and ability to solve this real world problem.

This paper is organized as follows. Details of the particle swarm optimization, proposed algorithm and comparisons with other notable methods are described in Section 2. In Section 3, how this algorithm is used to predict the oil price and the numerical results are expressed. Finally, Section 4 presents the conclusions of the paper.

2. PARTICLE SWARM OPTIMIZATION

The particle swarm optimization as a smart metaheuristic optimization algorithm is simulated based on the social behavior of birds within a flock and fish in schools. In this algorithm, each candidate solution is represented as a particle having a velocity to search the feasible domain of the optimization problem. The experiences of each particle and its neighbors are utilized to adjust the position of the particle. In fact, if an enhanced solution is obtained by a particle, all other particles try to close that superior solution. The summation of particle's position $\vec{x}_i(t)$ and its velocity $\vec{v}_i(t)$ gives its new position according to the following equations.

$$\vec{v}_i(t+1) = w\vec{v}_i(t) + C_1 r_1(\vec{x}_{pbest_i} - \vec{x}_i(t)) + C_2 r_2(\vec{x}_{gbest} - \vec{x}_i(t)) \tag{1}$$

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{v}_i(t+1) \tag{2}$$

where, r_1 and $r_2 \in [0,1]$ represent two random numbers. The cognitive learning coefficient is shown by C_1, which is the attraction of a particle toward its best-quality location. The social learning coefficient is denoted by C_2, that is the attraction of a particle toward the whole swarm's best-quality location. The influence of the preceding velocities on the present one for a given particle is regulated by the inertia weight w. Further, $\vec{x}_{pbest_i}$ represents the best location of particle i, and $\vec{x}_{gbest}$ shows the best location amongst the particles of the whole swarm. In fact, the attractiveness of a particle toward the own best location and the best location of the neighbors is regulated via the learning coefficients. Based upon experiments reported in Reference [23], when C_1 is linearly descending and C_2 is linearly augmenting over the iteration according to the Eqs. (3) and (4), the better solutions would be achieved.

$$C_1 = C_{1i} - (C_{1i} - C_{1f})(\frac{t}{\max t}) \tag{3}$$

$$C_2 = C_{2i} - (C_{2i} - C_{2f})(\frac{t}{\max t}) \tag{4}$$

In which, the initial values of C_1 and C_2 are presented as $C_1 i$ and $C_2 i$, correspondingly. Further, the final values of C_1 and C_2 are shown by $C_1 f$ and $C_2 f$, respectively. The symbol of the present iteration is regarded as t. Moreover, the maximum value of the permissible iterations is illustrated by $\max t$. The adaptive inertia weight, which was introduced in [22], is utilized in this study and calculated as follows.

$$W(f) = \frac{1}{1 + 1.5e^{-2.6f}} \in [0.4, 0.9] \tag{5}$$

In which, the first and final values of the inertia weight are regarded as 0.4 and 0.9, correspondingly. Equations (6) and (7) provide the related relations to compute evolutionary coefficient f.

$$f = \frac{d_g - d_{\min}}{d_{\max} - d_{\min}} \in [0, 1] \tag{6}$$

$$d_i = \frac{1}{N-1} \sum_{j=1, j\neq i}^{N} \sqrt{\sum_{k=1}^{D} (x_i^k - x_j^k)^2} \tag{7}$$

In which, the mean distance between particle i and the other particles is illustrated by d_i, which is calculated employing the Euclidian metric. Furthermore, the number of the dimensions is shown by D, and the size of the population is illustrated by N. The mean distance related to the best global particle is presented as d_g. Moreover, via contrasting all the values of d_i, the

