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Self-adaptive Differential Evolution Based Optimal Power Flow for Units with Non-smooth Fuel Cost Functions

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This paper presents a self-adaptive differential evolution with augmented Lagrange multiplier method (SADE_ALM) for solving optimal power flow (OPF) problems with non-smooth generator fuel cost curves. The SADE_ALM is a modified version of conventional differential evolution (DE) by integrating mutation factor (F) and crossover constant (CR) as additional control variables. An augmented Lagrange multiplier method (ALM) is applied to handle inequality constraints instead of traditional penalty function method, whereas the sum of the violated constraint (SVC) index is employed to ensure that the final result is the feasible global or quasi-global optimum. The proposed algorithm has been tested with the IEEE 30-bus system with different fuel cost characteristics, i.e. 1) quadratic cost curve model, and 2) quadratic cost curve with rectified sine component model (valve-point effects). Numerical results show that the SADE_ALM provides very impressive results compared with the previous reports.

Keywords: Differential evolution, Non-smooth fuel cost function, Optimal power flow, Self-adaptation.

1. INTRODUCTION

Optimal power flow (OPF) is a large dimension nonlinear, nonconvex and highly constrained optimization problem that has been used widely for power system planning and operation. It is nonconvex due to existence of nonlinear AC power flow equations, non-smooth or nonconvex fuel cost functions (e.g., valve-point effects, multiple fuels [1]), or the flexible alternating current transmission system (FACTS) devices in the power system.

Conventional gradient based optimization techniques such as linear programming, nonlinear programming, quadratic programming, and interior point method, have been used to solve the OPF problems. The literatures of those approaches were reviewed by Momoh et. al. [2-3]. These methods rely on convex and continuous fuel cost function to obtain the global optimum solution, and as such, these curves must be approximated by continuous and monotonic functions. Therefore, the drawback of conventional gradient based method usually converges to sub-optimal solution when nonconvex characteristics of fuel cost function are considered [4]. Many heuristic algorithms such as evolutionary programming (EP) [4], tabu search (TS) [5], hybrid tabu search and simulated annealing (TS/SA) [6], improved tabu search (ITS) [7], and improved evolutionary programming (IEP) [8] have been proposed to solve the OPF problems. These techniques search for the global or quasi-global optimum for any type of objective function and constraints without any requirement of the gradient information, and the results reported were promising and encouraging for further research in this direction.

Recently, differential evolution (DE) has been increasing attention for a wide variety of engineering application including power engineering [1, 9, 10]. DE is an evolutionary algorithm (EA) that uses rather greedy selection and less stochastic approach to solve optimization problems than other classical EAs such as genetic algorithm (GA), evolutionary programming (EP), and evolutionary strategies (ES). The potentialities of DE

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are its simple structure, convergence property, quality of solution, and robustness [11-12]. However, tuning the DE's parameters – mutation factor (F), crossover constant (CR), and population size (NP) – is a tedious task due to complex relationship among parameters. The optimal parameter settings may never be found, and the final result may be trapped in a local optimum [1, 13].

In this paper, we present a self-adaptive differential evolution with augmented Lagrange multiplier method (SADE_ALM) [1] for solving the OPF problems with non-smooth generator fuel cost curves. Treated as additional control variables, the mutation factor (F) and the crossover constant (CR) are dynamically self-adaptive throughout the evolutionary process to avoid local optimal trapping. An augmented Lagrange multiplier method (ALM) [1] is applied to handle inequality constraints instead of traditional penalty function method, whereas the sum of the violated constraint (SVC) index is employed to ensure that the final result is the feasible global or quasi-global optimum.

