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Solution of Optimal Reactive Power Dispatch by a Hybrid GSA-SQP Algorithm

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***Abstract*—The optimal reactive power dispatch (ORPD) is achieved by optimal coordination of the equipment which control the reactive power flows in the power system. The (ORPD) can be mathematically formulated as a nonlinear, static and large-scale optimization problem with constraints. This paper deals with solving the ORPD problem using a new hybrid algorithm consisting of gravitational search algorithm (GSA) and sequential quadratic programming (SQP). The performance of this hybrid algorithm for the ORPD problem is studied and evaluated on the standard IEEE 30-bus test system with two different objective functions, namely minimization of real power loss and voltage profile improvement.**

***Index Terms*—Optimal reactive power dispatch; gravitational search algorithm; sequential quadratic programming; hybrid optimization algorithm.**

I. INTRODUCTION

The ORPD problem solution aims to optimize a chosen objective function through optimal adjustment of the power system control variables, under specified active power outputs of all generators (except at the slack bus P_{G1}), while at the same time satisfying the various equality and inequality constraints. Accordingly, the ORPD problem can be treated as a class of the optimal power flow (OPF) problem which is a nonlinear, non-convex, large-scale, static optimization problem with both continuous and discrete control variables [1], [2].

Previously, the classical optimization methods such as quadratic programming, Newton approach, dynamic programming, interior point methods, etc. were used to solve the ORPD problem. These methods are based on an estimation of the global optimum. However, due to difficulties of differentiability, non-linearity, and non-convexity, these methods failed to provide the global optimum and only reached the local one. Moreover, these methods exhibit some limitations, depending on the type of problem, e.g., when the objective function is not available in algebraic form [3]. Recently, many population-based methods such as differential evolution (DE) [3], biogeography based optimization (BBO) [4], particle swarm optimization (PSO) [5], gravitational search algorithm GSA [6], firefly algorithm (FA) [7], artificial bee colony (ABC) optimization [7], krill herd algorithm (KHA) and chaotic krill herd algorithm (CKHA) [8], *etc*. have been applied in solving the ORPD problems with different objective functions.

A combination of several optimization algorithms in hybrid algorithm allows them to exploit the strength of each algorithm [1]. Some of hybrid algorithms have been proposed in [8]–[10] to solve the ORPD problem

This paper proposes a hybrid algorithm of GSA with a local search technique based on SQP for solving the ORPD problem. In this approach, GSA is used as a global optimizer and SQP as a local optimizer to fine tune the solution.

II. PROBLEM FORMULATION

Generally, the ORPD problem can be formulated as follows

$$\min\ F(\mathbf{x},\ \mathbf{u}). \tag{1}$$

Subject to:

$$g(\mathbf{x},\mathbf{u}) = 0, \tag{2}$$

$$h(\mathbf{x},\ \mathbf{u}) \le 0, \tag{3}$$

$$\mathbf{u} \in \mathbf{U}, \tag{4}$$

where **x** is the vector of dependent variables consisting of slack bus power P_{G1}, load bus voltages V_L, generator reactive power outputs Q_G, and transmission line loadings S_l. Accordingly, vector **x** can be expressed as

$$\mathbf{x}^{\mathrm{T}} = [P_{\mathrm{G1}},\ V_{\mathrm{L1}}...V_{\mathrm{LNL}}, Q_{\mathrm{G1}}...Q_{\mathrm{GNG}}, S_{l1}...S_{l\mathrm{NTL}}], \tag{5}$$

where NL, NG and NTL are number of load buses, number of generators, and number of transmission lines, respectively.

u is the vector of control variables, consisting of generator voltages V_G, transformer tap settings T, and shunt VAR compensations Q_C. Hence, **u** can be expressed as

$$\mathbf{u}^{\mathrm{T}} = [V_{\mathrm{G1}}...V_{\mathrm{GNG}}, T_1...T_{\mathrm{NT}}, Q_{\mathrm{C1}}...Q_{\mathrm{CNC}}]. \tag{6}$$

F is the objective function to be minimized.

