Solution for Optimal Power Flow Problem in Wind Energy System using Hybrid Multi Objective Artificial Physical Optimization Algorithm

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***Abstract*--Normally, the nature of the wind energy as a renewable energy sources has uncertainty in generation. To solve the Optimal Power Flow (OPF) problem, this paper proposed a new Hybrid Multi Objective Artificial Physical Optimization (HMOAPO) algorithm, which does not need the control parameters unlike other meta-heuristic algorithms in the literature. Artificial Physical Optimization (APO), a moderately new population-based intelligence algorithm, shows fine performance on optimization problems. Moreover, this paper presents hybrid form of Animal Migration Optimization (AMO) Algorithm to precise the convergence characteristic of APO.The OPF problem is considered with six different test cases, the effectiveness of the proposed HMOAPO method is tested on IEEE 30-bus, IEEE 118-bus and IEEE 300-bus test system. The obtained results from the HMOAPO algorithm are compared with the other optimization techniques in the literature. The obtained comparison results indicate that proposed solution is effective to reach optimal solution for the OPF problem.**

***Keywords*--Renewable energy sources, Optimal Power Flow (OPF), meta-heuristic Algorithms, Artificial Physical Optimization (APO), Animal Migration Optimization (AMO).**

I. INTRODUCTION

Today's technological word fully depends on electricity; but the availability of electric source is low. The deficiency of electricity becomes the breaking point for emerging countries. Therefore, the research organizations tend into research to discover an appropriate solution for giving uninterruptable electricity. In this situation the usage of renewable energy sources are the superior solution, so these renewable energy systems are encouraged for electricity production [1, 2]. The most available renewable source in the world is wind and solar, the researches on these to area are under progressing butwind energy conversion is most promising research area because of its low complexity in installation and maintenance [3]. In wind energy acquisition the wind turbine is utilized and wind energy systems are directly integrated into the power system for power system usage. The integration of wind energy into existing power system presents a technical problems and that needs attention of voltage regulation, stability, power quality issues [4].

The power quality is an important customer focused measure and is significantly affected by the operation of a distribution and transmission network. The issue of power quality is of great importance to the wind turbine [6]. By aggregating multiple wind turbines as wind farm or park, greater amount of electrical power can be generated from it. To interconnect wind power to the utility grid, there must be an appropriate grid interconnection, control system and regulation to ensure high power quality, reliability and stability. However, the one of the most critical problems associated with wind power is that, the amount of power generated by the same is affected by the intermittent nature of wind flow and therefore become difficult to predict [7]. Therefore, in a wind integrated system, the nature of wind makes the above problem to be different in its modeling. It follows that, the grid integrated wind powered units, may introduce severe challenges to traditional generation scheduling methodologies and operation of power system [8]. For satisfactory grid integration, the wind power fluctuation may have to be balanced by other types of generation. Alternatively, to compensate for the power imbalance due to uncertainty of wind, additional cost may have to be added with the total power generation cost of the system [9].

The major goal of Optimal Power Flow (OPF) is to improve a target capacity such as cost of fuel by means of ideal change of the control variables simultaneously different equality and inequality constraints. For the main intend of economical and secure operation and planning of power systems, optimal power flow (OPF) is employed [10]. The objective of OPF is to reduce the cost of fuel,environmental pollution and also the power lost by the network.In power system economic load dispatch (ELD) is commonly used to find generation or fuel cost. The major goal of Economic Dispatch (ED) is to minimize the amount of total pollution caused by the environment. This can be done by avoiding the burning of fuels [11]. Economic Load

Dispatch (ELD) is determined as the technique in which the generation levels are allocated to the generating units. As a result the load of the system is totally and economically supplied. The ELD is a large-scale, highly non-linear, constrained optimization problem[12]. The main aim of ELD is conflicting in nature and to achieve an acceptable strategy of power dispatch within different system constraints and also it helps to keep the pollution within the limits and it reduces the fuel cost [13].

The problem of Optimal Power Flow can be solved by utilizing various techniques like linear programming, non-linear programming, interior-point technique, quadratic programming, sequential unconstrained minimization and newton based techniques and also it can be solved by the integration of optimization techniques like evolutionary programming (EP), particle swarm optimization (PSO), and sequential quadratic programming (SQP) [14]. There are two steps involved. In the first step, the solution space is investigated by both EP and PSO techniques. In the second step, SQP is utilized when there is a development in the result of first phase [15]. EP is a kind of global searching technique. It begins at the population of candidate solution and at last evaluation process is utilized to find the near global solution in parallel. GA is a search algorithm based on the mechanics of natural genetics and natural selection. The evolution procedure of organs with functional optimizations is integrated here. Reproduction, crossover and mutation are the three basic prime operators associated with GA. Based on the chromosomes,GA works. A set of binary digits which describes the control parameter coding is contained in these chromosomes which is composed themselves with genes [16] [17].