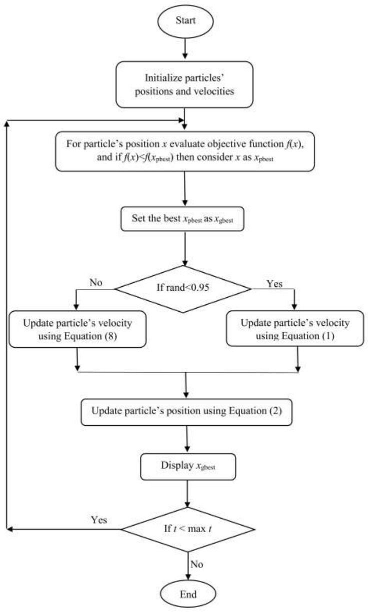

Fig. 1. Flowchart of the proposed PSO algorithm.

highest (d_{max}) and lowest (d_{min}) distances would be ascertained. Furthermore, the following novel velocity operator benefiting from the multi-crossover genetic method is proposed to augment the convergence speed and evade the local minima [24].

$$\vec{v}_i(t+1) = r(C_1\vec{x}_{gbest} - \vec{x}_{pbest_i}(t) - \vec{x}_i(t)) \tag{8}$$

In which, learning coefficient C_1 is linearly increased from 0.25 to 1.25 over iterations. Further, $r \in [0,1]$ represents a real random number.

Fig. 1 presents the flowchart of the optimization algorithm introduced in this study. The probabilities of %95 and %5 respectively are regarded for the implementation of the PSO and the new operator. Four prominent versions of the PSO algorithm, FIPS [19], DMS-PSO [20], CLPSO [21], and APSO [22], are utilized in order to assess the preciseness of the proposed approach. For all the tests, the following values are utilized for the learning coefficients: C_1i=2.5, C_1f=0.5, C_2i=0.5 and C_2f=2.5. Moreover, the population size, maximum iteration and dimension are regarded as 20, 10000 and 30, correspondingly.

Table 1 illustrates the summary of the mean and standard deviation fitness of the best particle found in thirty runs. According to the results provided in this table, the proposed approach illustrates a superior performance compared to the other mentioned algorithms. Further, Table 2 provides unbiased comparison of the convergence speed of the algorithms. Thirty runs are regarded for the assessment and execution of the algorithms. In this table, the comparison of the mean number of the function evaluations to achieve the threshold of 0.01 is provided. In fact, when the algorithm achieves the fixed threshold, the running of the algorithm is stopped and the preciseness of the algorithm is recorded. It is clear based upon the comparison results in Table 2, that the proposed PSO algorithm provides the quickest convergence speed compared to DMS-PSO, CLPSO, FIPS and APSO approaches. It is noticeable that the comparison results reported in Tables 1 and 2 have been taken from Reference [22].

3. LONG-TERM PREDICTION OF THE OIL PRICE

Various parameters such as the dollar price and inflation in America have always effects on the oil price. In this paper, the most effective parameters are selected from [25, 26] and used as input data to the algorithm for forecasting the long-term oil price. These quantities are also normalized by Eq. (9) formulated as follows.

$$\varsigma_n = \frac{\varsigma_R - \varsigma_{\min}}{\varsigma_{\max} - \varsigma_{\min}} \tag{9}$$

where, ς_n is the normalized form of considered parameter ς_R. Moreover, ς_{max} and ς_{min} respectively denote the maximum and minimum values of this parameters.

The objective function of the optimization process considered in this research study is the summation of the square of the difference between the actual oil prices and its predicted.

$$E(\varsigma) = \sum_{i=1}^{n} (P_i^{actual} - P_i^{predicted})^2 \tag{10}$$

where, P_i^{actual} represents ith actual value of the oil price, $P_i^{predicted}$ denotes ith predicted oil price, and n is the number of data. Moreover, two main evaluation criteria, root mean square error (RMSE) and mean absolute percentage error (MAPE), are applied.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (P_i^{actual} - P_i^{predicted})^2} \tag{11}$$

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{P_i^{actual} - P_i^{predicted}}{P_i^{actual}} \right|}{n} \tag{12}$$

