A Combined GA-ANN Strategy for Solving Optimal Power Flow with Voltage Security Constraint

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***Abstract*—This paper presents an strategy approach to solve the optimal power flow (OPF) problem for reactive power dispatch which generally requires many power flow calculations. Artificial neural networks are employed to learn in an offline mode and substitute the role of power flow in the OPF which is formulated as a mix integer nonlinear optimization with network loss minimization as the objective. This strategy is shown later in this paper that it helps improve the computational efficiency while slightly deteriorating the quality of solution. Simulation results reveal that the proposed method can speedup the computing procedure for 5 time faster than the conventional OPF while sacrificing a little accuracy. The line (L) indicator is taken into account as the constraint to ensure feasibility of optimal control variables in terms of voltage security margin. Genetic algorithm (GA) is employed as the optimization tool. The effectiveness of the method is verified on IEEE 30-bus system and compared with the conventional OPF solution where power flow is used.**

Keywords- ***Voltage Stability, Artificial Neural Network, Genetic Algorithm, Countermeasure, Optimal Power Flow***

I. INTRODUCTION

The optimal power flow (OPF) problem is an important tool for power system planning and operation to determine the optimal control parameter settings which maximizes or minimizes the desired objective function while subject to a number of constraints [1]. Voltage and reactive power control, known also as the optimal reactive power dispatch (ORPD), is an OPF sub-problem aiming to minimize the total transmission losses by rescheduling reactive power flow. The ORPD is by nature a mix-integer nonlinear optimization problem because some of the control variables, such as transformer tap ratios, output of shunt capacitors and reactors have a discrete nature whereby generator reactive power outputs and bus voltages are continuous variables.

There are a number of mathematical programming based approaches proposed to solve the OPF problem, such as linear programming (LP), quadratic programming (QP) or interior point (IP) method. An extensive literature survey on these approaches is given in [2]. These conventional methods are intrinsically fast but inefficient to deal with the discrete variables.

In recent years, the continuous research has led to many new developments on heuristic techniques such as artificial neural networks (ANN), simulated annealing (SA), tabu search (TS), particle swarm optimization (PSO) and genetic algorithm (GA). Many of these methods can overcome the difficulties in the modeling issue of complex objective function, discrete control variables and non-continuous search space. Many challenges in OPF and especially on the application of modern heuristic optimization are discussed in great details in [3].

To solve OPF by any of heuristic technique, it is necessary to run a large number of power flow analyses in order to check the feasibility of decision variables under investigation. Considering a population based approach such as GA with the population size of 20 as the example and 150 iterations are required to achieve the global solution, then 3000 (20×150) power flow solutions must be determined. If a single power flow analysis needs, for example, 0.25 second to complete, the whole GA process would take at least 12.5 minutes (3000× 0.25/60) in addition to the computation required by GA. This computing requirement would be cumbersome in the real practice and preventing the online implementation.

This paper presents an alternative approach so called GA-ANN to alleviate such a problem. A group of artificial neural networks (ANN) are offline trained by selected system quantities to perform the task equivalent to the power flow program in a general OPF problem. The k-mean clustering method [4] is applied to select the appropriate inputs for associated ANNs. If the ANNs learn the functions properly, they are capable of fast estimating the corresponding outputs with high accuracy. The voltage security margin determined by the line (L) indicator [5] is also taken into account in order to keep the system safe from the voltage collapse problem. Thereafter, the whole optimization process is solved by GA.

This paper is organized as follows. The general OPF formulation with voltage security constraint is presented in Section II. In the same section, the diagram showing the implementation process of the proposed strategy is depicted. Section III summarizes the L-indicator and explains involving NN procedures. Simulation results are presented in Section IV. Finally, the paper is concluded in Section V and outlooks on future research are discussed.

