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OPTIMAL POWER FLOW USING PARTICLE SWARM OPTIMIZATION WITH VOLTAGE STABILITY ENHANCEMENT

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***Abstract*— This Paper presents an efficient and reliable evolutionary-based approach to solve the optimal power flow (OPF) problem. The proposed approach employs particle swarm optimization (PSO) algorithm for optimal settings of OPF problem control variables. Incorporation of PSO as a derivative-free optimization technique in solving OPF problem significantly relieves the assumptions imposed on the optimized objective functions. The proposed approach has been examined and tested on the standard IEEE 26 bus test system with different objectives that reflect fuel cost minimization, voltage profile improvement, voltage stability enhancement. The proposed method which takes care of both voltage profile and voltage stability even while performing fuel cost minimization. The results are promising and show the effectiveness and robustness of the proposed approach.**

***Keywords*— Optimal power flow, Particle swarm optimization, Voltage stability enhancement.**

I. INTRODUCTION

In todays market due to deregulation of electricity the concept and practices have changed. Better utilization of existing power system resources to increase capabilities with economic cost becomes essential. The problem of optimal power flow (OPF) provides a solution. It is of current interest of many utilises and it has been marked as one of the most operational needs. In an interconnected power system, the objective is to find real and reactive power scheduling of each power plant in such a way to minimize the operating cost as well as maximize social welfare [1]. This means that the generators real and reactive powers are allowed to vary within certain limits so as to meet a particular load demand with minimum fuel cost. This is called the optimal power flow (OPF) problem. It is used to optimize the power flow solution of large scale power system. This is done by minimizing selected objective functions while maintaining generators capability limits, bus voltage limits & power flow limits in the transmission lines. Generally, the OPF problem is large scale highly constrained non linear non convex optimization problem.

First approaches of the complex OPF problem can be classified in: gradient methods [2], sequential quadratic programming [3, 4] , sequential linear programming [5] and interior points. The inconvenient of these techniques involve the slow convergence especially in the neighbourhood of the optimum for the first two, and a rather limited field of application such as the optimization of the decoupled active control variables for the third one. Interior point methods have been reported as computationally efficient; however, if the step size is not chosen properly, the sub-linear problem may have a solution that is infeasible in the original nonlinear domain [6]. In addition, interior point methods, in general, suffer from bad initial termination and optimality criteria and in most cases are unable to solve the nonlinear and quadratic objective functions [7]. The problem of OPF is highly non linear and multi dimensional optimization problem i.e., there exists more than one local optimum value. Therefore, conventional optimization methods that make use of derivative and gradients are, in general, not able to solve such multi dimensional problem. Hence, it becomes essential to develop optimization techniques that are efficient to overcome these drawbacks and handle such difficulties.

Even heuristic algorithm such as genetic algorithms (GA) [8] has some deficiencies which were found in the recent research on GA performance [9]. This degradation in efficiency is apparent in applications with highly epistatic objective functions where the parameters being optimized are highly correlated. In addition, the premature convergence of GA degrades its performance and reduces its search capability.

In this paper, a novel PSO based approach is proposed to solve the OPF problem. The problem is formulated as an optimization problem with mild constraints. In these study different objective functions has been considered to minimize the fuel cost, to improve voltage profile, to enhance voltage stability and method which takes care of both voltage profile and voltage stability has been presented and tested on IEEE 26 bus system to demonstrate the effectiveness of proposed approach using PSO.

II. BASIC PARTICLE SWARM OPTIMIZATION

Swarm behaviour can be modelled with a few simple rules. Schools of fishes and swarms of birds can be modelled with such simple models. Namely, even if the behaviour rules of each individual (agent) are simple, the behaviour of the swarm can be complicated. Reynolds utilized the following three vectors as simple rules in the researches on boid.

a. Step away from the nearest agent
b. Go towards the destination
c. Go to the centre of the swarm

The behaviour of each agent inside the swarm can be modelled with simple vectors. The research results are one of the basic backgrounds of PSO.

