A approach for monthly relative humidity prediction of target station using neighboring stations data

Babak Mohammadi

Department of Water Engineering, University of Tabriz, Tabriz, Iran
babakmsh@yahoo.com

Abstract: This study represents a new hybrid intelligent approach by integrating multilayer perceptron (MLP) with Cuckoo algorithm (CA) for prediction of monthly relative humidity. MLP-CA was applied to predict the relative humidity of any target station using the neighboring stations data. For this purpose, monthly relative humidity time series between years 2006 and 2015 of eight meteorological stations located at north of Iran were used. The ability of the proposed approach is compared with the MLP model using three performance criteria namely, root mean square errors (RMSE), the Nash-Sutcliffe efficiency (NS), Willmott's Index of agreement (WI). The results obtained indicated that the MLP-CA model performed significantly better than the MLP model for relative humidity prediction.

[Babak Mohammadi. **A approach for monthly relative humidity prediction of target station using neighboring stations data.** *Rep Opinion* 2017;9(5):78-83]. ISSN 1553-9873 (print); ISSN 2375-7205 (online). http://www.sciencepub.net/report. 6. doi:10.7537/marsroj090517.06.

Keywords: Cuckoo Algorithm; Hybrid model; Multilayer Perceptron; Relative humidity

1. Introduction

Predicting the Relative humidity is very important for Relative humidity plMLPing, agriculture, Civil Engineering projects, Electrical power demand, Ship Navigation, Satellite launch, Environmental Studies, agro-hydrologic plMLPing, etc. (Mohandes et al., 1998). Artificial Intelligence (AI) techniques successfully have been used extensively for Relative humidity predictions over the years. The major advantage of the AI is that they do not require a priori concept of the relations between input and output data (Gocic´ et al. 2015). Some recent examples include applications of multilayer perceptron (MLP) artificial neural networks (Mabel and Fernandez, 2008; Bilgili and Sahin 2010; Li and Shi 2010; Barati et al.2013; Bilgili and Sahin 2013; Khatibi et al. 2014; Dokur et al. 2015; Islam et al. 2016), Fuzzy Logic (Barbounis and Theocharis 2007; Damousis et al. 2004; Kariniotakis et al. 1996a; Wang et al. 2004), Genetic Programming (Ghorbani et al. 2010; Guven et al. 2008; Kalra and Deo 2007; Kalra et al. 2008; Khatibi et al. 2011; Ustoorikar and Deo 2008), as well as radial basis function (Beyer et al. 1994), recurrent neural networks (Kariniotakis et al. 1996b; More and Deo 2003) and support vector machines (Mohandes et al. 2004; Guo et al. 2011; Hu et al. 2013). Notably, the MLP technique are among the most frequently used. Finding the optimal values of input neurons, hidden layers, hidden neurons, activation function and especially weight values is the main purpose of MLP training to obtain further accuracy. Recently, a new global optimum algorithm, named Cuckoo Algorithm (CA) widely used for optimization problem training of MLP for example: software cost prediction (Kaushik et al. 2016), Speech Recognition System (Hassanzadeh et al., 2012), water level prediction (Soleymani et al., 2016), dynamic systems modeling (Nady et al., 2012). CA is a multimodal nature inspired metaheuristic optimization algorithm based on flashing behavior of fireflies (Yang, 2010). The above studies demonstrated that combined MLP with CA perform better than the MLP model. This assumption is tested in the present study, the objective of which is to combine the CA with MLP model as a hybrid approach (MLP-CA) for predicting relative humidity time series. Although CA has been used successfully in different fields, but to the best of our knowledge, there is no study in the literature investigates the ability of MLP and CA in relative humidity prediction. In order to prove the suitability of the hybrid MLP-CA approach, the results is compared with the MLP with back-propagation algorithm (MLP-BP) model. The purpose of this study is, for the first time, to investigate the applicability MLP-CA and comparison with MLP model to predict monthly relative humidity data sets in north-west of Iran.