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II. PROBLEM FORMULATION

A. Mathematical model

The OPRD minimizes the active power loss in the transmission system (P_{loss}) while satisfying a number of constraints listed below.

$$\min \quad P_{loss}(\boldsymbol{x}) \tag{1}$$

subject to

a) Generator bus voltage limits

$$u_{Gi}^{\min} \le u_{Gi} \le u_{Gi}^{\max} \qquad \forall i \in N_{PV} \tag{2}$$

b) Shunt compensator limits

$$q_{Ci}^{\min} \le q_{Ci} \le q_{Ci}^{\max} \qquad \forall i \in N_{Qc} \tag{3}$$

c) Transformer tap setting limits

$$a_i^{\min} \le a_i \le a_i^{\max} \qquad \forall i \in N_T \tag{4}$$

d) Load bus voltage limits

$$u_{Li}^{\min} \le u_{Li} \le u_{Li}^{\max} \qquad \forall i \in N_{PQ} \tag{5}$$

e) Voltage stability index limits

$$L_i \le L_i^{\max} \qquad \forall i \in N_{PQ} \tag{6}$$

where $\boldsymbol{N_{PV}}$ is the set of generator (PV) buses; $\boldsymbol{N_{Qc}}$ is the set of shunt compensators; N_T is the set of transformers; $\boldsymbol{N_{PQ}}$ is the set of load (PQ) buses. (3) and (4) are treated as discrete decision variables. The vector $\boldsymbol{x}$ contains control variables listed in (2)-(4).

The dependent (state) variables consisting of $\boldsymbol{u_L}$ and $\boldsymbol{L}$ are included in the GA process as a penalized fitness function as shown as;

$$F = P_{loss} + K_u \sum_{i \in N_{PQ}} h(u_{Li}) + K_l \sum_{i \in N_{PQ}} h(L_i) \tag{7}$$

where K_u and K_l are penalty coefficients for load bus voltage and L-indicator terms, respectively. The quadratic penalty function is defined by;

$$h(x_i) = \begin{cases} (x_i - x_i^{\max})^2 & \text{if } x_i > x_i^{\max} \\ (x_i^{\min} - x_i)^2 & \text{if } x_i < x_i^{\min} \\ 0 & \text{if } x_i^{\min} \le x_i \le x_i^{\max} \end{cases} \tag{8}$$

where x_i, x_i^{max} and x_i^{min} are ith dependent variables and the maximum and minimum limit, respectively.

B. Proposed optimization process

In stead of running power flow to determine load bus voltages and voltage stability indicator in any typical optimal power flow (OPF), the proposed GA-ANN method requires only a limited number of system information to carry out the similar task. The whole process can be shown as in Fig. 1 where NN-V1 to NN-V4 estimate load bus voltages ,NN-Lidx1 to NN-Lidx4 evaluate L-indicator values as constraints and NN-Loss gives the total active power loss as the objective. Multiple small neural networks are utilized rather than a single huge one because of better performance and training time.

The NN inputs are divided to two groups namely; control variables ($\boldsymbol{x}$) and constant variables ($\boldsymbol{c}$). The vector of control variables $\boldsymbol{x}$ containing $\boldsymbol{u_G}$, $\boldsymbol{q_C}$ and $\boldsymbol{a}$ are optimized over several iterations by the GA method. The vector of constant variables $\boldsymbol{c}$ containing selected real and reactive power demand ($\boldsymbol{p_D}$ and $\boldsymbol{q_D}$) and MVA flow over the lines ($\boldsymbol{s_F}$) are fixed because no load shedding or load reduction scheme is assumed to be conducted in this case.

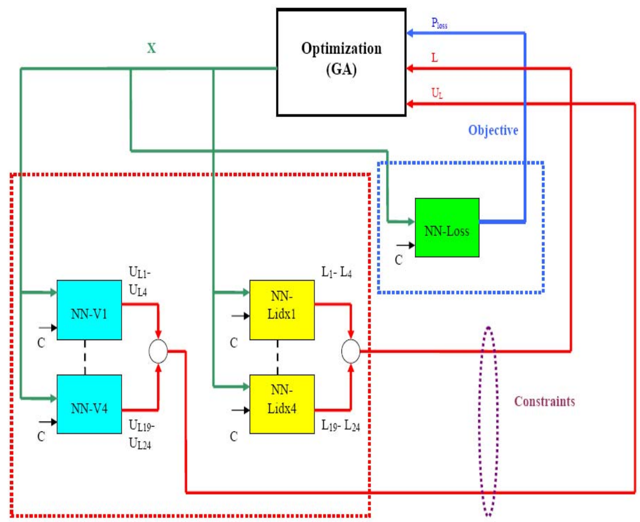


Figure 1. The proposed optimization process

III. NN PROCEDURES

A. Line indicator

In this paper, voltage security of the power system is continuously monitored through the value of line indicator (L-indicator) which it can be determined as in (9) [5]. The closer this value is to one, the closer the system is to collapse.