Boyd and Richerson examined the decision process of humans and developed the concept of individual learning and cultural transmission [10]. According to their examination, people utilize two important kinds information in decision process. The first one is their own experience; that is, they have tried the choices and know which sate has been better so far, and they know how good it was. The second one is other people's experiences, i.e., they have knowledge of how the other agents round them have performed. Namely, they know which choices their neighbours have found most positive so far and how positive the best pattern of choice was.

Each agent decides its decision using its own experiences and the experiences of others. The research results are also one of the basic background elements of PSO. According to the above background of PSO, Kennedy and Eberhart developed PSO through simulation of bird flocking in a two-dimensional space. The position of each agent is represented by its x, y axis position and also its velocity is expressed by v_x and v_y. Modification of the agent position is realized by the position and velocity information.

Bird flocking optimizes a certain objective function. Each agent knows its best value so far (p_{best}) and its x, y position. This information is an analogy of the personal experiences of each agent. Moreover, each agent knows the best value so far in the group (g_{best}) among (p_{best})s . This information is an analogy of the knowledge of how the other agents around them have performed. Each agent tries to modify its position using the following information:

a. The current positions(x, y),
b. The current velocities (v_x, v_y),
c. The distance between the current position and p_{best}.
d. The distance between the current position and g_{best}.

This modification can be represented by the concept of velocity (modified value for the current positions). Velocity of each agent can be modified by the following equation:

$$v_j^{k+1} = wv_j^k + c_1 rand_1 * (p_{best\ i} - s_i^k) + c_2 rand_2 * (g_{best} - s_i^k) \quad \textbf{(1)}$$

Where v_i^k is the velocity of agent i at iteration k, w is weighting function, c_1 and c_2 are weighting factors, $rand_1$ and $rand_2$ are random numbers between 0 and 1, s_i^k is current position of agent i at iteration k, $p_{best\ i}$ is the personal best of agent i, and g_{best} is the global best of the group. Namely, velocity of an agent can be changed using three vectors such like boid. The velocity is usually limited to a certain maximum value.PSO using eq.1 is called Gbest model. The following weighting function is usually utilized in eq.1:

$$w = w_{max} - ((w_{max} - w_{min}) / (iter_{max})) * iter \quad \textbf{(2)}$$

Where w_{max} is the initial weight, w_{min} is the final weight, $iter_{max}$ is the maximum iteration number and iter is current iteration number.

The meanings of the right hand side of (1) can be explained as follows [11]. The rhs of (1) consists of three terms (vectors). The first term is the previous velocity of the agent. The second and third terms, the agent will keep on "flying" in the same direction until it hits the boundary. Namely, it tries to explore new areas and, therefore, the first term corresponds with diversification in the search procedure. On the other hand, without the first term velocity of the "flying" agent is only determined by using its current position and its best position in history. Namely, the agents will try to converge to their p_{bests} and g_{best} and therefore, the terms correspond with intensification in the search procedure. As shown below, for example w_{max} and w_{min} are set to 0.9 and 0.4. Therefore, at the beginning of the search procedure, diversification is heavily weighted, while intensification is heavily weighted at the end of the search procedure such like simulated annealing (SA). Namely, a certain velocity, which gradually gets close to p_{bests} andg_{best}, can be calculated. PSO using (1),(2) is called inertia weights approach(IWA).

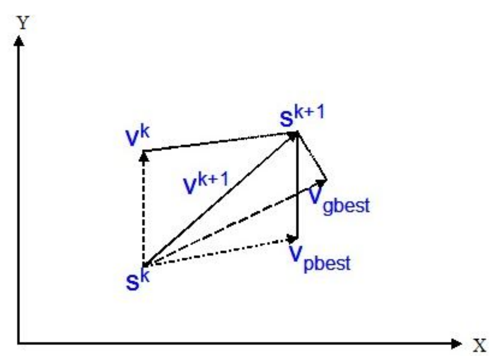

Figure-1 Concept of modification of a searching point by PSO.

s_i^k = current searching point

s_i^{k+1} = modified searching point

v_i^k = current velocity

v_i^{k+1} = Modified velocity

v_{pbest} = velocity based on p_{best}

v_{gbest} = velocity based on g_{best}

The current position (searching point in the solution space) can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad \textbf{(3)}$$

Figure-1 shows a concept of modification of a searching point by PSO, and Figure-1 shows a searching concept its current position using the integration of vectors as shown in the Figure-1.

