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Dynamic strategy based fast decomposed GA coordinated with FACTS devices to enhance the optimal power flow

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ABSTRACT

Under critical situation the main preoccupation of expert engineers is to assure power system security and to deliver power to the consumer within the desired index power quality. The total generation cost taken as a secondary strategy. This paper presents an efficient decomposed GA to enhance the solution of the optimal power flow (OPF) with non-smooth cost function and under severe loading conditions. At the decomposed stage the length of the original chromosome is reduced successively and adapted to the topology of the new partition. Two sub problems are proposed to coordinate the OPF problem under different loading conditions: the first sub problem related to the active power planning under different loading factor to minimize the total fuel cost, and the second sub problem is a reactive power planning designed based in practical rules to make fine corrections to the voltage deviation and reactive power violation using a specified number of shunt dynamic compensators named Static Var Compensators (SVC). To validate the robustness of the proposed approach, the proposed algorithm tested on IEEE 30-Bus, 26-Bus and IEEE 118-Bus under different loading conditions and compared with global optimization methods (GA, EGA, FGA, PSO, MTS, MDE and ACO) and with two robust simulation packages: PSAT and MATPOWER. The results show that the proposed approach can converge to the near solution and obtain a competitive solution at critical situation and with a reasonable time.

1. Introduction

The main objective of an OPF strategy is to determine the optimal operating state of a power system by optimizing a particular objective while satisfying certain specified physical and operating constraints. In its most general formulation, the OPF is a nonlinear, nonconvex, large-scale, static optimization problem with both continuous and discrete control variables. It becomes even more complex when flexible ac transmission systems (FACTS) devices are taken into consideration as control variables [1,2].

The global optimization techniques known as genetic algorithms (GA) [3], simulated annealing (SA) [4], tabu search (TS) [5], Evolutionary programming (EP) [6], Particle swarm optimization (PSO) [7], Differential evolution (DE) [8], which are the forms of probabilistic heuristic algorithm have been successfully used to overcome the non-convexity problems of the constrained economic dispatch (ED).

The literature on the application of the global optimization in the OPF problem is vast and [9] represents the major contributions in this area. In [3] authors present an enhanced genetic algorithm (EGA) for the solution of the OPF problem with both continuous and discrete control variables. The continuous control variables modeled are unit active power outputs and generator-bus voltage magnitudes, while the discrete ones are transformer-tap settings and switchable shunt devices. In [10] the authors proposed a simple combined genetic algorithm and evolutionary programming applied to the OPF problem in large-scale power systems, to accelerate the processes of the optimization, the controllable variables are decomposed to active and passive constraints. The active constraints are taken to minimize the fuel cost function; the passive constraints are taken and integrated to an efficient power flow problem to make corrections to the active power of the slack bus. Authors in [11] present a modified differential evolution (MDE) to solve the optimal power flow (OPF) with non-smooth cost function, in [12] authors present a novel string structure for solving the economic dispatch through genetic algorithm (GA). To accelerate the search process Authors in [13] proposed a multiple tabu search algorithm (MTS) to solve the dynamic economic dispatch (ED) problem with generator constraints, simulation results prove that this approach is able to reduce the computational time compared to the conventional approaches.

The power system academic has made great efforts to provide to scientific community simulation tools that cover different as-

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pects of power systems analysis. Some robust examples of these simulation packages are Power Systems Analysis Toolbox (PSAT) developed by Milano [14] and Matpower developed by Zimmerman et al. [15].

In general, conventional methods face problems in yielding optimal solution due to nonlinear and nonconvex characteristic of the generating units. The true global optimum of the problem could not be reached easily. The GA method has usually better efficiency because the GA has parallel search techniques. Due to its high potential for global optimization, GA has received great attention in solving optimal power flow (OPF) problems. The main disadvantage of GAs is the high CPU time execution and the qualities of the solution deteriorate with practical large-scale optimal power flow (OPF) problems [16].

To overcome the drawbacks of the conventional methods related to the form of the cost function, and to reduce the computational time related to the large space search required by GA, this paper presents an efficient parallel GA (EPGA) for the solution of large-scale OPF with consideration shunt FACTS devices under severe loading conditions. The length of the original chromosome is reduced successively based on the decomposition level and adapted with the topology of the new partition. Partial decomposed active power demand added as a new variable and searched within the active power generation variables of the new decomposed chromosome. The proposed strategy of the OPF problem is decomposed in two sub problems, the first sub problem related to active power planning to minimize the fuel cost function, and the second sub problem designed to make corrections to the voltage deviation and reactive power violation based in an efficient reactive power planning using multi Static Var Compensator (SVC).

Simulation results demonstrate that the proposed decomposed GA approach is superior to the standard GA and appears to be fast providing competitive results under critical situation compared to the conventional and global optimization methods reported in the literature recently.

2. Optimal power flow formulation

The active power planning problem is considered as a general minimization problem with constraints, and can be written in the following form:

$$\text{Min} \quad f(x,u) \tag{1}$$

$$\text{S.t}: \quad g(x,u) = 0 \tag{2}$$

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

$$x = [\delta \quad V_L]^T \tag{4}$$

$$u = [P_G \quad V_G \quad t \quad B_{\text{svc}}]^T \tag{5}$$

$f(x,u)$ is the objective function, $g(x,u)$ and $h(x,u)$ are respectively the set of equality and inequality constraints. x is the state variables and u is the vector of control variables. The control variables are generator active and reactive power outputs, bus voltages, shunt capacitors/reactors and transformers tap-setting. The state variables are voltage and angle of load buses. For optimal active power dispatch, the objective function f is total generation cost as expressed follows:

$$\text{Min } f = \sum_{i=1}^{N_g} \left(a_i + b_i P_{gi} + c_i P_{gi}^2 \right) \tag{6}$$

where N_g is the number of thermal units, P_{gi} is the active power generation at unit i and a_i, b_i and c_i are the cost coefficients of the ith generator.

The equality constraints $g(x)$ are the power flow equations.

The inequality constraints $h(x)$ reflect the limits on physical devices in the power system as well as the limits created to ensure system security.

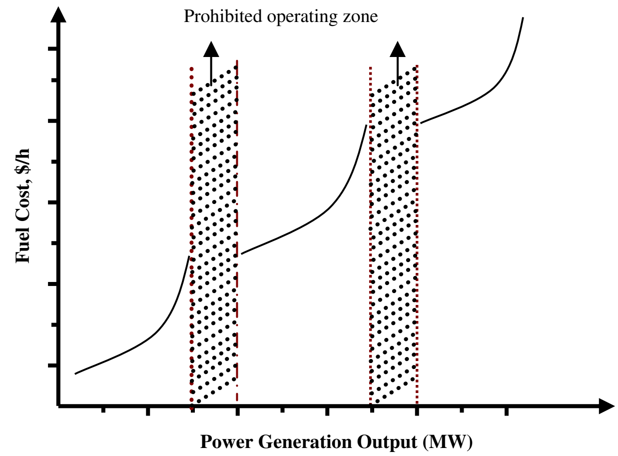

Fig. 1. Input–Output curve with prohibited operating zones.

