A Novel Chicken Swarm Neural Network Model for Crude Oil Price Prediction

Abdullah Khan, Rahmat Shah, Junaid Bukhari, Nasreen Akhter, Attaullah, Muhammad Idrees and Hilal Ahmad

Abstract For optimization applications, an innovative bio inspired algorithm of Chicken Swarm Optimization (CSO) is suggested, the CSO represents hierarchy of chicken swarm. Chicken Swarm Optimization extracts the chickens swarm intelligence that can be used efficiently to optimize problems. This research investigates performance of proposed model Chicken-Swarm Optimization in hybrid with neural network (Chicken S-NN) to find the local minima and slow convergence. Performance of the Chicken S-NN model is compared with ABCNN (Artificial Bee Colony Neural Network) and ABCBP (Artificial Bee Colony Back-Propagation). From the results of training and tested data, this is evident that the proposed (Chicken S-NN) algorithm performs better than the other models with respect to accuracy and Mean Square Error (MSE).

A. Khan (✉) · J. Bukhari · Attaullah · H. Ahmad
Institute of Business and Management Science, Agricultural University, Peshawar, Pakistan
e-mail: Abdullahdirvi@gmail.com

J. Bukhari
e-mail: baba.khan993@gmail.com

Attaullah
e-mail: Atta12319@yahoo.com

H. Ahmad
e-mail: hilal_a24@yahoo.com

R. Shah
Department of Computer Science, CECOS University of IT & Emerging Sciences, Peshawar, Pakistan
e-mail: rahmat@cecos.edu.pk

M. Idrees
Department of Agriculture Extension Education and Communication, Agricultural University, Peshawar, Pakistan
e-mail: dridreesext@yahoo.com

N. Akhter
Department of Computer Science, FAST National University, PFD Campus, Islamabad, Pakistan
e-mail: nasreen.akhtar@nu.edu.pk

1 Introduction

Forecasting the consumptions of crude oil prices has become one of the hot questions
in the area of research due to its wide usage and importance in the world economic
arrangements. Crude Oil price has been a part of the process of decision-making for
the growth in industries and the government planning in the short-term and long-term,
export strategy and for national reserves [1].

Generally, crude Oil prices forecast shows the future possibility in development
of relevant marketplace. Crude oil is crucial to the world economy. Similarly from
industrial point of view, it is vigorous production inputs while the prices are controlled
by supply and demand. Changes in crude Oil prices are driven at various levels with
collective or precautionary demands that are linked to the market concerns about the
availability of oil supplies in the future [2].

Unpredictability of the crude Oil prices has been debated and gagged in numerous
researches. The determination of this unpredictability in the prices of crude Oil gets
more importance for the periods during which crude Oil prices show fast and sudden
variations. Secondly, to predict the prices of crude Oil gets more significance in the
future, especially in periods of high volatility. There is considerable works aimed
in improving the abilities of econometric models to model the price of crude Oil
[3]. Many articles have already been successfully submitted ANN applications for
modeling and predicting a series of crude oil prices likewise for predicting time series
of the real world [4–10].

ANN offers other approaches to solve complex problems. In many different ANN
models, the most famous ANN is Multi layer Feed Neural Network (MLFF) and
Recurrent Neural Network (RNN). Feed forward neural network sends unidirectional
signals, from the level of input, hidden layers to output layer. While Recurrent Neural
Network hold a short term memory for activation feedback [11]. The network has
local feedback loops allowing storing previous state of hidden unit. This opportunity
makes it progressive as compared to a feed forward network, because the network
outputs are calculated from current inputs and hidden states, so it has at least one
feedback link [12].

The results of experiments prove that ANN performance is much higher in numer-
ous conventional models used for statistical purposes. Ability of ANN is to learn com-
plex as well as nonlinear time-series that are hard to using the traditional models.
ANN also has some disadvantages such as the performance of ANN is inconsistent
in some explicit situation. ANN can do accurate prediction [13]. While RNN can
perform particular nonlinear and dynamic behaviour. Which is applicable in differ-
ent area such are classification models of space and time, electrical power demand,
financial data forecasting [14], associative memories, forecasting, management opti-
mization and simplify sequences of patterns [12].

The complex application such as time-series prediction and nonlinear modeling makes RNN topologically more powerful and compact than FFNN. For complex problem fully recurrent networks are still complex, so using the partially recurrent networks, where the connections have particularly feedback, but contain selected set of association's feedback. Without any complication such model allows the system to memorize past history. Elman neural network is an example of partial RNN [11].

Some features make RNN algorithms less efficient and often requires a huge amount of time to form a network of even for moderate size of problem. RNN has complex error surface which makes many other training algorithms more flat stuck in local minima [14]. An artificial neural network is famous algorithm because of its ability to simplify and solve problems in function approximation, pattern classification, pattern matching and associative memories as well as its flexibility and competence. The success of ANN depends largely on their design, learning algorithm, and the choice of structures used during training [15]. ANN has ability to solve complex problem by classification prediction and forecasting nonlinear system and huge datasets with high accuracy. Without having prior knowledge, the neuron store, recognized, estimates and adopt new patterns on training, which make it superior and attractive model.

To overcome the weakness ANN many evolutionary techniques and global search techniques such as genetic algorithm, Ant Bee Colony (ABC), Particle Swarm Optimization (PSO), Cuckoo Search and Bat algorithm were used that formulates a kind of neural network more superior than conventional neural network models. CS algorithm provides more optimal solution then an efficient particle swarm algorithm and genetic algorithm [15]. Different modification have been done by various researchers such as GANN [16], CSBP, [17], BAT-BP, [18], ACPSOBP [14].