A. *PSO algorithm :*

Step-1: Generation of initial condition of each agent. Initial Searching points (s_i^0) and velocities (v_i^0) of each agent are usually generated randomly within the allowable range. The current searching point is set to p_{best} be for each agent. The best evaluated value of p_{best} is set tog_{best}, and the agent number with the best value is stored.

Step-2: Evaluation of searching point of each agent. The objective function value is calculated for each agent. If the value is better than the current p_{best} of the agent, the p_{best} value is replaced by the current value. If the best value of p_{best} is better than the currentg_{best}, g_{best} is replaced by the best value and the agent number with the best value is stored.

Step-3: Modification of each searching point. The current searching point of each agent is changed using (1), (2) and (3).

Step-4: Checking the exit condition. The current iteration number reaches the predetermined maximum iteration number, then exists. Otherwise, the process proceeds to step-2.

The features of the searching procedure of PSO can be summarized as follows:

- As shown in (1),(2) and (3), PSO can essentially handle continuous optimization problems.
- PSO utilizes several searching points, and the searching points gradually get close to the optimal point using their p_{bests} and g_{best} .
- The first term of the RHS (1) corresponds with diversification in the search procedure. The second and third terms correspond with intensification in the search procedure efficiently.
- The above concept is explained using only the x, y axis (two – dimensional space). However, the method can be easily applied to n-dimensional problems. Namely, PSO can handle continuous optimization problems with continuous state variables in an n-dimensional solution space.

Shi and Eberhart tried to examine the parameter selection of the above parameters [12, 13]. According to their examination, the following parameters are appropriate and the values do not depend on problems.

B. PSO implementation:

The proposed PSO based approach was implemented using MATLAB language. Initially, several runs have been done with different values of the PSO key parameters such as inertia weight and the maximum allowable velocity. In our implementation, the initial weight *w* (0) and the number of intervals in each space dimension *N* are selected as 1.0 and 10 respectively. Other parameters are selected as: number of particles n=50, decrement constant α = 0.98 , $c_1 = c_2$ = 2, and the search will be terminated if (a) the number of iterations since the last change of the best solution is greater than 50; or (b) the number of iterations reaches 500.

To demonstrate the effectiveness of the proposed approach, different cases with various objectives are considered in this study.

III. PROBLEM FORMULATION

The OPF problem is to optimize the steady state performance of a power system in terms of an objective function while satisfying several equality and inequality constraints. Mathematically, the OPF problem can be formulated as given:

$$\text{Min } F(x, u) \quad \textbf{(4)}$$

$$\text{Subject to } g(x, u) = 0 \quad \textbf{(5)}$$

$$h(x, u) \le 0 \quad \textbf{(6)}$$

Where *x* is a vector of dependent variables consisting of slack bus power P_{G1} , load bus voltages V_L, generator reactive power outputs Q_G and the transmission line loading S_1 , Hence , *x* can be expressed as given:

$$x^T = [\, P_{G1}, V_{L1} \dots\dots\dots V_{LNL}, Q_{G1} \dots\dots\dots Q_{GNG}, S_1 \dots\dots\dots S_{1nl}]$$

(7)

Where NL, NG and nl are number of load buses, number of generators and number of transmission line respectively. U is a vector of independent variables consisting of generator voltages V_G, generator real power outputs P_G except at the slack busP_{G1}, transformer tap settings T, and shunt VAR compensationQ_c. Hence u can be expressed as given:

$$u^T = [\, P_{G2\ldots}P_{GNG}, V_{G1}..V_{GNG}, T_1.....T_{NT}, Q_{C1}...Q_{CNC}] \quad (8)$$

Where NT and NC are the number of regulating transformers and shunt compensators respectively. F is the objective function to be minimized. g is the equality constraints that represents typical load flow equations and h is the system operating constraints.