Besides, in order to determine the most effective factors on the oil price forecasting, the following procedure is considered. At first, 24 effective parameters (z_i, $i = 1, 2, ...24$) for the prediction of the oil price are regarded which are shown in Table 3. A linear model (LM) according to Eq. (13) is used to predict the oil prices reported in Table 4 by the original PSO with population 50 and maximum number of iterations 500. It is remarkable that the data of Table 4 have been collected from U.S. energy information administration [25] and historical consumer price index data [26]. The obtained coefficients are substituted in the considered model as displayed in Eq. (14). As it could be seen from this equation, the most effective variables are recognized as the oil price in the last year, the economic growth of Australia, the economic growth of New Zealand and the world production of the crude oil, NGPL and other liquids, which are symbolized as x_1, x_2, x_3, and x_4 respectively. For the training phase, the data from the period of 1981 to 2004 are used, and for the prediction purpose, the data 2005 and 2006 are utilized as inputs (Table 4). Finally, a nonlinear model (NM) introduced in Eq. (15) is proposed to predict the long-term crude oil price.

$$\begin{aligned} LM = {} & w_1 + w_2z_1 + w_3z_2 + w_4z_3 + w_5z_4 + w_6z_5 + w_7z_6 + w_8z_7 + \\ & w_9z_8 + w_{10}z_9 + w_{11}z_{10} + w_{12}z_{11} + w_{13}z_{12} + w_{14}z_{13} + w_{15}z_{14} + \\ & w_{16}z_{15} + w_{17}z_{16} + w_{18}z_{17} + w_{19}z_{18} + w_{20}z_{19} + w_{21}z_{20} + w_{22}z_{21} + \\ & w_{23}z_{22} + w_{24}z_{23} + w_{25}z_{24} \end{aligned} \tag{13}$$

Table 1. Comparison of the accuracy of the five optimization algorithms on the benchmark functions

Function	Fitness	FIPS [19]	DMS-PSO [20]	CLPSO [21]	APSO [22]	Proposed algorithm
Sphere	Mean	$3.21 * 10^{-30}$	$3.85 * 10^{-54}$	$1.89 * 10^{-19}$	$1.45 * 10^{-150}$	0
	standard deviation	$3.60 * 10^{-30}$	$1.75 * 10^{-53}$	$1.49 * 10^{-19}$	$5.73 * 10^{-150}$	0
Schwefel	Mean	$1.32 * 10^{-17}$	$2.61 * 10^{-29}$	$1.01 * 10^{-13}$	$5.15 * 10^{-84}$	$1.04 * 10^{-162}$
	standard deviation	$7.86 * 10^{-18}$	$6.6 * 10^{-29}$	$6.51 * 10^{-14}$	$1.44 * 10^{-83}$	0
Ackley	Mean	$7.68 * 10^{-15}$	$8.52 * 10^{-15}$	$2.01 * 10^{-12}$	$1.11 * 10^{-14}$	$1.01 * 10^{-15}$
	standard deviation	$9.33 * 10^{-16}$	$1.79 * 10^{-15}$	$9.22 * 10^{-13}$	$3.55 * 10^{-15}$	$6.49 * 10^{-16}$
Griewank	Mean	$9.04 * 10^{-4}$	$1.31 * 10^{-2}$	$6.45 * 10^{-13}$	$1.67 * 10^{-2}$	0
	standard deviation	$2.78 * 10^{-3}$	$1.73 * 10^{-2}$	$2.07 * 10^{-12}$	$2.41 * 10^{-2}$	0

Table 2. Comparison of the convergence speed of the five algorithms on the benchmark functions