2.1. Non-smooth cost function with prohibited operation zones

The prohibited operating zones in the input–output performance curve for a typical thermal unit can be due to robustness in the shaft bearings caused by the operation of steam values or to faults in the machines themselves or in the associated auxiliary, equipment such as boilers and feed pumps. [3,4]. In practice when adjusting the operation output of a unit one must avoid the operation in the prohibited zones. Thus the input–output performance curve for a typical thermal unit can be represented as shown in Fig. 1.

$$P_i \in \begin{cases} P_i^{\min} \leqslant P_i \leqslant P_{i,1}^1 \\ P_{i,k-1}^u \leqslant P_i \leqslant P_{i,k}^1, \quad k = 2, \ldots, z_i \\ P_{i,z_i}^u \leqslant P_i \leqslant P_i^{\max} \end{cases} \tag{7}$$

z_i is the number of prohibited zones of unit i, k the index of prohibited zones of a unit i, $P_{i,k}^{1/u}$ is the lower/upper bounds of the kth prohibited zone of unit i.

3. Shunt facts modelling

3.1. Static VAR compensator (SVC)

The steady-state model proposed in [17] is used here to incorporate the SVC on power flow problems. This model is based on representing the controller as a variable impedance, assuming an SVC configuration with a fixed capacitor (FC) and thyristor-controlled reactor (TCR) as depicted in Fig. 2.

$$V = V_{\text{ref}} + X_{\text{sl}} I \tag{8}$$

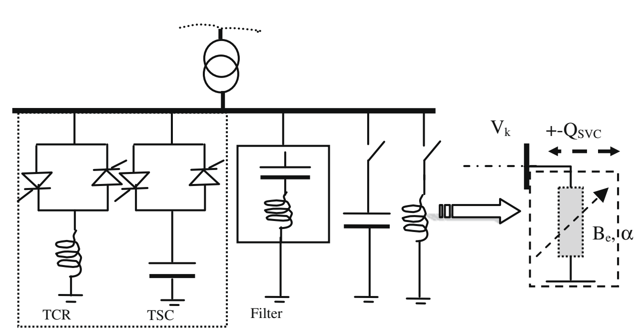

Fig. 2. SVC steady-state circuit representation.

X_{sl} are in the range of 0.02–0.05 p.u. with respect to the SVC base. The slope is needed to avoid hitting limits. At the voltage limits the SVC is transformed into a fixed reactance. The total equivalent impedance X_e of SVC may be represented by

$$X_e = X_C \frac{\pi/k_X}{\sin 2\alpha - 2\alpha + \pi(2 - 1/k_X)} \tag{9}$$

where $k_X = X_C/X_L$.

4. Strategy of the efficient parallel GA for OPF

4.1. Principle of the proposed approach

Parallel execution of various SGAs is called PGA (parallel genetic algorithm). parallel genetic algorithms (PGAs) have been developed to reduce the large execution times that are associated with simple genetic algorithms for finding near-optimal solutions in large search spaces. They have also been used to solve larger problems and to find better solutions. PGAs can easily be implemented on networks of heterogeneous computers or on parallel mainframes. The way in which GAs can be parallelized depends upon the following elements [18]:

- How fitness is evaluated.
- How selection is applied locally or globally.
- How genetic operators (crossover and mutation are used and applied).
- If single or multiple sub populations are used.
- If multiple populations are used how individuals are exchanged.
- How to coordinate between different sub populations to save the proprieties of the original chromosome.

In the proposed approach the sub populations created are dependent, efficient load flow used as a simple tool for flexible coordination to test the performance of the new sub populations generated.

Fig. 3 presents the principle of the efficient parallel GA proposed approach for active power planning coordinated with reactive power planning to adjust the voltage source and reactive power compensation within their specified constraints limits to reduce voltage deviation and the thermal transmission line.

In this study the controllable FACTS devices considered include shunt compensators (SVC).

The proposed algorithm decomposes the solution of such a modified OPF problem into two linked sub problems. The first sub problem is an active power generation planning solved by the proposed efficient genetic algorithm, and the second sub problem is a reactive power planning [18] to make fine adjustments on the optimum values obtained from the EPGA. This will provide updated voltages, angles and point out generators having exceeded reactive limits.

4.2. Decomposition mechanism

Problem decomposition is an important task for large-scale OPF problem, which needs answers to the following two technical questions.

1. How many efficient partitions needed?
2. Where to practice and generate the efficient inter-independent sub-systems?

The decomposition procedure decomposes a problem into several interacting sub problem that can be solved with reduced sub

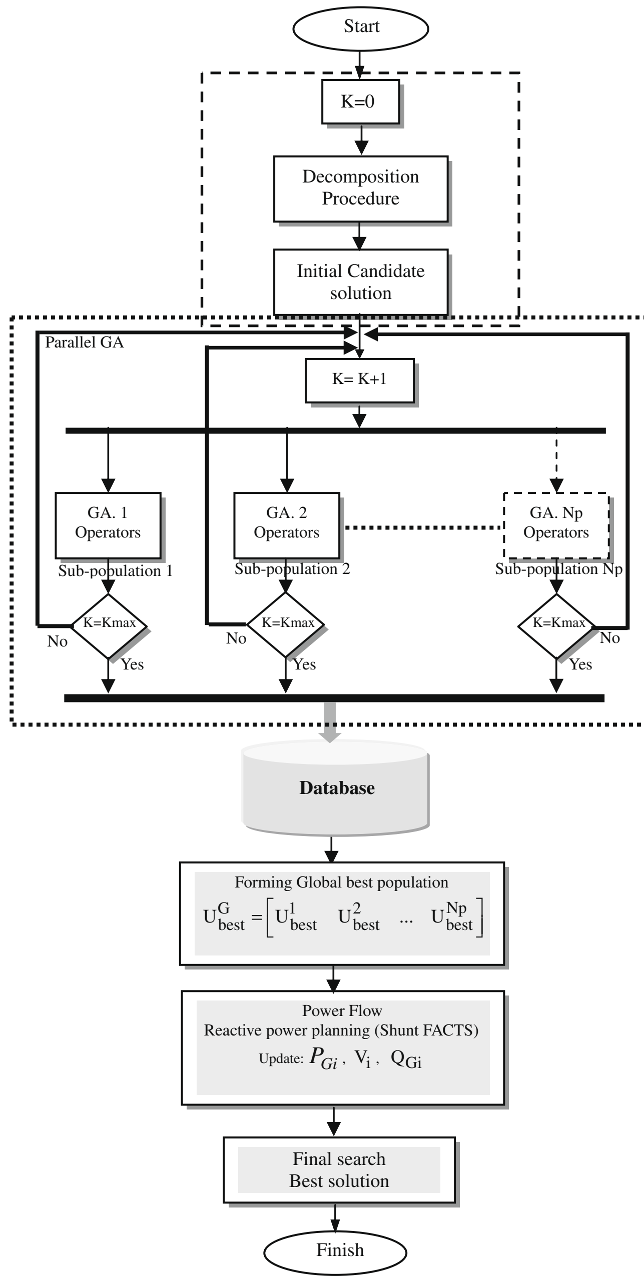

Fig. 3. Flowchart of the proposed EPGA approach-based OPF.

populations, and coordinate the solution processes of these sub problems to achieve the solution of the whole problem.