A. *Objective functions:*

In this paper, the objective(s) (J) is the objective function to be minimized, which is one of the following:

i. *Fuel Cost Minimization:*

It seeks to find the optimal active power outputs of the generation plants so as to minimize the total fuel cost. This can be expressed as follows:

$$J = \sum_i^{NG} f_i \ (\$ / h) \qquad \textbf{(9)}$$

Where f_i is the fuel cost of the ith generator
The generator cost curves are represented by quadratic function as

$$f_i = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (\$/\text{hr}) \qquad \textbf{(10)}$$

Where a_i b_i and c_i are the cost coefficients of the ith generator. The values of these coefficients are given in Table 1.The variation of the total fuel cost is shown in Fig.2 the total fuel cost obtained is $ 15,376.61 which is compared with the fuel cost obtained using Newton's method in [14] i.e., $ 15,441. It is clear that the fuel cost is greatly reduced by $ 74.

ii. *Voltage Profile Improvement:*

Bus voltage is one of the most important security and service quality indices. Considering only cost-based objectives in OPF problem may result in a feasible solution that has unattractive voltage profile. In this case, a two-fold objective function is proposed in order to minimize the fuel cost and improve voltage profile by minimizing the load bus voltage deviations from 1.0 pu. The objective function can be expressed as

$$J = \sum_i^{NG} f_i + w \ \sum_{i\in NL} |\, v_i - 1| \qquad \textbf{(11)}$$

Where w is a weighting factor. The variation of fuel cost is shown in Fig.3. It is evident that system voltage profile improved compared to case-1 ie., sum of voltage deviations is reduced from 0.2574 to 0.2572.However, the total generation cost in this case increased to 15633.9

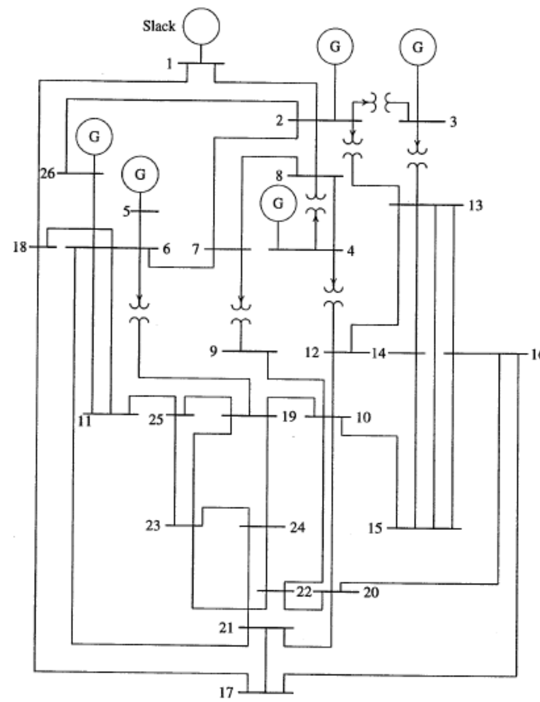

Figure-2 IEEE 26 Bus test system

Table-1 Generator production cost and limits

Gen No.	a_i	b_i	c_i	Min MW	Max MW	Min. MVAr	Max. MVAr
1	240	7.0	0.0070	100	500	0	0
2	200	10	0.0095	50	200	40	250
3	220	8.5	0.0090	80	300	40	150
4	200	11	0.0090	50	150	40	80
5	220	10	0.0080	50	200	40	160
6	190	12	0.0075	50	120	15	50

iii. *Voltage Stability Enhancement :*

Voltage profile improvement does not necessary implies a voltage secure system. Voltage instability problems have been experienced in systems where voltage profiles are acceptable [15]. Voltage secure system can be assured by enhancing the voltage stability profile throughout the whole power system.

In this case a two-fold objective function is proposed in order to minimize the fuel cost and enhance the voltage stability profile throughout the whole power network. In this

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study, voltage stability enhancement is achieved through minimizing the voltage stability indicator *L-index* [16] values at every bus of the system and consequently global power system *L-index.*

Generally, *L-index* at any bus varies between zero (no load case) and one (voltage collapse). In order to enhance the voltage stability and move the system far from the voltage collapse point, the following objective function is proposed

$$J = \sum_{i}^{NG} f_i + w\, L_{max} \qquad \textbf{(12)}$$

Where w is a weighting factor and L_{max} is the maximum value of *L-index* defined as

$$L_{max} = \max\,\{L_k, k = 1 \ldots\ldots NL\} \qquad \textbf{(13)}$$

Where w is a weighting factor. The variation of fuel cost is shown in Fig.4. It is evident that system voltage stability is enhanced compared to case-1 i.e., the voltage stability index value reduced to 0.1194 compared to the initial state of the system 0.1195. However, the total generation cost in this case increased to 15974.98

iv. Proposed method.

