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Social Emotional Optimization Algorithm for Solving Optimal Reactive Power Dispatch Problem

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***Abstract*— The main feature of solving Optimal Reactive Power Dispatch Problem (ORPD) is to minimize the real power loss and also to keep the voltage profile within the specified limits. Human society is a complex group which is more effective than other animal groups. Therefore, if one algorithm mimics the human society, the effectiveness maybe more robust than other swarm intelligent algorithms which are inspired by other animal groups. So in this paper Social Emotional Optimization Algorithm (SEOA) has been utilized to solve ORPD problem. The proposed algorithm (SEOA) has been validated, by applying it on standard IEEE 30 bus test system. The results have been compared to other heuristics methods and the proposed algorithm converges to best solution.**

***Keywords*— Social emotional, Optimal reactive power, Transmission loss**

I. Introduction

Reactive power optimization plays an important task in optimal operation of power systems. Many papers by various authors has been utilized various methods to solve the ORPD problems such as, gradient based optimization algorithm [1,2], quadratic programming, non linear programming [3] and interior point method [4-7]. In recent years standard genetic algorithm (SGA) [8] and the adaptive genetic algorithm (AGA) [9], Partial swarm optimization PSO [10-11] have been applied for solving ORPD problem. Due to the problem of unparalleled generation and transmission capability growth and also due to continuous increase in demand of electrical power the ORPD problem has become very complex. The inability of the power system to meet the demand for reactive power to preserve regular voltage profile in stressed situations is playing very important role for causing voltage collapse. In the past many pioneering algorithms such as Evolutionary Algorithm [12-13], Genetic algorithm [14-15], Evolutionary strategies [16-18], Differential Evolution [19-20], Genetic programming [21] and Evolutionary programming [22] are used to solve many firm problems in optimization. In SEOA methodology, each individual represents one person, while all points in the problem space constructs the status society. In this practical world, all individuals aim to seek the higher social status. Therefore, they will communicate through cooperation and competition to increase personal status, while the one with highest score will win and output as the final solution. In the experiments, social emotional optimization algorithm (SEOA) has a remarkable superior performance in terms of accuracy and convergence speed [22-26]. In this research paper social emotional optimization algorithm has been utilized to solve the ORPD Problems. This algorithm (SEOA) is applied to obtain the optimal control variables so as to improve the voltage stability level of the system. The performance of the proposed method has been tested on IEEE 30 bus system and the results are compared with the standard GA and PSO method.

II. Problem Formulation

The Optimal Power Flow problem has been considered as general minimization problem with constraints, and can be mathematically written as :

$$\text{Minimize } f(x, u) \qquad (1)$$

$$\text{Subject to } g(x,u)=0 \qquad (2)$$

and

$$h(x, u) \leq 0 \qquad (3)$$

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \qquad (4)$$

The control variables are the generator bus voltages, the shunt capacitors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \qquad (5)$$

or

$$u = \left(V_{g1}, \dots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \qquad (6)$$

Where Ng, Nt and Nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

III. OBJECTIVE FUNCTION

A. Active power loss

The goal of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be mathematically described as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (7)$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \quad (8)$$

Where gk : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. Pd: is the total active power demand, Pgi: is the generator active power of unit i, and Pgsalck: is the generator active power of slack bus.

B. Voltage profile improvement

For minimization of the voltage deviation in PQ buses, the objective function formulated as:

$$F = PL + \omega_v \times VD \quad (9)$$

Where ωv: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (10)$$

C. Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must envelop the total power demand and the power losses:

$$P_G = P_D + P_L \quad (11)$$

D. Inequality Constraints

The inequality constraints h(x,u) imitate the limits on components in the power system as well as the limits created to guarantee system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \quad (12)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \quad (13)$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \quad (16)$$

Where N is the total number of buses, NT is the total number of Transformers; Nc is the total number of shunt reactive compensators.