4.3. Justification for using efficient parallel continuous GA

4.3.1. Standard genetic algorithm

GA is a global search technique based on mechanics of natural selection and genetics. It is a general-purpose optimization algorithm that is distinguished from conventional optimization techniques by the use of concepts of population genetics to guide the optimization search. Instead of point-to-point search, GA searches from population to population. The advantages of GA over traditional techniques are [10]:

(i) It needs only rough information of the objective function and places no restriction such as differentiability and convexity on the objective function.

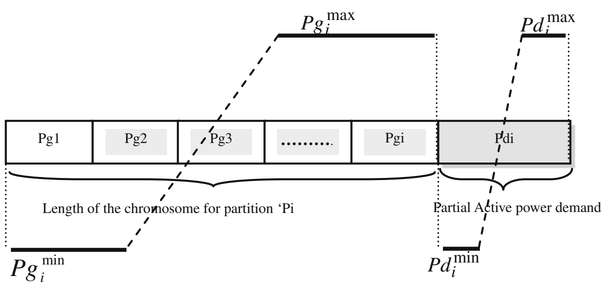

Fig. 4. Chromosome structure.

(ii) The method works with a set of solutions from one generation to the next, and not a single solution, thus making it less likely to converge on local minima.

(iii) The solutions developed are randomly based on the probability rate of the genetic operators such as mutation and crossover; the initial solutions thus would not dictate the search direction of GA.

4.3.2. Continuous GA applied to the OPF problem

The binary GA has its precision limited by the binary representation of variables; using floating-point numbers instead easily allows representation to the machine precision. This continuous GA also has the advantage of requiring less storage than the binary GA because a single floating-point number represents the variable instead of N_{bits} integers. The continuous GA is inherently faster than the binary GA, because the chromosomes do not have to be decoded prior to the evaluation of the cost function [10]. Fig. 4 shows the chromosome structure within the approach proposed.

4.3.2.1. Algorithm of the proposed approach.

4.3.2.1.1. Initialization based in decomposition procedure. The main idea of the proposed approach is to optimize the active power demand for each partitioned network to minimize the total fuel cost. An initial candidate solution generated for the global *N* population size.

1. For each decomposition level estimate the initial active power demand:

For NP = 2 Do

$$Pd_1 = \sum_{i=1}^{M1} PG_i \tag{10}$$

$$Pd_2 = \sum_{i=1}^{M2} PG_i = \mathrm{PD} - Pd_1 \tag{11}$$

where NP is the number of partition. Pd_1 the active power demand for the first initial partition, Pd_2 the active power demand for the second initial partition, and PD is the total active power demand for the original network.The following equilibrium equation should be verified for each decomposed level:For level 1:

$$Pd_1 + Pd_2 = \mathrm{PD} + P_{\mathrm{loss}} \tag{12}$$

2. Fitness evaluation based load flow.

For all sub-systems generated perform a load flow calculation to evaluate the proposed fitness function. A candidate solution formed by all sub-systems is better if its fitness is higher.

$$f_i = 1/(F_{\cos t} + \omega_l F_{li} + \omega_V F_{Vi}) \tag{13}$$

$$F_{Vi} = \sum_{j=1}^{nPQ} \left(\left|V_{PQij} - V_{PQij}^{\lim}\right|\right) / \left(\left|V_{PQij}^{\max} - V_{PQij}^{\min}\right|\right) \tag{14}$$

where f_i is the fitness function for sub-systems decomposed at level *i*. F_{li} denotes the per unit power loss generated by sub-systems at level i; $F_{\cos t}$ denotes the total cost of the active power planning

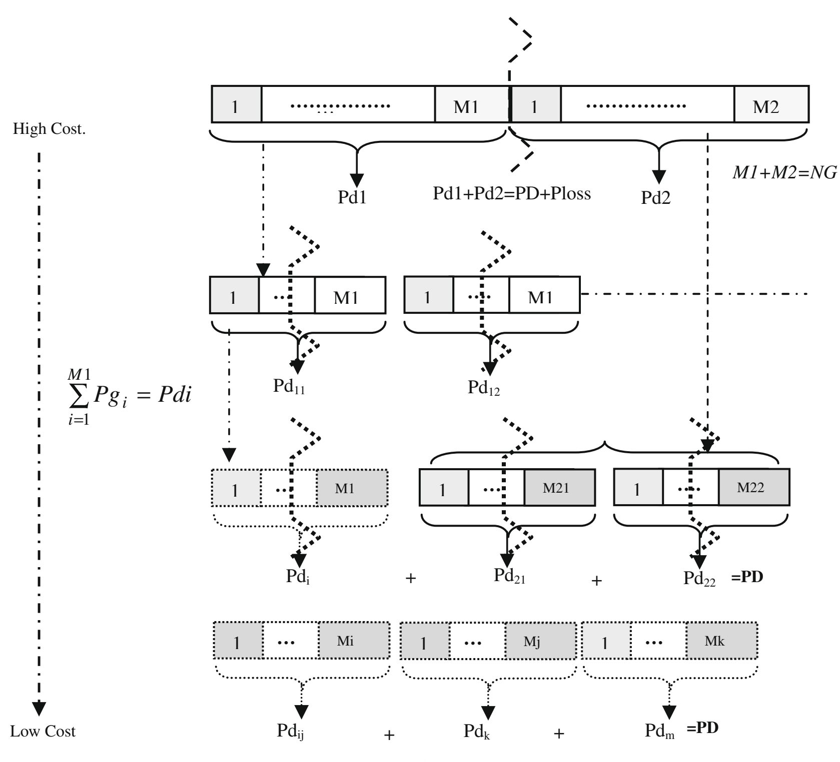

Fig. 5. Mechanism of search partitioning.

