OPTIMIZATION OF THE FUEL COST, REAL AND REACTIVE POWER LOSS IN IEEE-57 BUS SYSTEMS USING PSO

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ABSTRACT

This paper presents an Improved Particle Swarm Optimization with TimeVarying Acceleration Coefficient (IPSO-TVAC) based algorithm forsolving OPF problem of a power system. Minimization of total fuel cost, real & reactive power losses in an electric power system under with and without line outages is considered. The effectiveness of the proposed approachhas been tested in IEEE-57 bus system. The proposed IPSO-TVAC method is applied to optimize the objective functions such as fuel cost, real and reactive power loss under without and with line outage cases in IEEE-57 bus systems. Power flowcalculation is performed by Newton-Rapshon method using MATPOWER software package version 4.0b4, and it is developed by Zimerman R D. In MATPOWER, procedure used to explain OPF problem is interior point method. The proposed method is applied for 20 independent runs in IEEE- 57 bus system and based on the objective function, the optimal values are evaluated. The following are parameter settings of proposed algorithm. Particle size: 165, No. of generation: 200 for IEEE-57 bus system, Inertia weight: 0.9 to 0.4, c_{1i}, c_{2f} *=2.5,* c_{1f}, c_{2i}*=0.2,* C_r *= 0.6.*

Keywords: PSO, mixed integer handling method, IPSO-TVAC, fuel cost, real & reactive power losses

INTRODUCTION

The optimal power flow problem has emerged as a critical issue in power system design, operation, security, and economic scheduling in recent years. Later, other scholars were interested in the OPF problem. The OPF is a crucial tool that allows electric utilities to determine the economic operation & secure states in power systems. This study provides an IPSO-TVAC algorithm for solving mixed integer OPF problem with optimal adjustment of power systemcontrol variables under a set of equality & inequality criteria. The inequality constraints are handled using a penalty parameter-less constraint handling approach, whereas OPF control variables are handled using a mixed-integer handling method. The proposed method's effectiveness was tested in an IEEE-57 bus system with a base case & a contingency scenario, and results were compared to those reported in literature.

The optimum operation and development of power system networks has traditionally been based on economic criteria. For this aim, Economic Load Dispatch (ELD) has been used, and it is largely approved by most utilities. However, increased concernsabout maintaining system security, power quality, & a clean environment have compelled power system operators to consider additional goals in optimum management of power systems, such as improving system voltage profile, minimizing emissions, & operating under security constraints. All of these are sub-problems of the optimum power flow, which Carpentier described in (1962). A large number of research

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endeavors in this field have made use of optimization techniques. There are two key uses for optimum power flow.

- As a tool for making system-wide planning choices such as unit dedication, generating expansion organizing, and reactive energy planning.
- As an energy control system's power scheduling tool.

The OPF has mostly been used by utilities as a dispatching tool for operator advice in making off-line optimal operating decisions. Most electricity utilities throughout the world have recently undergone considerable reform. Electricity deregulation has resulted in new open market price structures, requiring the optimum operating philosophy of generating and transmission networks to alter. The OPF has been widely used in the restructured market operation & bid management. Security Constrained Optimal Power Flow (SCOPF) programs can perform control modifications to base or pre-contingency operation to prevent violations in post contingency settings. OPF differs from ED in that it continually informs the power flow of the transmission system as it approaches the goal function's lowest.

Traditional security analysis is centered on preventative control. Complete SCOPF seeks the best viable solution not just for the basic configuration, but also for all plausible scenarios. The following procedures are involved in a contingency restricted OPF.

- Solve the base case OPF without considering any contingencies.
- Conduct a contingency screening to determine the important scenarios.
- Perform AC power flow and find the contingency restrictions for each important contingency.
- Run off with all contingency limitations in place.
- Steps 3 and 4 should be repeated until convergence is reached.

As may be seen from the above, the entire SCOPF is exceedingly time demanding, and attaining its solution in real time remains a difficulty. Furthermore, comprehensive SCOPF findings forfeit the most important economic criterion. The SCOPF approach may become infeasible at times, particularly in the most extreme situations. Because the entire SCOPF formulation is extremely conservative & does not allow for post-contingency corrective operations, it is recommended that the system run in a "correctively secure" state, employing corrective control actions only when a contingency occurs to fulfill restrictions.