2. Material and Methods

2.1 Multilayer Perceptron Neural Networks (MLP) Artificial neural networks (MLP's) are parallel information processing systems consisting of a set of neurons arranged in layers. Multilayer feed-forward Perceptron back propagation learning algorithm (MLP-BP) consists of input layer, hidden layer and output layer and is one of the popular MLP architectures. The goal of back propagation (BP) algorithm is to minimize global error of MLP. The neurons are connected by a weight in each layer to the neurons in a subsequent layer during training. The sigmoid and the linear activation functions were used in the hidden and layer and the output layer, respectively. More details description about MLP method can be found in (Ghorbani et al. 2013). 2.2 Hybrid MLP- CA model The FCA developed by Yang (2010), is a swarm intelligence optimization technique based on the movement of fire flies. The solution of an optimization problem can be assumed as agent i.e. Cuckoo which glows in proportion to its quality. Consequently, each brighter Cuckoo attracts its partners, regardless of their sex, which makes exploration of the search space more efficient (Lukasik and Zak, 2009). Fire flies are attracted towards light. The entire swarm moves towards the brightest Cuckoo. So the attractiveness of the fireflies is directly proportional to their brightness. Furthermore, the brightness depends on the intensity of the agent (Kayarvizhy et al., 2014). The major issues in FCA development are the formulation of the objective function and the variation of the light intensity. The light intensity I (r), the attractiveness (β) and the cartesian distance between any two fireflies i and j can be represented as:

$$I(r) = I_O \exp(-\gamma r^2) \tag{1}$$

$$\beta(r) = \beta_O \exp(-\gamma r^2) \tag{2}$$

$$r_{ij} = \|x_i + x_j\| = \sqrt{\sum_{K=1}^{d} (x_{i,k} - x_{j,k})} \tag{3}$$

where γ is the light absorption coefficient; I (r) and I_O are the light intensity at distance r and initial light intensity from a Cuckoo,. β(r) and β_O are the attractiveness β at a distance r and r =0. The next movement of Cuckoo i can be represented as as:

$$x_i^{i+1} = x_i + \Delta x_i \tag{4}$$

$$\Delta x_i = \beta_O\, e^{-\gamma r^2}(x_j - x_i) + \alpha \epsilon_i \tag{5}$$

The first term in the Eq. (7) is due to the attraction, while the second term represents the randomization, with α as a randomization coefficient whose value is between 0 and 1 and ϵ_i is the random number vector derived from a Gaussian distribution (Ch et al., 2014). In this study optimal values for the weights of the MPL model was computed. 2.3 Study area and data used In the current research, the monthly relative humidity data of eight stations in Gilan province, North of Iran in the time period of 2006-2016 have been gathered from Iranian meteorological organization. The mentioned stations are named Talesh, Astara, Rudsar, Rasht, Bandar Anzali, and Lahijan, which their spatial local distribution can be seen in fig. 2. All stations are located between 37 º 7' to 38 º 21' north latitude and between 48 º 51' to 50 º 19' east longitude, while their altitude changes in the intervals of -23.6 to 34.2 meters above the sea level. The mean, maximum and minimum Relative humidity of each location are presented in Table 1. As can be seen form table 1, Talesh station has the lowest mean Relative humidity. of 3 mm, Moreover, the maximum value of the Relative humidity in the studied time period has been recorded in Bandar Anzali station with the value of 5.1 mm.