IV. STANDARD SOCIAL EMOTIONAL OPTIMIZATION ALGORITHM

In human society, all people do their work hardly to boost their social status. To obtain this purpose, people will try their bests to find the path so that more social wealth's can be compensated. Inspired by this phenomenon, a new population-based swarm, social emotional optimization algorithm has been proposed and in which each individual simulates a virtual person whose choice is guided by his emotion. In social emotional optimization algorithm methodology, each individual represents a practical person in each generation selection is based on his behaviour according to the corresponding emotion directory. After the behaviour is done, a status value is feedback from the society to confirm whether this behaviour is right or not. If this choice is right, the emotion index of the person will increase or otherwise it will decrease.

All individual's emotion indexes are set to 1 in first step, with this value; they will choice the following behaviour:

$$\vec{X}_j(1) = \vec{X}_j(0) \oplus Manner_1 \quad (17)$$

Where $\vec{X}_j(1)$ represents the social position of j's individual in the initialization period, the corresponding fitness value is denoted as the society status. Symbol means the operation, in this paper, we only take it as addition operation +. Since the emotion index of j is 1, the movement phase Manner1 is defined by:

$$Manner_1 = -k_1 \cdot rand_1 \cdot \sum_{W=1}^{L} \left(\vec{X}_W(0) - \vec{X}_j(0)\right) \quad (18)$$

Where k1 is a parameter used to control the emotion changing size, rand1 is one random number sampled with uniform distribution from interval (0,1). The worst L individuals are selected to provide a reminder for individual j to avoid the incorrect behaviour. In the initialization period, there is small emotion affection, therefore, in this period, there is a little good experience can be referred, so, Manner1 simulates the affection by the wrong experiences.

In t generation, if individual j does not obtain one better society status value than previous value, the j's emotion index is decreased as follows:

$$BI_j(t+1) = BI_j(t) - \Delta \quad (19)$$

Where Δ is a predefined value, and set to 0.05, this value is coming from experimental tests. If individual j is rewarded a new status value which is the best one among all previous iterations, the emotion index is reset to 1.0:

$$BI_j(t+1) = 1.0 \quad (20)$$

If $BI_j(t+1) > 1.0$ then $BI_j(t+1) = 0.0$.

In order to simulate the behaviour of human, three kinds of manners are designed, and the next behaviour is changed according to the following cases:

If $BI_j(t+1) < TH_1$, then

$$\vec{X}_j(t+1) = \vec{X}_j(t) \oplus Manner_2 \quad (21)$$

If $H_1 \leq BI_j(t+1) < TH_2$, then

$$\vec{X}_j(t+1) = \vec{X}_j(t) \oplus Manner_3 \quad (22)$$

Otherwise

$$\vec{X}_j(t+1) = \vec{X}_j(t) \oplus Manner_4 \quad (23)$$

Parameters TH1 and TH2 are two thresholds aiming to restrict the different behaviour manner. For Case1, because the emotion index is too small, individual j prefers to simulate others successful experiences. Therefore, the symbol Manner2 is updated with:

$$Manner_2 = k_3 \cdot rand_3 \left(\vec{X}_{jbest}(t) - \vec{X}_j(t)\right) + k_2 \cdot rand_2 \cdot \left(\overrightarrow{status}_{best}(t) - \vec{X}_j(t)\right) \quad (24)$$

Where $\overrightarrow{status}_{best}(t)$ represent the best society status position obtained from all people previously.

$$\overrightarrow{status}_{best}(t) = \arg min\left\{f\left(\vec{X}_W(h)\middle|1 \leq h \leq t\right)\right\} \quad (25)$$

$Manner_3$ is defined as

$$Manner_3 = k_3 \cdot rand_{\ 3} \cdot \left(\vec{X}_{j,best}(t) - \vec{X}_j(t)\right) + k_2 \cdot rand_{\ 2} \cdot \left(status_{best}(t) - \vec{X}_j(t)\right) - k_1 \cdot rand_1 \cdot \sum_{W=1}^{L}\left(\vec{X}_W(0) - \vec{X}_j(0)\right) \quad (26)$$

