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A new contingency selection algorithm for voltage security

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Abstract: A simple and efficient method for optimal selection of weights, along with higher order performance indices for voltage contingency selection, has been suggested in this paper. Some of the existing performance indices for voltage contingency selection has been critically reviewed. In this paper Artificial Neural Network (ANN)-based approach for contingency selection in voltage security assessment. The proposed approach applied Radial Basis Function (RBF) networks to forecast the voltage stability level of the system under contingency state. The RBF networks are trained off-line to capture the nonlinear relationship between the pre-contingency system state and the post-contingency stability level. Maximum L-index of the load buses in the system is taken as the indicator of voltage instability. A mutual information-based method is proposed to select the input features of the neural network. The effectiveness of the proposed approach is demonstrated through contingency ranking in IEEE 30-bus system. Simulation results show that the proposed method takes less time for training compared to back propagation neural network and has good generalization abilities.
Index Terms-- Contingency selection, Feature selection, Radial Basis Function network, Mutual information

I. INTRODUCTION

In MODERN energy management systems, contingency screening and analysis are basic and important functions. In the last two decades, many efficient methods for handling static contingencies have been developed. Most of the methods utilize the system equipment limits (e.g., transmission line current limits) and system operational limits (e.g., bus voltage magnitude limits) to form the contingency ranking index [1-7]. In recent years, research attention has been focused on the dynamic contingency analysis, which requires much more computation to handle the differential equations. Voltage stability analysis, however, has been somewhat amenable to static (power flow based) analysis. In voltage stability analysis, the behavior of interest is more on a region (or subsystem) than a single bus or rotating machine.

In recent years, research endeavors in the area of contingency selection have been directed towards artificial neural network [8],[9],[10],[11],[13]. Most of the authors have used feedforward neural networks with sigmoidal nonlinearities for model development. Any continuous function can be approximated to within an arbitrary accuracy by carefully choosing the parameters in the network provided the network structure is sufficiently large. But the shortcoming of this network is that it takes long time for training. Also, feedforward network with sigmoidal activation function in the hidden nodes has no inherent ability to detect the outliers. Even though training is done in off-line, short training time is preferred as one may have to retrain the networks on a regular basis as the topology or the system condition changes. Outliers can occur in practice, because it is hard to produce a complete training set representing all possible operating conditions of a power system.

In this paper, we propose Radial Basis Function (RBF) networks [12] to capture the nonlinear relationship between the pre-contingency system state and the post-contingency severity level following a contingency. RBF networks take less time for training and the distance-based activation function used in the hidden nodes gives the ability to detect the outliers during estimation [13]. While training the neural network, by selecting only the relevant attributes of the data as input features and excluding redundant ones, higher performance is expected with smaller computational effort. In this paper, we propose "mutual information" between the input variables and the output as the criterion to select the input features of the networks. The effectiveness of the proposed method is demonstrated through contingency selection in IEEE 30-bus test system.

The remainder of this paper is organized as follows: In Section II, the use of L-index for voltage stability analysis is reviewed. In Section III, the details of RBF networks and the methodology followed to configure the network from the input-output training data is explained. Various issues involved in developing the ANN-based model for contingency selection are given in Section IV. Section V presents the details of the application of the proposed model for contingency selection in IEEE 30-bus test system.

II. VOLTAGE STABILITY INDEX

A. Localized Concept

It is well known that for most system contingencies, the effects of outages on the system are of a local nature, which means that the major effects of a perturbation are limited to a certain neighborhood close to the original perturbation point. This concept has been well exploited in static security analysis, from the concentric relaxation method [11] to the complete bounding method [2]. Since the major concern in static security analysis is the violation of system operational limits, like the thermal limits of lines and the upper and lower voltage magnitude limits at buses, it is not necessary to take into account the control relations between load buses and generation buses. The system is just divided into the inner subsystem near the contingency, the outer subsystem that is not affected and the boundary subsystem, according to the contingency and system topology. Then the situation in the inner subsystem can be scrutinized by using sparse vector techniques [12].

In the study of voltage stability problems, we can also take advantage of the local nature of contingency effects. However, the local area (subsystem) studied must include the controlling buses (usually the generation buses) as well as those load buses that they control, and sometimes the boundary (interface) flow information. Thus, we may consider such a subsystem as a self-contained voltage control area with its reactive reserve basin. The contingency severity then can be studied based on the subsystem conditions. The problem then is how to properly define such a subsystem. Since all the buses in one voltage control area should structural observability and controllability have low impedance paths to each other, the electrical distance developed in [10] may be a good measure to decide the proper voltage control area.

The static voltage stability analysis involves determination of an index known as voltage stability index. This index is an approximate measure of closeness of the system operating point to voltage collapse. There are various methods of determining the voltage collapse proximity indicator. One such method is the maximum L-index of the load buses in the system proposed in [3]. It is a measure of the voltage collapse and is based on load flow analysis. Its value ranges from 0 (no load of system) to 1 (voltage collapse). The bus with the highest L index value will be the most vulnerable bus in the system. The L-index calculation for a power system is briefly discussed below:

Consider a N-bus system in which there are N_g generators. The relationship between voltage and current can be expressed by the following expression:

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \quad (1)$$

where I_G, I_L and V_G, V_L represent currents and voltages at the generator buses and load buses. Rearranging the above equation we get,

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (2)$$

where

$$F_{LG} = -\left[Y_{LL}\right]^{-1}\left[Y_{LG}\right] \quad (3)$$

is the sub matrix of the above hybrid matrix H.

The L-index of the jth node is given by,

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ji} \frac{V_i}{V_j} \angle\left(\theta_{ji} + \delta_i - \delta_j\right) \right| \quad (4)$$

where

V_i – Voltage magnitude of ith generator bus

V_j – Voltage magnitude of jth generator bus

θ_{ji} – Phase angle of the term F_{ji}

δ_i – Voltage phase angle of ith generator bus.

N_g – Number of generating units.

It was demonstrated that when a load bus approaches the voltage collapse point, the L-index approaches the numerical value of 1. Hence, for a system-wide voltage stability assessment, the index evaluated at any of the buses must be less than unity, and the maximum value of the L-index gives an indication of how far the system is from voltage collapse.