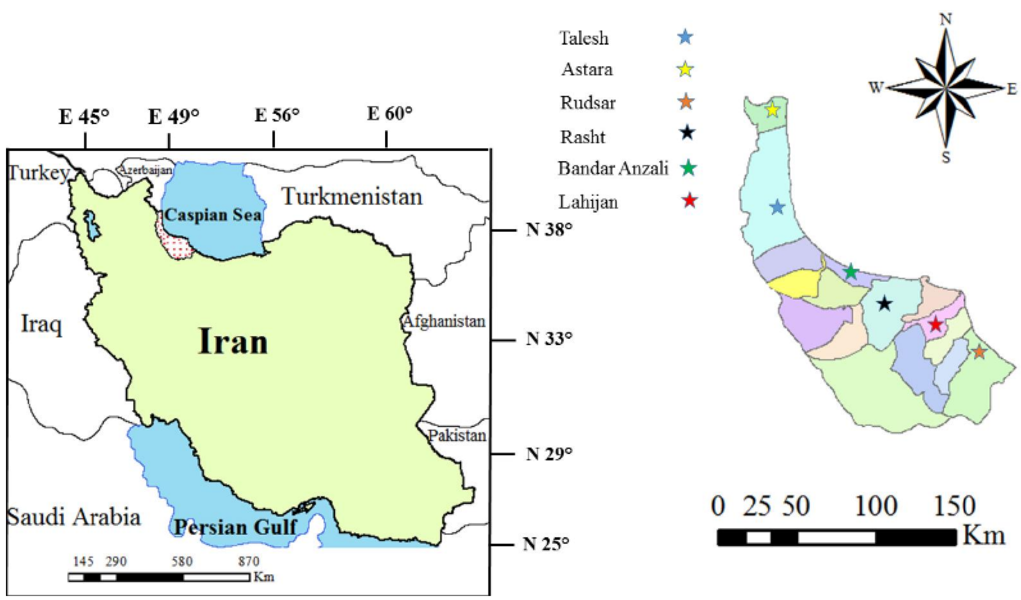

Fig. 1 Locations of studied stations in the map of the region.

Table. 1 Coordinates of studied stations in the region and the statistical characteristics of relative humidity data.

Station	Latitude	Longitude	Altitude (m)	Mean Relative humidity (mm)	Maximum Relative humidity (mm)	Minimum Relative humidity (mm)
Talesh	37 ° 50' N	48 ° 53' E	7	3	0	85
Astara	38 ° 21' N	48 ° 51' E	-21.1	3.9	0	84
Rudsar	37 ° 07' N	50 ° 19' E	-22	3.6	0	80
Rasht	37 ° 12' N	49 ° 38' E	24.9	3.8	0	78
Lahijan	37 ° 11' N	50 ° 00' E	34.2	3.9	0	85
Bandar Anzali	37 ° 28' N	49 ° 27' E	-23.6	5.1	0	90

In the current study, predictive models of relative humidity in a specific station using the correspondent values of relative humidity in neighboring stations have been carried out using MLP and MLP-CA methods. For that reason, the correlation coefficient of relative humidity among all stations two by two have been determined and presented in Table 2.

Table. 2 Correlation coefficient values of relative humidity among all studied stations two by two.

Station	Talesh	Astara	Rudsar	Rasht	Lahijan	Bandar Anzali
Talesh	1.00	0.94	0.88	0.91	0.90	0.91
Astara	0.94	1.00	0.84	0.89	0.88	0.89
Rudsar	0.88	0.84	1.00	0.92	0.91	0.88
Rasht	0.91	0.89	0.84	1.00	0.92	0.95
Lahijan	0.90	0.88	0.91	0.92	1.00	0.89
Bandar Anzali	0.91	0.89	0.88	0.95	0.89	1.00

As mentioned before, the values of relative humidity of neighboring stations (reference stations) have been used for predicting the correspondent values of each target station (as illustrated in Table 3). As can be seen from Table 3, the relative humidity values of Talesh, Astara, Rudsar, Rasht, Bandar Anzali stations were used for estimating the relative humidity values of Rasht station with the named models of MLP1, MLP-FCA1 and so on.

Table. 3 Reference and target stations in the studied region.

Target Station	Reference Station	Models	
Rasht	Talesh, Astara, Rudsar, Bandar Anzali, Lahijan,	MLP1	MLP-FCA1
Lahijan	Talesh, Astara, Rudsar, Rasht, Bandar Anzali,	MLP2	MLP-FCA2
Talesh	Astara, Rudsar, Rasht, Bandar Anzali, Lahijan,	MLP3	MLP-FCA3
Rudsar	Talesh, Astara, Rasht, Bandar Anzali, Lahijan,	MLP4	MLP-FCA4
Astara	Talesh, Rudsar, Rasht, Bandar Anzali, Lahijan,	MLP5	MLP-FCA5
Bandar Anzali	Talesh, Astara, Rudsar, Rasht, Lahijan,	MLP6	MLP-FCA6

2.4. Evaluation parameters

To evaluate the performance of the different MLP and MLP-FCA approaches, the following statistical score metrics were used.