The equality constraints (2) are the typical nonlinear power flow equations. Inequality constraints (3) are the functional operating constraints, such as: (i) Branch flow

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limits (MVA or A); (ii) Load bus voltage magnitude limits; (iii) Generator reactive power output limits; (iv) Slack bus active power output limits.

Constraints (4) define the feasibility region of the problem control variables such as: (i) Generator bus voltage magnitude limits; (ii) Transformer tap setting limits; (iii) Shunt VAR compensation limits.

It is worth mentioning that the control variables are self-constrained. The hard inequalities of dependent variables P_{G1}, V_L, Q_G and S_l can be incorporated in the objective function as quadratic penalty terms [2].

III. SOLUTION METHOD

The hybrid GSA-SQP algorithm consists of gravitational search algorithm and sequential quadratic programming.

In GSA, the search agents are a collection of masses which interact with each other based on the Newtonian gravity and the laws of motion [11]. In a system with N agents (masses), the position of the ith agent is defined by

$$X_i = \left(x_i^1, ..., x_i^d, ..., x_i^n\right), \tag{7}$$

where $i = 1,2,..., N$, n is the search spase dimension of the problem and x_i^d defines the position of the ith agent in the dth dimension.

The next position of the ith agent in the dth dimension can be calculated as follows

$$x_i^d\left(t+1\right) = x_i^d\left(t\right) + v_i^d\left(t+1\right), \tag{8}$$

where $x_i^d\left(t\right)$ is the position of the ith agent at the current iteration t and $v_i^d\left(t+1\right)$ is the velocity of the ith agent at iteration t+1, respectively. The equations for calculation of the velocity of the agents, $v_i^d\left(t+1\right)$, can be found in [11].

GSA as a probabilistic based multipoint search technique, has a drawback of, sometimes, converging to the values which may not be optimum. On the other hand, GSA searches a large solution space with excellent convergence providing approaching to the global optimum.

The SQP method seems to be the best nonlinear programming (NLP) method for constrained optimization problems [12], [13]. NLP methods, such as SQP, being single point search methods, have a drawback of being trapped in local optimum point, if the initial choice is nearer to the local optimum. The NLP method gives a global optimum solution, if the proper initial choice is made [13].

To use of the advantage of GSA and SQP methods, and at the same time to overcome the drawbacks of these methods, a hybridization of GSA with SQP is proposed in [14]. The SQP routine is incorporated in GSA as a local search mechanism to improve the convergence of GSA in subsequent iterations. First, the GSA algorithm is executed normally, and the best fitness per generation is selected in each iteration. From that best fitness, the corresponding best agent is set as the initial values of variables to the SQP method. Then, the SQP routine is executed depending on the adopted probability of local search α_{LS}, providing improvement of the best fitness obtained from GSA in the current iteration. In this way, the hybrid GSA-SQP algorithm gives the global optimum solution.

A. Implementation of Hybrid GSA-SQP

Proposed hybrid GSA-SQP algorithm has been applied to solve the ORPD problem. The elements of agent X_i are generator bus voltages, tap positions of regulating transformers and reactive power outputs of shunt VAR compensators, (n = NG + NT + NC).

The flow chart of the hybrid GSA-SQP algorithm used to solve the ORPD problem is shown in Fig. 1.