III. REVIEW OF RADIAL BASIS FUNCTION NETWORK

Radial basis function network [12] is a class of single hidden layer feedforward neural network. Fig 1 shows the schematic diagram of a RBF neural network. The input nodes pass the input directly and the first layer connections are not weighted. The transfer functions in the hidden nodes are similar to the multivariate Gaussian density function,

$$\phi_j(x) = \exp\left(-\frac{\left\|x-\mu_j\right\|^2}{2\sigma_j^2}\right) \qquad (5)$$

where x is the input vector, μ_j and σ_j are the center and the spread of the corresponding Gaussian function. Each RBF unit has a significant activation over a specific region determined by μ_j and σ_j, thus each RBF represents a unique local neighbourhood in the input space. The connections in the second layer are weighted and the output nodes are linear summation units.
The value of the k^th^ output node y_k is given by

$$y_k(x) = \sum_{j=1}^{h} w_{kj}\phi_j(x) + w_{k0} \qquad (6)$$

where w_{kj} is the connection weight between the k^{th} output node and j^{th} hidden node and w_{k0} is the bias term.

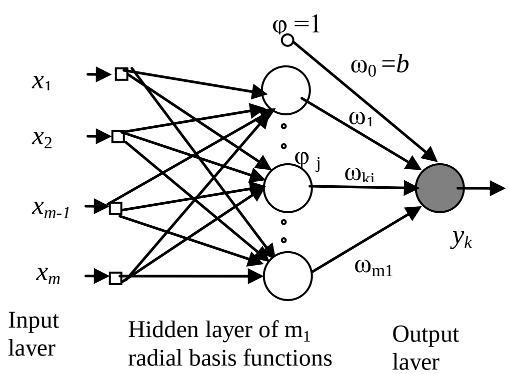

Fig1.Schematic Diagram of RBF neural network

The training in RBF networks is done in three sequential stages as against the single optimization procedure followed in back propagation network training. The first stage of the learning consists of determining the unit centers μ_j by the K-means clustering algorithm. Next, we determine the unit widths σ_j using a heuristic approach that ensures the smoothness and continuity of the fitted function. The width of any hidden node is taken as the maximum Euclidean distance between the identified centers. Finally, the weights of the second layer connections are determined by linear regression using a least-squares objective function.

RBF networks can be viewed as an alternative tool for learning in neural networks. While RBF networks exhibit the same properties as back propagation networks such as generalization ability and robustness, they also have the additional advantage of fast learning and ability to detect outliers during estimation.

IV. PROPOSED METHODOLOGY FOR CONTINGENCY SELECTION

The proposed method for contingency selection is based on RBF neural networks. The objective is to estimate the voltage stability level for each contingency and rank them according to their severity level. The study presented in this paper focuses on single line outages and the voltage stability level is expressed by the maximum L-index value.

For model development, a large number of training data is generated through off-line power system simulation. Pre-contingency state power flows are the input to the neural network and the maximum value of L-index following a contingency is the output of the network. A feature selection algorithm based on mutual information between the variables is applied to select the input features of each network. The selected features after normalization are presented to the RBF networks for training. After training, the networks are evaluated through a different set of input-output data. The above steps are repeated for every selected contingency. Once the networks are trained and tested, they are ready for estimating the L-index values at different operating conditions. These estimated values of L-index for different contingencies are ordered from highest to lowest. For the purpose of contingency selection, a threshold is set and those contingencies having the value of L-index greater than that threshold are selected for further analysis and the others are discarded. The various steps involved in the development of ANN-based model are presented in the following subsections.

A. Training Data Generation

The generation of the appropriate training data is an important step in the development of ANN models. For the ANN to accurately predict the output the training data should represent the complete range of operating conditions of the system under consideration. The training data for the development of ANN is generated through the following procedure:

- First, a range of situations is generated by randomly perturbing the load at all buses from the base case value and by adjusting the generator output in proportion to the output in the base case condition. For each load-generation pattern, load flow study is conducted to obtain the pre-contingency quantities.
- Next, for each load-generation pattern, the single line-outages specified in the contingency list is simulated sequentially and the L-index values are evaluated by conducting AC load flow.

B. Feature Selection

As most of the contingencies are localized in nature, all the variables in the input vector may not exert equal influence on the post-contingency L-values. Irrelevant and redundant attributes in the input not only complicate the network structure, but also degrade the performance of the networks. By selecting only the relevant variables as input features and excluding irrelevant ones, higher performance is expected with smaller computational efforts. The “mutual information” between the input variables and the output provides the basis for feature selection in this work.

(i) *Definition of Mutual Information*

The two stage feature selection technique has an irrelevancy filter and redundancy filter to remove irrelevant and redundant candidate inputs of S_I in the first and second stages, respectively. Both the filters are based on the mutual information (MI) criterion. Despite linear feature selection techniques, such as correlation analysis, MI can also evaluate nonlinear dependencies [2]. Both price spike occurrence and value have nonlinear relationships with their inputs. The MI of two continuous random variables *a* and *b*, denoted by $MI(a;b)$, is defined based on their joint probability density function $P(a,b)$ and respective individual probability density functions $P(a)$ and $P(b)$ as follows [7]:

$$MI(a;b) = \iint P(a,b)\log_2\left(\frac{P(a,b)}{P(a)P(b)}\right)da\,db$$

MI between two discrete random variables *a* and *b* with *N* and *M* discrete values, respectively, is as follows:

$$MI(a;b) = \sum_{n=1}^{N}\sum_{m=1}^{M} P(a_n,b_m)\log_2\left(\frac{P(a_n,b_m)}{P(a_n)P(b_m)}\right)$$

More details about the computation of MI can be found in [7].

