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Optimal Power Flow Solution Using Self-Evolving Brain-Storming Inclusive Teaching-Learning-Based Algorithm

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Abstract. In this paper, a new hybrid self-evolving algorithm is presented with its application to a highly nonlinear problem in electrical engineering. The optimal power flow problem described here focuses on the minimization of the fuel costs of the thermal units while maintaining the voltage stability at each of the load buses. There are various restrictions on acceptable voltage levels, capacitance levels of shunt compensation devices and transformer taps making it highly complex and nonlinear. The hybrid algorithm discussed here is a combination of the learning principles from Brain Storming Optimization algorithm and Teaching-Learning-Based Optimization algorithm, along with a self-evolving principle applied to the control parameter. The strategies used in the proposed algorithm makes it self-adaptive in performing the search over the multi-dimensional problem domain. The results on an IEEE 30 Bus system indicate that the proposed algorithm is an excellent candidate in dealing with the optimal power flow problems.

Keywords: Brain-Storming Optimization, Non-dominated sorting, Optimal power flow, Teaching-learning-based optimization.

1 Introduction

Computational intelligence and its derivatives have become very handy tools in the field on engineering, especially for the studies on nonlinear systems. Among the intelligent techniques, evolutionary computation has been of high interest in the field of engineering optimization problems [1]. Various algorithms such as Genetic Algorithm [2], Particle Swarm Optimization [3], Differential Evolution [4], Artificial Bee Colony [5] etc. have been already used in power engineering. The economically optimal power scheduling and stable steady state operation of an electrical grid is one of the major focus areas among them. This problem, which deals with the power flow and voltage states of an electrically connected network during steady state, is often referred to as optimal power flow (OPF) problem. OPF can have multiple objectives for which optimality is to be searched, but has major emphasis on economic schedule

of the power generation, along with minimizing the voltage deviations that could occur at the points at which loads to the system are connected. The intricate electrical interconnections, transformer taps for voltage stepping, steady state shunt compensation devices – all of them make the relations between the electrical variables highly complex and nonlinear. This demands requirement of smart methods for deciding the system variables. The conventional gradient-based techniques would end up with suboptimal solutions if applied to such an optimality problem with multiple constraints [1]. Relatively optimal solutions reported so far have been discovered using evolutionary computational techniques [4, 6].

Teaching–Learning–Based Optimization (TLBO) is a recent technique proposed to serve the purpose of nonlinear function optimization [7, 8]. The philosophical essence of the algorithm is based on the interaction of the learners in a class with the teacher of that class and among themselves. For the sake of simplicity, the learner with the highest advantage of knowledge is considered as the teacher for that instance of time and the classroom dynamics is expected to evolve the average level of the learners with respect to the teacher.

Brain Storm Optimization (BSO) is based on the controlled idea generation with the help of some flexible rules. It puts forth the philosophy that improvisation of ideas can be done through brainstorming sessions and piggybacking on existing ideas. Even though the concept of teacher is absent in brainstorming, both the optimization algorithms show mutual compatibility. The TLBO algorithm which has been proposed originally do not stress on controlled cross-fertilization of ideas within the learners. Hybridization of these two algorithms with excellent philosophical bases could give a better algorithm.

Considering the algorithmic sequence of TLBO, it is to be noted that control parameter in the TLBO algorithm is just a singular Teaching Factor. A self-evolving characteristic can be introduced to it to make the algorithm more guided and versatile in its evolution through the iterations. This methodology stresses the idea of self-improvisation in parallel to mutual-improvisations. In this paper the self-evolving hybrid algorithm is put into action by applying it on a multi-objective optimal load flow problem.

The following parts of paper are organized such – section 2 details the objective of optimal power flow and identifies two major objectives. The exact relation of electrical quantities and the constraints imposed are stated. Section 3 explains the algorithmic sequence followed by the proposed algorithm for its execution. Section 4 presents the application of the proposed algorithm on OPF problem along with the simulation results. The conclusions are given in section 5.

