Power System Security Assessment (PSSSA) Module Using GEORFA Technique

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Abstract. The electrical power system network contingency evaluation and it's ranking method is very importance in present power systems network for its secured operation under various contingencies. This paper proposes golden eagle optimizer (GEO) and random forest algorithm (RFA) to assess the online/offline power system static security assessment (PSSSA) module. To calculate the ranking of security of the system for its operational constraints, two indices are used, the first one is as active power performance index and the other one is voltage performance index. These are evaluated by using Newton–Raphson method of load flow for variable loading/fault conditions under line outage. The proposed PSSSA module is applied on power system with various operating states, load conditions and line outage contingencies, to calculate the performance indices for unknown faults and network conditions and rank them in ascending/descending order based on indices used for security assessment. This method is tested on a standard IEEE 30-bus system. The results are showing it a best way for assessing the security of power system. The results are compared obtained from the models and the load flow analysis in terms of simulation time and precision proves the proposed model is fast and robust for the assessment power system security under various contingencies. The proposed approach is implemented/simulated using the MATLAB Simulink platform and the performance is compared with the existing methods.

Keywords: Power system security · Golden Eagle Optimizer · Random Decision Forest · line outage contingencies

1 Introduction

The power system network is an important system which needs to be continuously in-service. This continuous operation even after contingencies is considered to be a secured network [1]. The power system network security assessment is an indicator whether the system is stable for a given contingency. The power system is operationally secured from serious disturbances or faults [2, 3]. The power system security enhancement contains three steps, the first one is the effect of contingency, the second one is security monitoring and the third one is taking appropriate control by means of optimization and controllers

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[4]. The contingency analysis for power system security assessment is the important task of which is discussed [5].

This paper proposes golden eagle optimizer (GEO) and random forest algorithm (RFA) to realize the online/offline power system security assessment (PSSSA). The two indices used here are for security assessment, one is active power performance index and the other one is voltage performance index, the indices are computed using Newton Raphson method of load flow for line outage contingencies. Rest of the manuscript is expressed in each section namely, Sects. 1 and 2 explain the introduction and the literature survey, Sect. 3 explains the solution methodology, Sect. 4 explains the proposed methodology, and Sect. 5 explains the result and discussion and then Sect. 6 shows the final conclusion.

2 Current Research Work in Literature: A Brief Review

Numerous work has initially persisted on bibliographies and it is based on PSS with several methods and aspects. Some of them reviews are as follows, A. Karami and K. M. Galougahi [6] have developed an auxiliary (supplemental) control that was formed for SS. M.H. Prabha et al. [7] have accomplished distributed generation (DG) systems that use solar energy was the innovative trends on power generation. The Static Synchronous Compensator (STATCOM) was developed by P. Hu et al. [8] to create a hybrid cascade multilevel converter (HCMC). Present study operations shows that the power system security is the most challenging task. For power system security with renewable energy, DG, trustworthy electric UG were joined. PSS in DS consists of VS, outages, swells, harmonics, flickers etc. Several methods were used by PSS viz, HCMC, SVC, artificial neural network and RFA, LSA, etc. Hybrid cascade multilevel converter consists of immense number of H bridge sub modules for minimizing the harmonics with each sub-module consists of incredible direct current capacitor. An NFPI logic controller presented creating the reference current. These above given drawbacks are stimulated to do this exploration works.

3 Assessment of Power System Security Using Contingency Ranking

PSS may examine via rating contingencies that are primarily related totally at the contingency severity. Classical approach entails weight glide evaluation. The contingencies evaluation entails the simulation character N1 line-outage contingency for strength gadget method. Appropriately to make the evaluation easy, it includes 3 simple steps like contingency creation, contingency selection and contingency evaluation (Fig. 1).

Creation of contingency: It contains a set of likely contingencies that occurs in PS. These procedures consist of creating lists for contingencies.

Contingency selection: the selection process is severe in the list of contingencies which leads to the bus voltage as well as limits the PV.

Contingency evaluation means calculating the security indices and giving ranking to them. The security actions means the actions taken for improving the security by means of optimization and controllers.