In this case a method was proposed which takes care of both voltage profile and voltage stability of the system. i.e., a method was proposed in which stable operating is achieved where voltage profile is improved and voltage stability is enhanced simultaneously. A three-fold objective function is proposed to minimize the fuel cost, improve voltage profile and to enhance voltage stability. The following objective function is proposed:

$$J = \sum_{i}^{NG} f_i + w \sum_{i \in NL} |v_i - 1| + w\, L_{max} \qquad \textbf{(14)}$$

Where w is a weighting factor. The variation of fuel cost is shown in Fig.5. It is evident that system voltage stability is enhanced compared to case-1 i.e., the voltage stability index value reduced to 0.1194 compared to the initial state of the system 0.1195. and also the line deviations reduced to 0.2569 compared to the initial state of the system 0.2574 . However, the total generation cost in this case increased to 17220.92

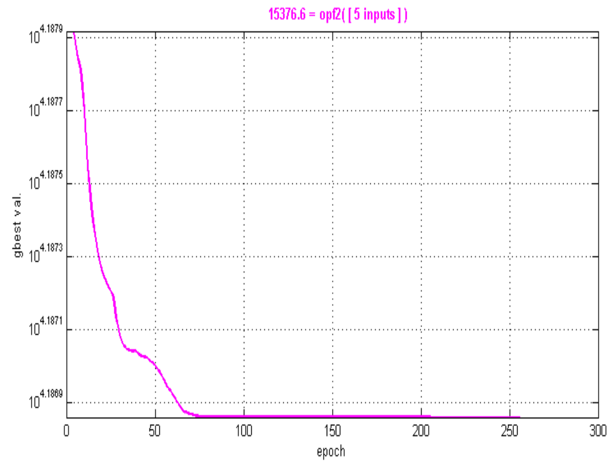

Figure 3 fuel cost variations for case-1

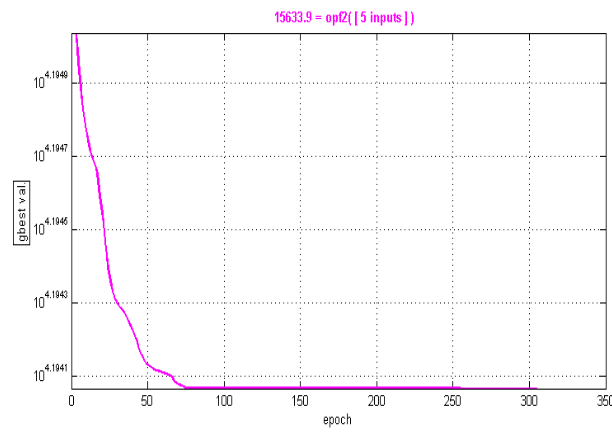

Figure 4 fuel cost variations for case-2

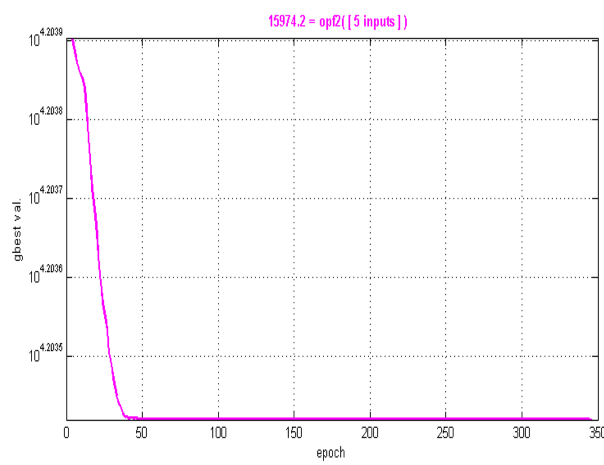

Figure 5 fuel cost variation for case-3

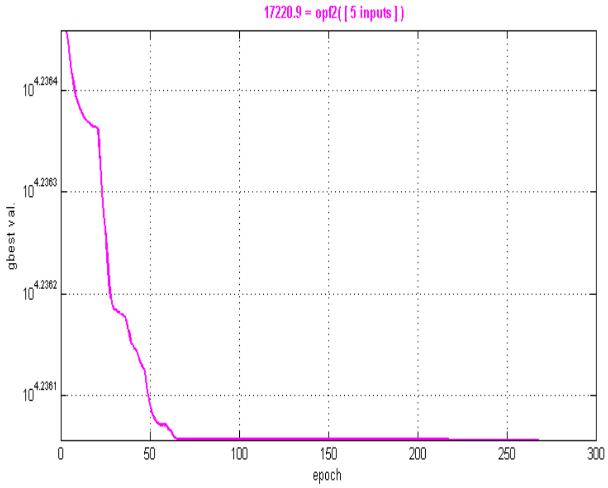

Figure 6 fuel cost variations for case-4

Table-2 optimal settings of IEEE 26 BUS system

	CASE-1 UNCOM	CASE-1 COM	CASE-2 UNCOM	CASE-2 CO M	CASE-3 UNCOM	CASE-3 COM	CASE-4 UNCOM	CASE4 COM
P1	446.0200	445.9510	446.9105	447.0057	442.2333	444.0166	448.2752	445.2643
P2	177.7015	177.6613	178.0310	178.1038	174.2118	175.7116	178.6778	176.4413
P3	258.8970	258.8984	256.4939	256.7973	254.4964	256.7121	256.7609	255.3623
P4	129.4152	129.4426	128.1529	127.2805	126.1507	127.6347	128.6544	126.9724
P5	175.0815	175.0573	176.7515	176.9065	170.0546	172.0784	174.9463	172.0941
P26	83.5063	83.5209	84.2822	84.4259	103.5745	94.4196	83.2895	94.4273
V1	1.0250	1.0250	1.0250	1.0250	1.0250	1.0250	1.0250	1.0250