Suppose that $x_i \in S_I$ is a candidate input and *y* is the target variable or forecast feature of the forecast process. For the prediction of price spike occurrence and value, *y* is a binary variable and real variable, respectively. More mutual information between x_i and *y*, i.e. more $MI(x_i;y)$, means that x_i is a more relevant feature for the forecast of *y*. Thus, the first stage or irrelevancy filter of the feature selection technique selects candidate inputs of S_I that their $MI(x_i;y)$ values are higher than a relevancy threshold *TH*1 and filters out the other irrelevant features. The second stage or redundancy filter removes redundant features among the selected candidate inputs of the irrelevancy filter. More mutual information between two candidate inputs x_i and x_k, or more $MI(x_i;x_k)$, results in their more redundant information. Therefore, the following redundancy criterion $RC(.)$ is defined:

$$RC(x_i) = \max_{x_m \in S_1 - \{x_i\}}\left[MI(x_i;x_m)\right]$$

where $S_1 \subset S_I$ denotes the subset of features selected by the irrelevancy filter in the first stage. Note that $x_m \in S_1 - \{x_i\}$ in (3), since each feature is fully redundant with itself and so we should exclude x_i from S_1. If $RC(x_i)$ becomes greater than a redundancy threshold $TH2$, x_i is considered as a redundant candidate input and so between this candidate and its rival, one feature should be filtered out. For instance, suppose that:

$$\arg \max_{x_m \in S_1-\{x_i\}} \left[MI(x_i;x_m) \right] = x_r$$

(4) In other words, x_i has the highest redundancy (mutual information) with x_r among all features of the subset S_1–{x_i}. We call x_r as the rival of x_i. If $MI(x_i;x_r)>TH2$, between x_i and its rival x_r, one feature should be eliminated. For this purpose, the relevancy factors of these features, i.e. $MI(x_i;y)$ and $MI(x_r;y)$, are considered and the feature with lower relevancy factor (less relevant feature or less effective feature for the forecast process) is filtered out. The redundancy filtering process is repeated for all features of S_1 until no redundancy measure of (3) becomes greater than $TH2$. The remaining features of S_1, owning RC[.] less than $TH2$, constitute the selected features of the two stage feature selection technique, denoted by S_C in Fig. 1. The subset S_C includes relevant and non-redundant candidate inputs of S_I. The thresholds $TH1$ and $TH2$ are degrees of freedom of the two stage feature selection technique. These thresholds and the adjustable parameters of the forecast engine are fine-tuned by a cross-validation procedure [2]. Since, both the stages of this feature selection technique are based on the MI criterion, hereafter we call it MI-MI also shown in Fig. 1.

MI-MI is an efficient dimension reduction method. However, it considers the whole common information of two candidate inputs as their redundant information. In this paper, a more accurate formulation of redundancy is proposed evaluating common information between two candidate inputs about forecast feature as their redundant information. This matter is graphically shown in Fig. 2. In this figure, x_i and x_k are two candidate inputs and y is the forecast feature. H(.) represents entropy function for a random variable measuring its uncertainty. Mathematical details of entropy function can be found in [7]. MI(.;.) functions and their relations with H(.) functions are also shown in Fig. 2. As seen from this figure, the whole common information between two candidate inputs x_i and x_k or $MI(x_i;x_k)$ is area 1+4. However, what is important for the forecast process is the common information of x_i and x_k about the target variable y. In other words, area 4 in Fig. 2 represents the real redundancy between x_i and x_k for the forecast process. In [7], it has been discussed that if two candidate inputs x_i and x_k are closely related, the area 1 in the figure is large and this can degrade the performance of the feature selection technique. In other words, two features may have a lot of common information (large area 1), while they have little common information about the target variable (small area 4). So, a feature with little redundant information about the target variable may be considered highly redundant and filtered out. Therefore, considering such measures for redundancy evaluation can be misleading and some examples in this regard are given in [7]. Several researchers in the area of machine intelligence and learning tried to solve this problem. As some examples, in an earlier work [8], Battiti used the sum of MI values between a feature and a set of pre-selected features as the redundancy measure of the feature. To compensate the effect of the overestimated redundancy, a user-defined parameter (β) was utilized to weight the redundancy term. In [9] a criterion, same as the Battiti's proposed criterion, was used to measure the redundancy, but the penalty factor (β) of [8] was changed in [9] such that the average of MI values between the candidate feature and pre-selected features was considered as the redundancy measure. However, the problem still remains and the redundancy measure is not exact. Kwak and Choi [7] changed the redundancy criterion. They used conditional mutual information (CMI) concept to correctly measure the redundancy among features (common information about the target variable). However, the CMI based approach of [7] is based on the following condition:

$$\frac{MI(x_i;x_k \mid y)}{MI(x_i;x_k)} = \frac{H(x_i \mid y)}{H(x_i)}$$

The above condition is hard to satisfy when information is concentrated on one of the regions. A more detailed discussion about these research works and their limitations can be found in [10]. Also, a combination of normalized mutual information and genetic algorithm is proposed for feature selection in this reference. However, their method is computationally expensive, since many trial solutions should be examined by the genetic algorithm.

In this paper, a new criterion with low computation burden is proposed to accurately measure redundancy between two candidate inputs in a forecast process without any limitation. This criterion is based on information theoretic criterion of interaction gain (IG). IG is defined for two random variables x_i and x_k in the context of the third variable y as follows [11,12]:

$$IG(x_i;x_k;y) = MI[(x_i,x_k);y] - MI(x_i;y) - MI(x_k;y)$$

where x_i,x_k is an argument of $MI[(x_i,x_k);y]$ and y is its another argument. In other words, $MI[(x_i,x_k);y]$ measures mutual information that joint variables x_i and x_k have with y.

The proposed redundancy criterion for two candidate inputs x_i and x_k, denoted by $RE(x_i;x_k)$, is defined as follows:

$$RE(x_i;x_k) = |IG(x_i;x_k;y)|$$

where |.| is the absolute value sign. For the acceptance of this redundancy criterion, we must show that: 1) It can correctly measure real redundancy between two candidate inputs 2) It can be computed with a reasonable computation burden.

B. Data Normalization

The first stage of RBF network learning is the identification of the cluster centers through K-means clustering algorithm which uses Euclidean distance as a measure of dissimilarity. Distance norms are sensitive to variations in the numerical ranges of the different features. For example, the Euclidean distance assigns more weighting to features with wide ranges than to those with narrow ranges. To overcome this problem, input data is normalized before presenting it to the clustering algorithm. The input data is normalized between 0 and 1 using the expression,

$$x_n = \frac{(x - x_{\min}) \times range}{(x_{\max} - x_{\min})} + \text{starting value}$$

where, x_n is the normalized value and $x_{\min}$ *and* $x_{\max}$ are the minimum and maximum values of the variable x.