LITERATURE REVIEW

PSO is recently developed optimization techniques among many attractive features, which is employed to overcome the difficulties of nonconvex optimization problems. PSO is an inhabitant based stochastic optimizationtechnique, motivated by behavior oforganisms such as fish schooling and bird flocking which has beendeveloped by Eberhart & Kennedy (1995). AlRashidi and El-Hawary (2009) have developed ahybrid particle swarm optimization technique to solve discrete optimal power flowproblem of valve point loading effect. Hybrid numerical methods search and PSO are suggested for constrained engineering design troubles by Zahara et al. (2009).

Valdez (2011) used an enhanced evolutionary method by fuzzy logic to combine PSO and GA. Mahmood Joorabian & Ehsan Afzalan (2014) have implemented a method to solve Hybrid Fuzzy Particle Swarm Optimization - Nelder Mead, in which different types of benchmark

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mathematical functions & optimal power flow problems are evaluated. But, due to premature convergence, this algorithm is utilized in some applications.

The problem of OPF has received a lot of attention of many researchers. In literature, approaches related to OPF problem with optimal adjustment of power system control variables have been presented. Several methods have been proposed to solve optimal power flow problem. Based on classical mathematics programming methods, OPF algorithms were solved by Gradient based method by Carpentier (1962) and non-linear programming by Dommel & Tinny (1968).

Alsac (1974) has given the solution scheme including exact outage-contingency constraints, to provide an optimal steadystate protected system operating point. Linear programming developed by Mota Palomino and Quintana (1986), quadratic programming by Burchett et al. (1984), Newton-based method by Santos (1995), interior point methods by Yan and Quintana (1999), & non linear quadratic programming approaches presented by Adapa et al. (1999) have effectively proved their competence in this field. These classical optimisation methods have been widely used for varieties of OPF troubles. But, these methods fail to deal the systems with complexnon convex, non smooth & non differentiable objective functions and constraints.

To overcome drawbacks of classical techniques, evolutionary algorithms namely genetic algorithm by Wu et al. (1998), Evolutionary programming by Yuryevich & Wong (1999), Particle Swarm Optimization (PSO) by Kennedy (1995) & Differential Evolution (DE) by Abido (2002) and simulated annealing by Roa Sepulveda & Pavez Lazo (2003) have been applied to solve different complex OPF problems.

Vesterstrom & Thomsen (2004) have developed a method to analyze comparative study of the differential evolution, PSO, as well as evolutionary approaches on numerical benchmark problems. But, there is evidence that these techniques cannot always provide good outcomes, especially when trading with complex multi objective problems. Abido (2006) has presented a technique for solving multi objective optimal VAR dispatch. Sayah & Zehar (2008) developed a method to solve modified DE algorithm for OPF with non smooth cost functions.

Chaturvedi et al. (2009) presented a method for solving PSO with mad particles for non-convex economic dispatch. A method to evaluate various OPF troubles of a power system by generators that could have convex or non convex fuel cost features with Biogeography Based Optimization (BBO) developed by Bhattacharya and Chattopadhyay (2010) and BBO has been proposed by Bhattacharya & Chattopadhyay (2011) for various economic load dispatch troubles. Serhat Duman et al. (2012) formulated a technique for solving optimal solution for OPF problem in a power system by using gravitational search algorithm.

A method to determine multi agent based DE approach to OPF problem is formulated by Sivasubramani & Swarup (2012). Iteration PSO by TVAC to solve non-convex economic dispatchproblem is discussed by Mohammadi-Ivatloo et al. (2012), in which the OPF problem is complicated, due to transmission losses. Rezaei Adaryani et al. (2013) have suggested a method tosolve multi objective OPF problems in an electric power system. Saraswat & Saini (2013) have offered a technique to find multi objective optimal reactive power dispatch in view of voltage stability in power systems by using hybrid fuzzy multi objective evolutionary algorithm.

