Reduction of Real Power Loss by Hybridization of Enhanced Particle Swarm Optimization with Successive Quadratic Programming

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Abstract
In this paper, Hybridization of Enhanced particle swarm optimization with successive quadratic programming (EPSOSQP) is introduced to solve optimal reactive power dispatch problem. Enhanced particle swarm optimization is revealed to converge rapidly to a near optimum solution, but the exploration process will become very slow around global optimum. On the divergent, successive quadratic programming is weak to escape local optimum but the capability of convergent speed around global optimum and the convergent accuracy is robust. In this case, Enhanced particle swarm optimization is used to augment global search ability and convergencespeed of algorithm. When the modification in fitness value is smaller than a threshold value, the searching process is swapped to successive quadratic programming. In this way, this hybrid algorithm finds an optimum solution more precisely. The proposed EPSOSQP algorithm has been tested on standard IEEE 57 bus test system and simulation results show clearly the better performance of the proposed algorithm in tunning the real power loss.

Keywords
Enhanced particle swarm optimization, successive quadratic programming, optimal reactive power, Transmission loss.

I. Introduction
Reactive power optimization places a significant role in optimal operation of power systems. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been implemented to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the intricacy in managing inequality constraints. The problem of voltage stability and collapse play a key role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is projected to increase the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to elucidate the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to calculate Reactive power reserve with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes Hybridization of Enhanced particle swarm optimization with successive quadratic programming (EPSOSQP) to solve reactive power dispatch problem. Particle swarm optimization [21,22] algorithm has characters of simple computation and rapid convergence capability. For the reason of its high flexibility, PSO has many applications. Infact, PSO has the problem of converging to undesired local solution or early convergence. SQP is nonlinear programming method that starts from a single searching point and finds a solution using the gradient information. Although this optimizing method is less time consuming than the population based search algorithms, its highly dependent on the initial estimate of solution[23, 24]. The proposed algorithm has been evaluated on standard IEEE 57 bus test system. The simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

II. Problem Formulation
The OPF problem is considered as a common minimization problem with constraints, and can be written in the following form:

Minimize \( f(x, u) \) \hspace{1cm} (1)

Subject to \( g(x,u)=0 \)

and \( h(x,u) \leq 0 \) \hspace{1cm} (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:

\( x = (P_1, \theta_1, \ldots, \theta_N, V_{L1}, \ldots, V_{LNL}, Q_{E1}, \ldots, Q_{EN})^T \) \hspace{1cm} (4)

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

\( u = (V_{E1}, \ldots, V_{EN}, T_1, \ldots, T_N, Q_{C1}, \ldots, Q_{CNe})^T \) \hspace{1cm} (6)

Where \( N_g, N_t \) and \( N_c \) are the number of generators, number of tap transformers and the number of shunt compensators respectively.
III. Objective Function

A. Active Power Loss
The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be mathematically described as follows:

\[ F = PL = \sum_{k \in \text{Nbr}} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij}) \]

or

\[ F = PL = \sum_{i \in N_g} P_{gi} - P_d = P_{gs} + \sum_{i \in \text{slack}} P_{gi} - P_d \]

(8)

Where \( g_k \) is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. \( P_d \): is the total active power demand, \( P_{gi} \): is the generator active power of unit i, and \( P_{gs} \): is the generator active power of slack bus.

B. Voltage profile improvement
For minimizing the voltage deviation in PQ buses, the objective function becomes:

\[ F = PL + \omega_d \times VD \]

Where \( \omega_d \): is a weighting factor of voltage deviation.

\[ VD = \sum_{i=1}^{N_{pq}} |V_i - 1| \]

(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 cover the total power demand and the power losses:

\[ P_g = P_d + P_L \]

(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 ensure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators:

\[ P_{gs}^{\min} \leq P_{gs} \leq P_{gs}^{\max}, i \in N_g \]

(12)

\[ Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max}, i \in N_g \]

(13)

Upper and lower bounds on the bus voltage magnitudes:

\[ V_i^{\min} \leq V_i \leq V_i^{\max}, i \in N \]

(14)

Upper and lower bounds on the transformers tap ratios:

\[ T_i^{\min} \leq T_i \leq T_i^{\max}, i \in N_T \]

(15)

Upper and lower bounds on the compensators reactive powers:

\[ Q_c^{\min} \leq Q_c \leq Q_c^{\max}, i \in N_c \]

(16)

Where \( N \) is the total number of buses, \( N_T \) is the total number of Transformers; \( N_c \) is the total number of shunt reactive compensators.