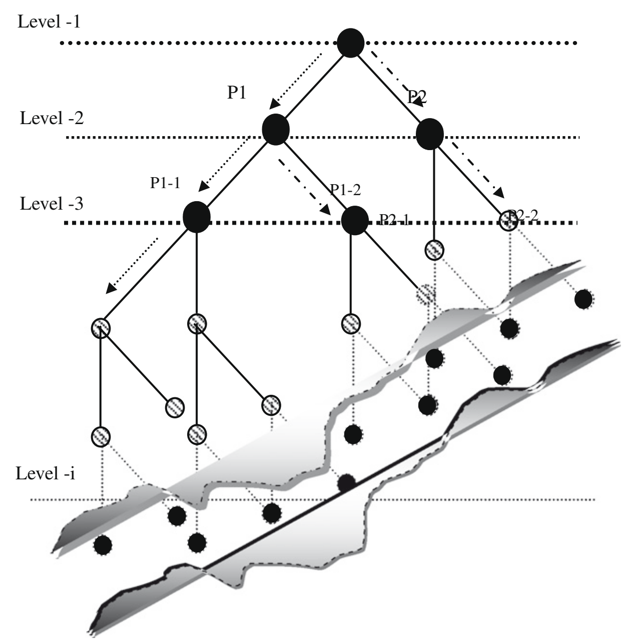

Fig. 6. Sample of network with tree decomposition.

related to the decomposition level i; F_{Vi} denotes the sum of the normalized violations of voltages related to the sub-systems at level i.

3. Consequently under this concept, the final value of active power demand should satisfy the following equations.

$$\sum_{i=1}^{N_g}(Pg_i) = \sum_{i=1}^{\mathrm{part}_i}(Pd_i) + p_{\mathrm{loss}} \tag{15}$$

$$Pg_i^{\min} \leqslant Pg_i \leqslant Pg_i^{\max} \tag{16}$$

4.3.3. Final search mechanism

- All the sub-systems are collected to form the original network, global data base generated based on the best results $U_{\mathrm{best}}^{\mathrm{Part}_i}$ of partition 'i' found from all sub populations.
- The final solution $U_{\mathrm{best}}^{\mathrm{Global}}$ is found out after reactive power planning procedure to adjust the reactive power generation limits, and voltage deviation, the final optimal cost is modified to compensate the reactive constraints violations. Fig. 5 illustrates the mechanism of search partitioning; Fig. 6 shows an example of tree network decomposition.

5. Application study

The proposed algorithm is developed in the Matlab programming language using 6.5 version. The proposed DGA is tested using modified IEEE 30-Bus system. The test examples have been run on a 2.6-GHz Pentium-IV PC. The generators data and cost coefficients are taken from [10].

5.1. Case studies on the IEEE 30-Bus system

5.1.1. Comparison with global optimization

The first test is the IEEE 30-Bus, 41-branch system, for the voltage constraint the lower and upper limits are 0.9 p.u and 1.1 p.u., respectively. The GA population size is taken equal 30, the maximum number of generation is 100, and crossover and mutation are applied with initial probability 0.9 and 0.01 respectively. For the purpose of verifying the efficiency of the proposed approach, we made a comparison of our algorithm with others competing OPF algorithm. In [10], they presented a standard GA, in [3] the authors presented an enhanced GA, and then in [19], they proposed an Improved evolutionary programming (IEP). In [20] they presented an optimal power flow solution using GA-Fuzzy system approach (FGA), and in [11] a modified differential evolution is proposed (MDE). The operating cost in our proposed approach is 800.8336 and the power loss is 8.92 which are better than the others methods reported in the literature. Results in Table 1 show clearly that the proposed approach gives better results. Table 2 shows the best solution of shunt compensation obtained at the standard load demand (Pd = 283.4 MW) using reactive power planning.

The operation costs of the best solutions for the new system composed by two partitions and for the new system composed by three partitions are 800.8336 \$/h and 800.9265, respectively, (0.0929 difference). The differences between the values are not

Table 1
Results of the minimum cost and power generation compared with: SGA, EGA, IEP, FGA and MDE for IEEE 30-Bus.

Variables	Our approach EPGA			SGA [10]	EGA [3]	IEP [19]	FGA [20]	MDE [11]
	NP = 1	NP = 2	NP = 3	Global optimization methods				
P_1 (MW)	180.12	175.12	174.63	179.367	176.20	176.2358	175.137	175.974
P_2 (MW)	44.18	48.18	47.70	44.24	48.75	49.0093	50.353	48.884
P_5 (MW)	19.64	20.12	21.64	24.61	21.44	21.5023	21.451	21.510
P_8 (MW)	20.96	22.70	20.24	19.90	21.95	21.8115	21.176	22.240
P_{11} (MW)	14.90	12.96	15.04	10.71	12.42	12.3387	12.667	12.251
P_{13} (MW)	12.72	13.24	12.98	14.09	12.02	12.0129	12.11	12.000
Q_1 (Mvar)	−4.50	−2.11	−2.03	−3.156	–	–	−6.562	–
Q_2 (Mvar)	30.71	32.57	32.42	42.543	–	–	22.356	–
Q_5 (Mvar)	22.59	24.31	23.67	26.292	–	–	30.372	–
Q_8 (Mvar)	37.85	27.82	28.22	22.768	–	–	18.89	–
Q_{11} (Mvar)	−2.52	0.490	0.48	29.923	–	–	21.737	–
Q_{13} (Mvar)	−13.08	−11.43	−11.43	32.346	–	–	22.635	–
θ_1°	0.00	0.00	0.00	0.000	–	–	0.00	–
θ_2°	−3.448	−3.324	−3.313	−3.674	–	–	−3.608	–
θ_5°	−9.858	−9.725	−9.623	−10.14	–	–	−10.509	–
θ_8°	−7.638	−7.381	−7.421	−10.00	–	–	−8.154	–
θ_{11}°	−7.507	−7.680	−7.322	−8.851	–	–	−8.783	–
θ_{13}°	−9.102	−8.942	−8.926	−10.13	–	–	−10.228	–
Cost (\$/h)	801.3445	800.8336	800.9265	803.699	802.06	802.465	802.0003	802.376
P_{loss} (MW)	9.120	8.920	8.833	9.5177	9.3900		9.494	9.459
Average CPU time (s)	~0.954			–	594.08	–	–	23.07

Table 2
Comparative results of the shunt reactive power compensation between EPGA and EGA [7] for IEEE 30-Bus.

Shunt no.	1	2	3	4	6	7	8	9
Bus no.	10	12	15	17	21	23	24	29
Best Q_{svc} (pu)	0.1517	0.0781	0.0295	0.0485	0.0602	0.0376	0.0448	0.0245
Best case bus (pu) [7]	0.05	0.05	0.03	0.05	0.05	0.04	0.05	0.03

Table 3
Transmission line loading after optimization compared to ACO and FGA for IEEE 30-Bus.