D. Network Training and Evaluation

For the prediction of maximum L-index for each line outage, separate RBF network is trained. The selected variables after normalization are presented to the network. Twenty iterations of the clustering algorithm followed by linear regression are performed to estimate the parameters of the network. As the value of basis functions is not known in advance, a trial-and-error procedure is followed to select the optimum number. After training, the networks are tested with the test data set to assess the generalization capability of the developed network.

V. SIMULATION RESULTS

This section presents the details of the simulation study carried out on IEEE 30-bus system for contingency selection using the proposed method. IEEE 30-bus system consists of 6 generators, 24 load buses and 41 transmission lines. The transmission line parameters and generator cost coefficients are given in [14]. For this test system, based on the contingency analysis conducted at different loading conditions, seven single line outages (1-2), (1-3), (10-20), (28-27), (4-12), (6-7) and (9-10) were identified as severe cases. The details of the ANN models developed to estimate the voltage stability level for these seven contingencies are presented here.

A. Performance of RBF Network

Based on the algorithm given in section IV.A, a total of 1000 input-output pairs were generated, with 750 for training and 250 for testing. The L-index proposed in [3] and presented in Section II is used as the voltage stability index. To select the input features, the input variable is divided into five levels and output is divided into three groups. Mutual information of each variable with respect to the output is evaluated using (7) and (8). For illustration, the mutual information between the input variables and the output for contingency (1-2) is shown in Fig 2. From this figure, it is evident that only a few variables are having significant information and the remaining variables have very less amount of information. The first few variables which have high mutual information value are selected as features to train the ANN, and the remaining variables are discarded from further consideration. The selected features for the seven models are presented in Table I.

After training, the generalization performances of the networks are evaluated with the 250 test data. The results of training and testing phase for all the seven models are presented in Table I. The results clearly show that the training of the RBF networks has been successful and the correct estimation of L-index has been achieved by the RBF network even for previously unseen data.

Table II presents the L-index values estimated using the developed ANN models for one particular loading condition along with the ranking of the contingencies. For comparison, the actual values of L-index calculated from AC load flow study are also presented. The result shows the agreement between the actual ranking and the ranking based on the output of the neural networks.

TABLE I. TRAINING AND TESTING PERFORMANCE OF RBF NETWORK

S.No	Line Outage	Selected Features	No of basis functions	Training Time (sec)	Testing Error (mse)
1	1-2	S_1:1,2,4,5,7	20	03280	1.8469×10^{6}
2	1-3	S_1:1,2,4,7	20	03120	1.9885×10^{5}
3	4-12	S_1: 11,12,14,15,18,28	30	0.4840	6.9183×10^{4}
4	6-7	S_1: 5,9	25	03750	7.3690×10^{5}
5	9-10	S_1: 12,14,27	25	0.4060	4.5218×10^{4}
6	10-20	S_1: 5,12,14,15,18,22,24	25	0.4060	3.7121×10^{4}
7	28-27	S_1:12,14,36,37,38,41	25	03910	4.669×10^{-4}

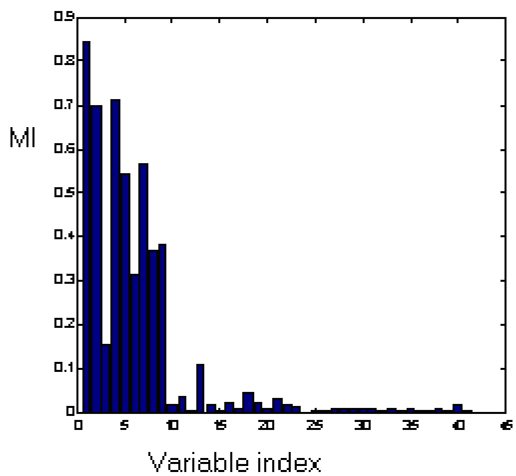

Fig. 2 Mutual information for variables in model 1-2

TABLE II
COMPARISON OF RBF OUTPUT AND LOAD FLOW RESULT

LINE OUTAGE	RBF OUTPUT		LOAD FLOW RESULTS	
	RANKING	L_{MAX}	RANKING	L_{MAX}
1-2	1	0.28	1	0.29
1-3	5	0.18	5	0.16
4-12	2	0.20	2	0.21
6-7	6	0.15	6	0.16
9-10	3	0.18	3	0.19
10-20	4	0.16	4	0.17
28-27	7	0.16	7	0.15

B. Comparison with Multilayer Perceptron Network

To compare the performance of the proposed RBF network-based approach with the commonly used neural network architecture, multilayer perceptron (MLP) networks are developed to estimate the L- index values. The networks are trained with the conjugate gradient algorithm to reach the same error level achieved by the RBF networks during the training. After training, the networks are tested with the test data.

TABLE III
COMPARISON OF RBF WITH MLP FOR MODEL (1-2)

TYPE OF NETWORK	NO OF HIDDEN NEURONS	CPU TIME	TESTING ERROR

RBF	20	0.332	0.000176
MLP	8	2.332	0.000394

The CPU time for training one particular model (1-2) is presented in Table III. From this table, it is observed that RBF networks take less time for training, but they require more number of hidden nodes as compared to multilayer perceptron networks. Apart from that the RBF network exhibits better generalization performance than the MLP network in most of the cases.

VI. CONCLUSION

This paper has presented a radial basis function network-based fast contingency selection method for voltage security assessment. A set of RBF networks have been trained to map the nonlinear relationship between the pre-contingency operating conditions and the post- contingency stability index. The problem of feature selection is addressed through mutual information between the input variables and the output security index. Simulation results on the IEEE 30-bus test system show that the proposed RBF network-based approach provides accurate estimation of post-contingency L-values for various operating conditions. Also, the proposed approach significantly reduces the development time.