2. OPF PROBLEM FORMULATION

The optimal power flow (OPF) problem is to optimize the total generator fuel cost function subject to power balance constraints and inequality constraints imposed on the operation of power system. Mathematically, the OPF problem can be formulated as follows:

$$Min\ \ J(X,U) \tag{1}$$

subject to

$$h(X,U)=0 \tag{2}$$

$$g(X,U)\leq 0 \tag{3}$$

where $J(X,U)$ is the objective function to be minimized, $h(X,U)$ is the equality constraints and represent typical power flow equations. $g(X,U)$ is the system operating constraints. U is the vector of state variables consisting of real power of slack generator P_{G1}, voltage magnitude of load buses V_L, reactive power of all generators Q_G, transformer and transmission line loadings S_l. Therefore, U can be expressed as $U^T=[P_{G1},V_{L1},...,V_{LNL},Q_{G1},...,Q_{GNG},S_{l1},...,S_{lNBR}]$, where NL, NG, and NBR are number of load buses, number of generators, and number of transformers and transmission lines. X is the vector of control variables consisting of real power of all generators excluding slack generator, voltage magnitude of all generators V_G, and transformer tap settings T.

Therefore, X can be expressed as $X^T=[P_{G2},...,P_{GNG},V_{G1},...,V_{GNG},T_1,...,T_{NT}]$ where NT is the number of regulating transformers. Generally, in the OPF problem, the objective function J is the total generator fuel cost, i.e.

$$J=\sum_{i=1}^{NG} f_i\left(P_{Gi}\right) \tag{4}$$

where $f_i\left(P_{Gi}\right)$ is the fuel cost function of the *i*th generator.

The system operating constraints can be described below.

1) Generation constraints: Real and reactive power outputs, and voltage magnitude of generators are restricted by the lower and upper limits, i.e.

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \qquad i \in NG \tag{5}$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \qquad i \in NG \tag{6}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \qquad i \in NG \tag{7}$$

2) Transformer constraints: Transformer tap settings are restricted by the lower and upper limits as follows:

$$T_i^{\min} \le T_i \le T_i^{\max}, \qquad i \in NT \tag{8}$$

3) Securities constraints: These include the constraints of voltage magnitude at load buses and power flow through transformers and transmission line (MVA loading) as follows:

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \qquad i \in NL \tag{9}$$

$$S_{li} \le S_{li}^{\max}, \qquad i \in NBR \tag{10}$$

As mentioned earlier, the fuel cost function of generating units is generally represented by simple quadratic function as shown in (11).

$$f_i\left(P_{Gi}\right) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{11}$$

where P_{Gi} is the real power of the *i*th generator, and a_i, b_i, and c_i are the fuel cost coefficients.

Considering valve-point effects [1], the fuel cost function of generating units consists of rectified sine components superimposed on the quadratic function as follows:

$$f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left| d_i \times \sin(e_i \times (P_{Gi}^{\min} - P_{Gi})) \right| \tag{12}$$

where $P_{Gi}^{\min}$ is the lower limit of real power of the *i*th generator, and d_i and e_i are fuel cost coefficients of the *i*th generator with valve-point effects.

It is worth mentioning that the inequality constraints of the control variables are self-constrained. In this paper, the inequality constraints of the state variables are handled using the augmented Lagrange multiplier (ALM) method. Generally, the penalty function method is the most popular methods for handling inequality constraints, due to its simple concept and convenience to implementation. However, the penalty function method does suffer from the complication that as the penalty parameter is increased toward infinity; the structure of the unconstrained problem becomes increasing ill-conditioned. Therefore, each unconstrained minimization problem becomes more difficult to solve, which has the effect of slowing the convergence rate of the overall optimization process. On the other hand, if the penalty parameters are too small, the constraint violation will not impose a high cost on the penalty function. Thus the optimal solution based on the penalty function may not be feasible, whereas the ALM method can be employed easily to handle inequality constraints without those difficulties [1, 14-15].

