Assessment of voltage stability based on power transfer stability index using computational intelligence models

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Article Info

ABSTRACT

In this paper, the importance of voltage stability is explained, which is a great problem in the EPS. The estimation of VS is made a priority so as to make the power system stable and prevent it from reaching voltage collapse. The power transfer stability index (PTSI) is used as a predictor utilized in a PSN to detect the instability of voltages on weakened buses. A PSI is used to obtain a voltage assessment of the PSNs. Two hybrid algorithms are developed. The (CA-NN) and the (PSO-NN). After developing algorithms, they are compared with the actual values of PTSI NR method. The algorithms installed on the 24 bus Iraqi PS. The actual values of PTSI are the targets needed. They are obtained from the NR algorithm when the input data is V_i, δ_i, P_d, Q_d for the algorithm. The results indicate that a weak bus that approaches voltage collapse and all results were approximately the same. There is a slight difference with the actual results and demonstrated classical methods are slower and less accurate than the hybrid algorithms. It also demonstrates the validation and effectiveness of algorithms (CA-NN, and PSO-NN) for assessing voltage-prioritizing algorithms (CA-NN). The MATLAB utilized to obtain most of the results.

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1. INTRODUCTION

Arrange of situations where system operators are unable to keep the voltage profile across a system within adequate operational limits constitutes the voltage stability problem in electric power systems. The imbalance between expansion of the system and growth in demand constitutes its long-term causes. Stability may be lost if a minor emergency arises in a system that is already stressed. This will cause a voltage collapse, which is the most serious result of voltage instability. The system will, after a voltage collapse, be dismantled due to the operations of protective devices in the system. It can be said that a stable power system is the spine of industrial and scientific development in every sector in today's world. The importance of frequent, thorough, power system stability studies is underscored by the frequent blackouts in many countries across the globe. The use of new technologies and controls has recently precipitated a significant growth of power systems across the globe. The need for dynamic security assessment of power systems has increased because of the rise in operations that may drive power systems into high stress conditions. A new method of evaluating the transient stability of power systems is proposed in [1-3]. It utilizes a probabilistic neural network (PNN). It explains how the PNN is utilized to evaluate transient stability. To verify the effectiveness

of the PNN method, its performance is compared with that of the MLP. A MATLAB neural network toolbox is used to develop the PNN and MLP networks.

A thorough analysis of the stability of the digital single-loop voltage control with linear P or R regulators is presented in [4]. An analysis of the effect of modulation delays and digital computation on system stability is done for the single-loop P or R voltage control schemes. In each case, the critical frequency, above which the nonnegative phase margin (PM) can be preserved, is gotten. Taking into account the effect of the discretization methods of the R controllers, the stability region of the single-loop R voltage is determined.

A new procedure for assessing and monitoring voltage stability margins based on ANNs with reduced input data set is developed in [5]. The establishment of the minimal input data set required for the monitoring and assessment of voltage stability is the ultimate purpose of this research. A method that considers the cascading failure of power systems to analysis their angle stability is proposed in [6]. The transfer probability between the elements in the set is calculated by applying the discrete Markov theory to define the cascading failure process thus establishing the system's operating condition set taking into account stochastic events based on the flow transfer theory. The fast processing characteristics of the MLP architecture and the richness provided by the dynamic simulation technique, with the aim of using it in real-life applications, is presented in [7]. The ANN field has, in the past few years, undergone rapid development. It promises potential advantages in efficient computation and the ease of acquiring knowledge. To make multilayer perception networks capable of indicating if and when a voltage collapse might happen in the future, a dynamic model of a power system was used to train it to acquire such capabilities. A sequence is proposed in [8] and a fast method of computing the minimum singular value of a Jacobian matrix is presented in [9]. A study of the application of static voltage stability indices on power systems is presented in this paper. The power system's steady-state voltage limit operating point was also examined. To extract non-dominated solutions the improvement of the particle swarm optimization algorithm and its implementation is proposed as shown in [10]. An external store is employed to save all non-dominated solutions during the process of evolution. A vague decision-making method is thereafter utilized to categorize these solutions according to their importance. A high temperature superconducting fault current limiter (HTS-FCL) capable of improving system stability and reducing short circuit currents is shown in [11]. Voltage magnitudes and phase values are used as inputs of ANN in [12]. It considerably enhanced the accuracy of the load active power margin estimation for the New England 29 bus system. Phasor measurement units (PMUs) can provide phase angles and voltage magnitudes for real time applications.