But this research proposed a new technique Chicken Swarm optimization (CSO) algorithm probes to boost the performance of neural network (NN). CSO development was credited to Xianbing Mengin 2014. Through observations of an individual or whole flock of chicken, the researchers extracted the chicken that have of mature intellectual ability, communication-skills and ability to learn and they exists in a strict hierarchical order in the flock. The CSO has the characteristics of simplicity and scalability, is a natural multi-swarm adaptive algorithm. CSO, a type of stochastic optimization algorithm that uses repetitive approach for solving the objective problem. CSO can only not handle continuous problems as well as discrete problems. In addition, configuration of parameters is simple [19].

The proposed model is trained on crude oil data to check the performance and then compared with others similar algorithms. The next remaining sections of the paper is organized such is Sect. 2, and Sect. 3, give the basic idea of Neural Network and Cuckoo search algorithm. Proposed technique is discussed in Sect. 4. Section 5, will represent experimental setup and results and discussion. Section 6, presents conclusion.
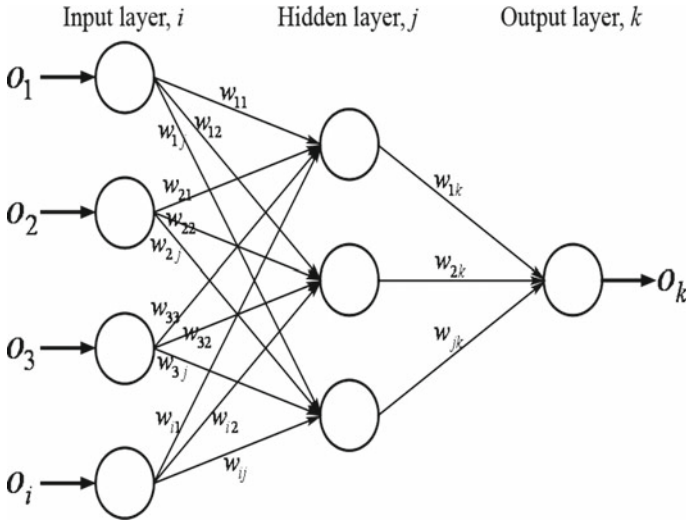
Fig. 1 Artificial Neural Network [25]

2 Artificial Neural Network

The concept of ANN is an engineering approach which is inspired by the concept of biological neurons. These neurons consist of inputs and outputs neurons that are interconnected with each other. Each neuron receives data from other neurons and weight of neurons link is added and output is generated for target neurons by applying activation function [20]. Layers of input feeds input to hidden layers and move forward direction to nodes in output layer. Nodes of input layer are configured based upon variables that are independent in dataset while dependent variables determined the output nodes. [21, 22]. There may more than one layer, but theoretical works such as [23] argues stating this that one hidden layer is enough for approximation any complex non linear function. Nodes in hidden layer is usually determined using trial an error [24]. Structure of ANN is shown in Fig. 1. ANN algorithm is used to process information in parallel. This can also be applied to model complex and non linear relationships through input output training from data sets that are collected from application domain.

The inherent capabilities of the Neural Network allow the algorithm to facilitate a non linear mapping of both input and output vectors [22, 25].

3 Chicken Swarm Optimization

Chicken Swarm optimization a new bio inspired algorithm developed by Meng et al. [26]. The Chicken Swarm optimization algorithm selected the behaviors of chickens

by the following rules. For simplicity, the behavior of chickens can be idealized in the procedures [27].

(1) In a chicken flock, there are several groups and each group consists of a rooster, some hens and chickens.
(2) As the chicken flock can be further divided into different groups and establish the identity of chickens, hens (hens and chicks). They all are dependent on the values of fitness of the chickens. The chicken with the best range of fitness values precede as roosters. The worst chickens with different health values will be elected as the chicks. Rest is to be considered as hens. Hens selects group randomly that which group to join. The relationship of mother and their child is also determined randomly.
(3) The hierarchy, relations of domination and the relationship between parents and children in a group remain unchanged.
(4) Chicken rate after network group to find food, and can avoid those that eats their own food. Assuming steal chickens were randomly good food that is found by others. Chicks look for food near to their own mother (hen). Prominent one has a benefit in the race for food.

The pseudo code of the Chicken Swarm optimization algorithm is

1. Initialize a population of N chickens and define the related parameters;
2. Evaluate the N chickens fitness values, $t = 0$;
3. While MSE < Stopping Criteria
4. If ($t \% G = 0$)
5. Rank the chickens' fitness values and establish a hierarchal order in the swarm;
6. Divide the swarm into different groups, and determine the relationship between
7. the chicks and mother hens in a group;
8. End if
9. For $i = 1 : N$
10. *If i == rooster*
11. Update its solution/location using Eq. (1);
12. End if
13. *If i == hen*
14. Update its solution/location using Eq. (3);
15. End if
16. *If i ==* chick
17. Update its solution/location using Eq. (6);
18. End if
19. Evaluate the new solution;
20. If the new solution is better than its previous one, update it;
21. End for
22. End wile

4   The Proposed Chicken S-NN Algorithm

Chicken swarm optimization is bio inspired constructed on behavior of chicken swarm. Like other bio-inspired algorithms of global research metaheuristic keep both local search and global search. Chicken swarm is composed of distinct groups and every individual group revising chicks, hens, and a rooster. Head rooster is a chicken with excellent value given the conditions. In mean while the worst chickens with peculiar fitness values are considered as chicks. The remaining is seen as chickens. Chicken will try the best food around parent (Hen). Chickens without exceptions indicate rational solutions in the proposed CS-NN algorithm (i.e. weight density and linked basis to optimize neural network in this investigation). The weight optimizing as well as the sizes of pack dilemma imitates the solution for various application [28]. Weight of optimization problem and size of the populace serve as quality of solution. In the beginning cycle, the initial values are taken for weights and biases for the said Chicken S-NN algorithm and pass these weights values to NN. In the following approach, Chicken swarm will modify weights and the value of biases with probable nest or solutions and the search will be continued by Chicken swarm for best possible solution or research for best possible weight value till last round of network or objective MSE is obtained.