Line	Rating (MVA)	EPGA: PD = 283.4 MW		ACO [21]	FGA [20]
		From bus *P* (MW)	To bus *P* (MW)	To bus *P* (MW)	To bus +(*P* (MW))
1–2	130	113.9200	−7.7300	−119.5488	117.211
1–3	130	60.7100	5.7000	−58.3682	58.3995
2–4	65	32.0600	4.3000	−34.2334	34.0758
3–4	130	56.8600	3.7900	−55.5742	54.5622
2–5	130	62.4200	4.9000	−62.4522	63.7783
2–6	65	43.3000	2.4400	−44.5805	45.3399
4–6	90	49.1700	−8.0100	−49.0123	50.2703
5–7	70	−11.7900	7.2300	11.2939	14.1355
6–7	130	34.9800	0.8800	−34.0939	33.9924
6–8	32	11.8500	−1.3200	−11.0638	13.6882
6–9	65	16.5700	−3.3400	−19.7631	22.4033
6–10	32	12.5400	0.0700	−13.1277	14.6187
9–11	65	−15.0400	−0.0700	10.4330	24.1764
9–10	65	31.6100	−3.8000	−30.1961	32.7929
4–12	65	31.2200	16.7200	−33.1670	30.5889
12–13	65	−12.9800	11.8000	12.1730	24.9376
12–14	32	7.6600	1.0500	−8.0453	7.6911
12–15	32	18.1000	1.4900	−18.1566	17.4525
12–16	32	7.2400	1.3600	−7.4961	6.34027
14–15	16	1.4000	−0.6800	−1.8340	1.2313
16–17	16	3.6900	−0.5400	−3.9715	3.2983
15–18	16	5.8900	1.9700	−6.2224	5.4066
18–19	16	2.6500	1.0000	−3.0140	2.3627
19–20	32	−6.8500	−2.4100	6.5015	8.5117
10–20	32	9.1500	3.3200	−8.7015	11.0315
10–17	32	5.3200	0.8600	−5.0285	9.861616
10–21	32	16.1000	3.9800	−15.8419	18.96153
10–22	32	7.7800	1.7400	−7.6778	9.0741
21–22	32	−1.4800	−0.6100	1.6585	2.0887
15–23	16	5.2100	−0.7000	−5.4613	4.5343
22–24	16	6.2600	1.0400	−5.9593	6.9397
23–24	16	1.9900	1.8800	−2.2388	1.14447
24–25	16	−0.5000	1.1200	0.5027	1.3934
25–26	16	3.5400	2.3600	−3.5000	4.2647
25–27	16	−4.0500	−1.2400	4.0748	5.633
27–28	65	17.3200	2.9500	−17.3814	19.7428
27–29	16	6.1900	−0.2900	−6.1070	6.4154
27–30	16	7.0600	0.8900	−6.9295	7.2897
29–30	16	3.7200	1.3500	−3.6705	3.7542
8–28	32	2.0700	−2.1900	−2.2067	3.3685
6–28	32	15.2900	−0.6800	−15.1747	16.5409
P_{loss} (MW)	8.8836			9.8520	9.494

significant compared to the original network without partitioning. This proves that the new sub-systems generated conserve the physical proprieties and performances of the original network. Table 3 shows that the line flows obtained are well under security limits compared to FGA algorithm and ACO algorithm [21].

5.1.2. Comparison with PSAT and MATPOWER OPF solver

For the purpose of verifying the robustness of the proposed algorithm we made a second comparison with PSAT and MATPOWER packages under severe loading conditions.

In this study the increase in the load is regarded as a parameter which affects the power system to voltage collapse.

$$\begin{cases} P_L = \mathrm{Kld} \cdot P_{oL} \\ Q_L = \mathrm{Kld} \cdot Q_{oL} \end{cases} \quad (17)$$

where, P_{oL} and Q_{oL} are the active and reactive base loads, P_L and Q_L are the active and reactive loads at bus L for the current operating point. Kld represents the loading factor.

The results including the generation cost, the power losses, reactive power generation, and the angles are shown in Table 4. We can clearly observe that the total cost of generation and power losses are better than the results obtained by PSAT and MATPOWER at both loading factor (Kld = 18% and Kld = 32%). For example at loading factor 32% (PD = 374.088) the difference in generation cost between our approach and to the two packages (1159.6 $/h compared to 1160.56 $/h and 1164.1706 $/h) and in real power loss (12.975 MW compared to 13.556 MW and 14.385 MW) obtained from MATPOWER and PSAT respectively. Table 5 depicts the results of minimum cost, power generation, power losses, reactive power generation, and angles. At loading factor Kld = 48.5%, the two simulation package (PSAT and MATPOWER) did not converge. The ap-

Table 4
Results of the minimum cost and power generation compared with: PSAT and MATPOWER package for IEEE 30-Bus.

Variables	Our approach EPGA		MATPOWER		PSAT	
	Kld = 18%	Kld = 32%	Kld = 18%	Kld = 32%	Kld = 18%	Kld = 32%
P_1 (MW)	192.66	199.30	200.00	200.0	200.00	200.0
P_2 (MW)	58.94	70.60	55.00	69.74	54.9925	69.9368
P_5 (MW)	23.22	29.08	23.70	28.40	23.6957	28.5135
P_8 (MW)	33.98	33.66	35.00	35.00	35.00	35.00
P_{11} (MW)	16.60	29.32	17.01	28.03	17.0154	28.2596
P_{13} (MW)	20.40	25.10	15.84	26.47	15.8827	26.7635
Q_1 (Mvar)	−5.26	−6.18	−13.94	−17.66	−15.6226	−9.4127
Q_2 (Mvar)	38.07	40.02	37.18	43.69	38.5416	60.4752
Q_5 (Mvar)	35.25	42.28	36.10	42.62	36.5254	49.5412
Q_8 (Mvar)	35.95	43.54	47.96	60.00	49.525	50.00
Q_{11} (Mvar)	1.150	2.06	3.680	6.910	4.6425	21.1631
Q_{13} (Mvar)	−11.73	−11.04	−11.68	−2.270	2.3642	19.7389
θ_1°	0.00	0.00	0.00	0.00	0.00	0.00
θ_2°	−3.684	−3.972	−4.028	−4.022	−4.0412	−4.026
θ_5°	−11.218	−12.002	−11.841	−12.518	−11.8475	−12.6009
θ_8°	−8.055	−8.588	−8.737	−9.065	−8.7607	−8.7792
θ_{11}°	−11.995	−6.847	8.931	−7.386	−8.9022	−7.0128
θ_{13}°	−9.344	−9.423	−10.642	−9.751	−10.6419	−9.8547
Cost ($/h)	993.6802	1159.6	993.98	1160.56	994.1047	1164.1706
P_{loss} (MW)	11.390	12.975	12.141	13.556	12.174	14.385

Table 5
Results of the minimum cost and power generation compared with PSAT and MATPOWER package for IEEE 30-Bus.