IV. Classical Particle Swarm Optimization
The key point of evolving PSO is the exchange over of information between creatures of the same species and offers some class of evolutionary benefit.

The technique for executing the global version of PSO is given by the following steps:

Step 1. Initialization of swarm position and velocity.
Step 2. Evaluation of particle’s fitness.
Step 3. Comparison to pbest (personal best).
Step 4. Comparison to gbest (global best).
Step 5. Update of every particle’s velocity and position:

\[ v_i(t + 1) = w_i v_i(t) + c_1 u_d [p_i(t) - x_i(t)] + c_2 u_d [p_g(t) - x_i(t)] \]

(17)

\[ x_i(t + 1) = x_i(t) + \Delta t v_i(t + 1) \]

(18)

Where \( w \) is the inertia weight; \( i = 1, 2, \ldots, N \) indicates the number of particles of population (swarm); \( t = 1, 2, \ldots \) \( t_{\text{max}} \) indicates the iterations, \( w \) is a parameter called the inertia weight; \( v_i = [v_{i1}, v_{i2}, \ldots, v_{in}]^T \) stands for the velocity of the \( i \)th particle, \( x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \) stands for the position of the \( i \)th particle of population, and \( p_i = [p_{i1}, p_{i2}, \ldots, p_{in}]^T \) represents the best previous position of the \( i \)th particle. Positive constants \( c_1 \) and \( c_2 \) are the cognitive and social components, respectively, which are the acceleration constants responsible for varying the particle velocity towards \( p_{\text{best}} \) and \( g_{\text{best}} \), respectively. Index \( g \) represents the index of the best particle among all the particles in the swarm. Variables \( u_d \) and \( u_s \) are two random functions in the range \([0, 1]\). Eq. (18) represents the position update, according to its previous position and its velocity, considering \( \Delta t = 1 \).

Step 6. Repeating the evolutionary cycle: Return to Step 2 until a stop criterion has been reached.

V. Enhanced Particle Swarm Optimization
In standard PSO algorithm, particle speed is only the function of current position. However in enhanced particle swarm optimization algorithm particle speed is related to the position alteration. The updating equation is as follows:

\[ v_{ij}(t + 1) = w_{ij}(t) + c_1 r_1 [p_{ij} - 2x_{ij}(t - 1)] + c_2 r_2 [p_{gj} - 2x_{ij}(t) + x_{ij}(t - 1)] \]

(19)
In order to augment the diversity of swarm, an oscillation segment is introduced to progress global convergence capability of algorithm. The updating equation is as follows:

$$v_{ij}(t + 1) = w_{ij}(t) + c_1 r_1 [P_{ij} - (1 + \xi_1)x_{ij}(t) + \xi_1 x_{ij}(t - 1)] + c_2 r_2 [P_{g,ij} - (1 + \xi_2)x_{ij}(t) + \xi_2 x_{ij}(t - 1)]$$  \hspace{1cm} (21)

where $\xi_1$ and $\xi_2$ are arbitrary numbers. In the global search algorithm, we usually anticipate that the algorithm has tremendous global search skill in the early of optimization process to evade the premature convergence, and later stage of optimization procedure we anticipate the algorithm has commanding local search capability and fast convergence speed. Based on these we take

$$\xi_1 < \frac{\sqrt{2}}{c_1 r_1} \text{ and } \xi_2 < \frac{\sqrt{2}}{c_2 r_2} \text{ in the early stage of algorithm and future stage of optimization process we take}$$

$$\xi_1 \geq \frac{\sqrt{2}}{c_1 r_1} \text{ and } \xi_2 \geq \frac{\sqrt{2}}{c_2 r_2} \text{ can make the algorithm asymptotic convergence.}$$

An arbitrary inertial weight is introduced to enhanced particle swarm optimization. We set inertia $w$ is a arbitrary number which obey certain random distribution. This can overcome $w$ linear decrease deficiency from two aspects. First of all, if at the early of evolution procedure closed to the best point, arbitrary $w$ may produce small value to quicken the convergence speed. In addition, if the best point can’t be found at the early stage, algorithm will not converge at the best point with $w$ linear decrease.

The updating equation is as follows:

$$w = \mu + \sigma \times N(0,1)$$
$$\mu = \mu_{min} + (\mu_{max} - \mu_{min}) \times \text{rand}(0,1)$$  \hspace{1cm} (22)

where $N(0,1)$ stands for standard normal distribution random number, and $\text{rand}(0,1)$ indicates random number between 0 and 1.