I: Nash–Sutcliffe coefficient (NS), expressed as:

$$NS = 1 - \left[\frac{\sum_{i=1}^{N} (O_i - P_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O}_i)^2} \right], 0 \le NS \le 1 \quad (6)$$

II: Root mean square error (RMSE) expressed as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_i - O_i)^2} \quad (7)$$

III: Willmott's Index of agreement (WI) (Willmott et al., 2012) expressed as:

$$WI = \left| 1 - \left[\frac{\sum_{i=1}^{N} (O_i - P_i)^2}{\sum_{i=1}^{N} (|P_i - \bar{O}_i| + |O_i - \bar{O}_i|)^2} \right] \right|, 0 \le WI \le 1 \quad (8)$$

Where O_i and P_i are the observed and predicted i^{th} value of the relative humidity, $\bar{O}$ is the average of observed O.

3. Analysis, results and discussion

Both studied methods, namely MLP and MLP-FCA, were implemented for prediction of relative humidity in each station using correspondent relative humidity values in neighboring ones. The recorded values of relative humidity in all stations covers the time period of 2006 to 2015. The mentioned dataset was divided to two separate parts for training (75mm of dataset) and testing (25mm of dataset) of defined models. Statistical parameters of mentioned models in all studied stations are presented in Table 4.

Table. 4 Statistical results of comparing different MLP and MLP-FCA models.

Models	Model Structure\Parameter	Training			Testing		
		RMSE (mm)	WI	NS	RMSE (mm)	WI	NS
MLP1	(5,13,1)	0.44	0.97	0.93	0.5	0.96	0.89
MLP2	(5,4,1)	0.58	0.97	0.93	0.67	0.95	0.88
MLP3	(5,15,1)	0.49	0.95	0.85	0.54	0.93	0.76
MLP4	(5,9,1)	0.62	0.93	0.79	0.72	0.89	0.59
MLP5	(5,10,1)	0.6	0.97	0.92	0.86	0.94	0.82
MLP6	(5,16,1)	0.65	0.89	0.65	0.74	0.86	0.52
MLP-FCA1	(5,13,1)	0.3	0.99	0.95	0.38	0.97	0.9
MLP-FCA2	(5,4,1)	0.37	0.99	0.97	0.41	0.99	0.95
MLP-FCA3	(5,15,1)	0.32	0.98	0.91	0.4	0.95	0.82
MLP-FCA4	(5,9,1)	0.35	0.98	0.93	0.51	0.93	0.76
MLP-FCA5	(5,10,1)	0.45	0.98	0.94	0.6	0.97	0.9
MLP-FCA6	(5,16,1)	0.46	0.94	0.78	0.54	0.9	0.69

As can be seen from table 4, the RMSE values for MLP models are ranging from 0.44 to 0.65 and from 0.5 to 0.86, while NS values are fluctuated between 0.65 to 0.93 and 0.52 to 0.89 at training and testing periods, respectively. Therefore, the minimum RMSE value for MLP models at testing period was found to be 0.5 for MLP1 in predicting relative humidity of Rasht station, while correspondent NS value was 0.96 for mentioned station. Moreover, MLP3 ranked the second best for prediction of relative humidity in Talesh station. Somehow different trend of MLPs was seen for MLP-FCA models. In the mentioned category, MLP-FCA1 with RMSE values of 0.3, 0.38 and NS value of 0.99, 0.97 had the best performances for estimating relative humidity in Rasht station in training and testing phases, respectively. Additionally, the predictions of relative humidity in Talesh station seemed to be the second best for MLP-FCA models. So, the overall result revealed that best MLP-FCA model can predict relative humidity values using the correspondent values of neighboring stations more precisely than ordinary MLP model. the scatter plot of observed and predicted values are presented in fig. 3.

It is obvious from fig. 2 that MLP-FCA models seem to be better than correspondent MLP models. In all cases, the estimates of MLP-FCA models seem to be closer to the exact line than those of the MLP models and also they are less scattered. In other words, although the predictions of MLP agree the observed relative humidity values with suitable accuracy, but the MLP-FCA models presented more precise predictions than correspondent MLP models.