Function	Function evaluation	DMS-PSO [20]	FIPS [19]	CLPSO [21]	APSO [22]	Proposed algorithm
Sphere	Mean	91496	32561	72081	7074	800
	Ratio%	100	100	100	100	100
Schwefel	Mean	91354	36322	66525	66525	938
	Ratio%	100	100	100	100	100
Ackley	Mean	100000	38356	76646	40736	714
	Ratio%	100	100	100	100	100
Griewank	Mean	97213	42604	81422	7568	854
	Ratio%	56.7	100	100	66.7	100

$$LM = 0.11 + 0.14z_1 - 0.10z_2 - 0.03z_3 + 0.26z_4 + 0.04z_5 - 0.13z_6 - 0.09z_7 + 0.06z_8 + 0.24z_9 - 0.008z_{10} - 0.36z_{11} + 0.06z_{12} - 0.19z_{13} + 0.21z_{14} - 0.11z_{15} - 0.21z_{16} - 0.11z_{17} + 0.05z_{18} + 0.07z_{19} + 0.04z_{20} + 0.04z_{21} + 0.03z_{22} + 0.15z_{23} + 0.57z_{24} \tag{14}$$

$$NM = w_1 + w_2x_1 + w_3x_2 + w_4x_3 + w_5x_4 + w_6x_1^{w_7}x_3 + w_8x_1x_4 + w_9x_3x_4 + w_{10}x_1x_3x_4 + w_{11}x_1^{w_{12}}x_3^{w_{13}}x_4^{w_{14}} \tag{15}$$

In the following, three optimization algorithms, involving the original PSO, PSO with linear and adaptive coefficients and proposed algorithm having the features depicted in Table 5 are employed to find the optimum values of the coefficients applied in Eq. (15). As it is evident, in this table, less number of particles and iterations are considered for the proposed algorithm to create more challenging conditions on it. Furthermore, the obtained coefficients (design variables) are illustrated in Eqs. (16) through (18), and the predicted values of the oil prices are compared in Table 6. The experimental results shown in this table indicate that the proposed optimization algorithm can yearly predict the oil price with the best RMSE and MAPE. Finally, for verification and validation, the results of this modeling are compared with the results of pervious published works in Table 7.

$$\text{NM by the Original PSO} = -0.074 + 0.619x_1 + 0.045x_2 - 0.011x_3 + 0.047x_4 + 0.0148x_1^{0.0371}x_3 + 0.279x_1x_4 + 0.036x_3x_4 + 0.063x_1x_3x_4 + 0.207x_1^{0.123}x_3^{0.358}x_4^{0.311} \tag{16}$$

$$\text{NM by the PSO with Linear and adaptive coefficients} = 0.009 + 0.75x_1 + 0.02x_2 + 0.02x_3 + 0.05x_4 + 0.02x_1^{0.008}x_3 + 0.08x_1x_4 + 0.05x_3x_4 + 0.006x_1x_3x_4 - 0.02x_1^{0.004}x_3^{0.007}x_4^{0.004} \tag{17}$$

$$\text{NM by the proposed algorithm} = -0.009 + 0.67x_1 + 0.008x_2 + 0.004x_3 + 0.084x_4 - 0.003x_1^{0.011}x_3 + 0.069x_1x_4 + 8.727x_3x_4 + 0.853x_1x_3x_4 - 0.024x_1^{0.0167}x_3^{0.0314}x_4^{0.205} \tag{18}$$

Table 5. Adjustment parameters of the original PSO, PSO with linear and adaptive coefficients and proposed algorithm

Method	Particle	Maximum iteration	C_1 and C_2	W
Original PSO	60	90	2	0.8
PSO with linear and adaptive coefficients	60	250	Linear	Adaptive
Proposed algorithm	55	80	Linear	Adaptive

Table 6. Comparison of results of three optimization algorithms for the long-term prediction of the crude oil price

Date	Actual oil price	Proposed algorithm	Original PSO	PSO with linear and adaptive coefficients
2006	66.45	66.28	62.53	56.96
2007	71.03	71.54	69.09	62.69
MAPE (%)		0.01	0.07	0.18
RMSE (%)		0.38	3.09	8.93

It can be deduced from Table 7 that the model introduced in this study significantly outperforms the other models in forecasting the oil price trend according to their MAPE values.