According to Ratnaweera et al. (2004), the Time Varying Acceleration Coefficients (TVAC) structure results in a healthy balance b/w social & cognitive components in first phase & later iterations. Because of the shortcomings of traditional PSO, the IPSO-TVAC method is utilized to solve mixed integer OPF problem under a set of equality & inequality constraints. Gonggui Chen et al. (2014) introduced a technique for solving multi-objective optimization using chaotic enhanced PSO, which is used to avoid local optimum trapping and increase solution quality while minimizing power losses.

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Finally, IPSO-TVAC is used to discover the optimal value of a certain objective function, in which TVAC provides a correct balance among cognitive & social elements in initial phase & subsequent iterations, and IPSO applies crossover operator to improve solution quality. It also prevents becoming stuck in a local optimum.

IEEE-57bus system

The IEEE-57 bus system has seven generators on buses 1, 2, 3, 6, 8, 9, &d 12, as well as 17 transformers with off-nominal tap ratios on branches 19, 20, 31, 35, 36, 37, 41, 46, 54, 58, 59, 65, 66, 71, 73, 76, & 80. Shunt VAR compensators are also being investigated for buses 18, 25, & 53. The lowest & maximum magnitudes of generator-bus voltage are considered to be 0.9p.u & 1.1p.u, respectively. The remaining buses' lowest and maximum voltage magnitudes are calculated to be 0.94 & 1.06 in p.u., respectively. Furthermore, regulating transformer tap settings & shunt capacitor VAR injection are treated as discrete variables. The transformer-tap settings are anticipated to range between [0.9, 1.1] p.u., with a 0.01p.u. step size.

The VAR injection of shunt capacitor is assumed to vary inrange [0, 0.3] p.u., with step size0.01p.u. The total systemdemand for active power is 12.508p.u & 3.364p.u for reactive power at 100 MVAbase. Bus 1 is taken as slack bus.

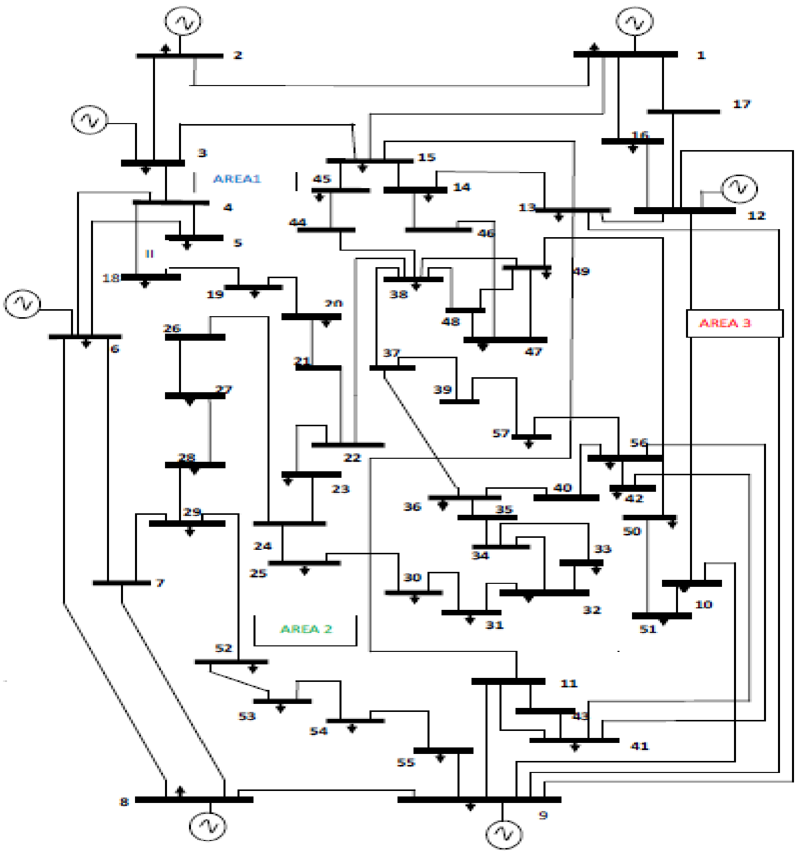

Figure1 Single line diagram ofIEEE-57 bus test system

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MINIMIZATION OF FUEL COST

UNDER NORMAL CONDITION

In this scenario, Table 1 shows optimum setup of control variables corresponding to the lowest fuel cost, with the lowest fuel cost obtained by suggested IPSO-TVAC approach being 41669.14 \$/hr, with an average of 41681.74 \$/hr & a maximum of 41716.65 \$/hr. Figure 1 depicts convergence characteristic related to lowest fuel cost. Figure 2 depicts the expense of generating 20 separate trail runs.