2 Objectives of Optimal Power Flow

The primary objective of the OPF problem is to satiate the load demand with minimum possible cost, simultaneously maintaining the voltage levels as seen by the loads around the expected value; all the while satisfying the physical limits of the components involved in generation and transmission. The objective of cost minimization can be expressed as below.

$$\text{Minimize } F(P_G) = \sum_{i=1}^{N_G} F_i(P_{G_i}) = \sum_{i=1}^{N_G} (c_i \cdot P_{G_i}^2 + b_i \cdot P_{G_i} + a_i) \quad (1)$$

The coefficient shown as a accounts for the fixed cost and the coefficients b and c account for the variable cost incurred from power production. P_{G_i} is the power generated by the i^{th} generator and N_G is the total number of generators. The active power supplied should follow the demand constraint given below.

$$\sum_{i=1}^{N_G} P_{G_i} = \sum_{j=1}^{N_D} P_{D_j} + P_{Loss} \quad (2)$$

Where P_{D_j} is the j^{th} load and N_D is the total number of loads. Each generator is restricted physically by a maximum and minimum quantity of power that it is capable of generating. For the i^{th} generator, it can be expressed as given below.

$$P_{G_i}^{Min} \leq P_{G_i} \leq P_{G_i}^{Max} \quad (3)$$

The total voltage deviation also acts as an objective to be minimized. The loads require near-per-unit values of voltage for stable operation. The expression of objective meant for minimization is given below.

$$\text{Minimize } F(V_L) = \sum_{k=1}^{N_L} |V_{L_k} - 1| \quad (4)$$

where V_{L_k} is the voltage of the k^{th} load bus (expressed in per unit) and N_L is the number of load buses. The voltage states of the network are directly dependent on the generator voltage settings, the network impedances, shunt admittances, transformer tapings which hence are the decision variables. The transformer taps given by T_t and the reactive power compensators given by Q_c are generally discretized values and hence discontinuous in their respective domain. A total of N_T transformer taps and N_C capacitors are considered as decidable parameters. The numerical bounds are expressed as below.

$$V_{G_i}^{Min} \leq V_{G_i} \leq V_{G_i}^{Max}, T_t^{Min} \leq T_t \leq T_t^{Max}, Q_c^{Min} \leq Q_c \leq Q_c^{Max} \quad (5)$$

The voltage states of the network, both magnitude and angle at each node of the network, can be computed using load flow analysis. This information obtained can further be used to calculate the power losses in the network. Below the Root-Mean-Square based phasor matrix calculations which are performed in load flow using the admittance matrix (Y) of an N bus system and the injected power are shown.

$$\left[I^{RMS-Phasor} \right]_{N \times 1} = \left[Y \right]_{N \times N} \times \left[V^{RMS-Phasor} \right]_{N \times 1} \quad (6)$$

$$S_i = P_i + jQ_i = V_i^{RMS-Phasor} \times \text{conjugate}(I_i^{RMS-Phasor}) \quad (7)$$

The powers thus computed are used in the equality constraints to match the injected power with demanded power. Power mismatches beyond tolerance would cause the load flow to fail in obtaining a convergent solution for the local search.

$$\begin{aligned} \sum_{i=1}^N |real(S_i^{injected} - S_i^{demanded})| &= 0, \\ \sum_{i=1}^N |imaginary(S_i^{injected} - S_i^{demanded})| &= 0 \end{aligned} \quad (8)$$

The objective is a highly nonlinear and highly restricted function of the following decision vector X .

$$X = \begin{bmatrix} P_{G_1} & \dots & P_{G_{N_G}} & V_{G_1} & \dots & V_{G_{N_G}} & T_1 & \dots & T_{N_T} & Q_1 & \dots & Q_{N_C} \end{bmatrix} \quad (9)$$

This gives a total of $(2N_G + N_T + N_C)$ decision variables which belong to four categories. The dimensionality of the problem can be very large as the number of buses increase. This makes the problem all the more challenging to solve.