VII.REFERENCES

1. Razmjooy, N., & Ramezani, M. (2019). Interval structure of Runge-Kutta methods for solving optimal control problems with uncertainties. Computational Methods for Differential Equations, 7(2), 235-251.
2. Seyyedeh Zeinab Fatemi Mostafa Shamsi Navid Razmjooy. “Collocation method for differential variational inequality problems”, International Journal of Numerical Modelling: Electronic Networks, Devices and Fields, https://doi.org/10.1002/jnm.2466.
3. Mohammad Makaremi, Navid Razmjooy, Mehdi Ramezani. “A new method for detecting texture defects based on modified local binary pattern,” Signal, Image and Video Processing, doi.org/10.1007/s11760-018-1294-9.
4. Navid Razmjooy, Fatima Rashid Sheykhahmad, Noradin Ghadimi. A hybrid neural network – world cup optimization algorithm for melanoma detection. Open Medicine. DOI: https://doi.org/10.1515/med-2018-0002. (ISI:IF:0.28)
5. Razmjooy, N., and M. Ramezani. "Solution of the Hamilton jacobi bellman uncertainties by the interval version of adomian decomposition method." Int Rob Auto J 4, no. 2 (2018): 113-117.
6. Razmjooy, Navid, and Mehdi Ramezani. "Uncertain Method for Optimal Control Problems With Uncertainties Using Chebyshev Inclusion Functions." Asian Journal of Control (2019). (ISI,Q1)
7. Razmjooy, Navid, and Mehdi Ramezani. "Optimal Control of Two-Wheeled Self-Balancing Robot with Interval Uncertainties Using Chebyshev Inclusion Method." Majlesi Journal of Electrical Engineering12, no. 1 (2018): 13-21. (SCOPUS, ISC)
8. Razmjooy, N., & Ramezani, M. (2017). Analytical solution for optimal control by the second kind Chebyshev polynomials expansion. Iranian Journal of Science and Technology, Transactions A: Science, 41(4), 1017-1026.
9. Navid Razmjooy, Mohsen Khalilpour, Mehdi Ramezani, “A New Meta-Heuristic Optimization Algorithm Inspired by FIFA World Cup Competitions: Theory and Its Application in PID Designing for AVR System”, J Control Autom Electr Syst, DOI 10.1007/s40313-016-0242-6, Vol. 27, Issue 4, pp 419-440, 2016.
10. Navid Razmjooy and Mehdi Ramezani, “An Improved Quantum Evolutionary Algorithm Based on Invasive Weed Optimization”, Indian J.Sci.Res.4 (2): 413-422, 2014.
11. Navid Razmjooya, B. Somayeh Mousavib,F. Soleymani, “A real-time mathematical computer method for potato inspection using machine vision”, *Computers and Mathematics with Applications* 63, pp. 268–279, 2012
12. N. Razmjooy, B. Somayeh Mousavi, P. Sargolzaei, F. Soleymani, “Image thresholding based on evolutionary algorithms”, *International Journal of the Physical Sciences*, Vol. 6(31), pp. 7203 - 7211, 30 November, 2011.
13. Payman Moallem; Navid Razmjooy; Bibi Somayeh Mousavi, “ Robust Potato Color Image Segmentation using Adaptive Fuzzy Inference System”, Iranian Journal of Fuzzy Systems, Articles in PressAvailable Online from 20 August 2014.
14. B. Somayeh Mousavi, P. Sargolzaei, Navid Razmjooy, V. Hosseinabadi, F. Soleymani, “Digital Image Segmentation Using Rule-Base Classifier”, *American Journal of Scientific Reaserches*, Issue 35, pp.17-23, 2011. (*ISI Listed Journal*).
15. Payman Moallem, Navid Razmjooy, “A Multi Layer Perceptron Neural Network Trained by Invasive Weed Optimization for Potato Color Image Segmentation”, *Trends in Applied Sciences Research*, vol7,pp. 38374-38374, 2012 (*ISI Journal, IF: 0.45*).