Variables	Loading factor Kld = 48.5% PD = 420.85 MW		
	Our approach	PSAT	MATPOWER
P_1 (MW)	199.98	Did not converge	Did not converge
P_2 (MW)	79.96		
P_5 (MW)	49.98		
P_8 (MW)	34.92		
P_{11} (MW)	30.00		
P_{13} (MW)	39.90		
Q_1 (Mvar)	−5.680		
Q_2 (Mvar)	41.62		
Q_5 (Mvar)	45.14		
Q_8 (Mvar)	53.31		
Q_{11} (Mvar)	2.910		
Q_{13} (Mvar)	−10.33		
θ_1°	0.000		
θ_2°	−3.761		
θ_5°	−11.907		
θ_8°	−8.972		
θ_{11}°	−7.228		
θ_{13}°	−8.237		
Cost ($/h)	1403.5		
P_{loss} (MW)	13.8960		

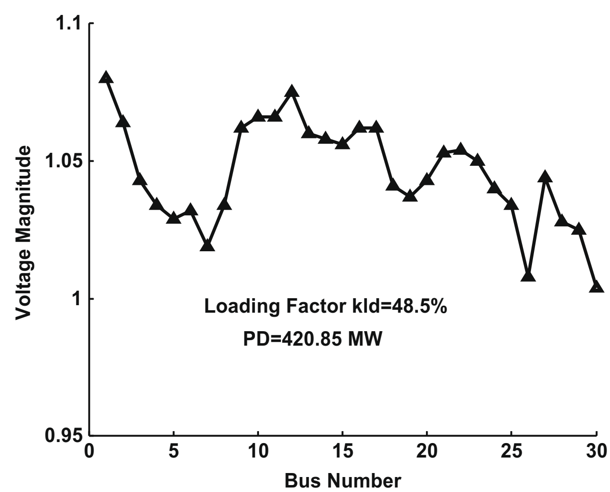

Fig. 7. Voltage profile of the IEEE 30-Bus at loading factor: Kld = 48.5%.

proach proposed gives acceptable solution, the minimum total cost is 1403.5 $/h. The security constraints are also checked for voltage magnitudes, angles and branch flows. Fig. 7 shows that the voltages magnitudes are within the specified security limits. Fig. 8 shows clearly that the transmission lines loading do not exceed their upper limits. Fig. 9 shows the reactive power exchanged between SVC controllers installed at a specified buses and the network.

5.2. Case study 2: 26-Bus test system with non-smooth cost function

This case study consisted of six generation units, 26 buses and 46 transmission lines [22]. All thermal units are within the ramp rate limits and prohibited zones. All data of this test system can be retrieved from [22,23]. In this case, the load demand expected to be determined was PD = 1263. The B matrix of the transmission loss coefficient is given by:

$$B_{ij} = 10^{-3} \cdot \begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 0.1 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0.0 & -1.0 & -0.6 \\ -0.1 & 0.1 & 0.0 & 0.24 & -0.6 & -0.8 \\ -0.5 & -0.6 & -0.6 & -0.6 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix} \tag{18}$$

$$B_{i0} = 10^{-3} \cdot [-0.3908 \quad -0.1297 \quad -0.7047 \quad -0.0591 \quad 0.2161 \quad -0.6635] \tag{19}$$

$$B_{00} = 0.056 \tag{20}$$

Table 6 shows the performance comparison among the proposed algorithms, a particle swarm optimization (PSO) approach [22], a novel string based GA [12], standard genetic algorithm (GA) method [22], multiple tabu search algorithm (MTS) [13], and the simulated annealing (SA) method [13]. The simulation results of the proposed approach outperformed recent optimization methods presented in the literature in terms of solution quality and time convergence.

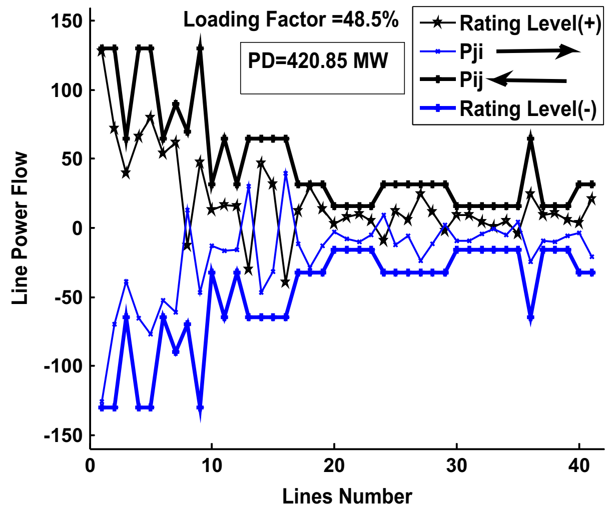

Fig. 8. Lines Power flow of the IEEE 30-Bus at critical loading factor Kld = 48.5%.

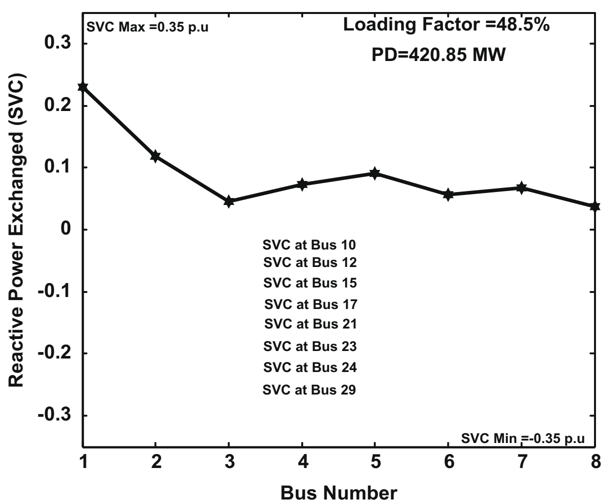

Fig. 9. Reactive power exchanged between SVC controllers and the IEEE 30-Bus network at loading factor: Kld = 48.5%.

The performance of the convergence characteristics for the three partitioned network are shown clearly in Fig. 10. The computational time of the proposed approach is reduced significantly in comparison to the other methods.

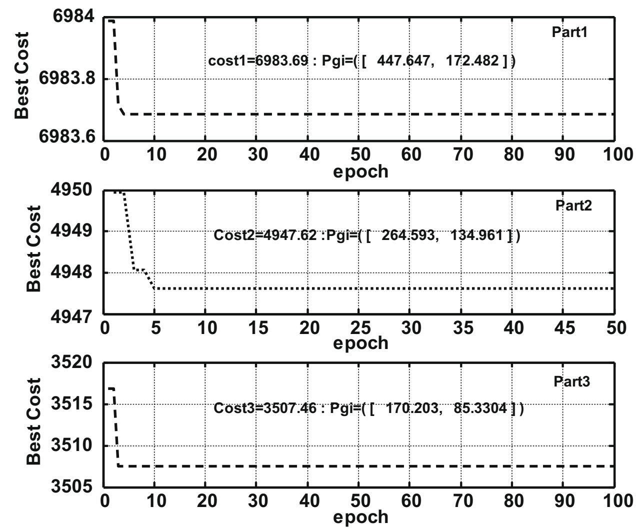

Fig. 10. Convergence characteristic of the three partition network 26-Bus.