3 Self-Evolving Brain-Storming Inclusive Teaching-Learning-Based Optimization Algorithm

The Brain Storm Optimization and Teaching-Learning-Based Optimization algorithms have been recently introduced in the research literature [9] and [7] respectively. While TLBO is based on excellence of learners inspired by the teacher, BSO stresses on information interchange through brainstorming. The following guidelines are used with reference to Osborn's Original Rules for Idea Generation in a Brain storming Process [10]: 1) Suspend Judgment 2) Anything Goes 3) Cross-fertilize (Piggyback) 4) Go for Quantity. The rule 3 emphasizes on the key idea of brain storming which is then incorporated into the teacher-learner-based algorithm to cross-fertilize the ideas from teaching phase and learning phase, so as to originate a new set of ideas, which if turns out to be superior, could replace inferior ideas. The Teaching Factor (T_F) used in TLBO can be made self-evolving through its adaptation from the temporal change in consecutive function values. The computational steps are detailed below.

3.1 Initialization

Being a population-based stochastic algorithm, the initialization procedure is done over a matrix of M rows and N columns. M denotes the population size and N is the dimensionality of the problem at hand. The algorithm runs for a total of T iterations

after which termination occurs. Considering an element x at m^{th} row and n^{th} column of the said matrix, initialization is done as shown below.

$$x_{(m,n)}^{(1)} = x_n^{\min} + (x_n^{\max} - x_n^{\min}) \times rand_{(m,n)} \quad (10)$$

where m and n are indices for row and column respectively. The random value used follows a uniform distribution of randomness within the range (0, 1). The valid existing ideas could be used as a base to start for new idea generation. Similarly, prior known and acknowledged solutions can be used as seeds in the initial matrix. A potential solution X from m^{th} row at time/iteration t is evaluated as shown below.

$$Y_m^{(t)} = f(X_m^{(t)}) = f\left(\begin{bmatrix} x_{(m,1)}^{(t)} & x_{(m,2)}^{(t)} & \dots & x_{(m,n)}^{(t)} & \dots & x_{(m,N-1)}^{(t)} & x_{(m,N)}^{(t)} \end{bmatrix}\right) \quad (11)$$

3.2 Teaching Phase

In this phase, the average of the class is considered by taking the mean of each dimension of the population. The mean vector V can be shown as

$$\overbrace{V}^{mean}_{(t)} = \left[\sum_{m=1}^M \left(\frac{x_{(m,1)}^{(t)}}{M} \right) \quad \dots \quad \sum_{m=1}^M \left(\frac{x_{(m,n)}^{(t)}}{M} \right) \quad \dots \quad \sum_{m=1}^M \left(\frac{x_{(m,N)}^{(t)}}{M} \right) \right] \quad (12)$$

The teacher for the current iteration is the best solution of the current population. In a multi-objective problem, the best ranked individual can be obtained by a suitable non-dominated sorting method. The mutation in this phase is as shown below.

$$\overbrace{X}^{new-1}_{(m,n)}^{(t)} = X_{(m,n)}^{(t)} + rand_{(m,n)}^{(t)} \times \left(\overbrace{X}^{teacher}_{(n)}^{(t)} - T_{F(m)}^{(t)} \times \overbrace{V}^{mean}_{(n)}^{(t)} \right) \quad (13)$$

where T_F shows the vector of teaching factors used for each learner. Since there is only this single type of control parameter present in original TLBO, it is possible to make it adaptive to the situation, making the algorithm self-evolving.

$$T_{F(m)}^{(t)} = T_{F(m)}^{(t-1)} + sign \left(\overbrace{Y}^{rank}_m^{(t)} - \overbrace{Y}^{rank}_m^{(t-1)} \right) \times rand_{(m)}^{(t)} \quad (14)$$

This is intelligent learning strategy in the proposed algorithm. The improvisation in the rank of the vector with respect to past would lead to reduction in teaching factor, indicating that the learner is performing well and has lesser need to contribute towards driving the class average corresponding to the current teacher. Considering depreciation in the rank, the individual would need to allow higher mutations between teacher and the average vectors and hence higher T_F value is required. When there is no change in the rank, the T_F value for that learner is kept constant.