The unconstrained minimization problem through the augmented lagrange function L_a can be defined by augmented the m-inequality constraints of the state variables with the objective function as shown below [1].

$$L_a = f(X,U) + r_g \sum_{j=1}^{m} \left\{ \max\left[g_j(X,U), -\frac{\beta_j}{2r_g} \right] \right\}^2 + \sum_{j=1}^{m} \beta_j \left\{ \max\left[g_j(X,U), -\frac{\beta_j}{2r_g} \right] \right\} \quad (13)$$

where $g_j(\cdot), j = 1,2,\ldots,m$, $m = 2(1 + NL + NG) + NBR$ are the m-inequality constraints of the state variables which can be defined as follows:

1) Real power of slack generator P_{G1}

$$g_1 = \left(-P_{G1} + P_{G1}^{\min}\right) \quad (14)$$

$$g_2 = \left(P_{G1} - P_{G1}^{\max}\right) \quad (15)$$

2) Voltage magnitude of load buses V_{Li}, $i = 1,2,\ldots,NL$

$$g_i = \left(-V_{Li} + V_{Li}^{\min}\right) \quad (16)$$

$$g_{i+1} = \left(V_{Li} - V_{Li}^{\max}\right) \quad (17)$$

3) Reactive power of generators Q_{Gi}, $i = 1,2,\ldots,NG$

$$g_i = \left(-Q_{Gi} + Q_{Gi}^{\min}\right) \quad (18)$$

$$g_{i+1} = \left(Q_{Gi} - Q_{Gi}^{\max}\right) \quad (19)$$

4) Transformer and transmission line loadings S_{li}, $i = 1,2,\ldots,NBR$

$$g_i = \left(S_{li} - S_{li}^{\max}\right) \quad (20)$$

r_g is the positive penalty multiplier, and $\beta_j s$ are the lagrange multiplier of the associated inequality constraints.

After the unconstrained minimization problem has been solved, the lagrange multipliers $\beta_j s$ and the penalty parameter r_g will be updated to create the new augmented lagrange function L_a as follows [1]:

$$\beta_j^{i+1} = \beta_j^i + 2r_g \left\{ \max\left[g_j(X,U), -\frac{\beta_j^i}{2r_g} \right] \right\} \quad (21)$$

$$r_g^{i+1} = \begin{cases} c_g \times r_g^i, & \text{if } r_g^i \le r_{g,\max} \\ r_{g,\max}, & \text{otherwise} \end{cases} \quad (22)$$

where c_g is the positive constant increasing rate, and $r_{g,\max}$ is the maximum penalty multiplier.

From (21), it can be seen that the Lagrange multipliers $\beta_j s$ are deterministically updated using the inequality constraint functions evaluated from the previous solution of the unconstrained minimization problem, while the penalty parameter r_g is increased by a constant rate until it reaches the predetermined maximum value as shown in (22). The algorithm is then repeated until termination. The detail of the proposed algorithm will be described in the next section.

3. SADE_ALM BASED OPTIMAL POWER FLOW (SADE_ALM-OPF)

The proposed self-adaptive differential evolution with augmented Lagrange multiplier method (SADE_ALM) consists of two iterative loops, i.e. the inner loop and the outer loop. The inner loop solves the unconstrained minimization problem through the augmented Lagrange function L_a using self-adaptive differential evolution (SADE). Figure 1 shows the chromosome structure of SADE. It can be seen that the mutation factor (F) and the crossover constant (CR) are embedded as additional control variables in the first and second positions of the n-dimensional parent vector X_j respectively. After the unconstrained minimization problem has been solved, the outer loop will update the Lagrange multipliers $\beta_j s$ and the penalty parameter r_g by the ALM method to create the new augmented Lagrange function L_a. The algorithm is then repeated until a termination criterion, i.e. maximum number of iterations or convergence of the optimal solution, is reached. The flowchart of the SADE_ALM when applied to solve the OPF problems is shown in Figure 2.

	1	2	3	4		*n*+2
X_j	F_j	CR_j	x_1	x_2	......	x_n

Figure 1: Chromosome structure of SADE.

3.1 The inner loop iteration

The inner loop solves the augmented Lagrange function L_a using self-adaptive differential evolution (SADE) of which its details can be described hereafter.