The proposed Chicken S-NN algorithm Pseudo code is as under:

Step 1: initializes Chicken swarm population
Step 2: Load the training data
Step 3: While MSE < stopping criteria

If ($t \% G = 0$)
Rank the chickens' fitness values and establish a hierarchal order in the swarm;
Divide the swarm into different groups, and determine the relationship between the
chicks and mother hens in a group; End if
For $i = 1 : N$
If $i =$ rooster Update its solution/location using Eq. (1);

$$x_{i,j}^{t+1} = x_{i,j}^t * \left(1 + rand\left(0, \partial^2\right)\right) \tag{1}$$

$$\partial = \begin{cases} 1 & \text{if } f_i \leq f_k \\ \exp\left(\frac{(f_k - f_i)}{|f_i| + \varepsilon}\right), & otherwise, \ k\varepsilon[1, N] \ K \neq i. \end{cases} \tag{2}$$

where rand($0 \sim \partial^2$) is a Gaussian distribution with mean 0 and standard deviation ∂^2. ϵ which is used to avoid zero-division-error, is the smallest constant in the computer. k, a rooster's index, is randomly selected from the roosters group, f is the fitness value of the corresponding x. End if
If $i ==$ hen Update its solution/location using Eq. (3)

$$x_{i,j}^{t+1} = x_{i,j}^t + S_1 * rand * \left(x_{r1,j}^t - x_{i,j}^z \right) + S_2 * \text{rand} * \left(x_{r2,j}^t - x_{i,j}^t \right) \qquad (3)$$

$$S_1 = \exp((f_i - f_{r1})/(abs(f_i) + \varepsilon)) \qquad (4)$$

$$S_2 = \exp(f_{r2} - f_i) \qquad (5)$$

End if
If $i =$ chick Update its solution/location using Eq. (6)

$$x_{i,j}^{t+1} = x_{i,j}^t + FL * \left(x_{m,j}^t - x_{i,j}^t \right) \qquad (6)$$

End if
Evaluate the new solution;
If the new solution is better than its previous one, update it;
End for
Step 4: Pass the chicken as weights to network
Step 5: Feed forward neural network runs using the weights initialized with chicken swarm
Step 6: Calculate the error
Step 7: Chicken Swarm keeps on calculating the best possible weight at each epoch until the network is converged.
End While

5 Results & Discussion

Primarily, the core concept behind this research is to improve slow convergence and obtains high accuracy. Before heading towards the results of simulation some terminologies used suchas structure of network, tools and technologies, as well as the dataset used for experiments have to be explained. Discussion of these are given below.

5.1 Preliminaries

Workstations used for experimentations comes equipped with a processor 2.33 GHZ (Intel Core i5 Processor) and Microsoft Windows 7 is used as Operating system. MATLAB version 2012 is used for simulation purposes. In comparison evaluation, learning rate and hidden layers are kept same. Three layers feed-forward neural networks have been used for models training. 5 nodes are fixed for hidden layers. Whereas the activation function used is log sigmoid function as transfer function from input till hidden layers and from hidden up to output layers. For evaluation

of each problem, 1000 Epochs is restricted for solitary trial. 25 trails are executed for every value to validate the algorithm. Result of each trail is saved in result file. Number of failures as well as Mean Square Error (MSE) is documented in one by one distinct files for independent trial on crude oil classification.

5.2   Data

The dataset for OPEC petroleum consumption in thousands of barrels per day (tb/d) are obtained from the EIA of the US Department of Energy, which is freely available online on the organization's official website [29]. Dataset are collected for the domestic petroleum consumption of each 12 OPEC member countries, including Algeria, Angola, Ecuador, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, UAE, and Venezuela. Also, the total petroleum consumption for OPEC is collected, given that it is the target forecasting value. The dataset are collected on yearly basis from 1980 to 2012 [30]. This research is based upon predicting OPEC of crude oil. Two different experiments are carried out on data division. Firstly the data is divided in two ways. In the first of applied technique, data is partitioned into 70 and 30%. 70% of the given data is used as training set and the rest of 30% data are used as testing set. While using second technique, data is partitioned into two slices of 60 and 40%. The first slice of 60% is used for training and on the other hand 40% of the remaining data is used for testing the data.

The dataset is normalized into a specified range of [0, 1] with the help of Eq. (7) to improve accuracy and convergence speed of prediction.

$$n_0 = \frac{k_{i-x}\min}{P_{\max-x}\min} \tag{7}$$

where

no	normalize dataset,
ki	raw dataset,
xmin	lowest value of dataset,
pmax	largest value of dataset [25].

5.3   Discussion

This section illustrates the performance of proposed Chicken Swarm Neural Network (Chicken S-NN) algorithm which is compared with Artificial Bee Colony Neural Network (ABCNN) and Artificial Bee Colony Back Propagation (ABCBP). The performance of the mentioned algorithm is measured in term of Epochs, Accuracy, Mean Square Error and CPU Time that can be seen in Table 1.

Table 1 Epochs, CPU time, accuracy and MSE for 12-5-1 NN-structure

Algorthms	Epochs		CPU time		Accuracy		MSE	
	Training (70%)	Testing (30%)	Training (70%)	Testing (30%)	Training (70%)	Testing (30%)	Training (70%)	Testing (30%)
Chicken S-NN	30	127	86.5244	352.7355	99.99807	99.99888	0.000101	0.000104
ABCNN	1000	1000	2134.577	1484.712	99.87918	99.82674	0.001202	0.001311
ABCBP	1000	1000	2087.435	2784.457	99.81945	99.70366	0.001271	0.000544

From Table 1 this can be viewed that the performance of proposed Chicken S-NN algorithm is better on crude oil data set as compared to ABCNN and ABCBP. From these results, this is evident that for 70% of training data, the proposed Chicken S-NN algorithm converges to the global minimum in 30 Epochs, consuming 86.52 s of CPU time and attain 99.99 accuracy with an average MSE equals to 0.0001. While the other models such as ABCNN obtain an accuracy of 99.87 together with an average MSE is 0.0012. Similarly, the accuracy of ABCBP is 99.81 with the average MSE is 0.001271.