3.3 Learning Phase

This phase makes the learners undergo self-improvement through differential mutation. The temporal gradients which are present between the learners are used to facilitate the mutation process.

$$\overbrace{X_{(m,n)}^{(t)}}^{new-2} = X_{(m,n)}^{(t)} + rand_{(m,n)}^{(t)} \times (X_{(m,n)}^{(t)} - X_{(\lambda,n)}^{(t)}) \times sign \left(\overbrace{Y_{\lambda}^{(t)}}^{rank} - \overbrace{Y_m^{(t)}}^{rank} \right) \quad (15)$$

3.4 Brain-Storming Phase

Here the amalgamation of both new populations occurs. A temporary matrix is created with intermixing from the populations from teaching and learning phases.

$$\overbrace{X_{(m,n)}^{(t)}}^{new-3} = \begin{bmatrix} \alpha_{(n)} & \beta_{(n)} \end{bmatrix} \times \begin{bmatrix} \overbrace{X_{(m,n)}^{(t)}}^{new-1} & \overbrace{X_{(m,n)}^{(t)}}^{new-2} \end{bmatrix}^T \quad (16)$$

where α and β are the multiplication factors which decides the extent of participation of both populations in the brain storming process. The factors are kept within certain limits to assure contribution to brain storming from both the phases. Similar to BSO, the population thus obtained is mutated like in BSO using a smooth and stochastically weighted nonlinear function.

$$\overbrace{X_{(m,n)}^{(t)}}^{cross-fertilized} = \overbrace{X_{(m,n)}^{(t)}}^{new-3} + \text{logsig} \left(\frac{T-2t}{2K} \right) \times rand_{(m,n)}^{(t)} \quad (17)$$

where K is the slope determining factor of the *logsig* function used. The current population's objective values along with the objective values of new populations are compared together to perform the reinsertion of the superior vectors.

4 Simulation Results

The proposed algorithm is tested so as to obtain optimal power flow solution for an IEEE 30-Bus, 6 generator system. The system data regarding the bus configurations and the line data can be found in [4] and are not presented here due to space constraints. Both objectives are individually optimized first and then used as seeds during consequent initialization. The algorithm is run for 10 trial runs and the best solution is presented in Table 1. All simulations are done in MATLAB R2011b software on a 3.4 GHz Core-i7 device with 8 GB of random access memory. The system is well known and has been studied before even in recent research literature [4, 6]. The real powers and voltages of buses {1, 2, 5, 8, 11, 13} are to be decided.

The transformer taps {11, 12, 15, 36} are to be adjusted and the extent of reactive compensations at {10, 12, 15, 17, 20, 21, 23, 24, 29} have to be determined. The fuel cost and voltage deviations are functionally dependent on these 25 parameters. The comparison of results from the proposed algorithm is performed in Table 2. It is very clear from the results that the proposed technique shows comparable performance to recent algorithms and is quite optimal considering the initial states shown in [4, 6].

Table 1. IEEE-30 Bus, 6 generator system – power generation, voltage magnitudes, transformer taps settings and reactive power values used for compensation

	Minimize $F(P_G)$	Minimize $F(V_L)$		Minimize $F(P_G)$	Minimize $F(V_L)$
P_{G1}	176.6350	171.6105	T_3	0.9755	0.9796
P_{G2}	48.2382	30.1370	T_4	0.9607	0.9659
P_{G3}	21.2394	48.5742	Q_1	4.4348	4.8671
P_{G4}	21.4096	10.0000	Q_2	4.1871	0.3153
P_{G5}	12.0488	16.9136	Q_3	4.2786	4.9994
P_{G6}	12.4177	15.7686	Q_4	4.7454	1.6107
V_{G1}	1.1000	0.9999	Q_5	3.6614	4.9912
V_{G2}	1.0877	1.0211	Q_6	5.0000	4.6549
V_{G3}	1.0622	1.0173	Q_7	4.6468	5.0000
V_{G4}	1.0700	1.0016	Q_8	5.0000	4.9721
V_{G5}	1.0986	1.0341	Q_9	2.1255	2.0984
V_{G6}	1.1000	1.0108	$F(P_G)$	799.1295	863.0816
T_1	1.0139	1.0526	$F(V_L)$	1.9557	0.0884
T_2	0.9069	0.9034	$Loss$	8.5885	9.6627