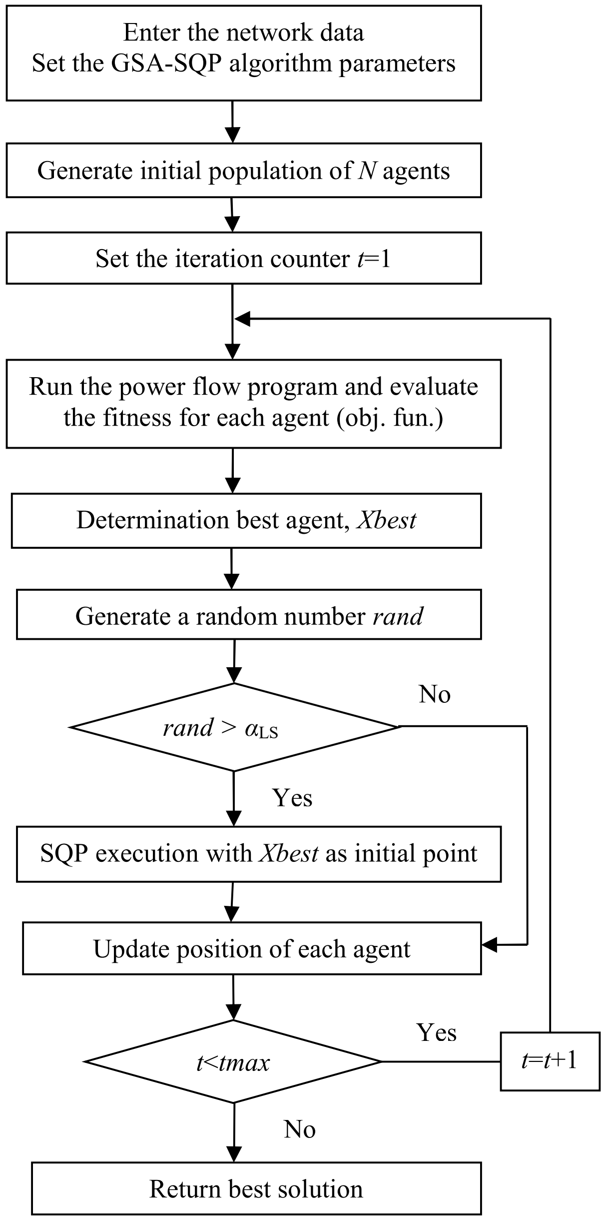

Fig. 1. Flowchart of hybrid GSA-SQP based ORPD solution.

The algorithm has been implemented in MATLAB 2011b computing environment and run on a 2.20 GHz, PC with 3.0 GB RAM. The **fmincon** solver with SQP method available in MATLAB optimization toolbox has been used as the local search mechanism.

The algorithm parameters used for the simulation are adopted as follows: α is set to 10 and G_0 is set to 100; The population size (N) and maximum iteration number ($tmax$) are set to 20 and 100, respectively, for all case studies. The probability of local search α_{LS} is set as follows:

$\alpha_{LS} = 1$ for $t \le tmax/2$, and $\alpha_{LS} = 0.95$ for $t > tmax/2$

where t is the current iteration.

IV. SIMULATION RESULTS

The proposed hybrid GSA-SQP algorithm has been tested on the standard IEEE 30-bus test system. The system data and the minimum and maximum limits for the control variables are given in [6] and [15]. The IEEE 30-bus test system has 19 control variables as follows: 6 generator voltage magnitudes, 4 transformer tap settings, and 9 shunt capacitor reactive power injections. The voltages of all load buses have been constrained within limits of 0.95 and 1.10 p.u. The total load demands of this test system are, P_{load} = 2.834 p.u. and Q_{load} = 1.262 p.u. at 100 MVA base. The active power outputs of the generators are specified as follows: P_{G2} = 80 MW, P_{G5} = 50 MW, P_{G8} = 20 MW, P_{G11} = 20 MW and P_{G13} = 20 MW. Bus 1 is selected as the slack bus.

TABLE I. OPTIMAL SETTINGS OF CONTROL VARIABLES.