It is necessary to control the power flow at the optimal range while the renewable energy sources are used in power systems. The main contribution of this paper is i) To formulate the optimal power flow problem as a multi objective optimization problem ii) And to utilize the Artificial Physical Optimization (APO) algorithm with Animal migration optimization as a solution to the OPF problem. The remainder of this paper is organized as follows: Some of the recent works related to our proposed method is explained in section 2. The proposed methodology with problem formulation is explained in section 3. The Experimental results of the proposed method and the comparison with existing methods are presented in section 4 followed by the conclusion in section 5.

II. RELATED WORKS

Some of the recent research work related to the OPF problem in wind energy system is listed as follows:-

Shanhe Jiang et.al [18] introduced “A novel hybrid particle swarm optimization and gravitational search algorithm for solving economic emission load dispatch problems with various practical constraints”. To solve economic emission load dispatch problem, in this paper PSO was integrated with GSA. Both the utilized approach was based on population. In PSO technique, the agents were taken as particle. Here the movement of each particle was based on both the past best solution of its own and the past best solution of its group. In GSA, the agents were taken as objects. Here the one object was fascinated by other objects through gravitational force. The agent in GSA was described through four types of parameters. The first parameter was the position of the mass in which solution to the problem was stated at specified search space. The second parameter was the inertial mass which decelerates its motion by reflection of its resistance. The third and fourth parameter was the active and passive gravitational mass. The estimation of both gravitational and inertial mass was done through fitness function. Both the algorithms were integrated by any one of the two procedures. (i.e.) one work starts after the completeness of the previous work and the other way was to employ co-evolutionary method to consider the swarm components as the components introduced by PSO-GSA. The result of this hybridized algorithm has showed improvement in performance.

Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay [19] developed “Hybrid Differential Evolution with Biogeography-Based Optimization for Solution of Economic Load Dispatch”. Here the issue of both convex and non-convex economic load dispatch was solved by the combination of differential evolution (DE) algorithm and biogeography-based optimization algorithm. The above combination of algorithms also solves problems like degradation of solution quality and low speed. The DE algorithm was based on population. Here functions like non-differentiable, nonlinear and multi-modal objective can be handled and a trial vector was constructed by each parent individual in order to produce new offspring. There were three types of basic operators was involved to enhance the population namely mutation, crossover, and selection. In Biogeography activities like the movement of one island to another, appearance and disappearance of new species were expressed. The quality of the solution will be degraded in later stage due to the existence of cross-over operation in evolutionary based algorithm whereas in BBO, cross-over operation was not contained. In order to solve complex optimization problems and to obtain solution, the properties of both the algorithms were combined together.

JiejinCai et.al [20] presented “A hybrid CPSO–SQP method for economic dispatch considering the valve-point effects”. In this paper, chaotic particle swarm optimization (CPSO) algorithm and sequential quadratic programming (SQP) were incorporated to retrieve the solution for economic power dispatch problem. Here the central optimizer was the CPSO and to enhance quality of the solution, the results were adjusted by SQP. The CPSO was designed based on tent equation. CPSO was a combination of PSO and CLS. Where global exploration was carried out in PSO and local search was done to the solutions of the PSO through CLS. IN SQP, there were three stages. In the first stage, the Hessian matrix contained in the lagrangian function was updated. Estimation of line search and merit function was done at the second stage and finally solution was acquired for the problem of quadratic programming. The optimal power generation of each unit which was submitted to operation was found by the hybridization of CPSO-SQP technique.

BehnamMohammadi-Ivatloo et.al [21] discussed “Nonconvex Dynamic Economic Power Dispatch Problems Solution Using Hybrid Immune-Genetic Algorithm”. The cost needed for operation was reduced and also the solution for the problem of dynamic economic dispatch (DED) in a non-convex solution space was found by the consolidation of immune algorithm (IA) and genetic algorithm (GA). In IA, when the extraneous molecules was arrived in the immune system of human body a reaction occurs. Even though this algorithm does not contains any knowledge about that molecules, they were analyzed by this algorithm after some time and also solution for the removal of these molecules was found. Here the extraneous molecules was known as antigens and the reaction of the immune system was known as antibodies. The antibodies should be balanced with the unknown antigens. The antibodies were given by the objective function, its combined constraints from the antigens and the solutions which enhance them. Some antibodies was generated by the human body at the initial stage and those antibodies was compared with the newcomer antigens and the identical properties between them was estimated. This estimation was known as affinity factor.

K. Vaisakh et.al [22] designed "Solving dynamic economic dispatch problem with security constraints using bacterial foraging PSO-DE algorithm". Here issues like non-smooth, non-convex nature due to valve-point loading effects, ramp rate limits, spinning reserve capacity, prohibited operating zones and security constraints was shown in DED problem. The above mentioned problems can be defeated by the integration of Bacterial foraging Particle Swarm Optimization (BPSO) with differential evolution (DE) algorithm. The BPSO was a combination of Bacterial Foraging Optimization Algorithm and PSO. The bacteria with positive foraging strategies was selected by the PSO operator in the updating process of every chemo-tactic step, in order to obtain reduced cost. In our new BPSO-DE approach, the first step was the substitution of velocity in place of delta. In the second step, through the calculation of fitness function the population of best fitness in the current generation and the value for global best fitness was obtained. In the third step, the position of generation was changed to a new position. In the fourth step, to retrieve the losses from power, apparent power in the lines and voltages of load was retrieved by the load flow operation which was done with those new populations produced at the previous step. In the fifth step the violations was verified for the line flows and load voltages. If it contains violations then penalty terms were added to the fitness function of both BPSO and DE. Both the fitness functions were compared for every bacterial population and the best value was stored in a separate variable. The best value of fitness, real power generation cost, voltages, line flows, power losses for the given time interval were updated for all the bacterial population as pbest and global best (gbest). After that the procedure for next chemo-tactic step was repeated.