Furthermore for 30% testing data, the proposed Chicken S-NN algorithm performs well and converges to the global minimum in 127 Epochs obtaining 99.99 percent of average accuracy with an MSE equals to 0.000104. The accuracy of ABCNN and ABCBP is 99.82674 and 99.70366 respectively, with an average MSE of ABCNN is 0.001311 and ABCBP has an average MSE equals to 0.000544. Results of different models applied on data set has been illustrated below.

Figures 2, 3 and 4 display convergence performance of suggested Chicken S-NN algorithm, ABCNN and ABCBP on 70% Training data set of crude oil dataset.

The convergence of proposed Chicken S-NN algorithm, ABCNN and ABCBP can be seen in Figs. 1, 2 and 3 together with their MSE.

Figures 1, 2 and 3 shows that the proposed Chicken S-NN algorithm performs well and reaches to global minima in 30 Epochs.

Figures 5, 6 and 7 showed the Convergence Performance of proposed Chicken S-NN algorithm, ABCNN and ABCBP on 30% testing data of crude oil.
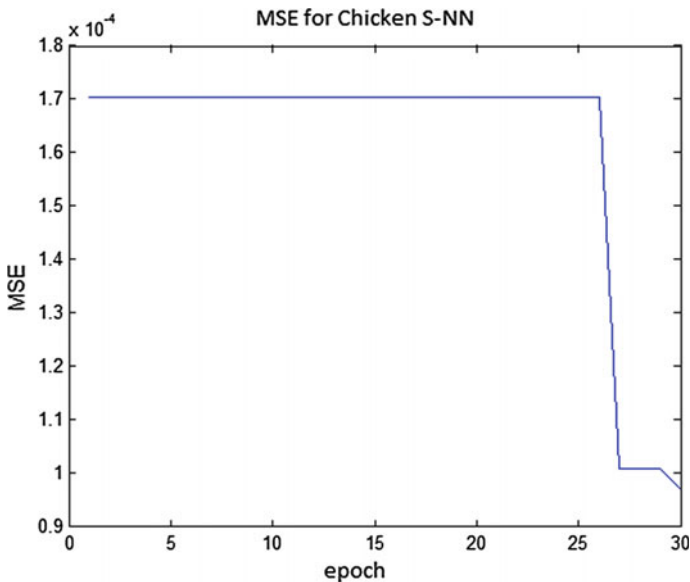

Fig. 2 MSE convergence performance of Chicken S-NN algorithm for 70% training dataset

The accuracy of proposed Chicken S-NN algorithm, ABCNN and ABCBP can be seen in Figs. 5, 6 and 7 together with their MSE.

Figures 5, 6 and 7 show that the proposed Chicken S-NN algorithm performs better and converges to the global minima in 127 Epochs.

Figures 8 and 9 displays a comparison of actual and predicted value of proposed Chicken S-NN algorithm. This can be seen clearly that the predicted value of proposed Chicken S-NN algorithm is near to the actual value.

Table 2 represents the performance of proposed Chicken S-NN Algorithm, ABCNN and ABCBP algorithm. Results show that the proposed Chicken S-NN algorithm performs superior than rest of the models. This is apparent from results that for 60% of training data, the proposed Chicken S-NN algorithm meets to global minima in 15 Epochs while consuming 47 s of CPU time with an average accuracy matches to 99.99% and 9.23E−05 is their average MSE. Whereas ABCNN model shows 99.50 average accuracy and reach an MSE of 0.000366. The accuracy of ABCBP model is 99.60 and gets an MSE of 0.004226.

Similarly on 40% testing data Chicken S-NN algorithms perform better and reaches to the global minima in 36 Epochs while gaining 99.99 percent of average accuracy and MSE equals to 0.004226. The other two models ABCNN and ABCBP gain 99.80 and 99.30 average accuracy respectively. ABCNN achieve MSE of 0.001054 while ABCBP gets 0.004226 averages MSE.

Figures 10, 11 and 12 of Chicken S-NN algorithm, ABCNN and ABCBP shows the convergence performance on 60% training data of crude oil prices. The average accuracy of suggested algorithm Chicken S-NN and other two models ABCNN and ABCBP can be viewed in Figs. 10, 11 and 12 with their MSE. In Fig. 9 show that the
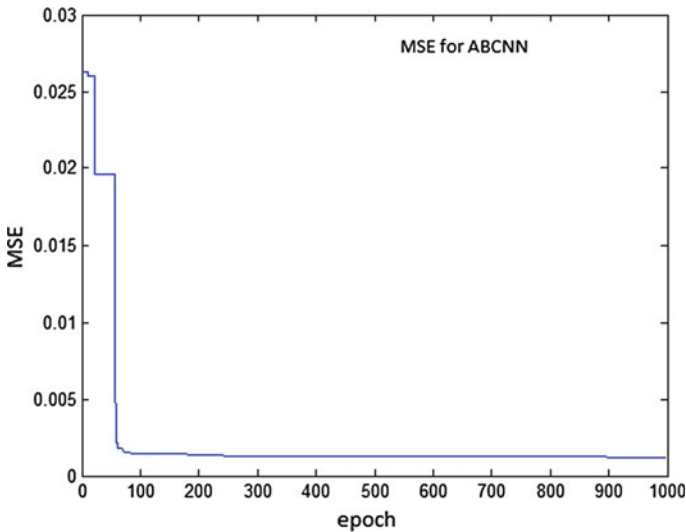