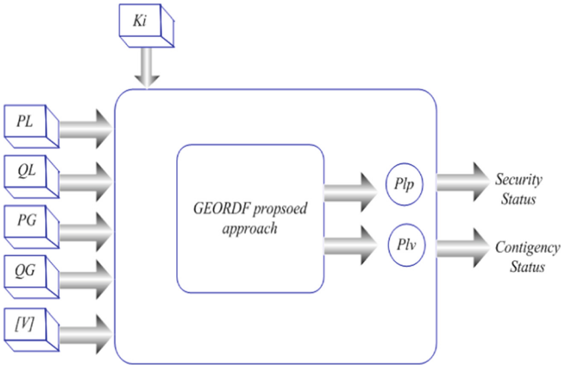

Fig. 1. Architecture of power system static security assessment module

3.1 Security Indices for Contingency Ranking and Assessment of Security

Here, to measure the security of the system, 2 efficiency indexes were utilized for defining SS as far as AP, violating the limiting voltages. Efficiency indexes were utilized for obtaining severity of contingencies such as,

Active Power Performance Index (PIP): It determines, whether the extent of line over loading is shown below,

$$pL_P = \sum_{l=1}^{n_l} \left(\frac{w}{2N}\right)\left(\frac{p_l}{p_i^{Max}}\right)^{2N} \tag{1}$$

Voltage Performance Index (PIV): It decides the limits of bus voltage violations that are displayed underneath,

$$pL_V = \sum_{l=1}^{n_l} \left(\frac{w}{2N}\right)\left(\frac{\left(|v_I| - \left|v_I^{SP}\right|\right)}{\Delta v_I^{Lim}}\right)^{2N} \tag{2}$$

In this, the min as well as the max voltage boundaries are, Vmin as 0.95 pu, Vmax as 1.05 pu. In the system the value of indices is greater and complex which is not secure.

4 Proposed Methodology of Golden Eagle Optimizer and Random Decision Forest

The details explanation of proposed Golden eagle optimizer and Random Decision Forest are expressed as follows.

4.1 Method of Golden Eagle Optimization

The inspiration drawn for optimization from the intelligence golden eagle for its attack for food movement keeps on changing/controlling its speed changes with angular direction in a flying path to hunt the prey, which is very important [9]. Many way of behave to cruise with search around the prey from the initial stage to final stage of the hunting. The initial stage of hunting is to search around the prey and the final stage of hunting is to attack the prey in different ways. The GE used these 2 ways for catching the prey in probable region using less time.

Step 1: The Golden Eagle Motion
GE optimization is depending on the GE's motion, which is like spiral. Every GE spiral movement memorizes the best solution of location that it got continuously updates it. The eagle attacks the prey and cruise for searching of its better food.

Step 2: Selection of food Prey
The food for GE will choose an appropriate prey and hunt with travel in every attempt. The prey modeled is a great solution ever discovered by gathering of GE methods in GEO. The GE is memorized as best solutions. At each iteration, from flock memory, the search agent chooses the target prey. In cruise with attacks, the vector for every GE is computed the relation of selected prey. When the memory is updated the new position is greater than the prior position. The selection method of the prey is a vital role of golden eagle optimization. Selection place may occur in its own memory in the basic way of each GE prey.

Step 3: Attack on prey
The eagle attacks is placed by set of vector begin with GE local current position obtained from the end of location gives from the food the eagle registered memory. These vectors with attack variable (AV) placed as golden eagle I represented given equation.

$$a_1 = \overrightarrow{x_F^*} - \overrightarrow{x_I} \tag{3}$$

Here, ai gives attack vector of the eagle i, $X^{\rightarrow}i$ represents existing position of golden eagle i and $XF*$ which implies the suitable location to visit so far eagle F. While the attack vector is used to guide the population of the GE towards the suitable visited location used to highlight the phase exploitation at GEO.