$$L_j = \left| 1 - \sum_{i \in \alpha_G} \underline{F}_{ji} \frac{\underline{U}_i}{\underline{U}_j} \right| \tag{9}$$

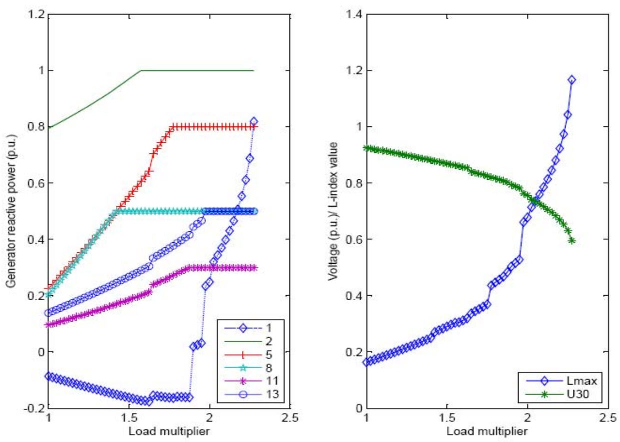
where α_G is the set of generator buses; $\underline{U}_j$ is the complex voltage of bus j and $\underline{F}_{ij}$ is component of the complex gain matrix determined by

$$\underline{\mathbf{F}}^{LG} = -\underline{\mathbf{Y}}_{LL}^{-1} \underline{\mathbf{Y}}_{LG} \tag{10}$$

where $\underline{\mathbf{Y}}_{LL}$ is the load bus self admittance matrix and $\underline{\mathbf{Y}}_{LG}$ is the mutual admittance matrix between generator and load buses.

L^{max} defined by $\mathbf{max}\{L_j\}$where $j \in \alpha_L$ (α_L is the set of load buses) is taken as a stability indicator of the whole power system.

To show characteristic of L-indicator, power demand at all load buses of the IEEE 30 bus system are increased by a load multiplier. Generator reactive power limits are imposed so that when its operating constraint is violated, it is fixed at the respective limit and bus status is converted to PQ bus as shown in Fig. 2(a). The corresponding behavior of L-indicator can be observed from Fig. 2(b) where it indicates that the system is at the verge of collapse at the system loading condition of 2.2 times higher than the base load.



(a) (b)

Figure 2. (a) Generator reactive power (b) L^{max} versus voltage at weakest bus (bus 30)

B. Database generation

Extensive supervised training must be carried out on an offline basis before ANNs can be used on the online mode. To achieve this, a database encompassing realistic operating conditions, in terms of random load, generation mix and outages, is required. In this paper, random loading conditions are simulated according to (11) and (12); [6]

$$P_d^i(k) = P_{d0}^i \Delta L(k) + 2(0.5 - \varepsilon_p^i(k)) P_{d0}^i \Delta P^i \tag{11}$$

$$Q_d^i(k) = Q_{d0}^i \Delta L(k) + 2(0.5 - \varepsilon_q^i(k)) Q_{d0}^i \Delta Q^i \tag{12}$$

where

$P_d^i(k)$ and $Q_d^i(k)$ are real and reactive power demand at bus i of load pattern k, respectively;

P_{d0}^i and Q_{d0}^i are real and reactive power demand at bus i of base load condition, respectively;

$\Delta L(k)$ is the fractional change of bus power of load pattern k (in this case varied randomly between 0.8 to 1.3);

ΔP^i and ΔQ^i are maximum allowable fractional real and reactive power change at bus i, respectively;

$\varepsilon_p^i(k)$ and $\varepsilon_q^i(k)$ are uniformly uncorrelated random variables for real and reactive power perturbation at bus i of load pattern k, respectively.