Table 2. Comparison of results based on [4, 6]

Method	Optimal fuel cost (in \$/hr)	Optimal total voltage deviations
Gradient-based approach	804.853	-
Improved GA	800.805	-
PSO	800.41	-
DE	799.2891	0.1357
AGAPOP	799.8441	0.1207
Proposed algorithm	799.1295	0.0884

As seen from Table 2, the proposed hybrid algorithm is very effective in finding optimality of the objectives. The time difference in algorithms is negligible owing to high computational capabilities of modern day processors.

5 Conclusion

A hybrid algorithm is proposed based on two algorithms, TLBO and BSO, which have mutually compatible philosophical bases. The proposed algorithm is easily modified to be self-evolving since the original algorithm has only a single type of control

parameter. The algorithm is successfully applied to highly complex optimal power flow problem with multiple objectives. The results indicate that the proposed algorithm is an excellent candidate for intelligent decision-making leading to economic-cum-stable operation of the power network. The flexibility and generic nature of the algorithm makes it suitable for optimizations on electrical networks spread over a large area or even those inside a building. The algorithm has higher memory requirement during its intermediate stages, but that disadvantage is trivial in the current world scenario of high end memory availability.

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References

1. Back, T., Fogel, D., Michalewicz, Z.: Handbook of evolutionary computation. Oxford University Press, New York (1997)
2. Bakirtzis, A., Petridis, V., Kazarlis, S.: Genetic algorithm solution to the economic dispatch problem. *IEE Gen. Trans. Dist.* 141(4), 377–382 (1994)
3. Gaing, Z.L.: Particle swarm optimization to solving the economic dispatch considering the generator constraints. *IEEE Trans. on Power Syst.* 18(3), 1187–1195 (2003)
4. Abou El Ela, A.A., Abido, M.A., Spea, S.R.: Optimal power flow using differential evolution algorithm. *Electric Power Systems Research* 80(7), 878–885 (2010)
5. Nayak, S.K., Krishnanand, K.R.: Panigrahi, B.K., Rout, P.K.: Application of Artificial Bee Colony to Economic Load Dispatch Problem with Ramp Rate Limits and Prohibited Operating Zones. In: *IEEE Proc. on Nature and Biologically Inspired Computing*, pp. 1237–1242 (2009)
6. Attia, A.F., Al-Turki, Y.A., Abusorrah, A.M.: Optimal Power Flow Using Adapted Genetic Algorithm with Adjusting Population Size. *Electric Power Components and Systems* 40(11), 1285–1299 (2012)
7. Rao, R.V., Savsani, V.J., Vakharia, D.P.: Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems. *Computer-Aided Design* 43(3), 303–315 (2011)
8. Krishnanand, K.R., Panigrahi, B.K., Rout, P.K., Mohapatra, A.: Application of Multi-Objective Teaching-Learning-Based Algorithm to an Economic Load Dispatch Problem with Incommensurable Objectives. In: Panigrahi, B.K., Suganthan, P.N., Das, S., Satapathy, S.C. (eds.) *SEMCCO 2011, Part I. LNCS*, vol. 7076, pp. 697–705. Springer, Heidelberg (2011)
9. Shi, Y.: An Optimization Algorithm Based on Brainstorming Process. *Int. J. of Swarm Intel. Res.* 2(4), 35–62 (2011)
10. Osborn, A.F.: *Applied imagination: Principles and procedures of creative problem solving*. Charles Scribner's Son, New York (1963)