Three methods are developed in this paper. Two are hybrid algorithms (PSO-NN and CA-NN). The third method is used to evaluate the PTSI's real values. A comparison of the three algorithms was then made. The MATLAB software was used to obtain all the results. The results validate the use of the new algorithm to estimate the voltage stability assessment. The algorithms were tested on the 24 bus Iraqi power system network.

2. POWER TRANSFER STABILITY INDEX (PTSI)

There are many indicators through which it is possible to determine the voltage stability of the electrical power system, but the PTSI indicator is easy to apply and quickly obtain results compared to other indicators. It is useful, in voltage stability analysis, to assess the power systems' voltage stability by utilizing a PTSI and scalar magnitudes that can be observed as the system parameters changes. These indices can be employed by operators to intuitively determine when the system is close to voltage collapse. This knowledge will enable them to react in a timely manner. As shown in Figure 1, the PTSI is derived from the consideration of a simple two bus Thevenin equivalent system with a slack bus linked to a load bus by a one branch [13]. The proposed PTSI index can be defined as (1).

$$PTSI = \frac{2S_L Z_{Thev}(1+\cos(\beta-\alpha))}{E_{Thev}^2} \qquad (1)$$

where, α is the phase angle of the load impedance, β is the phase angle of the Thevenin impedance, E_{Thev} is the Thevenin voltage, S_L is the apparent power and Z_{Thev} is the Thevenin impedance.

In (1) the PTSI at every bus is evaluated utilizing the impedance and load impedance phase angles, load voltage and voltage Thevenin. The PTSI value ranges from 0 to 1 (voltage collapse). The PTSI index value should be kept at less than one to maintain a secure condition [14]. In this part, the voltage stability of power system is studied by gradually increasing the loads until the voltage collapse point is reached, the load is increased regarding as loading factor (λ) which leads to voltage collapse point of power systems.

$$P_L = \lambda P_{Lo} , Q_L = \lambda Q_{Lo} \qquad (2)$$

where, P_{Lo} is the initial active power at any load bus, Q_{Lo} is the initial reactive power at any load bus and λ is the loading factor.
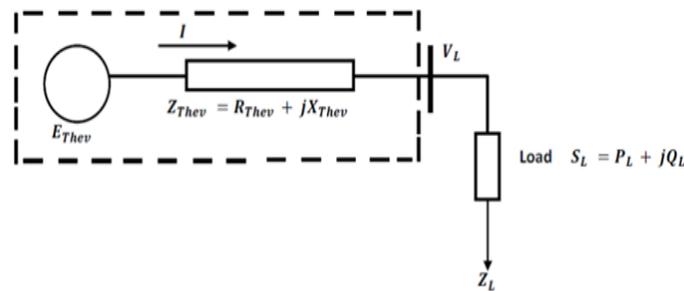
Figure 1. Single line diagram for two bus Thevenin equivalent network

3.   MATERIALS AND METHODS

The aim in this paper is to study the 400 kV network and its transmission lines and bus bars of Iraqi electrical networks. This network has 30 transmission lines with a total length of 3664.6 Km and 24 bus bars. Its configuration is shown in [15, 16]. The following materials and methods are used to simulate the results.

3.1. Artificial neural network (ANN)

Artificial neural network (ANN) serves the objective providing a model which has the ability to relate very complex input [V_i, δ_i, P_d, Q_d] and output [PTSI] datasets. Network training means finding optimal values for the various network weights and biases. Typically, different types of techniques are used to find appropriate values for ANN weights and biases [17, 18]. An ANN is a network of neurons interconnected through weights and biases [19]. A typical ANN model is shown in Figure 2.
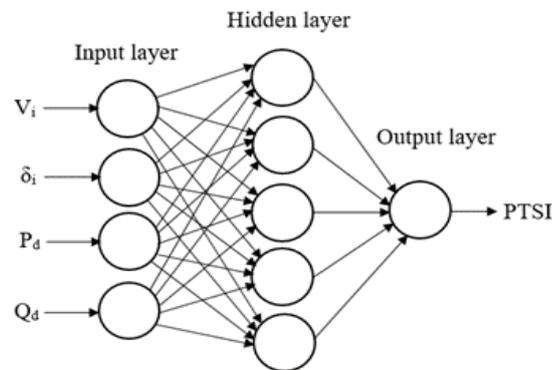
Figure 2. Architecture of ANN

3.2. Hybrid algorithm cultural-neural network (CA-NN) for PTSI

As shown in Figure 3, the CA is comprised of three major components: communication protocol, population space and belief space [20, 21]. In this technique, the desired solution can be achieved by applying basic cultural factors such as creating a population space and a belief space, accepting and updating the belief space, creating progeny vectors by mutation and selecting the best vectors. The method presented here generates the original vectors uniformly distributed within limits on the number of iterations.