16. Navid Razmjooy, B. Somayeh Mousavi, Mohsen Khalilpour, Hossein Hosseini, “Automatic selection and fusion of color spaces for image thresholding”, *Signal, Image and Video Processing*, Vol.1 (1), pp.1-12, DOI 10.1007/s11760-012-0303-7.
17. B. Somayeh Mousavi, Fazlollah Soleymani, Navid Razmjooy, “Color image segmentation using neuro fuzzy system in a novel optimized color space”, *Neural Comput & Applic*, DOI 10.1007/s00521-012-1102-3 .
18. B. Somayeh Mousavi, Fazlollah Soleymani, Navid Razmjooy, “Semantic image classification by genetic algorithm using optimised fuzzy system based on Zernike moments”, *Signal, Image and Video Processing*, DOI 10.1007/s11760-012-0311-7 .
19. Payman Moallem, Navid Razmjooy and Mohsen Ashourian, “Computer vision-based potato defect detection using neural networks and support vector machines”, *International Journal of Robotics and Automation*, Vol. 28, No. 2, 2013.
20. P. Moallem, N. Razmjooy, “Optimal threshold computing in automatic image thresholding using adaptive particle swarm optimization”, *Journal of Applied Research and Technology*, vol.10, pp.703-712, Oct.2012.
21. H. Hosseini, M. Farsadi, A. Lak, H. Ghahramani, N. Razmjooy, “A novel method using imperialist competitive algorithm (ICA) for controlling pitch angle in hybrid wind and PV array energy production system”, *International Journal on Technical and Physical Problems of Engineering*, vol.4, no.2, pp.145-152, 2012.
22. M. Khalilpour, N. Razmjooy, A. Danandeh, M. Rostamzadeh, “Optimal Bidding Strategy in Power Market before and after Congestion Management using Invasive Weed Optimization, *Research Journal of Applied Sciences*, *Engineering and Technology*, vol. 5, no, 4, pp. 130-1338, 2013.
23. M. Khalilpour, Kh. Valipour1, H. Shayeghi, N. Razmjooy, “Designing a Robust and Adaptive PID Controller for Gas Turbine Connected to the Generator”*, Research Journal of Applied Sciences*, *Engineering and Technology*, Vol. 5(5), pp. 1543-1551, 2013.
24. M. Rostamzadeh, K. Valipour, J. Shenava, M. Khalilpour, N. Razmjooy, “Optimal Location and Capacity of multi-Distributed Generation for Loss Reduction and Voltage Profile Improvement Using Imperialist Competitive Algorithm”*, Artificial Intelligence Research*, vol.1n2, pp.56, DOI: 10.5430/air.
25. Razmjooy, Navid, B. Somayeh Mousavi, Fazlollah Soleymani, and M. Hosseini Khotbesara. "A computer-aided diagnosis system for malignant melanomas." Neural Computing and Applications23, no. 7-8 (2013): 2059-2071.
26. Navid Razmjooy, bb. Somayeh Musavi, F. Soleymani “A Hybrid Neural Network-Imperialist Competitive Algorithm for Skin Color Segmentation”, Mathematical and Computer Modelling, vol. 57, pp.848–856, 2013.
27. M. Khalilpour, N. Razmjooy, “Congestion Management Role in Optimal Bidding Strategy using Imperialist Competitive Algorithm”, *majlesi journal of energy management*, Vol.1 (2), 2012.
28. Hossein Hosseini, Morteza Farsadi, Mohsen Khalilpour, Navid Razmjooy, “ Hybrid Energy Production System with PV Array and Wind Turbine and Pitch Angle Optimal Control by Genetic Algorithm (GA)”, *Journal of World’s Electrical Engineering and Technology*, Vol.1 (1), pp. 1-4, 2012.
29. Hossein Hosseini, Behrooz Tusi, Navid Razmjooy, Mohsen Khalilpoor , “ Optimum Design of PSS and SVC Controller for Damping Low Frequency Oscillation (LFO)”, Journal of World’s Electrical Engineering and Technology, Vol.1 (1), pp. 5-11, 2012.
30. Hosseini, Hossein, Behrooz Tousi, and Navid Razmjooy. "Application of fuzzy subtractive clustering for optimal transient performance of automatic generation control in restructured power system." Journal of Intelligent & Fuzzy Systems26, no. 3 (2014): 1155-1166.
31. Hosseini, Hosssein, Behrooz Tousi, Navid Razmjooy, and Mohsen Khalilpour. "Design robust controller for automatic generation control in restructured power system by imperialist competitive algorithm." IETE Journal of Research59, no. 6 (2013): 745-752.
32. Kamal Yavarian, Mohsen Khalilpour and Navid Razmjooy,” Transmission Line Congestion Management by Specifying Optimal Placement of FACTS Devices Using Artificial Bee Colony Optimization”, Research Journal of Applied Sciences, Engineering and Technology, vol.6(23), pp. 4350-4357, 2013.
33. Mohsen Khalilpour and Navid Razmjooy,” A Hybrid Method for Gesture Recognition”, Journal *of World’s Electrical Engineering and Technology*, Vol.2 (3), 2013.
34. Navid Razmjooy, S. Shahram Naghibzadeh, bb. Somayeh Musavi, “Digital Red Eye Correction in Digital Photos” International Journal of Computer Applications, Vol. 95(9), 2014 .
35. Payman Moallem; Navid Razmjooy; Bibi Somayeh Mousavi, “ Robust Potato Color Image Segmentation using Adaptive Fuzzy Inference System”, *Iranian Journal of Fuzzy Systems*, Vol. 11, No. 6, pp. 47-65, 2014.
36. Razmjooy, Navid, Mehdi Ramezani, and Noradin Ghadimi. "Imperialist competitive algorithm-based optimization of neuro-fuzzy system parameters for automatic red-eye removal." International Journal of Fuzzy Systems 19, no. 4 (2017): 1144-1156.
37. Navid Razmjooy, Madadi A., Alikhani H., Mohseni M. "Comparison of LQR and Pole Placement Design Controllers for Controlling the Inverted Pendulum”, *Journal of World’s Electrical Engineering and Technology*, Vol.3 (2), 2014.