Table 1 Optimal settingof control variables for fuel costminimization

Control Variables	IPSOTVAC	GSA	EADPSO	ABC
	Case 1	Case 1	Case 1	Case 1
P_{G2} (p.u)	0.810138	0.9263	0.7512	0.900328
P_{G3} (p.u)	0.445117	0.45318	0.4404	0.445147
P_{G6} (p.u)	0.786705	0.72355	0.9534	0.742003
P_{G8} (p.u)	4.6179	4.64743	4.5535	4.548475
P_{G9} (p.u)	1	0.84999	0.9302	0.968847
P_{G12} (p.u)	3.576311	3.63951	3.5929	3.627722
V_{G1} (p.u)	1.0613	1.05941	1.0696	1.0423
V_{G2} (p.u)	1.0577	1.05759	1.0671	1.0411
V_{G3} (p.u)	1.0523	1.06	1.0612	1.0385
V_{G6} (p.u)	1.0566	1.06	1.0624	1.0549
V_{G8} (p.u)	1.067	1.05999	1.0681	1.064
V_{G9} (p.u)	1.046	1.05999	1.0433	1.0369
V_{G12} (p.u)	1.0541	1.0459	1.0411	1.0406
T_{19}(p.u)	1	0.9	1.0995	0.9375
T_{20} (p.u)	1.01	0.9	1.0999	1.05
T_{31} (p.u)	0.94	0.90856	1.0973	0.975
T_{35} (p.u)	1.01	1.05921	1.0575	0.95
T_{36} (p.u)	1.02	0.99921	0.9382	1.0125
T_{37} (p.u)	1.08	0.92201	1.0329	1
T_{41} (p.u)	1.03	0.93243	0.9987	1.0125
T_{46} (p.u)	1.02	1.08828	0.9651	0.9125
T_{54} (p.u)	0.9	1.03902	0.9358	0.9
T_{58} (p.u)	0.99	1.04318	0.9852	1.0125
T_{59} (p.u)	1.02	1.02494	0.9692	0.9875
T_{65} (p.u)	1.01	0.95425	0.9678	1
T_{66} (p.u)	1	0.92897	0.9434	0.9625
T_{71} (p.u)	1.04	1.09942	0.9845	0.9625
T73 (p.u)	1.05	0.96948	1.0041	0.9625
T76(p.u)	0.97	1.062	0.9819	0.925

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T80 (p.u)	1.06	1.09388	1.0299	0.9875
QC18 (p.u)	0.13	0.15243	0.2966	0.16
QC25(p.u)	0.18	0.14403	0.1161	0.15
QC53(p.u)	0.18	0.15102	0.1231	0.14
PG1(p.u)	1.433932	1.42369	1.4413	1.428106
Fuel cost ($/hr)	41669.14	41695.87	41,697.54	41693.959
Vdev(p.u)	1.3818	-	1.3466	-
Ploss(p.u)	0.0162103	-	0.1549	-