Step 4: Cruise (exploration)
The calculation of cruise vector (CV) depends on AV. CV consist of vectors of tangent vectors that is perpendicular and circles to the AV. The cruise is thought by the linear speed of GE corresponds to the prey. The n-dimension of CV, placed within tangents for hyper plane. Equation (4) reveals that the vector from the hyper equation of the dimension of space.

$$\begin{aligned} &\mathrm{H_1X_1 + H_2X_2 + \ldots + H_NX_N} \\ &= \mathrm{D} \Rightarrow \sum_{\mathrm{J=1}}^{\mathrm{N}} \mathrm{H_JX_J} = \mathrm{D} \end{aligned} \tag{4}$$

where, $H^{\rightarrow\rightarrow\rightarrow} = [h1,\ h2,\ \ldots,\ hn]$ specifies normal vector, $X = [x1,\ x2,\ \ldots,\ xn]$ is variables vector, $P^{\rightarrow\rightarrow} = [p1, p2, \ldots, pn]$ is the arbitrary point of $d = H^{\rightarrow\rightarrow\rightarrow}$ and hyper plane, $P^{\rightarrow\rightarrow} = \Sigma hjpjni = 1$. Let $X^{\rightarrow}\ i$ is eagle i location as the arbitrary point of hyper plane, $A^{\rightarrow}\,i$ implies AV as normal hyper plane, in which, $C^{\rightarrow}\,i$s the CV of GE i at iteration t and it is expressed in Eq. (4).

Step 5: Movement to locations
The dislocation of Golden eagle which are given in vector 1 for GE at the iteration t is given in the Eq. (5)

$$\Delta X_I = \vec{R}_1\, P_A \frac{\vec{a_I}}{\left\| \vec{a_I} \right\|} + \vec{R}_2\, P_c \frac{\vec{C_I}}{\left\| \vec{C_I} \right\|} \tag{5}$$

The *pat* is the attack coefficient of the iteration t and pct in the cruise coefficient the t iteration is changed to the golden eagles, which affects through cruise, attack. The random vector R1, R2, these element lies at [0, 1] interval. *PC* and *PA* will be discussed later. The $\|\vec{cI}\|$ and $\|\vec{aI}\|$ the Euclidean norm of cruise and attack vector are also calculated in Eq. (6)

$$\left\| \vec{a_I} \right\| = \sqrt{\sum\nolimits_{J=1}^{N} A_J^2},\ \|\vec{C_i}\| = \sqrt{\sum\nolimits_{j}^{n} = 1 c_J^2} \tag{6}$$

Step 6: The movement conducts from exploration to the exploitation
The above method gives the highest tendency to move quickly reaching path of hunt flight, which shows the maximum inclination for attacking in the other states. From the movement is improved through iteration by iteration and checked with end results. The best solution is obtained through optimizer which applied at various stages.

4.2 Prediction of Load Demand Using RFA

RDF method consists of ML ensemble procedure including predicting procedure. Two hyper parameters are in RFA such as all the nodes having the number of splitting's in the sub-set as well as trees in forest. Complexity can be distinguished in to two mean times [10]. The first complexity shows the training samples which are chosen arbitrarily and select good sequences. Second complexities showing that all trees having max forests. Old datasets consists of RDF which is predicts the loads demand in the proposed strategy and it is shown in step by step,

Step 1: In RFA classification technique, at first we consider $x(t)$ is the input (training set), Z specifies the result, i.e. $Z\,(P_l,\ P_{PV}, P_{WT})$. Where P_l specifies demands in powers; powers in photovoltaic are represented as P_{PV} and WT power is represented as P_{WT}.
Step 2: RFA classifier method is generated by the mixture of DT. Initially, Y a number of trees in the forests are deliberated for making DT and creates $Y = \{x_1(t),\ x_2(t), \cdots x_n(t)\}$ which consist of bootstrap samples.
Step 3: Training RFA related to inputs as well as targets. This method shows that in every tree, little amount of trees are crossed as well as it generates the result as Z (one for each tree). Related with most extreme vote, we get the last ideal outcome.

Step 4: Forecast procedure contains input variables such as RFA which is ranked for calculating the main variable. The significant variables are detected though it correlates with PE with OOB. Measuring Errors of OOB is shown below,

$$OOB_{error} = Z^{RDF(tar)} - Z^{RDF(out)} \tag{7}$$

For improving the RFA method, more datasets are handled in all samples.