III. A PROPOSED OPTIMIZATION SOLUTION TO OPF PROBLEM

In a wind energy system, Optimal Power Flow (OPF) is a Multi-objective optimization problem that seeks to find out a compromise solution to minimize the fuel cost, power loss, emission and maintaining voltage stability. The Solution of optimal power flow (OPF) problem aims to optimize a selected objective function through optimal adjustment of the power system control variables while at the same time satisfying the various equality and inequality constraints. According to the results of previous investigations, Animal Migration Optimization (AMO) and Artificial Physical Optimization (APO)have better performance for solving optimizations problems. In this work, weintend to propose a Hybrid Multi objective Artificial Physical Optimization (HMOAPO) is to solving the OPF (Optimal Power Flow) problem in wind energy system.The architecture of our proposed work is shown in below figure 1.

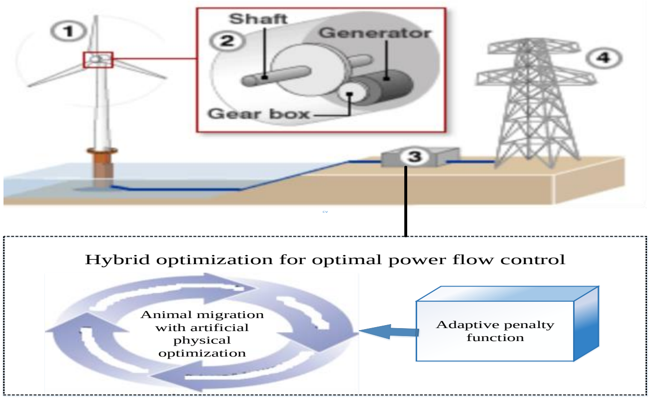

Figure 1: architecture of our proposed work

To enhance the performance of APO, this work applies an Animal Migration algorithm (AMO) which follows three main rules for each individual and also to overcome the drawback of premature convergence. In addition, the MOAPO is combined with Adaptive Penalty Function to handle equality and inequality constrains associated with OPF problems. The adaptive penalty function (APF), which convert a constrained problem into an unconstrained one where the 'Penalty Function' penalize the infeasible solutions to move towards desirable feasible solutions.

3.1 OPF Problem Definition

The OPF problem is considered as a general optimization problem. The OPF problem expects to minimize the total fuel cost function while fulfilling the total load, different equality and inequality constraints. Likewise, the optimal values of the control variables in the power system are resolved in the OPF problem. Mathematical expression belonging to the problem is described as follows.

$$Min\,(OF_1, OF_2, OF_3, OF_4, OF_5, OF_6)^T \tag{1}$$

Subject to:

$$P_{Gi} - P_{Di} = |V_i| \sum_{j=1}^{N} |V_j| \left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right), \ \forall i \in N, \tag{2}$$

$$Q_{Gi} + Q_{Ci} - Q_{Di} = |V_i| \sum_{j=1}^{N} |V_j| \left(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}\right), \ \forall_i \in N, \tag{3}$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \forall i \in N_g, \tag{4}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \forall i \in N_g, \tag{5}$$

$$|V_i^{\min}| \le |V_i| \le |V_i^{\max}|, \forall i \in N, \tag{6}$$

$$t_k^{\min} \le t_k \le t_k^{\max}, \forall k \in N_t, \quad (7)$$

$$S_{li} \le S_{li}^{rated}, \forall i \in nbr, \quad (8)$$

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}, \forall i \in N_c, \quad (9)$$

$$LSI_{ij} = \frac{4X_{ij}Q_j}{\left[|V_i|\sin\left(\theta + \delta_i - \delta_j\right)\right]^2} \le 1 \quad (10)$$

$$\theta = \tan^{-1}\left(\frac{X_{ij}}{R_{ij}}\right), \quad (11)$$

$$Q_j = \frac{|V_i||V_j|}{|Z_{ij}|}\sin\left(\theta + \delta_i - \delta_j\right) - \frac{|V_j|^2}{|Z_{ij}|}\sin\theta. \quad (12)$$

In this work, the objective function of the OPF problem is proposed as the total generation cost including valve-point effect, loss minimization and prohibited zones. The power flow equations are considered as the equality constraints. The transmission limits and other security limits are used as inequality constraints. The vectors are defined as state variable and control variable vectors can be defined as follows:

$$\left[P_{g-1}......P_{g-Ng}, V_{g-1}.......V_{g-Ng}, T_1........T_{Nt}, Q_{c-1}........Q_{c-Nc}\right]. \quad (13)$$

Where P_g, V_g, T_{Nt}, Q_c are described as the active power of the slack bus, the voltage magnitude of the load buses, active power output of the generators except at the slack bus, the reactive power of the generators respectively.

$$\left[Q_{g-1}......Q_{g-Ng}, V_{PQ-1}.......V_{PQ-N_{PQ}}, S_{l_1}......S_{l_{nbr}}\right]. \quad (14)$$

Where Q_g, V_{PQ} and S_l are defined as the reactive power generation at bus, the voltage of load bus and the line flow, respectively.