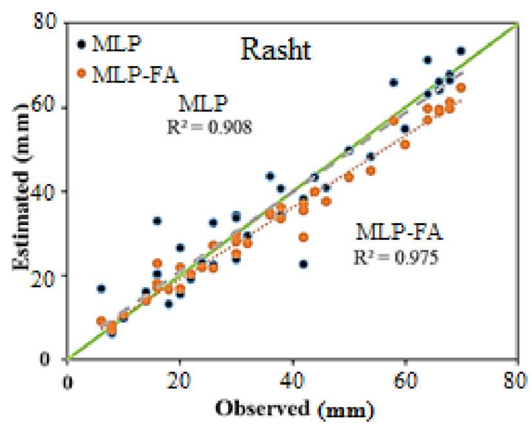

Fig. 2. Scatter plots of observed (x-axis) and predicted values (y-axis) of relative humidity at different stations

4. Conclusion

By the quick development of relative humidity, precise and dependable approaches for relative humidity forecasting are required. This paper examines the capabilities of MLP and MLP-FCA models in predicting relative humidity values of specific stations using correspondent values of neighboring stations. For that end, the relative humidity values of 8 synoptic stations in Gilan province, Iran have been prepared in the time period of 2006 to 2015. Then, the performances of mentioned methods in estimating relative humidity of each station using other seven neighboring stations have been analyzed. Results revealed that the MLP-FCA models were powerful tools for relative humidity prediction and provided more satis C Actory results than ordinary MLP models. Conclusively, MLP-FCA models could be recommended for relative humidity estimation with high degree of confidentiality.

Corresponding Author:
Babak Mohammadi
Department of Water Engineering
University of Tabriz, Tabriz, Iran
Telephone: +989364108282
E-mail: babakmsh@yahoo.com

References

1. Ahmadi I (2016) A novel Method to water level prediction using RBF and FCA. Water Resources Management. 30(9):3265-3283. Smith MD, Wilcox JC, Kelly T, Knapp AK. Dominance not richness determines invasibility of tallgrass prairie. Oikos 2004;106(2):253–62.
2. Burton T, Sharpe D, Jenkins N, Bossanyi E (2001) Wind Energy Handbook.
3. Li G, Shi J (2010) on comparing three artificial neural networks for wind speed forecasting. Applied Energy. 87(7):2313-2320.
4. Bilgili M, Sahin B (2010) comparative analysis of regression and artificial neural network models for Wind speed prediction. 109(1):61-72.
5. Barati H, Haroonabadi H, Zadehali R (2013) Wind speed forecasting in south Coasts of Iran: An Application of Artificial Neural Networks (MLPs) for Electricity Generation using Renewable Energy. Bulletin of Environment, pharmacology and life Sciences. 2(6):30-37.
6. Barbounis TG, Theocharis JB (2007) a locally recurrent fuzzy neural network with application to the wind speed prediction using spatial correlation. Neurocomputing. 70(7-9):1525-1542.
7. Beyer h, Costanzo C, Heinemm LP D, Resise C (1994) Short range forecaste of PV energy production using satellite image analysis. In 12th European photovoltaic Solar Energy Conference. Amesterdam, Netherlands.1718-1721.
8. Bilgili M, Sahin B (2013) Wind speed Prediction of Target Station from Reference Stations Data. Energy Sources. 35(5):455-466.
9. Burton T, Jenkins N, Sharpe D, Bossanyi E (2001) Wind Energy Handbook. Second Edition. Wiley Publication. United Kingdom. 1-729.
10. Ch S, Sohani SK, Kumar D, Malik A, Chahar BR Nema AK, Panigrahi BK, Dhiman RC (2014) a Support Vector Machine-Cuckoo Algorithm based forecasting model determine malaria transmission. 129:279-288.
11. Dokour E, K urban M, Ceyhan S (2015) Hybrid model for short term wind speed forecasting using empricial mode decomposition and artificial neural network.420-423.
12. Damousis IG, Alexiadis MC, Theocharis JB, Dkopoulos PS (2004) a fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. IEEE Transaction on Energy Conversion. 19(2):352-361.
13. Ghorbani MA, Khatibi R, Hosseini B, Bilgili M (2013) Relative importance of parameters affecting wind speed prediction using artificial neural networks. Theor Appl Climatol 114(1):107–114.
14. Ghorbani MA, Khatibi R, Aytek A, Makarynskyy O, Shiri J (2010) sea water level forecasting using genetic programming with Artificial Neural Networks. Computer & Goesciences. 36(5):620-627.
15. Gocić M, Motamedi SH, Shamshirband SH, Petković D, Ch S, Hashim R, Arif M (2015) Soft computing approaches for forecasting reference evapotranspiration. Computers and Electronics in Agriculture. 113: 164-173.
16. Guo J, Zho J, Qin H, Zou Q, Li Q (2001) Monthly streamflow forecasting based on improved support vector machine model. Expert Systems with Applications. 38(10):13073-13081.
17. Guo Z, Zhao J, Zhang W, Wang J (2011) Acorrected hybrid approach for wind speed prediction in Hexi Corridor of China. Energy. 36(3):1668-1679.
18. Guven A, ASCE M, Gunal M (2008) Genetic programming Approac for prediction of local Scour Downsttream of Hydraulic Structures. Journal of irrigation and Drainage Engineering.134 (2):241-249.
19. Hu J, Wang J, Zeng G (2013) a hybrid forecasting approach applied to wind speed time series. Renewable Energy. 60:185-194.
20. Hasanzadeh T, CAez K, Seyfi G (2012) a speech recognition system based on structure Equivalent Fuzzy Neural Network trained by Cuckoo. Biomedical Engineering. International conference. 63-67.
21. Islam MS, Mohandes M, Rehman S (2016) Vertical extrapolation of wind speed using artificial neural network hybrid system. Neural Computing and Applications.1-11. DOI: 10.1007/s00521-016-2373-x.
22. Kariniotakis GN, Stavrakakis GS, Nogaret EF (1996) Wind power forecasting using advanced neural networks models. IEEE Transactions on Energy Conversion. 11(4):762-767.
23. Kayarvizhy N, Kanmani S, Uthariaraj R (2014) MLP models optimized using swarm intelligence algorithms. WSEAS Transactions on Computers. 13: 501-519.
24. Kaushik A, Tayal DKR, Yadav K, and Kaur A (2016) Integrating Cuckoo algoritm in artificial