V2	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02
V3	1.0250	1.0250	1.0250	1.0250	1.0250	1.0250	1.0250	1.0250
V4	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05
V5	1.045	1.045	1.045	1.045	1.045	1.045	1.045	1.045
V26	1.015	1.015	1.015	1.015	1.015	1.015	1.015	1.015
T11	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01
T12	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
T15	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
T36	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01
T19	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
T9	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
QC1	0	4	0	4	0	4	0	4
QC4	0	2	0	2	0	2	0	2
QC5	0	5	0	5	0	5	0	5
QC6	0	2	0	2	0	2	0	2
QC9	0	3	0	3	0	3	0	3
QC11	0	1.5	0	1.5	0	1.5	0	1.5
QC12	0	2	0	2	0	2	0	2
QC15	0	0.5	0	0.5	0	0.5	0	0.5
QC19	0	5	0	5	0	5	0	5
$\sum P_G$	1270.6	1270.5	1270.6	1270.5	1270.7	1270.5	1270.7	1270.6
COST	15,377.81	15,376.61	15,634.15	15,633.90	16578.20	15974.98	17301.42	17220.92
LDEV	0.2564	0.2574	0.2562	0.2572	0.2582	0.2597	0.2563	0.2569
LIND	0.1197	0.1195	0.1198	0.1196	0.1196	0.1194	0.1196	0.1194
LOSSES	7.6215	7.5314	7.6042	7.5197	7.7139	7.5731	7.6040	7.5617

IV. CONCLUSIONS

In this paper a basic PSO based approach to OPF problem has been presented. The proposed approach utilizes the global and local exploration capabilities of PSO to search for optimal settings of control variables. Different objective functions have been considered to minimize the fuel cost, to improve the voltage profile, to enhance the voltage stability and a new method was proposed. The proposed approach has been tested and examined to demonstrate its effectiveness and robustness. The proposed method ensured line deviations and voltage stability in tandem got improved in tandem. This proposed method takes care of all the above three objectives.

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