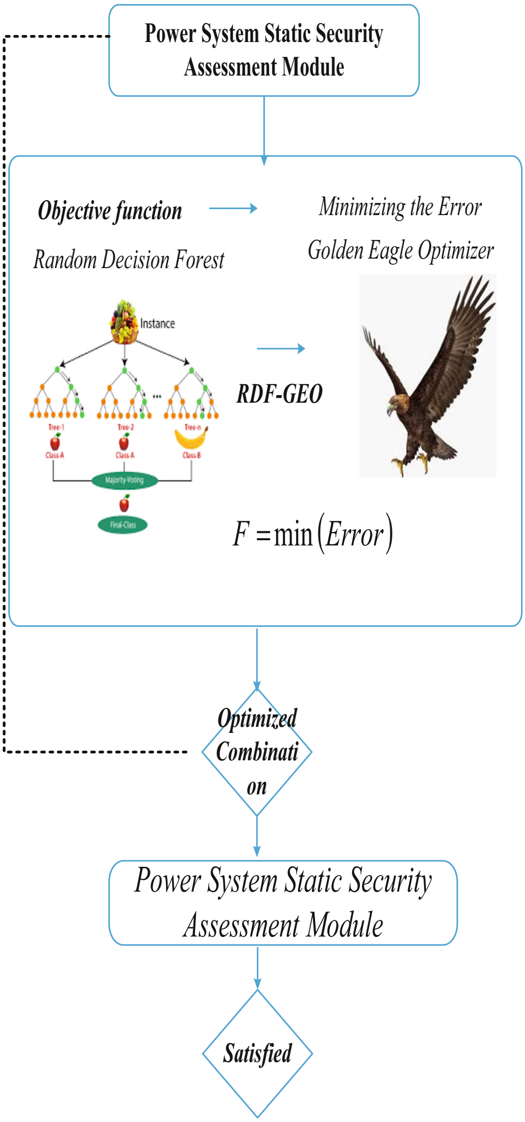

Fig. 2. Flowchart of proposed GEO-RFA method

Step 5: To raise the accuracies for prediction, its variables are calculated. Variables of data's which are important is measured, after the completion of train process which is expressed as,

$$V_{I}^{(tr)} = \frac{1}{T}\left(\frac{\sum_{xa\in\phi^{c(tr)}} \begin{array}{c} I(l_b = C_a^{tr}) - \\ \sum_{xa\in\phi^{c(tr)}} I(l_b = C_{a,nz}^{tr}) \end{array}}{\phi^{c(tr)}}\right) \tag{8}$$

where, $\phi^{c(tr)}$ specifies OOB trail specimen tree which is different, amount of trees are expressed as tr, sum of tree specifies as T, $C_a^{(tr)}$ specifies the forecast the classes to every trail specimen, values samples as X_a a, b specifies sum of trail specimens per leaves of trees, each trees in forest. VI lessens the accuracies, which are neither be less nor high (Fig. 2).

5 Result and Discussion

In this session, the power system security assesses the severity of system using proposed approach. A detail explanation in results is expressed as follows. Figure 3 shows MSE Vs iterations of proposed method. Here the MSE is 1.75×10^{-3} at no iteration, then it become degreased to zero at 11^{th} iteration. Then it is zero for all iterations. MSE vs iterations of existing method are displays in Fig. 4. Simulations are performed to obtain the minimum mean square error by changing parameter. The high Mean square error of existing approach is 1.7×10^{7} at the iteration of 12. The mean square error is present only at the iteration of 5 to 28 and other iterations it become zero. From Figs. 3 and 4, it is conclude that the proposed approach MSE is minimum than the existing method.