Where $\overrightarrow{X}_{j,best}(t)$ denotes the best status value obtained by individual j previously, and is defined by

$$\vec{X}_{j,best}(t) = \arg min\left\{f\left(\vec{X}_j(h)\middle|1 \leq h \leq t\right)\right\} \quad (27)$$

For $Manner_4$ is defined as

$$Manner_4 = k_3 \cdot rand_{\ 3} \cdot \left(\vec{X}_{j,best}(t) - \vec{X}_j(t)\right) - k_1 \cdot rand_1 \cdot \sum_{W=1}^{L}\left(\vec{X}_W(0) - \vec{X}_j(0)\right) \quad (28)$$

Manner2 ,Manner3 andManner4 refer to three different emotional cases. In the first case, one individual's movement is protective, aiming to preserve his achievements in Manner2 due to the still mind. With the increased emotion, more rewards are expected, so inManner3 ,a temporized manner in which the dangerous avoidance is considered by individual to increase the society status. Furthermore, when the emotional is larger than one threshold, it simulates the individual is in surged mind, in this manner, he lost the some good capabilities, and will not listen to the views of others, Manner4 is designed to simulate this phenomenon.

SEOA Algorithm for reactive power problem

- Step 1. Initializing all individuals respectively, the initial position of individuals randomly in problem space.
- Step 2. Computing the fitness value of each individual according to the objective function.
- Step 3. For individual j, determining the value .
- Step 4. For all population, determining the value .
- Step 5. Determining the emotional index according to Eq. (21)-(23) in which three emotion cases are determined for each individual.
- Step 6. Determining the decision with Eq. (24)-(28), respectively.
- Step 7. Creation of mutation operation.
- Step 8. If the criterion is satisfied, output the best solution; otherwise, go to step 3.

V. SIMULATION RESULTS

SEOA algorithm has been tested on the IEEE 30-bus, 41 branch system. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. The variables limits are listed in table 1.

TABLE 1
INITIAL VARIABLES LIMITS (PU)

Control variables	***Min.value***	***Max.value***	***Type***
Generator: Vg	0.90	1.10	Continuous
Load Bus: VL	0.95	1.05	Continuous
T	0.95	1.05	Discrete
Qc	-0.12	0.36	Discrete

The transformer taps and the reactive power source installation are discrete with the changes step of 0.01. The power limits generators buses are represented in Table2. Generators buses are: PV buses 2,5,8,11,13 and slack bus is 1.the others are PQ-buses.

TABLE 2
GENERATORS POWER LIMITS IN MW AND MVAR

Bus n°	P_g	P_{gmin}	P_{gmax}	Q_{gmin}
1	98.00	51	202	-21
2	81.00	22	81	-21
5	53.00	16	53	-16
8	21.00	11	34	-16
11	21.00	11	29	-11
13	21.00	13	41	-16

TABLE 3
VALUES OF CONTROL VARIABLES AFTER OPTIMIZATION AND ACTIVE POWER LOSS

Control Variables (p.u)	***SEOA***
V1	1.0420
V2	1.0388
V5	1.0202
V8	1.0350
V11	1.0719
V13	1.0415
T4,12	0.00
T6,9	0.02
T6,10	0.90
T28,27	0.90
Q10	0.10
Q24	0.10
PLOSS	4.2908
VD	0.8990

The proposed approach succeeds in maintenance the dependent variables within their limits. Table 4 summarize the results of the optimal solution obtained by PSO, SGA and SEOA methods. It reveals the decrease of real power loss after optimization.

TABLE 4
COMPARISON RESULTS

SGA[9]	***PSO[10]***	***SEOA***
4.98 Mw	4.9262Mw	4.2936Mw

VI. CONCLUSION

In this paper, the proposed SEOA has been successfully implemented to solve ORPD problem. The main advantage of the algorithm is solving the objective function with real coded of both continuous, discrete control variables, and easily handling nonlinear constraints. The proposed algorithm has been tested on the IEEE 30-bus system .And the results were compared with the other heuristic methods such as SGA and PSO algorithm reported in the literature.

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