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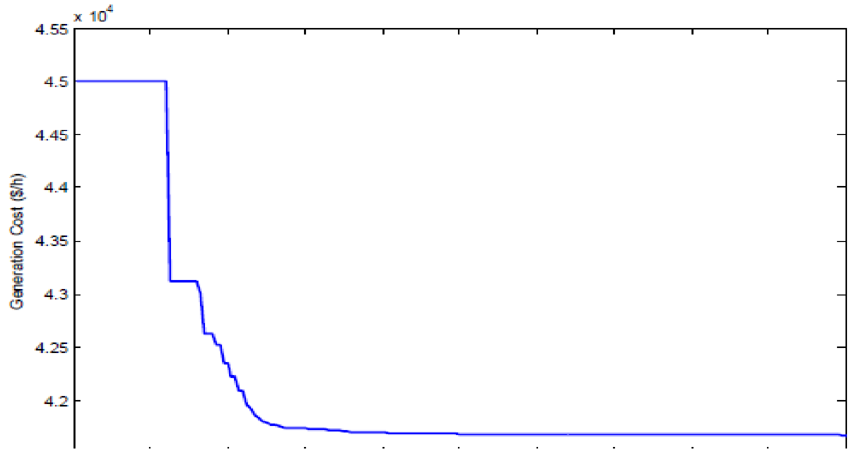

Figure 1 Fuel cost convergencecharacteristics in IEEE-57 bussystem

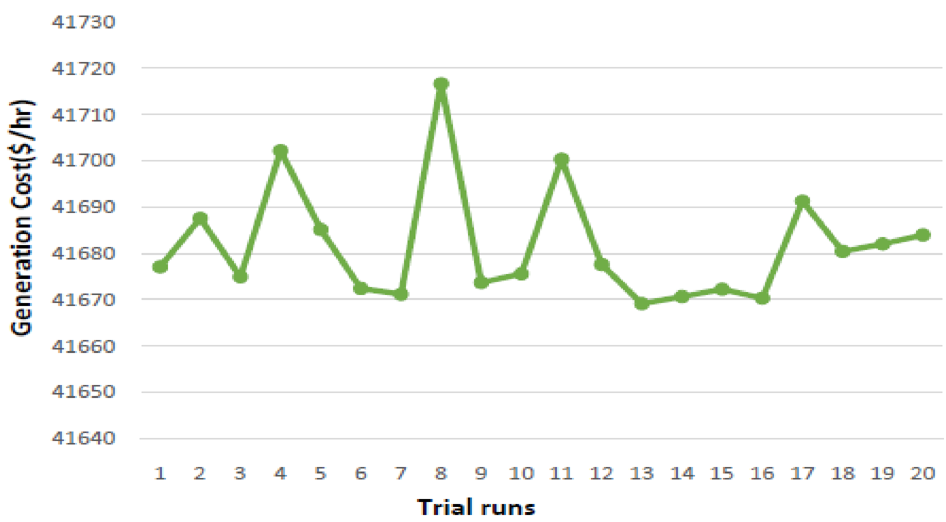

Figure 2 Generation cost Vs independent trial runs

Table 2 compares the results achieved utilizing the proposed IPSO-TVAC approach to previous findings reported in the literature. Table 2 shows that the suggested method produces a lower minimum fuel cost than alternative algorithms. The best solution achieved using the GSA method, however, is an impossible solution. Voltage amplitude violations exist on load buses 18, 19, 20, 26, 27, 28, 29, 30, 31, 32, 33, 42, 51, 56, and 57.

Table 2 Comparison of fuel cost minimization in IEEE-57 bus system

Method	Fuel cost ($/hr)
IPSO-TVAC	**41669.14**

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ABC	41693.9
GSA	41695.8717[a]

a - Infeasible solution

Table 3 presents comparison results obtained for fuel cost minimization in IEEE-57 bus system for20 independent trial runs. FromTable 3, it is clear that proposed algorithm gives better results for largesystems.

Table 3 Comparison offuel cost minimization in IEEE-57 bussystem for 20 independent trial runs

Method	Fuel cost ($/hr)		
	Minimum	Average	Maximum
IPSO-TVAC	41669.14	41681.74	41716.65
ABC	41693.9589	41778.6732	41867.8528

UNDER CONTINGENCYCONDITION

Four distinct contingency scenarios are explored, including outage of lines 1-2, 3-4, 1-16, & 1-17. Table 4 shows appropriate control variable settings for various line interruptions. The suggested IPSO- TVAC technique yields an approximate fuel cost of 41767.52889 $/hr for line 1-2 outages. The suggested IPSO-TVAC technique yields an affordable fuel cost of 41669.96138$/hr for line 3-4 outages. The suggested IPSO-TVAC technique yields a minimum fuel cost of 41711.88825 $/hr for outages of lines 1-16. The suggested IPSO-TVAC technique yields a minimum fuel cost of 41762.37802 $/hr for outages of lines 1-17. Table 4 clearly shows that the suggested IPSO-TVAC algorithm produces superior results than existing techniques. Figure 3 depicts the convergence characteristic for gasoline cost reduction after a line 3-4 outage.