Control variables	Limits		Initial	Case 1	Case 2
	Lower	Uper			
V_{G1} (p.u.)	0.95	1.1	1.05	1.10000	1.00676
V_{G2} (p.u.)	0.95	1.1	1.04	1.09432	1.00167
V_{G5} (p.u.)	0.95	1.1	1.01	1.07479	1.01752
V_{G8} (p.u.)	0.95	1.1	1.01	1.07671	1.01135
V_{G11} (p.u.)	0.95	1.1	1.05	1.10000	1.00944
V_{G13} (p.u.)	0.95	1.1	1.05	1.10000	1.02033
T_{6-9} (p.u.)	0.9	1.1	1.078	1.04021	1.02489
T_{6-10} (p.u.)	0.9	1.1	1.069	0.90000	0.90000
T_{4-12} (p.u.)	0.9	1.1	1.032	0.97871	1.00152
T_{28-27} (p.u.)	0.9	1.1	1.068	0.96611	0.96949
Q_{C10} (MVAR)	0	5	0	5.00000	5.00000
Q_{C12} (MVAR)	0	5	0	5.00000	2.51832
Q_{C15} (MVAR)	0	5	0	5.00000	5.00000
Q_{C17} (MVAR)	0	5	0	5.00000	0.00000
Q_{C20} (MVAR)	0	5	0	5.00000	5.00000
Q_{C21} (MVAR)	0	5	0	5.00000	5.00000
Q_{C23} (MVAR)	0	5	0	3.70176	5.00000
Q_{C24} (MVAR)	0	5	0	5.00000	5.00000
Q_{C29} (MVAR)	0	5	0	2.68988	2.61327
P_{loss} (MW)	-	-	5.82225	**4.54271**	5.96236
VD (p.u.)	-	-	1.14966	2.00789	**0.08657**

A. Case 1: Minimization of Real Power Loss [16]

$$F_1 = P_{loss}(\mathbf{x}, \mathbf{u}) = \sum_{L=1}^{NTL} P_L, \tag{9}$$

where P_L is the real power losses at line L and NTL is the number of transmission lines.

The optimal settings of control variables are given in Table I. Figure 2 shows the comparative convergence profiles of GSA and proposed hybrid GSA-SQP for Case 1. It may be observed from this figure that the hybrid GSA-SQP explores the global optima thanks to exploration and exploitation of GSA in the first part of the iterative process and local search ability of SQP in subsequent iterations.

B. Case 2: Voltage Profile Improvement, that is Minimization of the Load Bus Voltage Deviations [16]

$$F_2 = VD(\mathbf{x}, \mathbf{u}) = \sum_{i=1}^{NL} \left| V_i - V_i^{ref} \right|, \tag{10}$$

where NL is the number of load buses and V_i^{ref} is the reference value of the voltage magnitude of the ith bus, which is usually set to 1 p.u.

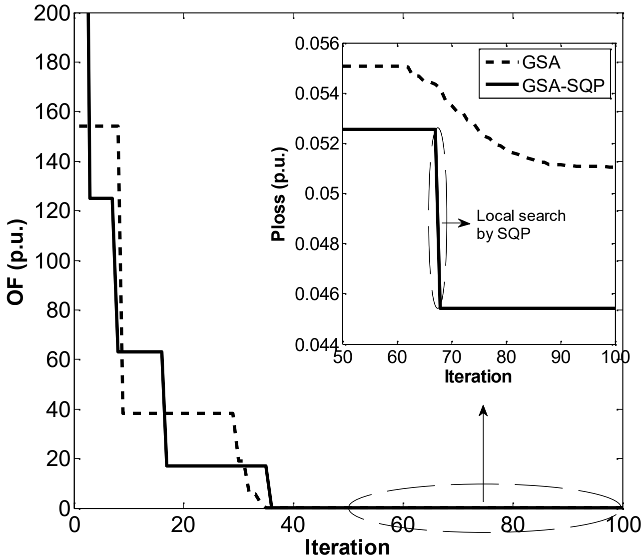

Fig. 2. Convergence of algorithms for Case 1.

The optimal results for Case 2 are given in Table I.

C. Comparative Study

Under the same system data, control variable limits and constraints, the results for Case 1 and Case 2 obtained using the hybrid GSA-SQP approach reported in this paper are compared to some other algorithms reported in the literature as shown in Table II.