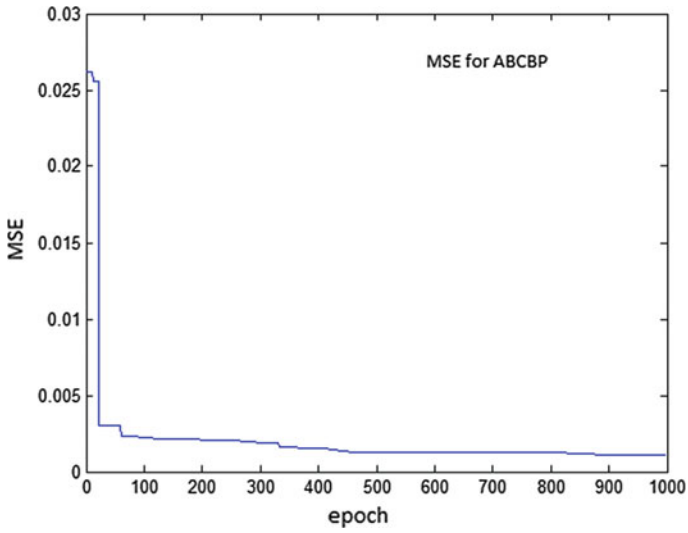**Fig. 3** MSE convergence performance of ABCNN algorithm for 70% training dataset

Fig. 4 MSE convergence performance of ABCBP algorithm for 70% training dataset
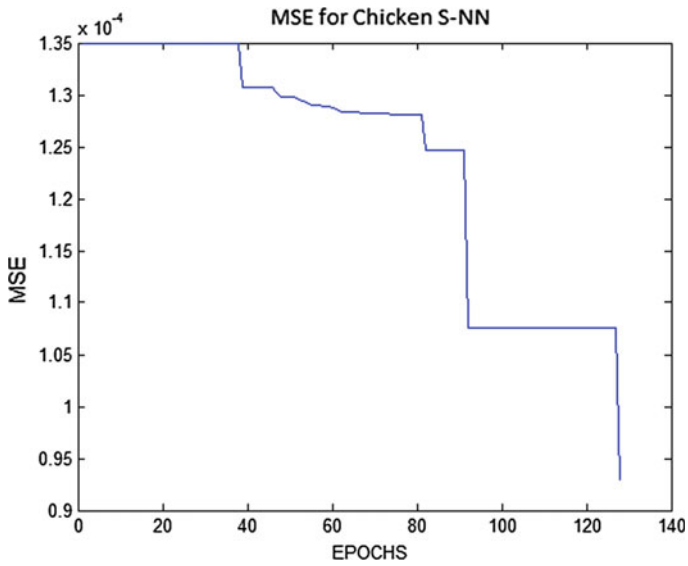

Fig. 5 MSE convergence performance of Chicken S-NN algorithm for 30% testing dataset
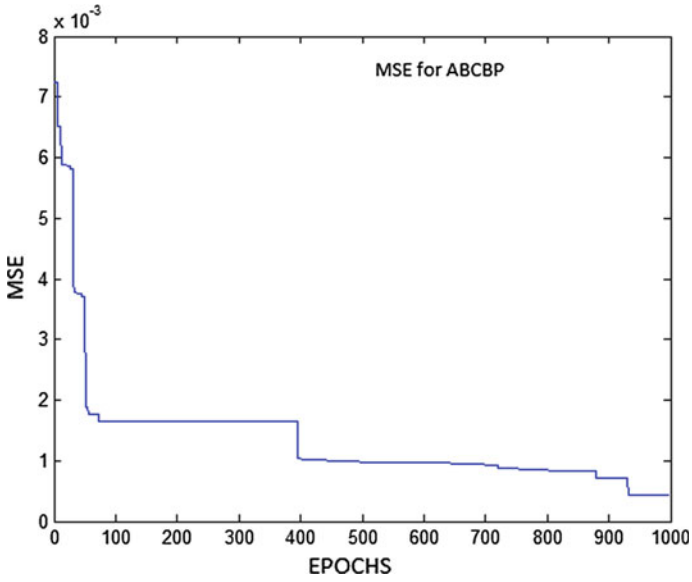
Fig. 6 MSE convergence performance of ABCBP algorithm for 30% testing dataset
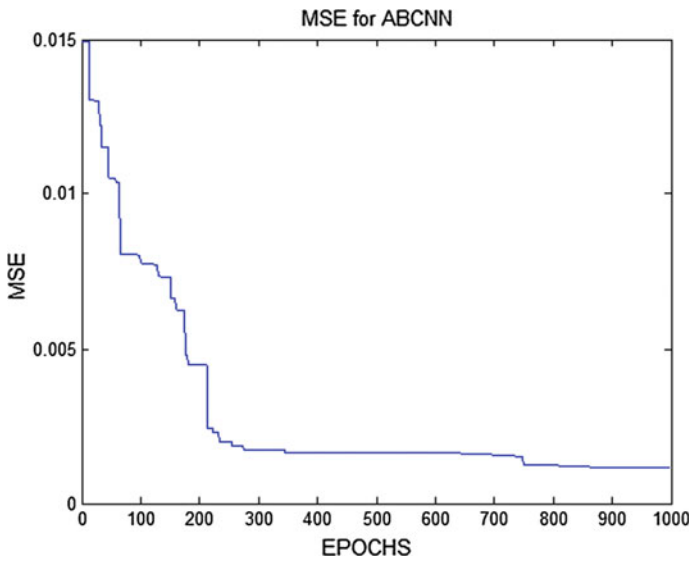

Fig. 7 MSE convergence performance of ABCNN algorithm for 30% testing dataset

Table 2 Epochs, CPU time, accuracy and MSE for 12-5-1 NN-structure

| Algorithms | Epochs | | CPU time | | Accuracy | | MSE | |
	Training (60%)	Testing (40%)	Training (60%)	Testing (40%)	Training (60%)	Testing (40%)	Training (60%)	Testing (40%)
Chicken S-NN	17	36	47	99	99.99	99.99	9.23E−05	0.000107
ABCNN	1000	1000	1497	1418	99.50	99.80	0.000366	0.001054
ABCBP	1000	1000	1789	1495	99.60	99.30	0.001332	0.004226