Compared to other meta-heuristic algorithm, CA is a robust method. It has a better and fast convergence rate; it is more computationally efficient and it is a well-suited optimization method for many multi-objective optimization problems [22]. The cultural approach is used in this paper to find the PTSI in power system networks to make an assessment of the voltage stability. To select the best weights for a neural network, the proposed method expands cultural-neural network CA-NN. The first CA proposed is a process of social development in which behavioral traits are learned. This is presented in [23]. The CA is a high-level

searching method which passes acquired knowledge from one generation to the other making succeeding generations more knowledgeable and more equipped to survive. The basic idea of using CA with neural network is to influence the assessment operator so that the current knowledge stored in the search space can be properly exploited. The CA is used to find the best weights for neural networks; then they are both used to assess the voltage stability of power systems. The CA-NN is employed to improve the search process to increase its precision and make it faster. From the power flow, obtain $[V_i, \delta_i, P_d, Q_d]$ as the input data, and the PSTI (actual) values are the targets. The CA mathematical model is derived from (3-8).

$$l_j^{t+1} = \begin{cases} x_{i,j}^t & if\ x_{i,j}^t \leq l_j^t \\ l_j^t & otherwise \end{cases} \tag{3}$$

$$u_j^{t+1} = \begin{cases} x_{i,j}^t & if\ x_{i,j}^t \geq u_j^t \\ u_j^t & otherwise \end{cases} \tag{4}$$

$$X_i^k = u_j^{t+1} - l_j^{t+1} \tag{5}$$

$$\sigma = \alpha * X_i^k \tag{6}$$

$$dx = \sigma * randn \tag{7}$$

$$X_i^{k+1} = X_i^k + dx \tag{8}$$

where, l_j^t and u_j^t represent the lower and upper limits of parameter j in general t. The higher limit's recounting and its values are similar to the former one. It can be deducted by analogy. X_i^k and X_i^{k+1} represent the culture normative at iteration k and k+1 respectively.

The settings of CA-NN: The population size is 30, the maximum number of iterations is 70, the acceptance ration is 0.35, and alpha is 0.3.
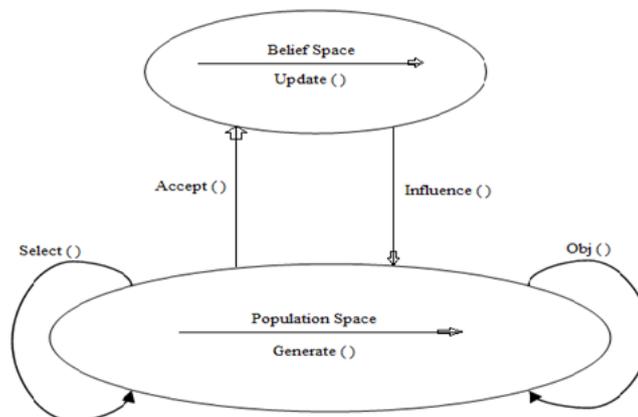

Figure 3. Framework of CA

3.3. Hybrid algorithm particle swarm optimization-neural network (PSO-NN) for PTSI

Inspired by insect swarms, the PSO is derived from the simulation of social rather than from natural evolution as is the case in the evolutionary (genetic) algorithms. The algorithm is very simple. Being a population-based algorithm, it has proven to be a great tool for solving optimization problems. The PSO model is made up of several particles (each representing a possible solution to a numerical problem) that moves about searching for space. Every particle has a velocity vector (V_i) and a position vector (X_i). Every particle, connected to the best solution (fitness) it has achieved so far, follow its coordinates in the problem space. This value is called p_{best}. The overall best value is another best value traced by the global version of the particle swarm optimizer. Its position is gotten by any particle in the population. The position is referred to as g_{best}. At each time, the PSO model involves varying the velocity of each particle towards its g_{best} and p_{best}. Weighted numbers are utilized to weight the acceleration. In (9) presents the velocity vector [24, 25].