<u>3.1.1 Initialization</u>

Set maximum iteration number of the inner loop (N_i), convergence tolerance ($\varepsilon_{\Delta x}$), and then create the initial population size NP, associated with their lower and upper limits as follows:

$$x_{ij} = x_{ij,low} + \rho_{ij} \times \left(x_{ij,hi} - x_{ij,low}\right) \tag{23}$$

$$F_j = F_{j,low} + \rho_{1j} \times \left(F_{j,hi} - F_{j,low}\right) \tag{24}$$

$$CR_j = CR_{j,low} + \rho_{2j} \times \left(CR_{j,hi} - CR_{j,low}\right) \tag{25}$$

where x_{ij} is the OPF control variable i of the n-dimensional parent vector X_j, $x_{ij,low}$, and $x_{ij,hi}$ are the lower and upper limits of x_{ij}, F_j is the mutation factor for individual X_j, $F_{j,low}$, and $F_{j,hi}$ are the lower and upper limits of F_j, CR_j is the crossover constant for individual X_j, $CR_{j,low}$, and $CR_{j,hi}$ are the lower and upper limits of CR_j, and ρ_{ij}, ρ_{1j}, and ρ_{2j} are uniformly distributed random numbers within $[0,1]$ for individual x_{ij}, F_j, and CR_j respectively.

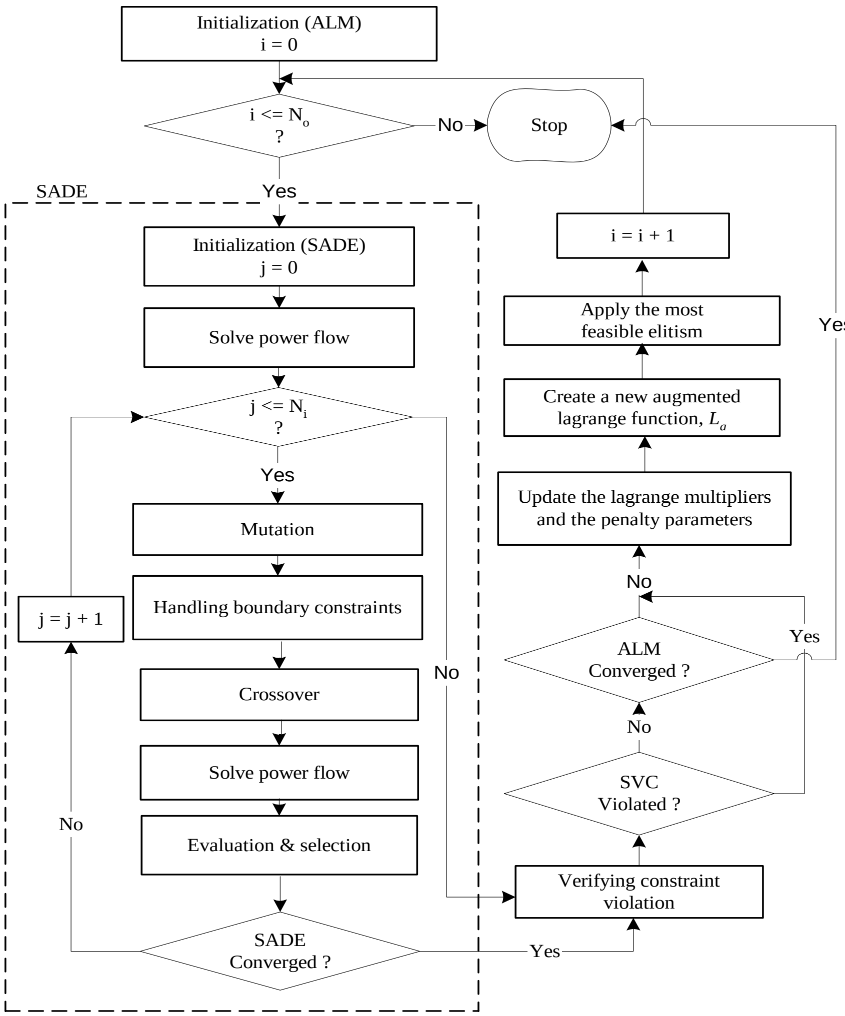

Figure 2: Flowchart of SADE_ALM-OPF.