Fig. 8 Actual via predict data convergence of proposed algorithms for 70% training and 30% testing dataset

Predict via Actual data of Chicken S-NN for 70% training data

Predict via Actual data of Chicken S-NN for 30% Testing data
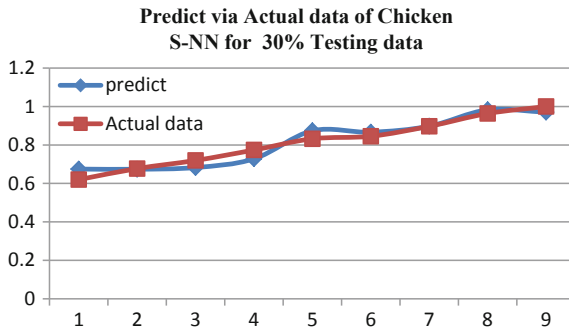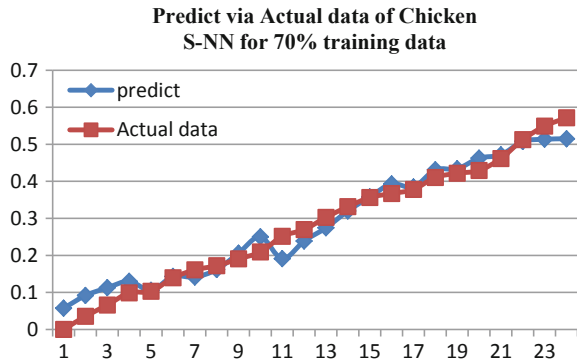
Fig. 9 Actual via predict data convergence of proposed algorithms for 70% training and 30% testing dataset

suggested Chicken S-NN algorithm performs better and converges to global minima in 15 Epochs.

The average accuracy of suggested algorithm Chicken S-NN and other two models ABCNN and ABCBP can be viewed in Figs. 13, 14 and 15 with their MSE. Figures 13, 14 and 15 shows that the suggested Chicken S-NN algorithm performs better and converges to global minima in 36 Epochs.

Figure 16 illustrates comparison of predicted value and actual value. Proposed algorithm Chicken S-NN performs very well and predicts almost near to the actual value.

6   Conclusion

Chicken Swarm is an assumptive based optimization algorithm inspired by chicken capabilities. Chicken-swarm algorithm has capability to search both local and global large space in the candidate solution. This paper proposed Chicken swarm based Neural Network to investigate and to overcome the shortcoming of NN algorithm. The
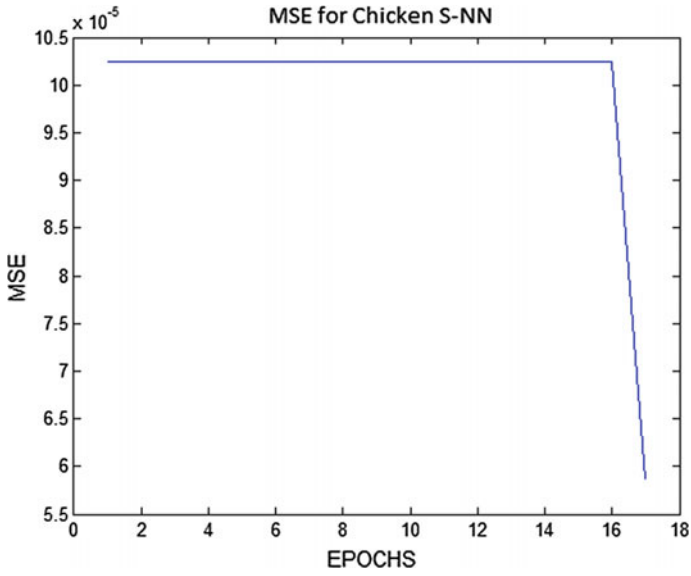
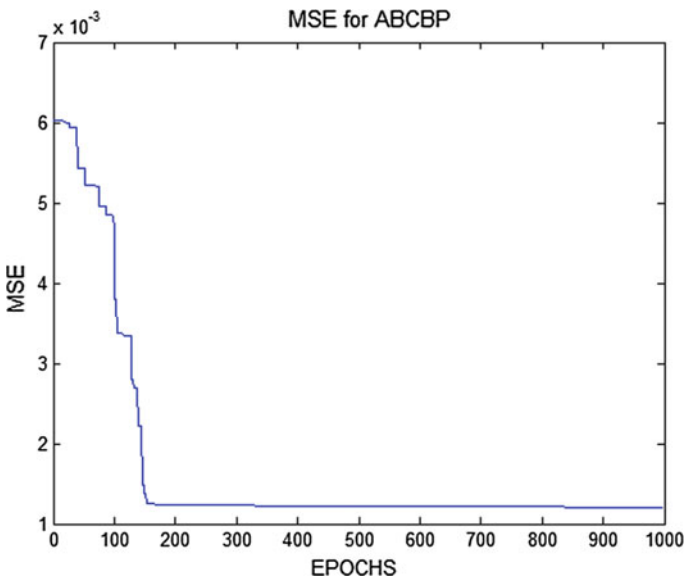**Fig. 10** MSE convergence performance of Chicken S-NN algorithm for 60% training dataset

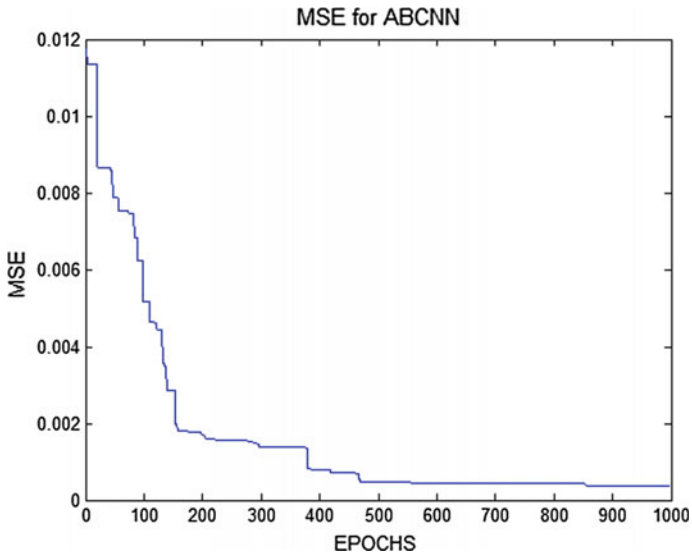**Fig. 11** MSE convergence performance of ABCBP algorithm for 60% training dataset