$$V_i^{k+1} = wV_i^k + c_1r_1\left(p_{best,i}^k - X_i^k\right) + c_2r_2\left(g_{best,i}^k - X_i^k\right) \tag{9}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{10}$$

The position of every particle is in every iteration, updated utilizing this velocity vector as depicted in (10). The setting of PSO-NN: The population size is 30, the maximum number of iterations is 70, inertia weight $w=1$, the inertia weight damping ratio is 0.99, the global learning coefficient is $c2=2.0$ and the personnel learning coefficient is $c1=1.5$.

3.4. Objective function and proposed algorithms

In this paper the objective function can be defined in (11).

$$J = \sum \frac{(net\_f(inputs) - targets)^{\wedge}2}{length(net\_f(inputs)} \tag{11}$$

The proposed CA-NN algorithm and PSO-NN algorithm of calculated J for detected voltage collapse point are implemented as [26, 27]:

Step 1: collect the input data $[V_i, \delta_i, P_d, Q_d]$ and output data (i.e. target) [PTSI].
Step 2: Normalization of data, initialized weights and biases were randomly, initialization of (CA or PSO).
Step 3: Create network feed forward ANN, function activated and initial PTSI.
Step 4: Determine the objective function value.
Step 5: Cheek max iteration is reached (Yes or No), if Yes go to step 6, while if No go to step 2.
Step 6: Create network of backpropagation ANN and new weight
Step 7: Cheek the objective function (MSE) is min (Yes or No), if Yes go to step 8, while if No go to step 2.
Step 8: Print the store result (final PTSI).

4. SIMULATION RESULTS AND DISCUSSION

This paper shows the effectiveness of the proposed algorithms (CA-NN and PSO-NN) in finding the PTSI and testing on the 24 bus Iraqi power system [28, 29] to sect proof of the resilience of the proposed methods as demonstrated in Table 1.

Table 1. PTSI values based on NR, CA-NN and PSO-NN for the 24 bus Iraqi power network

PQ Bus	V p.u.	Calculated NR	CA-NN	PSO-NN
12	0.976	0.9891	0.9973	0.9687
13	0.978	0.9721	0.9920	0.9631
15	1.027	0.9883	0.9796	0.9774
16	1.033	0.9834	0.9941	0.9814
17	0.899	0.0085	0.0123	0.0525
18	0.899	0.6208	0.6325	0.6938
19	1.015	0.9941	0.9955	0.9896
20	1.010	0.9874	0.9981	0.9981
21	0.942	0.9561	0.9508	0.9928
22	1.022	0.9836	0.9413	0.9756
23	0.899	0.8189	0.7732	0.8102
24	0.895	0.8892	0.8932	0.8692
		Calculation of MSE	4.0323×10^{-4}	8.2547×10^{-4}

All the results are obtained using MATLAB programming. When the methods are compared, it is evident that the MSE between them is very small. The CA-NN has less MSE than PSO-NN. The input data and target data, in both cases, are the Hybrid intelligent algorithms' input data. The $[V_i, \delta_i, P_d, Q_d]$ from the power flow and the actual values of PSTSI are targets. A MATLAB code was developed to calculate the targets' PTSI. If a bus has a PTSI value close equal to or close to 1, it is the most vulnerable in the system. It can be used to find areas of weakness which needs attention in the system [30, 31]. The Hybrid CA-NN mentioned above has a very good algorithm that can be used to solve constrained optimization problems. It can support the general tools for constrained optimization problems as well as express, store and integrate constrained knowledge and filed knowledge. The 24 bus Iraqi network demonstrates that voltage collapse can be reached but with this condition, the voltage will have unacceptable values of less than (0.9).

As shown in Figure 4, after 60 iterations, the CA-NN algorithm's in the 24 bus has about 4.4×10^{-4} as its best solution while after 60 iterations; the PSO-NN algorithm's best solution is about 1.04×10^{-3}. The regression rate is R=0.99736 for CA-NN and R=0.99634 for PSO-NN as shown in Figures 5 and 6 respectively. With errors of 4.0323x10-4 and 8.2547x10-4 respectively as shown in Table 1, the PSTI values are almost the same.