Table 4 Optimal setting ofcontrol variables for different lineoutages ofIEEE- 57 bus system

Control Variable (p.u.)	Optimal value			
	Outage of line1-2	Outage of line 3-4	Outage of line1-16	Outage of line1-17
P_{G2}	0.605762	0.935562	0.798972	0.801813
P_{G3}	0.453797	0.451371	0.44878	0.44945
P_{G6}	0.759943	0.68464	0.76977	0.719733
P_{G8}	4.641956	4.606872	4.59284	4.624268
P_{G9}	1	0.9516	0.991345	1
P_{G12}	3.71906	3.59628	3.649535	3.673246
V_{G1}	1.0385	1.0655	1.0546	1.0656
V_{G2}	1.0209	1.0642	1.0526	1.0622
V_{G3}	1.0338	1.0588	1.0485	1.0533
V_{G6}	1.0422	1.0567	1.0589	1.0578
V_{G8}	1.0573	1.0756	1.0721	1.0671

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V_{G9}	1.0299	1.0497	1.044	1.042
V_{G12}	1.0286	1.0493	1.0417	1.04
T_{19}	1.01	0.92	1.02	1.04
T_{20}	1.01	1.07	1.06	1.04
T_{31}	1	1.01	1.07	1.02
T_{35}	1.01	1.09	1	0.96
T_{36}	1.1	0.97	1.05	0.99
T_{37}	0.99	1.02	1.01	1
T_{41}	0.99	1	1	0.99
T_{46}	0.98	0.97	0.97	0.94
T_{54}	1.03	0.9	0.9	1.01
T_{58}	0.99	0.98	0.97	0.99
T_{59}	0.98	0.97	0.97	0.98
T_{65}	1	0.99	0.97	0.98
T_{66}	0.98	0.95	0.94	0.95
T_{71}	0.97	0.99	0.98	1.03
T_{73}	1	0.98	0.97	1
T_{76}	0.97	0.96	0.95	0.99
T_{80}	0.99	1	0.99	1.01
Q_{C18}	0.16	0.13	0.11	0.18
Q_{C25}	0.2	0.17	0.17	0.12
Q_{C53}	0.15	0.12	0.14	0.14
$\mathbf{P_{G1}}$	1.492857	1.917147	1.414275	1.408648
FuelCost($/hr)	41767.528	41669.961	41711.888	41762.378
MATPOWER cost ($/hr)	41801.3	41736	41779.6	41823.5

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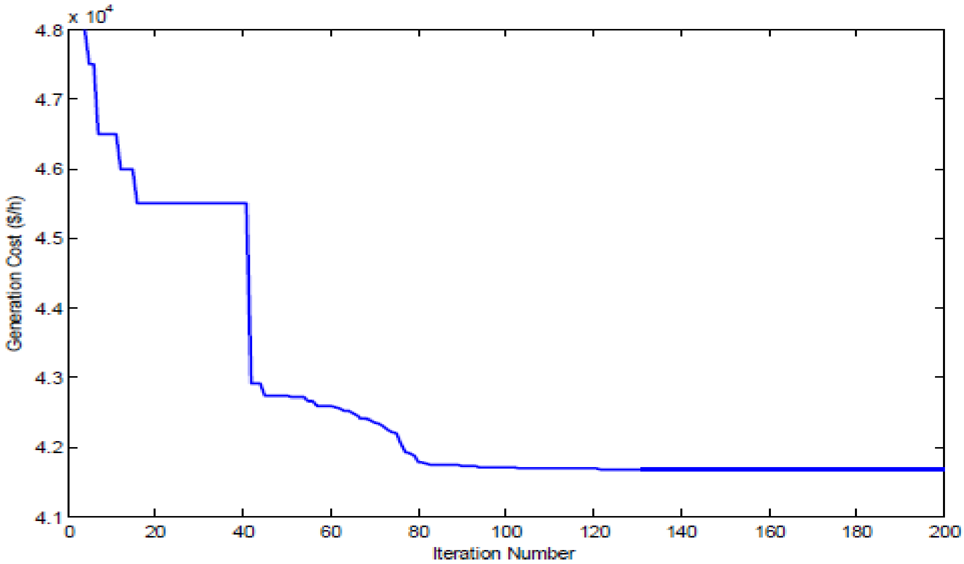