An individual X_j in a population represents a candidate of OPF solution. Each individual consists of F_j, CR_j, and OPF control variables x_{ij} including real power of all generators excluding slack generator, voltage magnitude of all generators, and transformer tap settings.

3.1.2 Power flow solution

For each individual X_j, the Newton-Raphson (NR) power flow is applied to determine the state variable of the associated X_j. If the power flow of any individuals fails to converge, such individuals will be removed and replaced by new randomly generated individuals. This process is repeated until the power flow calculations of such individuals are converged.

3.1.3 Mutation

For each individual X_j, a mutant vector X_j' is created according to the following expression.

$$x'_{ij} = x_{ij,r_3} + F_j \times \left(x_{ij,r_1} - x_{ij,r_2} \right) \tag{26}$$

$$F'_j = F_{j,r_3} + F_j \times \left(F_{j,r_1} - F_{j,r_2} \right) \tag{27}$$

$$CR'_j = CR_{j,r_3} + F_j \times \left(CR_{j,r_1} - CR_{j,r_2} \right) \tag{28}$$

where r_1, r_2, and r_3 are randomly chosen indices such that r_1, r_2, and $r_3 \in (1, NP)$ and $r_1 \neq r_2 \neq r_3$.

3.1.4 Handling boundary constraints

In the event that mutation causes control variables, x'_{ij}, F'_j, and CR'_j, exceeded their boundary constraints, i.e. lower or upper limit, such variables will be set to the nearest boundary.

3.1.5 Crossover

To increase the diversity of the mutant vectors, crossover is introduced to create the trial vector X''_j based on a series of $n-1$ binomial experiments [11-12] as follows:

$$x''_{ij} = \begin{cases} x'_{ij},\ \forall \rho_{ij} \le CR_j \quad \text{or} \quad i = i_{rand} \\ x_{ij,}\ \text{otherwise} \end{cases} \tag{29}$$

$$F''_j = \begin{cases} F'_j,\ \forall \rho_{1j} \le CR_j \quad \text{or} \quad i_{rand} = 1 \\ F_{j,}\ \text{otherwise} \end{cases} \tag{30}$$

$$CR''_j = \begin{cases} CR'_j,\ \forall \rho_{2j} \le CR_j \quad \text{or} \quad i_{rand} = 2 \\ CR_{j,}\ \text{otherwise} \end{cases} \tag{31}$$

where ρ_{ij}, ρ_{1j}, and ρ_{2j} are the uniformly distributed random number within [0,1] for individual x''_{ij}, F''_j, and CR''_j respectively, and $i_{rand} \in (1, n+2)$ is a generated random integer number to ensure that the trial vector X''_j is different from its associated parent vector X_j.

3.1.6 Evaluation and selection

To create the new population in the next generation $G+1$, the fitness value or the augmented objective value in (13) of the trial vector $X''^{(G)}_j$ is compared with its parent vector $X^{(G)}_j$ in the same way as in the classical DE as shown below.

$$X^{(G+1)}_j = \begin{cases} X''^{(G)}_j, \ \text{if } L_a\left(X''^{(G)}_j \right) \le L_a\left(X^{(G)}_j \right) \\ X^{(G)}_j, \ \text{otherwise} \end{cases} \tag{32}$$

The inner loop will be terminated according to two defined criteria, i.e. 1) maximum iteration number of the inner loop (N_i), and 2) convergence of the optimal solution defined by (33)

$$\Delta X_{opt} \leq \varepsilon_{\Delta X} \tag{33}$$

where $\varepsilon_{\Delta X}$ is a convergence tolerance value of ΔX_{opt}, determined by

$$\Delta X_{opt} = \left\| X_{opt}^{(G)} - X_{opt}^{(G-1)} \right\|_{\infty} \tag{34}$$

where $\left\| . \right\|_{\infty}$ is the infinity-norm, $X_{opt}^{(G)}$ and $X_{opt}^{(G-1)}$ are the optimal solution obtained at current generation (G) and previous generation ($G-1$) respectively.