Table 3. Candidate features for the prediction of the crude oil price (superior features are bolded)

World Consumption Oil	World Production Gas	World Population	World Production of Crude Oil, NGPL and other liquids
GDP for Developing Countries	Economic Growth of Australia	Economic Growth of Belgium	Economic Growth of Canada
Economic Growth of Denmark	Economic Growth of France	Economic Growth of Germany	Economic Growth of Greece
Economic Growth of Italy	Economic Growth of Japan	Economic Growth of Netherland	Economic Growth of New Zealand
Economic Growth of Norway	Economic Growth of Portugal	Economic Growth of Spain	Economic Growth of Switzerland
Economic Growth of United Arab	Economic Growth of United State	America Dollar Compared to the Canadian Dollar	Crude oil price in the previous year

Table 4. Data used for training and testing phases related to the optimization process

	Input					Output	
	Year	Crude Oil Price ($ barrel)	Economic Growth of Australia	Economic Growth of New Zealand	World Production of Crude Oil, NGPL and other liquids (1000*barrels day)	Year	Crude Oil Price ($ barrel)
Train	1981	90.49	3.4	3.3	59,785.98	1982	75.86
	1982	75.86	3.2	4.3	57,242.68	1983	67.12
	1983	67.12	-2.3	2.7	57,130.58	1984	63.62
	1984	63.62	4.6	4.9	58,619.41	1985	57.51
	1985	57.51	5.2	0.8	58,203.23	1986	30.26
	1986	30.26	4.8	2.1	60,642.58	1987	35.9
	1987	35.9	2.1	1.6	61,245.32	1988	28.94
	1988	28.94	5.4	-0.2	63,484.08	1989	33.97
	1989	33.97	4.5	0.5	64,624.49	1990	40.67
	1990	40.67	2.9	0	65,473.06	1991	34.09
	1991	34.09	-0.3	-1.3	65,376.32	1992	31.53
	1992	31.53	0.6	1.1	65,420.11	1993	26.66
	1993	26.66	4	6.4	65,854.39	1994	24.27
	1994	24.27	3.8	5.3	67,283.30	1995	25.26
	1995	25.26	4.1	4.2	68,849.17	1996	29.96
	1996	29.96	2.2	6.3	70,375.58	1997	26.69
	1997	26.69	2.1	4	72,583.02	1998	16.8
	1998	16.8	3.6	3.7	73,993.42	1999	22.79
	1999	22.79	3.3	7	73,120.77	2000	36.54
	2000	36.54	3.7	4.1	75,918.18	2001	29.86
	2001	29.86	2	3.5	75,845.51	2002	29.12
	2002	29.12	3.8	4.9	75,079.79	2003	34.6
	2003	34.6	3.2	3.9	77,614.99	2004	45.78
	2004	45.78	4.1	3.6	80,965.92	2005	58.83
Test	2005	58.83	2.8	3.2	82,477.89	2006	66.45
	2006	66.45	3.1	2.2	82,433.02	2007	71.03

Table 7. Comparison of results of different methods for the prediction of the crude oil price

Method	MAPE (%)
Fuzzy linear regression [27, 28]	0.46
Multi-objective fuzzy regression [29]	0.45
Flexible neural network-fuzzy [30]	0.19
This research	0.01

4. CONCLUSION

Since the oil market is the most important global energy market plays a major role in the world's economy, the prediction of the oil price has been regarded as a notable research topic by many researchers. In this paper, the long-term oil price forecasting has been represented by a new version of the PSO algorithm that utilizes a novel convergence operator. The effective parameters of the oil price have been identified and employed as the inputs of the optimization algorithms. The performance of the proposed algorithm has been challenged and compared with other prominent optimization algorithms for solving the mathematical test functions as well as the long-term prediction of the oil price.

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