Objective function

In this paper, the objective function of the OPF problem is defined as minimization of the total fuel cost of the power generation system. The total fuel cost can be mathematically defined as follows:

$$OF_1 = \sum_{i=1}^{Ng}\left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i\right) \quad (15)$$

Where PG_i are represented as the active power output of the i^{th} generator, respectively. a_i, b_i and c_i are the fuel cost coefficients of the i^{th} generator.

3.2 The generation cost minimization with Valve Point Loading (VPL) effect

The generation cost with valve-point effect is presented as follows:

$$OF_2 = \sum_{i=1}^{Ng}\left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i\right) + \left|d_i \times \sin\left(e_i \times \left(P_{Gi}^{\min} - P_{Gi}\right)\right)\right| \quad (16)$$

Where d_i and e_i are coefficients of the valve-point effect of the i^{th} generator. Typical curve related to fuel cost with and without valve-point effect of the generation units is shown in Figure2.

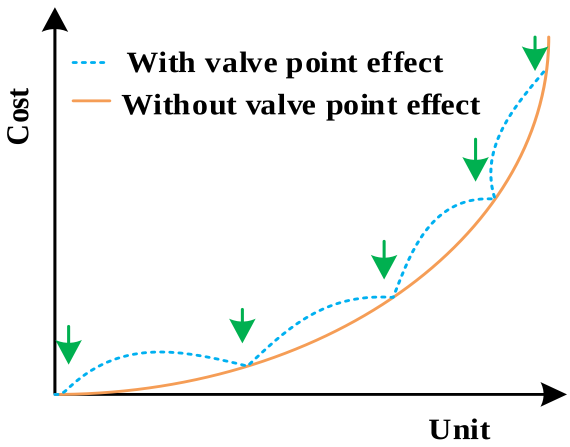

Figure 2: Typical curve related to fuel cost with and without valve-point effect of the generation units

Let $W_{j,k}\left(P_{W\,j,k}\right)$ be the electrical energy cost of wind power of the j^{th} wind farm and the k^{th} wind power generator. Therefore, the cost of the wind unit can be defined by:

$$W_{j,k}\left(P_{W\,j,k}\right) = \psi_{j,k}\hat{P}_{j,k} + \psi_{z_1,j,k} \times \left(\tilde{P}_{j,k} - \hat{P}_{j,k}\right) + \psi_{z_2,j,k}\left(\tilde{P}_{j,k} - \hat{P}_{j,k}\right) \quad (17)$$

Which, $\hat{P}_{j,k}$, $\tilde{P}_{j,k}$ are expected and available generation output of the unit j in the wind farm k (MW). $\psi_{j,k}$, $\psi_{z_1,j,k}$ and $\psi_{z_2,j,k}$ are namely direct, overestimation and underestimation electrical wind energy cost coefficient of the unit j in the wind farm k ($/MWh).

3.3 Generating units with Prohibited Operating Zones (POZs)

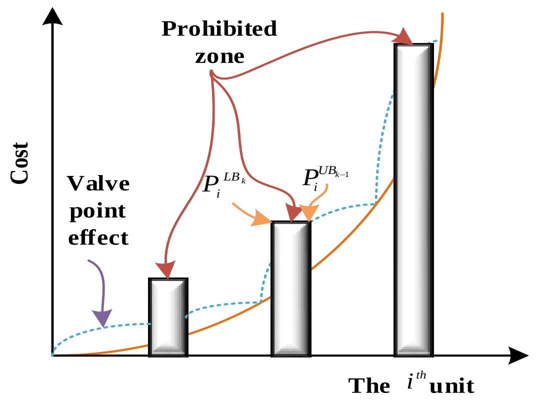

Figure 3: Topology of cost function with prohibit zone constraint and valve point effect

The physical limitations of the power plant components, prohibited operating zones (POZs) are occurred in a hydro-generating unit. This constraint dictates several feasible sub-regions for hydro-generating units as shown in Figure 3 and can be expressed by:

$$\begin{cases} P_i^{\min} \le P_i \le P_i^{LB_1} \\ \vdots \\ P_i^{UB_{k-1}} \le P_i \le P_i^{LB_k} \\ P_i^{UB_k} \le P_i \le P_i^{\max} \end{cases}, i = 1,2,......, N_g, k = 1,2,....., N_k \quad (18)$$

Which, $P_i^{UB_{k-1}}$ and $P_i^{LB_k}$ are upper and lower limits of the k^{th} sub-regions of the i^{th} unit, respectively. N_g and N_k are the number of thermal units and sub-regions.