3.2 The outer loop iteration

After the inner loop has converged, the outer loop is started by using the ALM method to handle the inequality constraints of the state variables. The details of the outer loop can be described as shown below.

3.2.1 Initialization

Set maximum iteration of the outer loop (N_o), the constrain violation tolerance (ε_{SVC}), the Lagrange multiplier βs, and the penalty parameters r_g including c_g, and $r_{g,\max}$.

3.2.2 Verifying constrain violation

The constrain violation of the optimal solution obtained from the inner loop (X_{opt}^{*}) is verified through the sum of the violated constraints (SVC) index as shown in (35) and (36).

$$SVC \leq \varepsilon_{SVC} \tag{35}$$

$$SVC = \sum_{j=1}^{m} \left\{ \max \left[g_j \left(X_{opt}^{*} \right), 0 \right] \right\} \tag{36}$$

where $g_j(\cdot)$, $j = 1,2,\ldots,m$ are the m-inequality constraints of the state variables as explained in section 2.

3.2.3 Creating a new unconstrained minimization problem

To create a new unconstrained minimization problem for the next inner loop iteration, the new augmented lagrange function L_a is created by updating the lagrange multiplier βs and the penalty parameter r_g according to (21), and (22) respectively.

3.2.4 Appling the most feasible elitism

To improve the efficiency of the proposed algorithm, the most feasible elitism (X_{elite}) is employed by replacing the worst individual X_j which has the highest fitness value for the next inner loop iteration. The elitist member is initialized by using the optimal solution obtained from the first inner loop iteration. Then, it is updated according to the extent of the violated SVC value and the total generator fuel cost in (4) as follows:

1) If $SVC\left(X_{elite}^{(K-1)}\right) > \varepsilon_{SVC}$, then

$$X_{elite}^{(K)} = \begin{cases} X_{opt}^{*(K)}, \text{ if } SVC\left(X_{opt}^{*(K)}\right) \leq SVC\left(X_{elite}^{(K-1)}\right) \text{and } J\left(X_{opt}^{*(K)}\right) \leq J\left(X_{elite}^{(K-1)}\right) \\ X_{elite}^{(K-1)}, \quad \text{otherwise} \end{cases} \tag{37}$$

2) If $SVC\left(X_{elite}^{(K-1)}\right) \le \varepsilon_{SVC}$, then $X_{elite}^{(K)} = \begin{cases} X_{opt}^{*(K)}, \text{ if } J\left(X_{opt}^{*(K)}\right) \le J\left(X_{elite}^{(K-1)}\right) \\ X_{elite}^{(K-1)}, \quad \text{otherwise} \end{cases}$ (38)

where $X_{elite}^{(K)}$ and $X_{elite}^{(K-1)}$ are the elitist members of the current (K) and previous ($K-1$) iteration of the outer loop respectively, and $X_{opt}^{*(K)}$ is the optimal solution obtained from the current (K) iteration of the inner loop.

The outer loop will be terminated according to the same criteria as defined for the inner loop, i.e. 1) maximum iteration number of the outer loop (N_o), and 2) convergence of the optimal solution.

4. SADE_ALM-OPF IMPLEMENTATION RESULTS

The proposed SADE_ALM for solving the OPF problems was tested on the IEEE-30 bus test system given in Alsac and Stott [16]. To demonstrate the effectiveness of the proposed algorithm, SADE_ALM was tested and compared with EP [4], TS [5], TS/SA [6], ITS [7], and IEP [8] based on different fuel cost characteristics, i.e. 1) quadratic cost curve model, and 2) quadratic cost curve with rectified sine component model (valve-point effects). For each case, 10 independent runs were conducted. The parameters of SADE_ALM for all cases were set as follows: $NP = 20$, $F = [0.2,1]$, $CR = [0.1,1]$, $r_g = 10^3$, $c_g = 100$, $r_{g,\max} = 10^8$, $N_i = 10^3$, $N_o = 5$, $\varepsilon_{\Delta X} = 10^{-3}$, $\varepsilon_{SVC} = 10^{-7}$. Additionally, the lagrange multiplier (βs) of inequality constraints were initialized using zeros values for all cases.