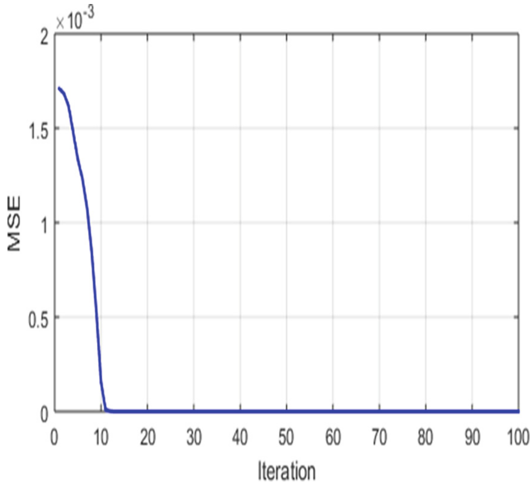

Fig. 3. MSE vs iterations of proposed method

Figure 5 shows the active power performance index vs contingency of proposed and existing approach. To test the RFA model, the N-1 line outage contingency base case optimization is simulated to obtain performance indices that are comparable to indices obtained using the MFNN and RBFN. RFA's performance is very accurate in predicting performance indices based on the indices obtained by MFNN, RBFNN analysis. Figure 6 shows the voltage performance is indexed with proposed as well as existing approach. The GEORFA approach, the voltage performance index is 2.2 at contingency 1 and it is reduced to 2.1 at contingency 10. After, it reduced to reach 1.95 at contingency 18. Again, it slightly increased to 2 and reduced to 1.5 at the contingency of 37. The voltage performance index of the proposed approach is reduced to less value than the existing approach.

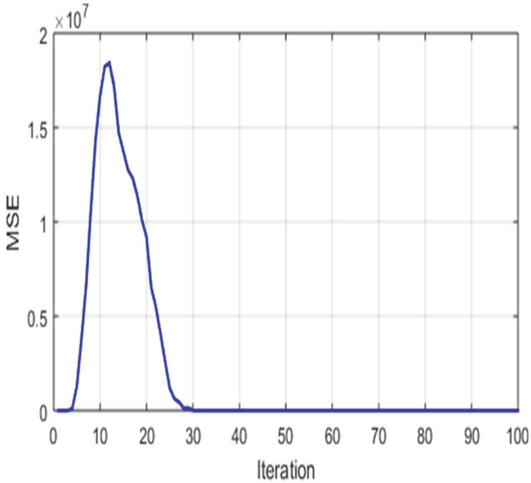

Fig. 4. MSE vs iterations of existing RBFN method

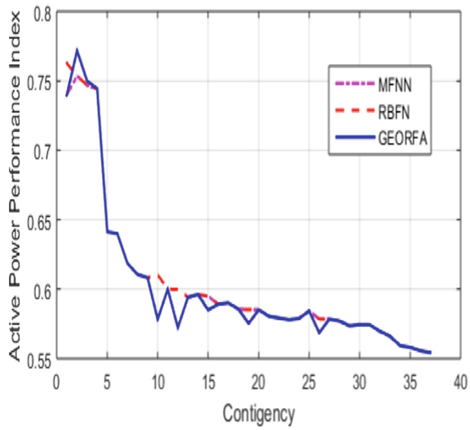

Fig. 5. Active power performance index vs contingency of proposed and existing techniques

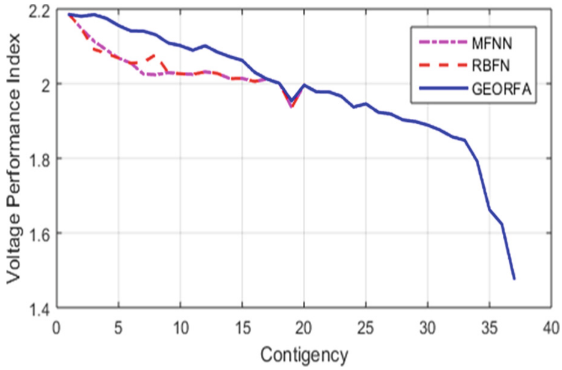

Fig. 6. Voltage performance indexed with proposed as well as existing approach

6 Conclusion

This manuscript proposed an effective PSSSA model for security assessment by contingency rankings under N1 line-outage contingency. This model makes use of twoNNlife cycles such as GEO, RFA, that are trained for more operational conditions, line-outage contingencies, for predicting the efficiency indices as well as rank of contingencies linked with severity. The proposed method is examined, where, the simulation output shows, the proposed module is fast in time, correct as well as robustness in predicting the severity, ranking the contingencies for hidden network condition. Consequently, the proposed PSSSA methods are possible by observing the online security.

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