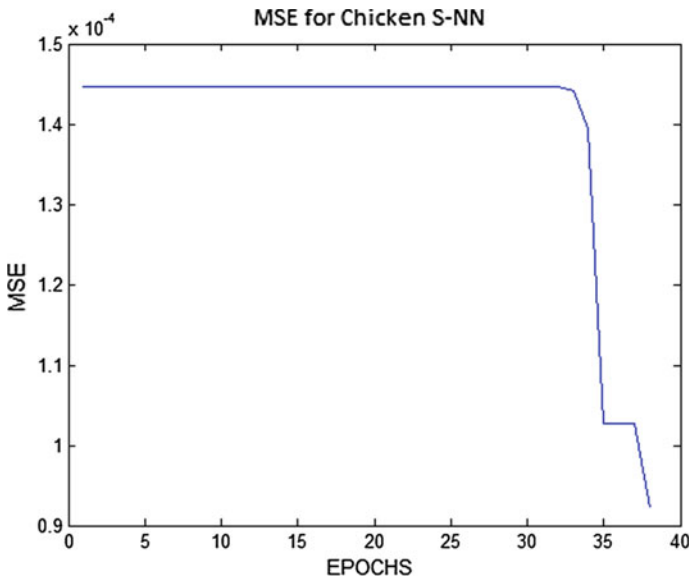**Fig. 12** MSE convergence performance of ABCNN algorithm for 60% training dataset

Fig. 13 MSE convergence performance of Chicken S-NN algorithm for 40% testing dataset
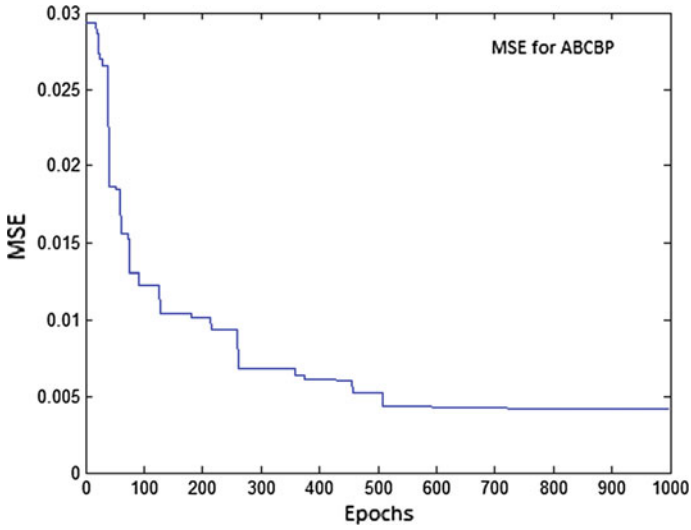
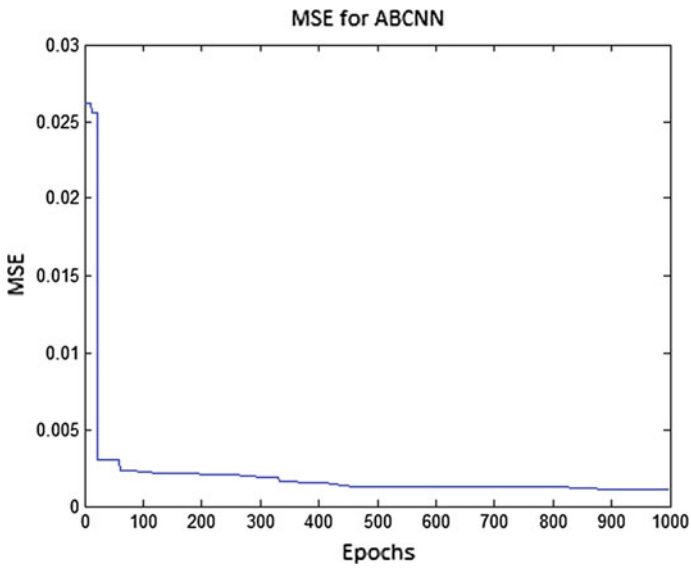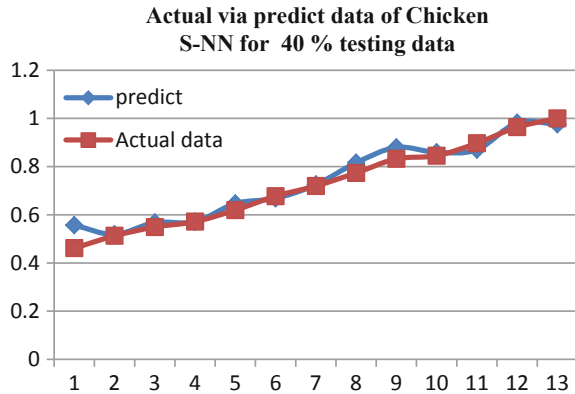**Fig. 14** MSE convergence performance of ABCBP algorithm for 40% testing dataset

Fig. 15 MSE convergence performance of ABCNN algorithm for 40% testing dataset

Fig. 16 Actual via predict data convergence of proposed algorithms for 40% testing dataset

Actual via predict data of Chicken S-NN for 40 % testing data

performance of the proposed Chicken S-NN model is better to Artificial Bee Colony Back Propagation (ABCBP) and Artificial Bee Colony Neural Network (ABCNN). The network is trained as well tasted on the basis of Crude Oil price dataset. The simulation result concludes that the proposed model outperforms existing methods like ABCBP, and ABCNN in term of MSE accuracy. From Experiments it is also clear that with Chicken swarm neural network avoid the slow convergence and convergence to optimal solution.