The additional power generation is assigned to each generating units based on a set of randomly generated participation factors. Random changes of key system parameters, for instance topology, generator force outage, shunt compensation and transformer settings are considered. Power flow solutions, line flow and L-indicator of the corresponding operating states are stored in the database which will be used both in training and testing.

C. Training and Testing

8000 different operating points are generated where 6000 of which are used for training associated ANNs. Back-propagation training algorithm using Lavenberg-Marquart optimization in MATLAB neural network toolbox is applied. The performance of trained ANNs is carefully examined to ensure of accuracy when they are implemented in the optimization loop.

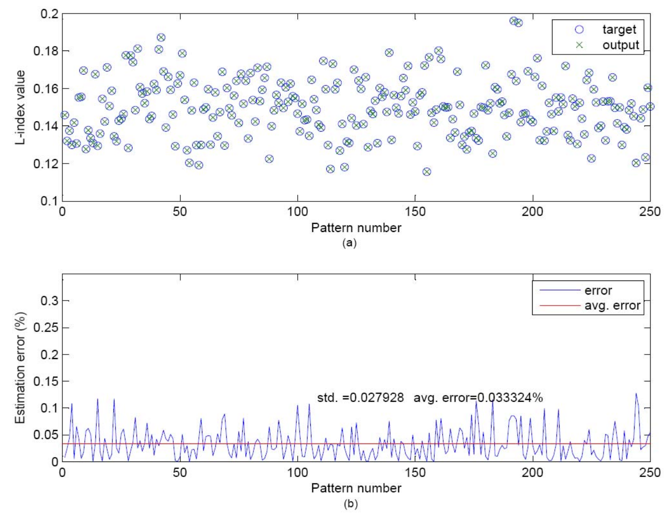


Figure 3. Generalization test of L^{max} (a) value (b) estimation error

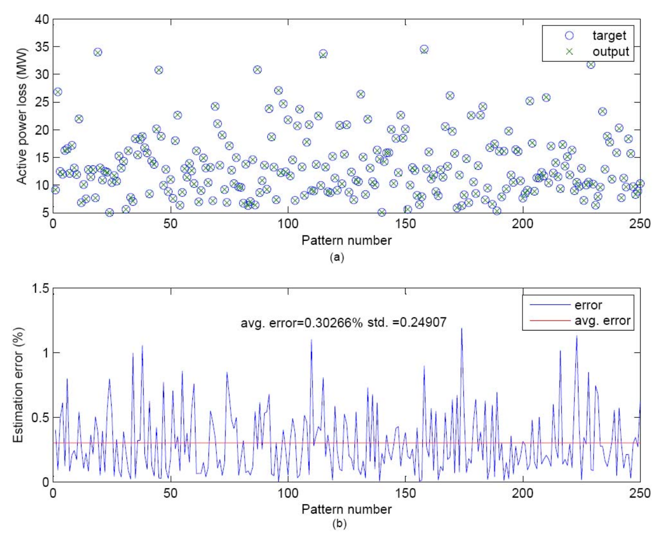


Figure 4. Generalization test of P_{loss} (a) value (b) estimation error

Figs. 3 and 4 show some examples of generalization capability test. 250 unforeseen patterns are given to the trained ANN dedicated to estimation of L-indicator in Fig. 3 and active power loss (P_{loss}) in Fig. 4. It is clearly shown that the estimation of ANN is very accurate with the average value of estimation error less than 1%.

IV. SIMULATION RESULTS

The modified IEEE 30 bus system used in this paper consist of 6 generators, 24 load buses, 41 transmission lines and 4 tap changing transformer. Among 24 load buses, 9 of which are equipped with shunt reactive power sources.

To show the effectiveness of the proposed method, the operating condition number 6900 which is stored in the generated database and never been presented during the NN training is used. P_{loss} at the initial state is 11.4151 MW as shown in Fig. 5.