The program was developed based on free numerical software SCILAB 4.0 [17] on personal computer 2.8 GHz Pentium IV processors and 256 MB total memory.

Table 1: Comparison of the total generator fuel costs for case 1

Algorithm	Fuel Cost ($/hr.)				Average computational time (minutes)
	Best cost	Average cost	Worst cost	S.D. of cost	
EP [8]	802.907	803.232	803.474	0.226	66.693
TS [8]	802.502	802.632	802.746	0.080	86.227
TS/SA [8]	802.788	803.032	803.291	0.187	62.275
ITS [8]	804.556	805.812	806.856	0.754	88.495
IEP [8]	802.465	802.521	802.581	0.039	99.013
SADE_ALM	802.404	802.407	802.411	0.003	15.934

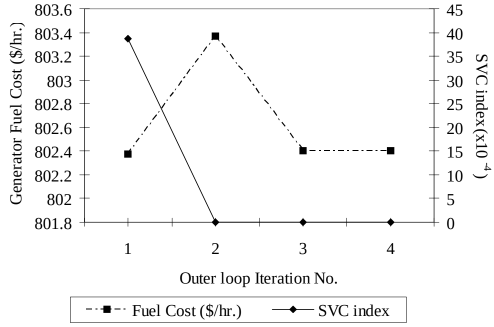

Figure 3: Outer loop convergence characteristic of SADE_ALM for case 1.

4.1 Case 1: The OPF with quadratic fuel cost functions

For this case, bus 1 is the slack bus of the system and the generator cost curves of all the generators are represented by quadratic function as shown in (11). The generator cost coefficients are given in Table A.1 [4, 8]. The simulation results are shown in Table 1 and the outer loop convergence characteristic of SADE_ALM is shown in Figure 3.

4.2 Case 2: The OPF for units with valve-point effects

In this case, the generator fuel cost curves of generator at bus 1 and 2 are represented by quadratic functions with rectified sine components using (12). Bus 5 is selected as the slack bus of the system to allow more accurate control over units with discontinuities in cost curves [4]. The generator cost coefficients of those two generators are given in Table A.2 [4, 8]. The simulation results are shown in Table 2 and the outer loop convergence characteristic of SADE_ALM is shown in Figure 4.

Table 2: Comparison of the total generator fuel costs for case 2

Algorithm	Fuel Cost ($/hr.)				Average computational time (minutes)
	Best cost	Average cost	Worst cost	S.D. of cost	
EP [8]	955.508	957.709	959.379	1.084	61.419
TS [8]	956.498	958.456	960.261	1.070	88.210
TS/SA [8]	959.563	962.889	966.023	2.146	65.109
ITS [8]	969.109	977.170	985.533	6.191	85.138
IEP [8]	953.573	956.460	958.263	1.720	93.583
SADE_ALM	944.031	954.800	964.794	5.371	16.160

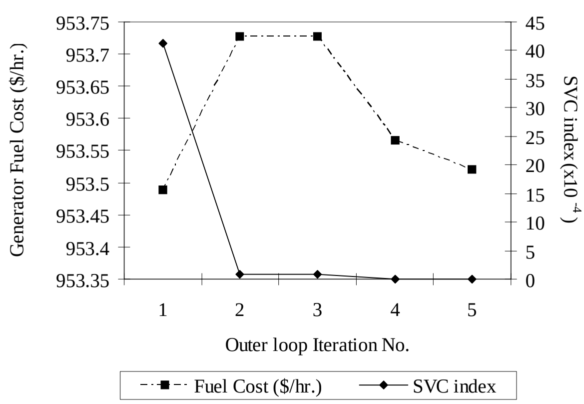

Figure 4: Outer loop convergence characteristic of SADE_ALM for case 2.