Power Loss Minimization

The total real power loss in power systems is represented by

$$OF_3 = \sum_{i=1}^{N}\sum_{j=1}^{N}\left[\alpha_{ij}\left(P_iP_j + Q_iQ_j\right) + \beta_{ij}\left(Q_iP_j + P_iQ_j\right)\right] \quad (19)$$

Which

$$\alpha_{ij} = \frac{r_{ij}}{V_iV_j}\cos\left(\delta_i - \delta_j\right), \beta_{ij} = \frac{r_{ij}}{V_iV_j}\sin\left(\delta_i - \delta_j\right),$$

$V_i \prec \delta_i$ is the complex voltage at the bus i^{th}. $Z_{ij} = r_{ij} + jx_{ij}$ is the ij^{th} element of [Zbus] impedance matrix. P_i and P_j are the active power injections at the i^{th} and j^{th} buses, respectively. Q_i and Q_j are the reactive power injections at the i^{th} and j^{th} buses, respectively. N is the number of buses.

L-index minimization

The voltage stability index (VSI) which ensures secure operations and is written as follows

$$OF_4 = \sum_{i=1}^{N}\left(\frac{|V_i| - V_{avg}}{dV}\right), V_{avg} = \left(\frac{|V_{\max}| - |V_{\min}|}{2}\right) \text{ and} \quad (20)$$

$$dV = \left(\frac{|V_{\max}| - |V_{\min}|}{2}\right), \quad (21)$$

Where n is selected to be equal 1.Finally, wind power can be expressed by the piecewise linear as follows:

$$\widehat{P}_{i,k} = \widehat{P}_{h,j,k}\begin{cases} D_{1,j,k}T_{j,k} - T_{ci,j,k} \le T_{j,k} \le T_{1,j,k}D_{1,j,k}(T_{1,j,k} - T_{ci,j,k}) + D_{2,j,k}(T_{j,k} - T_{1,j,k}), \\ \quad T_{1,j,k} \le T_{j,k} \le T_{2,j,k} \\ D_{1,j,k}(T_{1,j,k} - T_{ci,j,k}) + D_{2,j,k}(T_{2,j,k} - T_{1,j,k}) + D_{3,j,k}(T_{j,k} - T_{2,j,k}), T_{2,j,k} \\ \quad \le T_{j,k} \le T_{h,j,k} \\ 1, T_{h,j,k} \le T_{j,k} \le T_{co\,j,k} \\ 0, otherwise \\ j = 1,2,...N_w, k = 1,2,...N_f \end{cases} \quad (22)$$

Which, Di,j,k is slope of section j of the wind unit w in wind farm f (MWs/m). Tci,j,k, Tco,j,k, Ti,j,k and Th,j,k are cut-in wind speed, cut-out wind speed, breakpoint of segment i and rated wind speed, for all the wind units w in the wind farm (m/s), respectively.

Artificial Physical Optimization

APO is a nature-inspired metaheuristic method inspired by natural physical forces based on artificial physics (AP) framework [23]which is developed by Spear et al. Based on the similarity among the AP method and population-based optimization algorithm, recently some authors proposed APO and tested its optimization performance [24–27]. APO can be described briefly as follows

Assume the optimization problem can be expressed as

$$\min \; f(x^d)$$
$$s.t. \quad x_d^{\min} \le x^d \le x_d^{\max}, \quad d = 1,2,........, D$$

Where D is the dimension of the problem, $x_{\min}^d$ and $x_{\max}^d$ are the minimum and maximum limits of variable x^d.

The particle's position signifies the solution to the optimization problem. The position of particle i is defined as

$$X_i = \left[x_i^1, x_i^2,......., x_i^d,......., x_i^D\right], \qquad i = 1,2,.........NP.$$

Where NP is the number of individuals in APO; x_i^d is the position of the i^{th} individual in d^{th} dimension.

Step 1: Population Initialization.

The NP individual'spositions is randomly formed in the n-dimensional decision space. The NP individual'svelocities is set to be zero.

Step 2: Fitness calculation.

Compute the fitness of each individual according to the objective function.

Step 3: Force calculation.

In the APO, the process of optimizationis continuously performed by moving the individuals toward the promising region until the optimal solutions is found. And the rules for moving the individuals are decided by the forces act on each other. The rules can be expressed by the following equations:

IV. SIMULATION RESULTS AND COMPARISONS

The proposed algorithm is developed in the Matlab programming language using 6.5 version. The proposed method 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 [19].

4.1. Case Studies on the IEEE 30-Bus System

A.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 APO 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. Figure 4 shows the topology of standard IEEE 30 bus system.