5.3. Case study 3 on the IEEE 118-Bus

To investigate the robustness of the proposed approach the algorithm was implemented and tested to the standard IEEE 118-Bus model system (54 generators, 186 (line + transformer) and 99 loads). The system load is 4242 MW and base MVA is 100 MVA. In this model, there are 54 generators and they are consists of different 18 characteristic generators [10]. The proposed approach is compared to the real Genetic Algorithm proposed in [10]. The results depicted in Table 7 show clearly that the proposed approach gives much better results than the others method. The difference in generation cost between these two studies (6347.2 $/h compared to 8278.9 $/h) and in real power loss (106.788 MW compared to 94.305 MW).

The optimum active powers are all in their secure limits values and are far from the physical constraints limits. The security constraints are also checked for voltage magnitudes and angles. Reactive power planning [11,12] applied in the second step based in practical fuzzy rules. Fig. 11 shows the topology the standard IEEE 118-Bus, Fig. 12 shows that the reactive power generations are on their security limits; Fig. 13 shows the reactive power exchanged between the SVC Compensators installed at critical buses and the network. Fig. 14 demonstrates that the voltage profiles for all buses are enhanced based in reactive power planning sub problem.

Table 6
Results of the minimum cost and power generation compared with global optimization methods for 26-Bus test system.

Generators (MW)	SA [13]	New-string GA [12]	GA [22]	MTS [13]	PSO [22]	Our approach
Part 1						
Pg_1	478.1258	446.7100	474.8066	448.1277	447.4970	448.0451
Pg_2	163.0249	173.0100	178.6363	172.8082	173.3221	172.0835
Part 2						
Pg_3	261.7143	265.0000	262.2089	262.5932	263.4745	264.5932
Pg_4	125.7665	139.0000	134.2826	136.9605	139.0594	134.9605
Part 3						
Pg_5	153.7056	165.2300	151.9039	168.2031	165.4761	170.2452
Pg_6	90.7965	86.7800	74.1812	87.3304	87.1280	85.2884
Total PG	1276.1339	1275.73	1276.03	1276.0232	1276.01	1275.20
Ploss (MW)	13.1317	12.733	13.0217	13.0205	12.9584	12.2160
Cost ($/h)	15461.10	15447.00	15459.00	15450.06	15450.00	15,439
CPU time (s)	–	8.36	–	1.29	14.89	1.4380

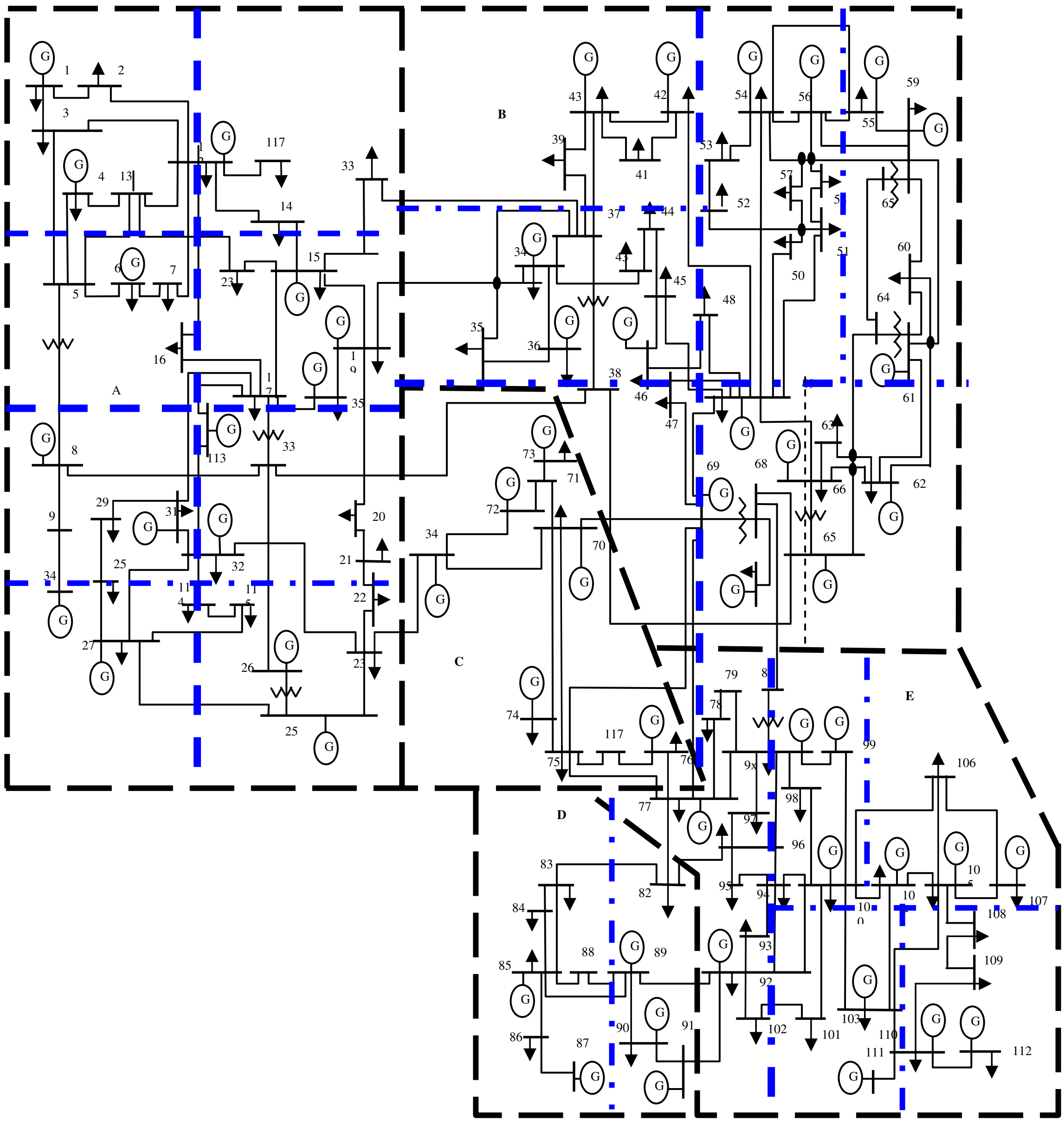

Fig. 11. Topology of the IEEE 118-Bus test system.

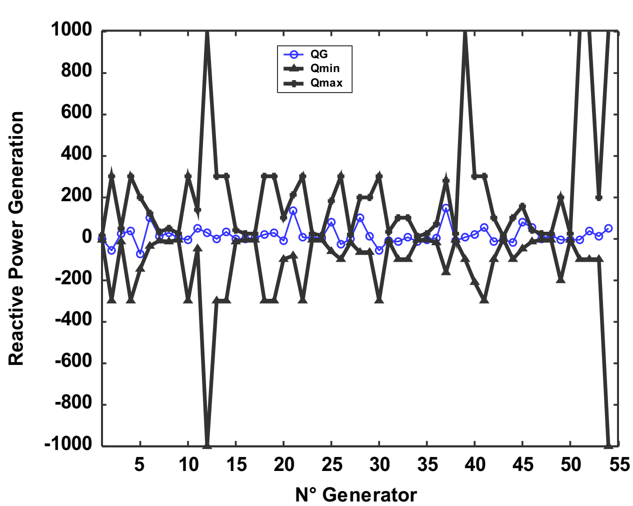

Fig. 12. Reactive power generation of IEEE 118-Bus electrical network with shunt compensation (Pd = 4242 MW).