Figure 3 Convergencecharacteristics for outageof lines 3-4 in IEEE-57 bussystem

POWERLOSS

MINIMIZATION OF REAL POWERLOSS

The high quantity of reactive power flow leads in system actual power loss. Minimizing actual power loss allows for optimized reactive power flow across lines. According to Table 5, cost of real power loss without a lineoutage is 45388.21 $/hr & 45465.42 $/hr. Figure 4 depicts the convergent sign associated with real power loss.

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Table 5 Best controlvariables settings for voltagedeviation, realpower loss & reactive powerloss in IEEE- 57 bussystem

Control Variables	VD		Ploss		Qloss	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
P_{G2}(p.u)	99.9957	100	0.004	0.0004	65.7114	79.2533
P_{G3}(p.u)	93.0965	118.856	140	140	103.2094	96.0196
P_{G6}(p.u)	64.674	0	100	100	70.0016	68.6779
P_{G8}(p.u)	261.6824	416.5684	304.4612	303.314	371.4973	373.9643
P_{G9}(p.u)	100	78.3724	100	99.9998	75.1355	66.1681
P_{G12}(p.u)	289.0638	337.414	410	410	176.0593	229.3761
V_{G1}(p.u)	1.0312	1.0646	1.0501	1.0551	1.0546	1.0391
V_{G2}(p.u)	1.0326	1.0606	1.0436	1.0483	1.0444	1.0199
V_{G3}(p.u)	1.0347	1.0462	1.0458	1.0496	1.0467	1.0391
V_{G6}(p.u)	1.0339	1.0259	1.0373	1.0438	1.0517	1.0489
V_{G8}(p.u)	1.0499	1.0714	1.041	1.0444	1.0565	1.0651
V_{G9}(p.u)	1.0209	1.0237	1.0242	1.0291	1.0381	1.04
V_{G12}(p.u)	1.015	0.984	1.0339	1.0386	1.0528	1.0504
T_{19}(p.u)	1.04	1.04	0.97	0.98	1.05	0.93

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T_{20}(p.u)	1.03	0.9	1	1.08	1.02	1.02
T_{31}(p.u)	0.97	1.02	1.04	1.04	1.01	1.07
T_{35}(p.u)	1.01	1	0.96	1.04	0.97	0.99
T_{36}(p.u)	1.05	1.08	1.08	0.94	1.02	1.05
T_{37}(p.u)	1	1.01	1.01	1	1.04	1.02
T_{41}(p.u)	1.03	1.03	0.97	0.98	0.99	1.01
T_{46}(p.u)	0.92	0.92	0.95	0.95	1	0.96
T_{54}(p.u)	0.9	0.9	0.95	0.9	0.97	0.92
T_{58}(p.u)	0.95	0.95	0.97	0.97	0.98	0.96
T_{59}(p.u)	0.98	0.99	0.96	0.96	0.94	1.02
T_{65}(p.u)	1	0.99	0.96	0.96	1	1.01
T_{66}(p.u)	0.9	0.9	0.92	0.93	1.05	1.03
T_{71}(p.u)	0.94	0.99	0.95	0.96	0.97	1
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
T_{76}(p.u)	0.91	0.9	0.98	0.96	1	0.97
T_{80}(p.u)	1.02	1.02	0.97	0.98	1.08	1.09
Q_{C18}(p.u)	0.1	0	0.07	0.21	0.16	0.12
Q_{C25}(p.u)	0.15	0.17	0.15	0.12	0.14	0.16
Q_{C53}(p.u)	0.28	0.25	0.13	0.22	0.26	0.18
P_{G1}(p.u)	3.660361	2.215339	2.065012	2.087589	4.195787	3.665539
Cost ($/hr)	44572.157	48009.788	45388.2102	45465.4152	47989.1839	50790.9198
Ploss(p.u)	0.02129	0.02839	0.01028	0.02036	0.0002935	0.0002143