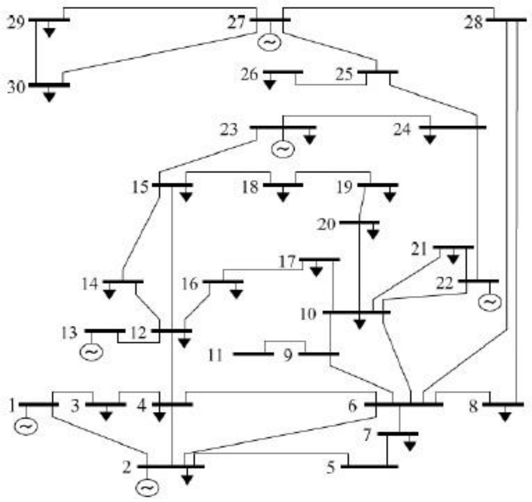

Figure 4: IEEE 30 bus system

For the purpose of verifying the efficiency of the proposed approach, we made a comparison of our algorithm with others competing OPF algorithm. In [19], they presented a standard GA, in [3] the authors presented an enhanced GA, and then in [20], they proposed an Improved evolutionary programming (IEP). In [21] 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 I show clearly that the proposed approach gives better results.

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			Global optimization methods				
	NP=1	NP=2	NP=3	SGA[19]	EGA[3]	IEP[20]	FGA[21]	MDE [11]
P1(MW)	180.12	175.12	174.63	179.367	176.20	176.2358	175.137	175.974
P2(MW)	44.18	48.18	47.70	44.24	48.75	49.0093	50.353	48.884
P5(MW)	19.64	20.12	21.64	24.61	21.44	21.5023	21.451	21.510
P8MW)	20.96	22.70	20.24	19.90	21.95	21.8115	21.176	22.240
P11(MW)	14.90	12.96	15.04	10.71	12.42	12.3387	12.667	12.251
P13(MW)	12.72	13.24	12.98	14.09	12.02	12.0129	12.11	12.000
Q1(Mvar)	-4.50	-2.11	-2.03	-3.156	-	-	-6.562	-
Q2(Mvar)	30.71	32.57	32.42	42.543	-	-	22.356	-
Q5(Mvar)	22.59	24.31	23.67	26.292	-	-	30.372	-
Q8(Mvar)	37.85	27.82	28.22	22.768	-	-	18.89	-
Q11(Mvar)	-2.52	0.490	0.48	29.923	-	-	21.737	-
Q13(Mvar)	-13.08	-11.43	-11.43	32.346	-	-	22.635	-
θ1(deg)	0.00	0.00	0.00	0.000	-	-	0.00	-
θ2(deg)	-3.448	-3.324	-3.313	-3.674	-	-	-3.608	-
θ5(deg)	-9.858	-9.725	-9.623	-10.14	-	-	-10.509	-
θ8(deg)	-7.638	-7.381	-7.421	-10.00	-	-	-8.154	-
θ11(deg)	-7.507	-7.680	-7.322	-8.851	-	-	-8.783	-
θ13(deg)	-9.102	-8.942	-8.926	-10.13	-	-	-10.228	-
Cost ($/hr)	801.34	800.83	800.92	803.699	802.06	802.465	802.0003	802.376
Ploss (MW)	9.120	8.920	8.833	9.5177	9.3900		9.494	9.459
CPU time(s)	~0.954	-	-	594.08	-	23.07		

Table II shows the best solution of shunt compensation obtained at the standard load demand (Pd=283.4 MW) using reactive power planning.

Table 2. Comparative Results Of The Shunt Reactive Power Compensation Between EPGA And EGA [7] For IEEE 30-Bus

Shunt N°	1	2	3	4	6	7	8	9
Bus N°	10	12	15	17	21	23	24	29
Best Qsvc [pu]	0.1517	0.0781	0.029	0.0485	0.0602	0.0376	0.0448	0.0245
Best case bsh [pu] [7]	0.05	0.05	0.03	0.05	0.05	0.04	0.05	0.03

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 significant compared to the original network without partitioning. This proves that the new subsystems generated conserve the physical proprieties and performances of the original network. Table III shows that the line flows obtained are well under security limits compared to FGA algorithm and ACO algorithm [22].

Table 3. Transmission Line Loading After Optimization Compared To ACO And FGA For IEEE 30-Bus

		EPGA: PD=283.4 MW		ACO [22]	FGA [21]
Line	Rating (MVA)	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
Ploss (MW)		8.8836		9.8520	9.494

B.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 work the increase in the load is regarded as a parameter which affects the power system to voltage collapse.

$$\begin{cases} P_L = Kld.P_{oL} \\ Q_L = Kld.Q_{oL} \end{cases} \tag{23}$$

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.