For all test cases, the results from ten test runs of SADE_ALM do not violate any constraints. Tables 1-2 show that best and average fuel costs of SADE_ALM are lower than those obtained by TS, TS/SA, ITS, EP, and IEP. For case 1, the best generator fuel cost of SADE_ALM in Table 1 provides very similar result with conventional gradient based method reported by Alsac and Stott [16]. For case 2, the best generator fuel cost of EP, and TS reported by Yuryevich and Wong [4], and Abido [5] respectively are less expensive than SADE_ALM in Table 2. However, the best solution given in Yuryevich and Wong [4] ($919.89/hr.) violates reactive power of generator at bus 1 by -252.04 %, and line loading 1-2 by +17%. Finally, the best solution given in Abido [5] ($919.715/hr) also has the violation on the limit of line loading 1-2 by +4.1%.

The optimal values of the best solution given by IEP [8] and SADE_ALM for each case are shown in Table 3.

Table 3: Comparison of IEP and SADE_ALM optimal results for each case

Optimal solution	Case 1		Case 2	
	IEP [8]	SADE_ALM	IEP [8]	SADE_ALM
P_{G1} (MW)	176.2358	176.1522	149.7331	193.2903
P_{G2} (MW)	49.0093	48.8391	52.0571	52.5735
P_{G5} (MW)	21.5023	21.5144	23.2008	17.5458
P_{G8} (MW)	21.8115	22.1299	33.4150	10.0000
P_{G11} (MW)	12.3387	12.2435	16.5523	10.0000
P_{G13} (MW)	12.0129	12.0000	16.0875	12.0000
V_{G1} (p.u.)	1.0500	1.0500	1.0500	1.0493
V_{G2} (p.u.)	1.0377	1.0381	1.0398	1.0271
V_{G5} (p.u.)	1.0091	1.0112	1.0145	1.0081
V_{G8} (p.u.)	1.0176	1.0190	1.0254	1.0109
V_{G11} (p.u.)	1.0880	1.0911	1.1000	1.0732
V_{G13} (p.u.)	1.0837	1.0891	1.0758	0.9634
t_{11}	1.0070	1.0556	1.0336	0.9612
t_{12}	0.9741	0.9000	0.9568	1.0680
t_{15}	1.0117	1.0070	0.9953	1.0118
t_{36}	0.9442	0.9420	0.9536	0.9041
Fuel Costs ($/hr.)	802.465	802.404	953.573	944.031

5. CONCLUSION

A self-adaptive differential evolution with augmented Lagrange multiplier method (SADE_ALM) was applied to solve the OPF problems for generators with non-smooth fuel cost functions. The effectiveness of the proposed algorithm has been tested on the IEEE 30-bus system with different fuel cost characteristics. The SADE_ALM is successfully and effectively implemented to find the global or quasi-global optimum of the OPF problems. Numerical results show that the SADE_ALM total generator fuel cost is less expensive than other approaches, i.e. tabu search (TS), hybrid tabu search and simulated annealing (TS/SA), improved tabu search (ITS), evolutionary programming (EP), and improved evolutionary programming (IEP). The proposed SADE_ALM shows promising capability for solving the OPF problems due to significant generator fuel cost savings.

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APPENDIX

Table A.1: Generator cost coefficients in case 1

Bus No.	Real power output limit (MW)		Cost Coefficients		
	Min	Max	a	b	c
1	50	200	0.00375	2.00	0
2	20	80	0.01750	1.75	0
5	15	50	0.06250	1.00	0
8	10	35	0.00834	3.25	0
11	10	30	0.02500	3.00	0
13	12	40	0.02500	3.00	0

Table A.2: Generator cost coefficients in case 2

Bus No.	Real power output limit (MW)		Cost Coefficients				
	Min	Max	a	b	c	d	e
1	50	200	0.00160	2.00	150	50	0.063
2	20	80	0.01000	2.50	25	40	0.098