### VI. Successive Quadratic Programming (SQP)

SQP is based on iterative formulation and the solution of quadratic programming sub-problems. The sub-problem is acquired by linearizing the constraints and approximating the Lagrangian function quadratically.

$$L(x, \lambda) = J(x) + \sum_{i=1}^{m} \lambda_i \Psi_i(x)$$  \hspace{1cm} (23)

Each iteration, an approximation of the Hessian of the Lagrangian function $H_{fi}$ is made. The procedure starts from given iteration $x_k$, then, the following quadratic programming (QP) sub-problem is formed to solve:

$$\min_{x} \frac{1}{2} d^T H_{ki} d + \nabla J(x_k)^T d \hspace{1cm} (24)$$
$$\nabla J_i(x_k)^T d + \Psi_i(x_k) = 0, i = 1, \ldots, m_e \hspace{1cm} (25)$$
$$\nabla J_i(x_k)^T d + \Psi_i(x_k) \geq 0, i = m_e + 1, \ldots, m \hspace{1cm} (26)$$

This sub-problem is a quadratic programming (QP) sub-problem whose solution is used to form a exploration direction for a line search procedure. In other words, the solution is used to form the next iteration:

$$x_{k+1} = x_k + \alpha_k d_k$$  \hspace{1cm} (27)

### VII. Hybridization of Enhanced Particle Swarm Optimization With Successive Quadratic Programming

PSO algorithm is a global algorithm, which has a robust ability to find global optimistic result. However, it has a drawback that the search around global optimum is very slow. The SQP algorithm, on the contrary, has robust ability to find local optimistic result for nonlinear system identification problem, but its ability to find the global optimistic result is feeble. By unifying the Enhanced PSO with SQP, a new algorithm referred to as EPSOSQP hybrid algorithm is formulated in this paper. Similar to the PSO algorithm, the EPSOSQP algorithm’s searching process is also started from initializing a group of arbitrary particles. First, EPSO algorithm is run to quest the global best position in the solution space. Then SQP algorithm is used to quest around the global optimum. In this way, this hybrid algorithm may find an optimum more rapidly and precisely.

**Step 1:** Initialize the positions and velocities of a group of particles arbitrarily.

**Step 2:** Estimate each initialized particle’s fitness value

**Step 3:** If the highest iterative iterations are arrived, go to Step 7, else, go to Step 4.

**Step 4:** The best particle of the current particles is stored. If the change between the current best particle fitness value and its former one is smaller than a predefined value, goto step 7, else continue.

**Step 5:** The positions and velocities of all the particles are updated according to Eq. (20) and Eq. (21), and then a group of new-fangled particles is produced.

**Step 6:** Update the inertia weight for each particle according to Eq. (22) and go to step 2.

**Step 7:** Use SQP algorithm to quest around global best, which is found by EPSO to find better solutions. In this case, the best solution obtained by EPSO is considered as the preliminary guess for SQP algorithm.

### VIII. Simulation Results

The proposed hybrid EPSOSQP algorithm for solving ORPD problem is tested for standard IEEE-57 bus power system. The IEEE 57-bus system data consists of 80 branches, 7 generator-buses and 17 branches under load tap setting transformer branches.
The possible reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. In this case, the search space has 27 dimensions, i.e., the seven generator voltages, 17 transformer taps, and three capacitor banks. The system variable limits are given in Table I. The preliminary conditions for the IEEE-57 bus power system are given as follows:

\[ P_{\text{req}} = 12.421 \text{ p.u.}, \quad Q_{\text{req}} = 3.334 \text{ p.u.} \]

The total initial generations and power losses are obtained as follows:

\[ \sum P_g = 12.7723 \text{ p.u.}, \quad \sum Q_g = 3.4553 \text{ p.u.}, \]

\[ P_{\text{loss}} = 0.27444 \text{ p.u.}, \quad Q_{\text{loss}} = -1.22434 \text{ p.u.} \]

Table II shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after EPSOSQP based optimization which are within their acceptable limits. In Table III, a comparison of optimum results obtained from proposed EPSOSQP with other optimization techniques for optimal reactive power dispatch (ORPD) problem mentioned in literature for IEEE-57 bus power system is given. These results indicate the robustness of proposed EPSOSQP approach for providing better optimal solution in case of IEEE-57 bus system.

**IX. Conclusion**

In this paper, the EPSOSQP has been successfully implemented to solve Optimal Reactive Power Dispatch problem. The proposed algorithm has been tested on the standard IEEE 57-bus system. The results are compared with other heuristic methods and the proposed algorithm demonstrated its effectiveness and robustness in minimization of real power loss and various system control variables are well within the acceptable limits.

**References**