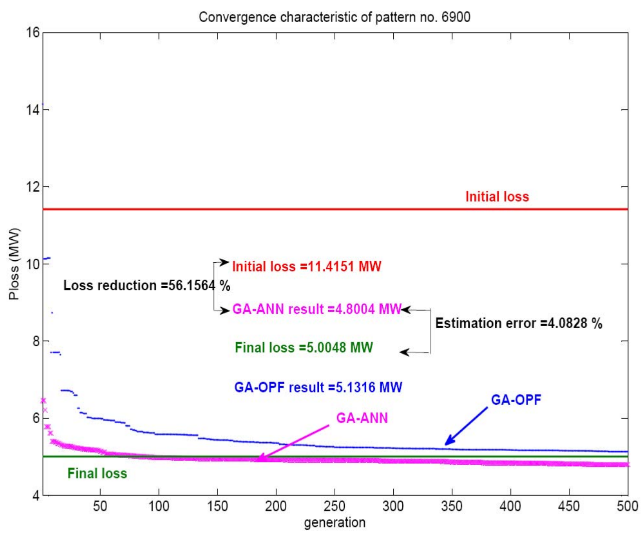


Figure 5. Simulation results

By adopting the GA-ANN to adjust the reactive power related control variables, estimated P_{loss} at the final state (after optimization) becomes 4.8004 MW. Therefore, 56.16% reduction is achieved. It has to be noted here that this value is the result of NN-Loss. Therefore, the estimation error is inevitable. The exact value of P_{loss} at the final state can be determined by setting system control parameters equal to the optimized result of control variables and running power flow at that demand level. By doing this, the final P_{loss} is 5.0048 MW. The error of estimation in this case is 4.0828 % which is acceptable in practical applications.

Comparing the GA-ANN with the conventional GA-based OPF (GA-OPF), the results of both methods are tabulated in Table I (a) and (b). The value of P_{loss} and system voltage stability indicator L^{max} are shown in Table II. It is clear that both methods result in a very close solution. Voltage stability is also improved as reflected in reduction of L^{max}. Considering the computational aspect, the proposed method is much faster than the GA-OPF (approximately 5 times faster).

Besides the computational aspect, it should be further observed that the proposed GA-ANN method requires fewer input information to perform OPF calculation. In the conventional OPF formulation, all system data, such as network parameters, generation and load level and transformer tap setting need to known as inputs for power flow program. On the other hand, GA-ANN needs only few of them to perform the same task because a representative of system quantities sharing statistical similarity determined by k-mean cluster method is used as the inputs.

TABLE I. SIMULATION RESULTS (A-B) THE OPTIMAL CONTROL VARIABLES

	GA-ANN	GA-OPF
q_{c1}	-0.03	-0.05
q_{c2}	0.18	0.11
q_{c3}	0.0075	0.0075
q_{c4}	0.065	0.05
q_{c5}	0.05	0.05
q_{c6}	0.025	0.06
q_{c7}	0.09	0.15
q_{c8}	0.175	0.0375
q_{c9}	0.02	0.04

(A)

	GA-ANN	GA-OPF
a_1	0.93	1.05
a_2	0.93	0.96
a_3	0.97	0.99
a_4	1.01	0.99
u_{G1}	1.0486	1.0026
u_{G2}	1.0432	0.9997
u_{G3}	1.0188	0.9737
u_{G4}	1.0389	0.9878
u_{G5}	1.1	1.0434
u_{G6}	1.1	1.004

(B)

TABLE II. SIMULATION RESULTS : P_{LOSS} ,L^{MAX} AND CPU TIME

	Initial	GA-ANN	GA-OPF
P_{loss} (MW)	11.4151	5.0048	5.1316
L^{max}	0.1775	0.1546	0.1529
Time (s)	-	78.92188	438.2813

CONCLUSION

This paper presents an alternative strategy to speedup the OPF process by utilizing multiple neural networks dedicatedly trained to conduct the same tasks as a power flow program. Very good generalization of trained networks has been obtained and estimation error is very minimal (less than 5% in all cases). Once properly implemented, the proposed GA-ANN is capable of performing OPF calculation with much less time and the results are quite accurate comparing to the conventional GA-OPF method. Due to the fast computation and the requirement of less information, the GA-ANN has a good potential to be integrated as a part of online security monitoring and control system. This topic is now under the authors' current investigation. The other heuristic technique, such as particle swarm or ant colony optimization can substitute GA in order to achieve better performance.

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