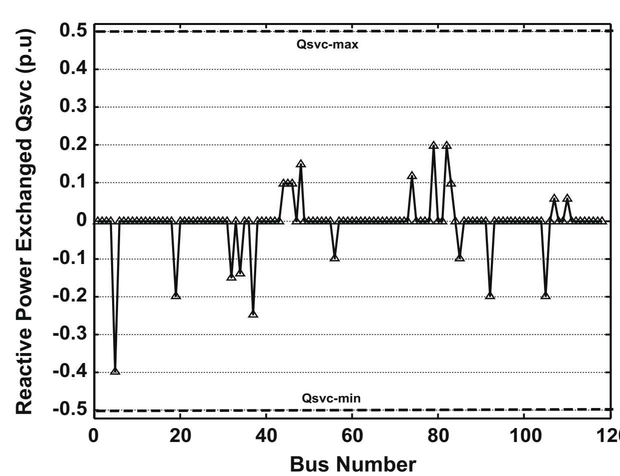

Fig. 13. Reactive power compensation based SVC compensators exchanged with the IEEE 118-Bus electrical network (Pd = 4242 MW).

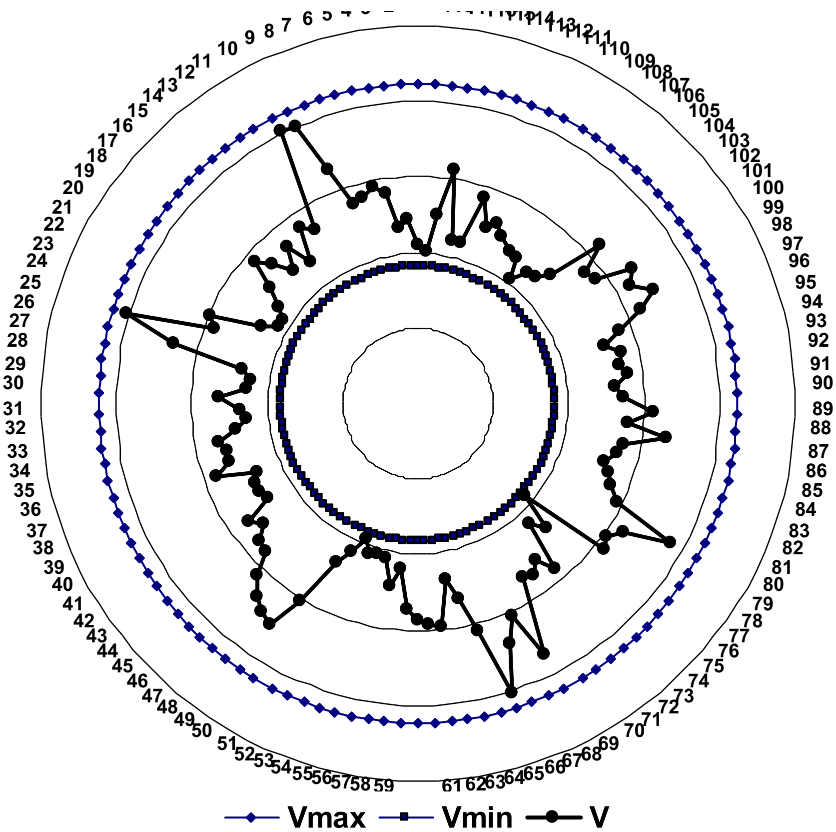

Fig. 14. Voltage profiles of IEEE 118-Bus electrical network.

Table 7
Results of the minimum cost and power generation compared with GA for IEEE 118-Bus.

Gen	Type	EPGA	GA [10]	Gen	Type	EPGA	GA [10]
1	#1	10.840	11.99	65	#11	402.60	456.61
4	#1	11.280	33.603	66	#11	120.06	134.99
6	#1	16.840	10.191	69	#12	523.05	316.59
8	#1	21.380	10.038	70	#1	26.700	24.148
10	#2	258.86	162.09	72	#1	21.940	31.967
12	#3	92.760	63.06	73	#1	14.040	43.362
15	#1	10.000	28.439	74	#1	25.480	10.149
18	#1	10.000	10.398	76	#1	28.020	16.45
19	#1	10.780	10.023	77	#1	15.820	12.131
24	#1	10.060	13.178	80	#13	370.54	445.55
25	#4	289.98	282.02	85	#1	47.260	18.717
26	#5	411.80	376.55	87	#14	27.400	44.402
27	#1	13.700	29.683	89	#15	392.38	322.79
31	#6	43.100	67.232	90	#1	10.000	20.24
32	#1	11.020	14.144	91	#1	10.000	21.206
34	#1	12.160	12.912	92	#1	10.000	19.163
36	#1	10.300	12.639	99	#1	10.000	10.161
40	#1	14.180	66.505	100	#16	312.88	318.47
42	#1	15.100	19.805	103	#17	82.840	47.058
46	#7	73.420	13.345	104	#1	10.000	39.387
49	#8	101.24	217.88	105	#1	10.000	18.515
54	#9	40.820	52.24	107	#1	40.820	10.248
55	#1	13.140	14.431	110	#1	18.620	10.554
56	#1	14.520	23.335	111	#18	56.280	28.67
59	#10	157.26	59.497	112	#1	12.060	10.833
61	#10	41.920	195.11	113	#1	11.340	22.311
62	#1	11.820	43.015	116	#1	10.380	28.272
Cost ($/h)t		6347.2	8278.9				
Losses (MW)		106.788	94.305				

6. Conclusion

Efficient parallel GA combined with practical rules is studied for optimal power flow under severe loading conditions (voltage stability).

The main objective of the proposed approach is to improve the performance of the standard GA in term of reduction time execution for an online application to large-scale power system and the accuracy of the results with consideration of load incrementation. To save an important CPU time, the original network was decomposed in multi sub-systems and the problem transformed to optimize the active power demand associated to each partitioned network. Numerical testing and a comparative analysis show that the proposed algorithm, in most the cases, outperforms other recent approaches reported in the literature.

It is found the proposed approach can converge at the near solution and obtain a competitive solution at critical situations.

As for the future work along this line, the author will strive to develop an adaptive and a flexible algorithm to generalize the application of the proposed approach to large-scale power systems (up to 300-Bus) and with the possibility for an online application.

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