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%
P1(MW)	192.66	199.30	200.00	200.0	200.00	200.0
P2(MW)	58.94	70.60	55.00	69.74	54.9925	69.9368
P5(MW)	23.22	29.08	23.70	28.40	23.6957	28.5135
P8(MW)	33.98	33.66	35.00	35.00	35.00	35.00
P11(MW)	16.60	29.32	17.01	28.03	17.0154	28.2596
P13(MW)	20.40	25.10	15.84	26.47	15.8827	26.7635
Q1(Mvar)	-5.26	-6.18	-13.94	-17.66	-15.6226	-9.4127
Q2(Mvar)	38.07	40.02	37.18	43.69	38.5416	60.4752
Q5(Mvar)	35.25	42.28	36.10	42.62	36.5254	49.5412
Q8(Mvar)	35.95	43.54	47.96	60.00	49.525	50.00
Q11(Mvar)	1.150	2.06	3.680	6.910	4.6425	21.1631
Q13(Mvar)	-11.73	-11.04	-11.68	-2.270	2.3642	19.7389
θ1(deg)	0.00	0.00	0.00	0.00	0.00	0.00
θ2(deg)	-3.684	-3.972	-4.028	-4.022	-4.0412	-4.026
θ5(deg)	-11.218	-12.002	-11.841	-12.518	-11.8475	-12.6009
θ8(deg)	-8.055	-8.588	-8.737	-9.065	-8.7607	-8.7792
θ11(deg)	-11.995	-6.847	8.931	-7.386	-8.9022	-7.0128
θ13(deg)	-9.344	-9.423	-10.642	-9.751	-10.6419	-9.8547
Cost ($/hr)	993.6802	1159.6	993.98	1160.56	994.1047	1164.1706
Ploss MW	11.390	12.975	12.141	13.556	12.174	14.385

The results including the generation cost, the power losses, reactive power generation, and the angles are shown in Table IV. 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 V 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.

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
P1(MW)	199.98	Did not Converge	Did not Converge
P2(MW)	79.96		
P5(MW)	49.98		
P8(MW)	34.92		
P11(MW)	30.00		
P13(MW)	39.90		
Q1(Mvar)	-5.680		
Q2(Mvar)	41.62		
Q5(Mvar)	45.14		
Q8(Mvar)	53.31		
Q11(Mvar)	2.910		
Q13(Mvar)	-10.33		
θ1(deg)	0.000		
θ2(deg)	-3.761		
θ5(deg)	-11.907		
θ8(deg)	-8.972		
θ11(deg)	-7.228		

θ13(deg)	-8.237		
Cost ($/hr)	1403.5		
Ploss (MW)	13.8960		

The approach 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. The security constraints are also checked for voltage magnitudes, angles and branch flows. Fig. 5 shows that the voltages magnitudes are within the specified security limits. Fig. 6 shows clearly that the transmission lines loading do not exceed their upper limits. Fig. 7 shows the reactive power exchanged between SVC Controllers installed at a specified buses and the network.

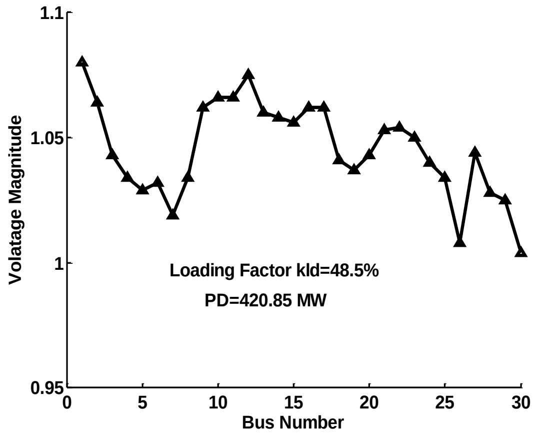

Figure 5. Voltage profile at loading factor: kld=48.5%

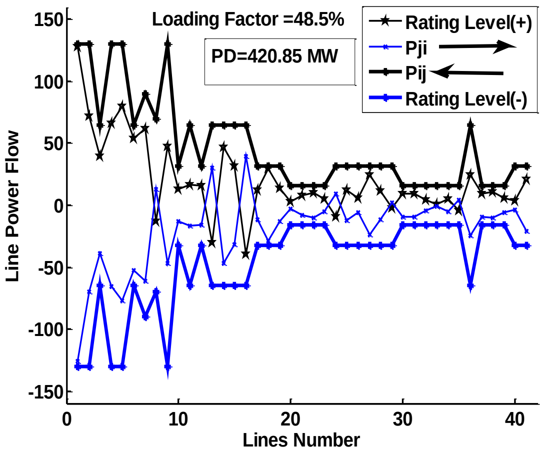

Figure 6. Lines Power flow at critical loading Factor Kld= 48.5%.

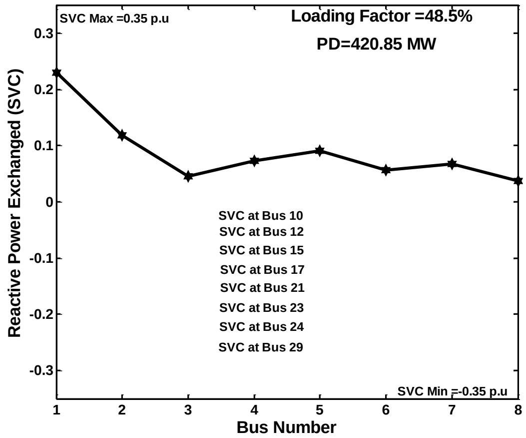

Figure 7. Reactive power exchanged between SVC Controllers and the Network at loading factor: Kld=48.5%.