For Case 1, it can be seen in Table II that the methods reported in [6], and [8]–[10] resulted in a lesser minimum of the real power losses than the proposed hybrid GSA-SQP approach. However, after the power flow computation with control variables reported in these references, those results can be considered as infeasible or incorrect solutions. The results obtained by our power flow program were checked and verified by MATPOWER power flow program [17].

Reasons for infeasibility of those results are summarized as follows:

– The results in [6] represent an infeasible solution because the reactive powers of the generators at buses 2 and 8 are -116.97 MVAr and 79.67 MVAr, respectively; which violate their corresponding lower limits as reported in [14]. Moreover, lower voltage limits are violated at all load buses except at buses 3, 4, 6, 7, 9 and 28; and the exact P_{loss} is 7.16681 MW for this violated case.

– For the optimum control variables given in [8], [9] and [10], the exact values of P_{loss} as obtained from the power flow computations are 5.12528 MW, 5.19018 MW and 5.30568 MW, respectively.

For Case 2, the results obtained from the proposed hybrid GSA-SQP algorithm was compared to the methods reported in [6]–[10]. Some of those results are infeasible or incorrect solutions, as obtained from the power flow computations:

– The best result given in [6] is an infeasible solution because reactive powers of the generators at buses 1 and 2 are -146.27 MVAr and 164.69 MVAr, respectively; which violate their corresponding limits as reported in [14]. The exact VD is 0.18744 p.u. for this violated case.

– The best result given in [8] is an infeasible solution because the reactive power of the generator at bus 1 is -42.64 MVAr; which violate its corresponding limits as reported in [14]. In addition, the bus voltages at buses 18–20, 23–27 and 29–30, are lower than 0.95 p.u. The exact *VD* is 1.04072 p.u. for this violated case.

– The optimum control variables given in [9] represent an infeasible solution because the reactive power of the generator at bus 1 come -50.67 MVAr; which violate their lower limits. Moreover, lower voltage limits are violated at buses 18-27 and 29-30. The exact *VD* is 1.13131 p.u. for this violated case.

– For the optimum results in [10], the exact value of *VD* is 0.25206 p.u., as obtained from the power flow computations.

TABLE II. COMPARISON OF THE SIMULATION RESULTS FOR CASE 1 AND CASE 2.

Algorithms	Case 1		Case 2	
	P_{loss} (MW)	*VD* (p.u.)	P_{loss} (MW)	*VD* (p.u.)
DE [3]	4.5550	1.9589	6.4755	0.0911
BBO [4]	4.5511	-	-	-
PSO [5]	4.6282	1.0883	-	-
CLPSO [5]	4.5615	0.4773	-	-
GSA [6]	4.51431	0.87522	6.911765	0.067633
FA [7]	4.5691	1.7752	6.34	0.1157
ABC [7]	4.6022	0.7378	5.88	0.135
CKHA [8]	3.2400	1.3364	8.2400	0.0416
ALC-PSO [9]	4.4793	0.8425	6.2800	0.0437
QODE [10]	2.6867	0.4609	9.2745	0.0607
GSA	5.10615	1.55834	6.89782	0.23243
SQP	5.06908	0.99667	5.54686	0.09312
Hybrid GSA-SQP	**4.54271**	2.00789	5.96236	**0.08657**

V. CONCLUSIONS

In this paper a novel hybrid GSA-SQP algorithm has been proposed and successfully applied to solve ORPD problem. The proposed approach has been tested an investigated on the IEEE 30-bus test system. The results indicate that the hybrid GSA-SQP algorithm provides effective and robust high-quality solution. The hybrid GSA-SQP explores the global optima thanks to exploration and exploitation of GSA in the first part of the iterative process and local search ability of SQP in subsequent iterations.

The results obtained using hybrid GSA-SQP were compared with those reported in the literature. The comparison showed that the proposed method gives better solutions than other technique in the literature. In addition, the paper shows that some of the results reported in the literature are incorrect or infeasible.

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