neural network models for accurate software cost predictions. Journal of Software. 28(8):665-688.
25. Kalra R, Deo MC (2007) Genetic programming for retrieving missing information in wave records along the west coast of india. Applied Ocean Research. 29(3):99-11.
26. Karla R, Deo MC, Kumar R, Agarwal VK (2008) Genetic programming to estimate coastal waves from deep water measurments. Journal of Ecology & Development. 10:67+.
27. Khatibi R, Ghorbani MA, Kashani MH, Kisi O (2011) Comparison or three artificial intelligent techniques for discharge routing. Journal of Hydrology. 403(3-4):201-212.
28. Khatibi R, Ghorbani MA, Naghipour L, Jothiprakash V, CAthima TA, CAzeli C Ard MH (2014) Inter-comparison of time series models of lake levels predicted by several modeling strategies. Journal of Hydrology. 511: 530-545.
29. Lukasik S, Zak S (2009) Cuckoo Algorithm for Continuous Constrained Optimization Tasks. International Conference on Computational Collective Intelligence. pp. 97–106. DOI: 10.1007/978-3-642-04441-0_8.
30. Mohandes MA, Shafiqur R, Halawani TO (1998) a neural networks approach for wind speed prediction. Renewable Energy. 13(3):345-354.
31. Mohandes MA, Halawani TO, Rehman S, Hussain AA (2004) Spport vector machines for wind speed prediction. Renewable Energy. 29(6):939-947.
32. More A, Deo MC (2003) Forecasting wind with neural networks. Marine Structure. 16(1):35-40.
33. Mable MC, Fernandez E (2008) analysis of wind power generation and prediction using MLP: A case study. Renewable Energy. 33(5):986-992.
34. Nady S, Karmakar M, Sarkar PP, Das A, Abraham A, Paul D (2012) Agent based adaptive Cuckoo back-propagation neural network training method for dynamic systems. Hybrid intelligent.12TH international conference.449-454.
35. Soleymani SA, Goudarzi S, Anisi MH, Hassan WH, Idna Idris MY, Shamshirband S, Noor NM, system. 12th international conference.449-454.
36. Ustoorikar K, Deo MC (2008) Filling up gaps in wave data with genetic programming. Marine Structures. 21(2-3):177-195.
37. Wang X, Wang Y, Wang L (2004) improving fuzzy c-means clustering based on feature-weight learning. Pattern Recognition Letters. 25(10):1123-1132.
38. Willmott CJ, Robeson SM, Matsuura K (2012) A refined index of model performance. 32(13):2088-2094.
39. Yang XS (2010) Cuckoo algorithm, stochastic test functions and design optimization. Journal Bio-Inspired Computation. 2(2): 78–84.

5/23/2017