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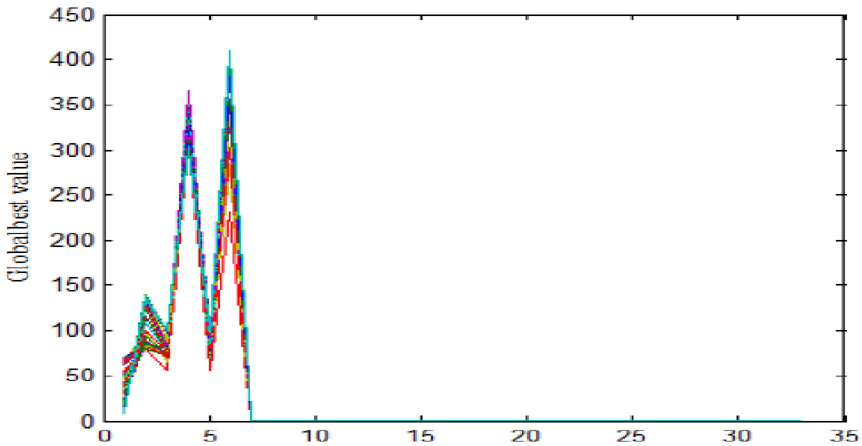

Figure 4Convergence characteristic of real powerloss in IEEE-57bus system

MINIMIZATION OF REACTIVE POWERLOSS

System safety is achieved as long as system operator supplies sufficient reactive power. Voltage drop & voltage instability arise as aresult of a shortage of reactive power. Table 5 shows the ideal control variable setting for reactive power loss. The cost of reactive power loss without a line outage is 47989.18 $/hr, while the cost with a line outage is 50790.92 $/hr. Among these results, reactive electrical cost without line loss is greater, whereas voltage deviation cost with line outage is lower.

Table 6 displays the statistical results of 20 IPSO-TVAC runs for all instances. In statistical analysis, either discrete or continuous variables on a single feature are available for a large number of individuals. Minimum value, maximum value, average value, & the standard deviation are all assessed in this statistical examination. The lower standard deviation figures in this table demonstrate the system's efficacy.

Table 6 Statisticalanalysis of 20 independent runs ofIEEE-57 bus system

Case	Minimum	Maximum	Average	Standard Deviation	Simulationtime(sec)		Vdev(v)		Ploss(p.u))		Qloss(p.u)	
					Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
uel cost($/hr)	41669.14	41681.7	41716.65	4017.173	4010.45	4109.47	1.53	1.44	0.1492	0.1644	-0.605087	-0.38.56
Voltage Deviation (p.u.)	0.616539	0.76906	0.695412	0.05554	4074.39	5184.86	1.6	0.79	0.2129	0.2839	-0.311508	0.1625
Real power loss(p.u)	0.0100041	0.0107539	0.0101961	0.26264	5466.25	4358.16	1.21	1.53	0.1028	0.2036	-0.735359	-0.3148
Reactive power loss (p.u)	6.17E-12	1.69E-05	2.45E-06	6.39E-06	7496.81	14275.30	1.23	1.6	0.2935	0.2143	2.63E-04	-0.1717

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CONCLUSIONS

The IPSO-TVAC method is proposed in this work to tackle the SCOPF problem. To address the inequality restrictions on dependent variables, a penalty parameter free technique is utilized. The suggested method has been tested on astandard IEEE-57 bus systemwith various objectives. Under typical conditions, the minimal fuel cost achieved using the suggested technique in the IEEE-57 bus system is 41669.14 $/hr, which is less than cost acquired using the ABCalgorithm, which is 41693.9 $/hr. The simulation findings are also compared to those reported in the literature. The suggested approach produces improved results in all circumstances under the IEEE-57 bus system.

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