References

1. Yu L, Wang Z, Tang L (2015) A decomposition–ensemble model with data-characteristic-driven reconstruction for crude oil price forecasting. Appl Energy 156:251–267
2. Barunik J, Malinska B (2015) Forecasting the term structure of crude oil futures prices with neural networks. arXiv preprint arXiv:1504.04819
3. Bildirici M, Ersin ÖÖ (2013) Forecasting oil prices: smooth transition and neural network augmented GARCH family models. J Petrol Sci Eng 109:230–240
4. Shabri A, Samsudin R (2014) Daily crude oil price forecasting using hybridizing wavelet and artificial neural network model. Math Prob Eng 2014:201402 (10 pages). https://doi.org/10.1155/2014/201402
5. Lackes R, Börgermann C, Dirkmorfeld M (2009) Forecasting the price development of crude oil with artificial neural networks. In: Distributed computing, artificial intelligence, bioinformatics, soft computing, and ambient assisted living. Springer, pp 248–255
6. Khazem H, Mazouz A (2013) Forecasting the price of crude oil using artificial neural networks. Int J Bus Mark Decis Sci 6(1)
7. Mirmirani S, Li HC (2004) A comparison of VAR and neural networks with genetic algorithm in forecasting price of oil. Adv Econ 19:203–223
8. Kulkarni S, Haidar I (2009) Forecasting model for crude oil price and commodity futures prices using artificial neural networks. Int J Comput Sci Inf Secur 2(1):81–88
9. Yu L, Wang S, Lai KK (2008) Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm. Energy Econ 30(5):2623–2635

10. Hu JWS, Hu YC, Lin RRW (2012) Applying neural networks to prices prediction of crude oil futures. Math Prob Eng 2012:959040 (12 pages). https://doi.org/10.1155/2012/959040
11. Nawi NM, Khan A, Rehman MZA (2014) New optimized Cuckoo Search Recurrent Neural Network (CSRNN) algorithm. In The 8th international conference on robotic, vision, signal processing & power applications. Springer
12. Nawi NM, Khan A, Rehman M (2012) CSLMEN: a new optimized method for training Levenberg Marquardt Elman network based Cuckoo search algorithm
13. Khashei M, Bijari M (2014) Fuzzy artificial neural network p, d, q model for incomplete financial time series forecasting. J Intell Fuzzy Syst Appl Eng Technol 26(2):831–845
14. Nawi NM et al (2015) Weight optimization in recurrent neural networks with hybrid meta-heuristic Cuckoo search techniques for data classification. Math Probl Eng 501:868375
15. Nawi NM, Khan A, Rehman MZ (2013) A new cuckoo search based Levenberg-Marquardt (cslm) algorithm. In: Computational science and its applications–ICCSA 2013. Springer, pp 438–451
16. Chiroma H et al (2014) Optimization of neural network through genetic algorithm searches for the prediction of international crude oil price based on energy products prices. In: Proceedings of the 11th ACM conference on Computing Frontiers. ACM
17. Nawi NM, Khan BV, Rehman MZ (2013) A new back-propagation neural network optimized with cuckoo search algorithm. In: Computational science and its applications–ICCSA 2013. Springer, pp 413–426
18. Nawi NM, Rehman MZ, Hafifie N, Khan A, Siming A (2014) Bat-BP: a new bat based back-propagation algorithm for efficient data classification
19. Chen YL, P He, Zhang Y (2011) Combining penalty function with modified chicken swarm optimization for constrained optimization. In: First international conference on information sciences, Machinery, materials and energy. Atlantis Press
20. Sharma V, Rai S, Dev A (2012) A comprehensive study of artificial neural networks. India Int J Adv Res Comput Sci Softw Eng 2(10)
21. Haykin S (2005) Neural network: a comprehensive foundation. Pearson Education, New Delhi
22. Peter GZ, Patuwo B, My H (2001) A simulation study of artificial neural networks for nonlinear timeseries forecasting. Comput Oper Res 28:381–396
23. Hornick KSM, White H (1999) Multilayer feed forward networks are universal approximates. Neural Netw 2:359–366
24. Pan TY, Wamg RY (2004) State space neural networks for short term rainfall-runoff forecasting. J Hydrol 297(1–4):34–50
25. Chiroma H, Abdul-Kareem S, Khan A, Nawi NM, Gital AYU, Shuib L, Herawan T (2015) Global Warming: predicting OPEC carbon dioxide emissions from petroleum consumption using neural network and hybrid cuckoo search algorithm. PLoS ONE 10(8)
26. Meng X et al (2014) A new bio-inspired algorithm: chicken swarm optimization. In: Advances in swarm intelligence. Springer, pp 86–94
27. Hafez AI, Zawbaa HM, Emary E, Mahmoud HA, Hassanien AE (2015) An innovative approach for feature selection based on chicken swarm optimization. In: 2015 7th International Conference of Soft Computing and Pattern Recognition (SoCPaR), IEEE, pp 19–24
28. Khan A et al (2017) Chicken S-BP: an efficient chicken swarm based back-propagation algorithm. In: Herawan T et al (eds) Recent advances on soft computing and data mining: the second international conference on Soft Computing and Data Mining (SCDM-2016), Bandung, Indonesia, August 18–20, 2016 Proceedings, Springer International Publishing, Cham, pp 122–129
29. Energy Information Administration of the US Department of Energy. [Online]. Available http://www.eia.gov/. 2014
30. Chiroma H et al (2016) A new approach for forecasting OPEC petroleum consumption based on neural network train by using flower pollination algorithm. Appl Soft Comput 48:50–58