38. Maryam honarmand1, Navid Razmjooy, Bibi Somayeh Moosavi, " Texture Classification Using Optimized Neural Networks Based on Firefly Algorithm*", Technical Journal of Engineering and Applied Sciences*, Vol. 4 (4), Pp. 485-492, 2014, 2014.
39. Navid Razmjooy, Mehdi Ramezani, "Using Quantum Gates to design a PID Controller for Nano robots", *International Research Journal of Applied and Basic Sciences*, Vol, 8 (12): 2354-2359, 2014
40. F. Ebrahiminezhad, N. Razmjooy," An Intelligent-based Mechatronics System for Grading the Iranian's Export Pistachio Nuts into Hulled and Non-hulled Groups", *Indian J. Sci. Res* 7, no. 1 (2014): 1063-1071.
41. Navid Razmjooy , Mohsen Khalilpour, "A Robust Controller For Power System Stabilizer By Using Artificial Bee Colony Algorithm", *Tech J Engin & App Sci.*, vol.5, no.3, pp. 106-113, 2015
42. Navid Razmjooy , Mohsen Khalilpour, "Optimum Control of Hydro-Turbine Connected to the equivalent network for Damping Frequency Oscillation Using Invasive Weed Optimization (IWO) Algorithm", *Intl. Res. J. Appl. Basic. Sci*. Vol., 9 (7), 1204-1211, 2015
43. Razmjooy N, Ramezani M, Nazari E. using lqg/ltr optimal control method for car suspension system. SCRO Annual Report Journal. 2015 Feb 26;3.
44. Rashid Sheykhahmad, Fatima, Navid Razmjooy, and Mehdi Ramezani. "A Novel Method for Skin Lesion Segmentation." International Journal of Information, Security and Systems Management 4.2 (2015): 458-466.
45. Razmjooy, Navid, and Mohsen Khalilpour. "A new design for PID controller by considering the operating points changes in Hydro-Turbine Connected to the equivalent network by using Invasive Weed Optimization (IWO) Algorithm." International Journal of Information, Security and Systems Management 4.2 (2015): 468-475.
46. Navid Razmjooy and Mehdi Ramezani, "Training Wavelet Neural Networks Using Hybrid Particle Swarm Optimization and Gravitational Search Algorithm for System Identification", *International Journal of Mechatronics, Electrical and Computer Technology*, Vol. 6(21), Jul. 2016, PP. 2987-2997.
47. N. Razmjooy, M. Ramezani, A. Namadchian, "A New LQR Optimal Control for a Single-Link Flexible Joint Robot Manipulator Based on Grey Wolf Optimizer", *Majlesi Journal of Electrical Engineering*, Vol. 10, No. 3, September 2016, 53-60.
48. A. Namadchian, M. Ramezani, N. Razmjooy, "A New Meta-Heuristic Algorithm for Optimization based on Variance Reduction of Guassian Distribution", *Majlesi Journal of Electrical Engineering*, Vol. 10, No. 4, Dec.2016, 49-56.
49. Razmjooy, Navid, Ali Madadi, and Mehdi Ramezani. "Robust Control of Power System Stabilizer Using World Cup Optimization Algorithm.", International Journal of Information, Security, and Systems Management (2016), 5(1), pp. 524-531,
50. do Nascimento, D. A., Iano, Y., Loschi, H. J., Razmjooy, N., Sroufe, R., Oliveira, V. D. J. S., ... & Montagner, M. (2019). Sustainable Adoption of Connected Vehicles in the Brazilian Landscape: Policies, Technical Specifications and Challenges. Transactions on Environment and Electrical Engineering, 3(1), 44-62.
51. Monteiro, A. C. B., França, R. P., Estrela, V. V., Iano, Y., Khelassi, A., & Razmjooy, N. Health 4.0 as an Application of Industry 4.0 in Healthcare Services and Management. Vol 2 (4), Medical technologies journal, 2019.
52. Abedinia, Oveis, Nima Amjady, and Ali Ghasemi. "A new metaheuristic algorithm based on shark smell optimization." *Complexity* 21.5 (2016): 97-116.
53. Abedinia, Oveis, et al. "Solution of economic load dispatch problem via hybrid particle swarm optimization with time-varying acceleration coefficients and bacteria foraging algorithm techniques." *International Transactions on Electrical Energy Systems* 23.8 (2013): 1504-1522.
54. Abedinia, Oveis, Bart Wyns, and Ali Ghasemi. "Robust fuzzy PSS design using ABC." *Environment and Electrical Engineering (EEEIC), 2011 10th International Conference on*. IEEE, 2011.
55. Abedinia, Oveis, Nima Amjady, and Hamidreza Zareipour. "A new feature selection technique for load and price forecast of electrical power systems." *IEEE Transactions on Power Systems* 32.1 (2017): 62-74.
56. Abedinia, Oveis, and Nima Amjady. "Short-term wind power prediction based on Hybrid Neural Network and chaotic shark smell optimization." *international journal of precision engineering and manufacturing-green technology* 2.3 (2015): 245-254.
57. Shayanfar, Heidar Ali, et al. "Design Rule-Base of Fuzzy Controller in Multimachine Power System Stabilizer Using Genetic Algorithm." *IC-AI*. 2010.
58. Abedinia, Oveis, and Nima Amjady. "Short-term load forecast of electrical power system by radial basis function neural network and new stochastic search algorithm." *International transactions on electrical energy systems* 26.7 (2016): 1511-1525.
59. Abedinia, Oveis, Ali Ghasemi, and Nasser Ojaroudi. "Improved time varying inertia weight PSO for solved economic load dispatch with subsidies and wind power effects." *Complexity* 21.4 (2016): 40-49.
60. Abedinia, Oveis, et al. "Design of robust PSS to improve stability of composed LFC and AVR using ABC in deregulated environment." *13th International conference on Artificial Intelligence (ICAI 2011)*. 2011.
61. Amjady, Nima, and Oveis Abedinia. "Short term wind power prediction based on improved Kriging interpolation, empirical mode decomposition, and closed-loop forecasting engine." *Sustainability* 9.11 (2017): 2104.

62. Abedinia, Oveis, Morteza Dadash Naslian, and Masoud Bekravi. "A new stochastic search algorithm bundled honeybee mating for solving optimization problems." *Neural Computing and Applications* 25.7-8 (2014): 1921-1939.
63. Armaghani, Saber, Nima Amjady, and Oveis Abedinia. "Security constrained multi-period optimal power flow by a new enhanced artificial bee colony." *Applied Soft Computing*37 (2015): 382-395.
64. Abedinia, Oveis, and Ebrahim S. Barazandeh. "Interactive Artificial Bee Colony based on distribution planning with renewable energy units." *Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES*. IEEE, 2013.
65. Abedinia, O., N. Amjady, and Mohammad S. Naderi. "Multi-objective environmental/economic dispatch using firefly technique." *Environment and Electrical Engineering (EEEIC), 2012 11th International Conference on*. IEEE, 2012.
66. Abedinia, Oveis, and Nima Amjady. "Net demand prediction for power systems by a new neural network-based forecasting engine." *Complexity* 21.S2 (2016): 296-308.
67. Tohidi, Akbar, et al. "Experimental study of a disturbance rejection controller for dfig based wind energy conversion systems." *ASME 2014 Dynamic Systems and Control Conference*. American Society of Mechanical Engineers, 2014.
68. Abedinia, Oveis, and Nima Amjady. "Day-ahead price forecasting of electricity markets by a new hybrid forecast method." *Modeling and Simulation in Electrical and Electronics Engineering* 1.1 (2015): 1-7.
69. Abedinia, Oveis, David Raisz, and Nima Amjady. "Effective prediction model for Hungarian small-scale solar power output." *IET Renewable Power Generation* 11.13 (2017): 1648-1658.
70. Abedinia, O., et al. "Multiobjective environmental and economic dispatch using imperialist competitive algorithm." *International Journal on Technical and Physical Problems of Engineering (IJTPE)* 11 (2012): 63-70.
71. Ghasemi, A., et al. "Optimal placement and tuning of robust multimachine PSS via HBMO." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2011.
72. Abedinia, O., Mohammad S. Naderi, and A. Ghasemi. "Robust LFC in deregulated environment: Fuzzy PID using HBMO." *Environment and Electrical Engineering (EEEIC), 2011 10th International Conference on*. IEEE, 2011.
73. Abedinia, O., et al. "Multi-machine power system oscillation damping: Placement and tuning PSS VIA multi-objective HBMO." *International Journal of Technical and Physical Problems of Engineering* 4.3 (2012): 12.
74. Shayanfar, H. A., et al. "PSO-IIW for Combined Heat and Power Economic Dispatch." *International Journal on Technical and Physical Problems of Engineering (IJTPE)* 4.11 (2012): 51-55.
75. Ghasemi, A., et al. "PSO-TVAC Algorithm for Multi Objective PSS Design in Multi-Machine Power System." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2011.
76. Abedinia, O., et al. "Fuzzy PID based on firefly algorithm: load frequency control in deregulated environment." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2012.
77. Shayanfar, H. A., et al. "Optimal PID power system stabilizer tuning via artificial bee colony." *Technical and Physical Problems of Engineering"(IJTPE)* 12 (2012): 75-82.
78. Tohidi, Akbar, et al. "Multivariable adaptive variable structure disturbance rejection control for DFIG system." *Complexity*21.4 (2016): 50-62.
79. Abedinia, O., et al. "Optimal congest management based VEPSO an electricity market." *Int J Tech Phys Probl Eng* 4.2 (2012): 56-62.
80. Shayanfar, H. A., et al. "Solving optimal unit commitment by improved honey bee mating optimization." *International Journal on Technical and Physical Problems of Engineering (IJTPE)* 4 (2012): 38-45.
81. Abedinia, O., et al. "Modified invasive weed optimization based on fuzzy PSS in multi-machine power system." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2012.
82. Shayanfar, H. A., et al. "GSA to tune fuzzy controller for damping power system oscillation." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2011.
83. Abedinia, O., N. Amjady, and Mohammad S. Naderi. "Multi-stage Fuzzy PID Load Frequency Control via SPHBMO in deregulated environment." *Environment and Electrical Engineering (EEEIC), 2012 11th International Conference on*. IEEE, 2012.
84. Shayeghi, H., et al. "Optimal thermal generating unit commitment with wind power impact: a PSO-IIW procedure." *International Journal on Technical and Physical Problems of Engineering (IJTPE)* 4.2 (2012): 90-97.
85. Bipirayeh, K., O. Abedinia, and H. A. Shayanfar. "Optimal Multi-Stage Fuzzy PID Bundled PSOTVAC in Multimachine Environment." *International Journal on Technical and Physical Problems of Engineering (IJTPE)* 14: 37-43.