The ranking is different according to the method used, the arrangement listed from the weakest bus to the strongest bus such that, the ranking of the NR method are {17, 18, 23, 24, 21, 13, 16, 22, 20, 15, 12, 19}, for the PSO-NN algorithm they are {17, 18, 23, 24, 22, 21, 15, 13, 16, 19, 12, 20}, and for the CA-NN algorithm they are {17, 18, 23, 24, 22, 21, 15, 13, 16, 19, 12, 20}.
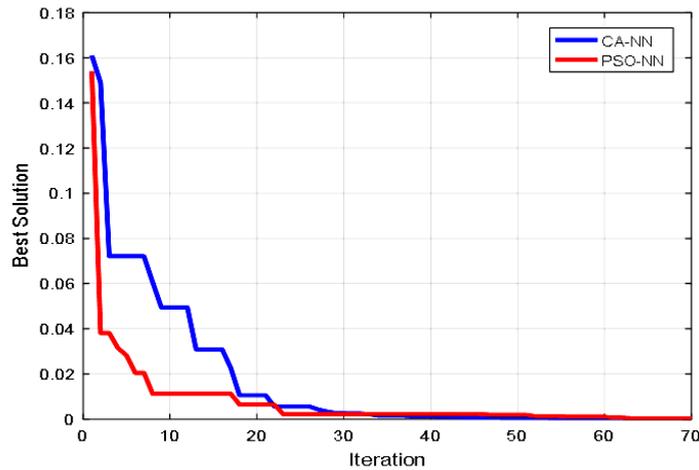

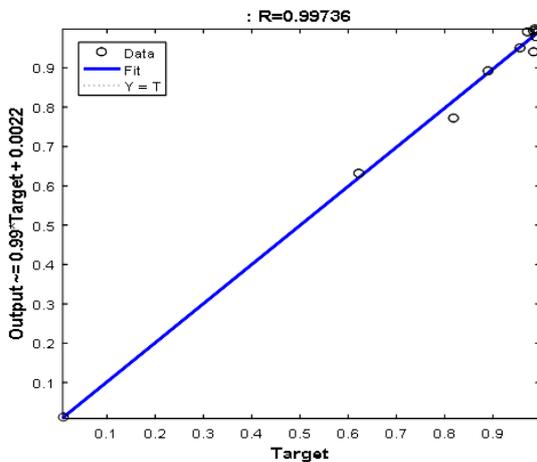Figure 4. Convergence characteristics of the best solutions
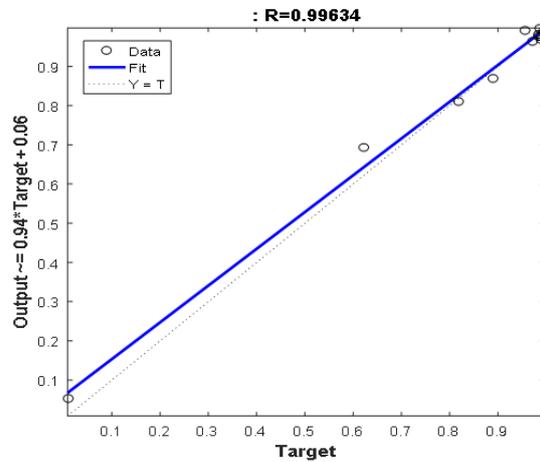

Figure 5. Regression plot for CA-NN

Figure 6. Regression plot for PSO-NN

5. CONCLUSION

The voltage instability problems refer to loading increasing, weakness networks, and the length of transmission lines. In this paper, the MATLAB code for the Hybrid intelligent algorithm (CA-NN, PSO-NN and classical method NR) is implemented to measure the PTSI as a voltage assessment method. At first the actual values of PTSI calculated from the NR method are used as the targets and the input data into the hybrid intelligent algorithm were [V_i, δ_i, P_d, Q_d]. The 24-bus Iraqi power system was the system in which the methods were tested. For every method utilised, the ranking of the power transfer stability index was done. The accuracy and speed of the hybrid methods utilized are the most important factors to their function as voltage assessment power systems. After comparing the methods, it was found that the PTSI is an effective and efficient indicator of voltage stability. The results obtained demonstrate that there is a match between the

input and out data (targets). It is proven that the hybrid methods are effective. It is also shown that the CA-NN and PSO-NN methods are, with a small error to behalf like a CA-NN algorithm, fast and efficient analyzers.

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