86. Shayanfar, H. A., et al. "Economic load dispatch using strength pareto gravitational search algorithm with valve point effect." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2012.
87. Shayanfar, H. A., et al. "Wind power prediction model based on hybrid strategy." *Proceedings of the International Conference on Scientific Computing (CSC)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2016.
88. Amjady, N., et al. "Market Optimization Using Fuzzy Based Multiobjective Harmony Search Algorithm." *International Journal on Technical and Physical Problems of Engineering (IJTPE)* 12: 9-15.
89. Bekravi, M., and O. Abedinia. "A new multi-objective meta heuristic algorithm based on environmental/economic load dispatch with wind effect." *Technical and Physical Problems of Engineering* 5.2 (2013): 15.
90. Abedinia, O., N. Amjady, and Mohammad S. Naderi. "Optimal congestion management in an electricity market using Modified Invasive Weed Optimization." *Environment and Electrical Engineering (EEEIC), 2012 11th International Conference on*. IEEE, 2012.
91. Duan, Min, et al. "A novel hybrid prediction model for aggregated loads of buildings by considering the electric vehicles." *Sustainable Cities and Society* 41 (2018): 205-219.
92. Abedinia, Oveis, and Nima Amjady. "Optimal Distribution of Reactive Power based on Shark Smell Optimization with Pareto Criterion in Power System." (2016): 133-144.
93. Bagheri, Mehdi, et al. "Enhancing Power Quality in Microgrids With a New Online Control Strategy for DSTATCOM Using Reinforcement Learning Algorithm." *IEEE Access* 6 (2018): 38986-38996.
94. Bagheri, Mehdi, et al. "Direct and Indirect Prediction of Net Demand in Power Systems Based on Syntactic Forecast Engine." *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*. IEEE, 2018.
95. Kuspan, Bekarys, et al. "The Influence of Electric Vehicle Penetration on Distribution Transformer Ageing Rate and Performance." *2018 7th International Conference on Renewable Energy Research and Applications (ICRERA)*. IEEE, 2018.
96. Mussin, Nauryzbay, et al. "Transformer Active Part Fault Assessment Using Internet of Things." *2018 International Conference on Computing and Network Communications (CoCoNet)*. IEEE, 2018.
97. Shayanfar, H. A., et al. "Optimal Sizing and Placement of Distribution Generation Using Imperialist Competitive Algorithm." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2012.
98. Abedinia, O., N. Amjady, and H. A. Shayanfar. "Generation Expansion Planning base on Modified Shuffled Frog Leaping in Restructured Environment." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2013.
99. Shayanfar, H. A., O. Abedinia, and N. Amjady. "Distribution Planning with Renewable Energy Units based on Modified Shuffled Frog Leaping Algorithm." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2013.
100. Abedinia, O., N. Amjady, and H. A. Shayanfar. "A Hybrid Artificial Neural Network and VEPSO based on Day-ahead Price Forecasting of Electricity Markets." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2014.
101. Shayanfar, H. A., O. Abedinia, and N. Amjady. "Optimal Damping of Oscillation in Multi-machine Power System by Renewable Energy Effects." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2014.
102. Shayanfar, H. A., et al. "Optimal Placement of Wind Turbines: Improved Honey Bee Mating Optimization." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2013.
103. Shayanfar, H. A., O. Abedinia, and N. Amjady. "Solving Unit Commitment Problem Based on New Stochastic Search Algorithm." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2015.
104. Yosefi, A., et al. "Design Robust PID Controller for Hydro-turbine governing with ABC Algorithm." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2012.

105. Abedinia, O., N. Amjady, and H. A. Shayanfar. "Optimal Design of SVC and Thyristor-Controlled Series Compensation Controller in Power System." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2015.

106. Shayanfar, H. A., et al. "Improved ABC and Fuzzy Controller Based on Consonant FACTS Devices." *Proceedings on the International Conference on Artificial Intelligence (ICAI)*. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2016.