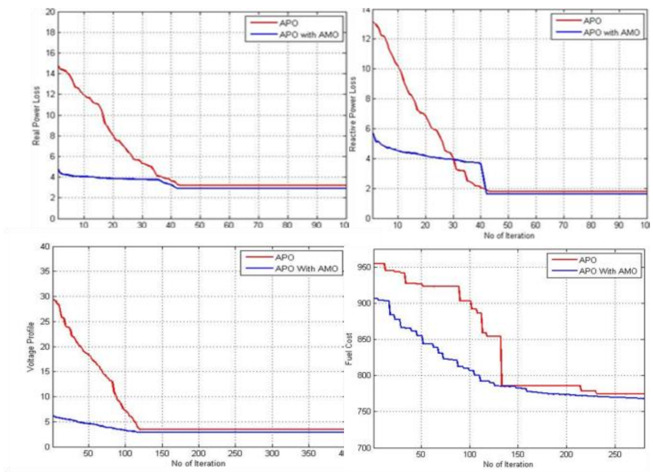

Figure 8: Convergence of IEEE 30 bus system

The convergence values of IEEE 30 bus system on multi objective basis is shown in above figure 8. The variation with real power loss, reactive power loss, voltage profile and fuel cost for the standard IEEE 30 bus system with combined APO with AMO and APO is presented and it shows the importance of utilizing APO with AMO than APO.

4.2 Case study 2 on IEEE 26-bus test system with non-smooth cost function

This case study consisted of six generation units, 26 buses and 46 transmission lines [23]. All thermal units are within the ramp rate limits and prohibited zones. All data of this test system can be retrieved from [23-24]. In this case, the load demand expected to be determined was PD=1263. The B matrix of the transmission loss coefficient is given by:

$$B_{ij} = 10^{-3}.\begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 0.1 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0.0 & -1.0 & -0.6 \\ -0.1 & 0.1 & 0.0 & 0.24 & -0.6 & -0.8 \\ -0.5 & -0.6 & -0.6 & -0.6 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix} \quad (24)$$

$$B_{i0} = 10^{-3}.[-0.3908 \quad -0.1297 \quad -0.7047 \quad -0.0591 \quad 0.2161 \quad -0.6635] \quad (25)$$

$$B_{00} = 0.056 \qquad (26)$$

Table 6 shows the performance comparison among the proposed algorithms, a particle swarm optimization (PSO) approach [23], a novel string based GA [12], standard genetic algorithm (GA) method [23], 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.

Table 6. Results of the Minimum Cost and Power Generation Compared with Global Optimìuization methods for 26-Bus test System

Generators (MW)		SA[13]	New-string GA [12]	GA [23]	MTS[13]	PSO[23]	Our Approach
P_{g1}	Part 1	478.1258	446.7100	474.8066	448.1277	447.4970	448.0451
P_{g2}		163.0249	173.0100	178.6363	172.8082	173.3221	172.0835
P_{g3}	Part 2	261.7143	265.0000	262.2089	262.5932	263.4745	264.5932
P_{g4}		125.7665	139.0000	134.2826	136.9605	139.0594	134.9605
P_{g5}	Part 3	153.7056	165.2300	151.9039	168.2031	165.4761	170.2452
P_{g6}		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[$/hr]		15461.10	15447.00	15459.00	15450.06	15450.00	15439
CPU time(s)		-	8.36	-	1.29	14.89	1.4380

The computational time of the proposed approach is reduced significantly in comparison to the other methods.

4.3. 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 [19]. The proposed approach is compared to the real Genetic Algorithm proposed in [19]. The results depicted in Table VI show clearly that the proposed approach gives much better results than the other 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).

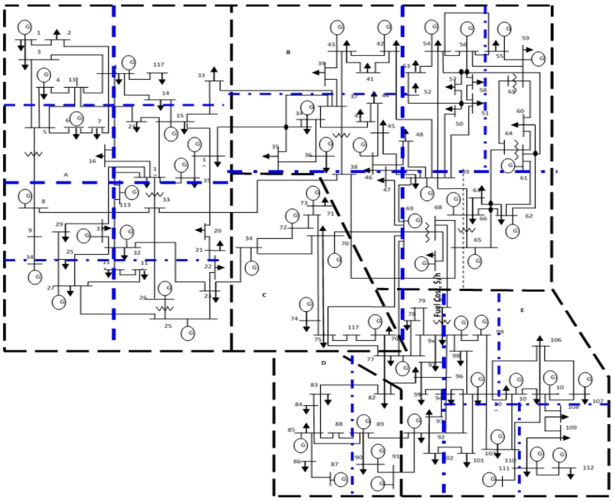

Figure. 9 Topology of the IEEE 118-Bus test system.

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. Figure. 9 shows the topology the standard IEEE 118-Bus. Fig. 10 shows that the reactive power generations are on their security limits; Fig. 11 shows the reactive power exchanged between the SVC Compensators installed at critical buses and the network. Fig. 12 demonstrates that the voltage profiles for all buses are enhanced based in reactive power planning sub problem.

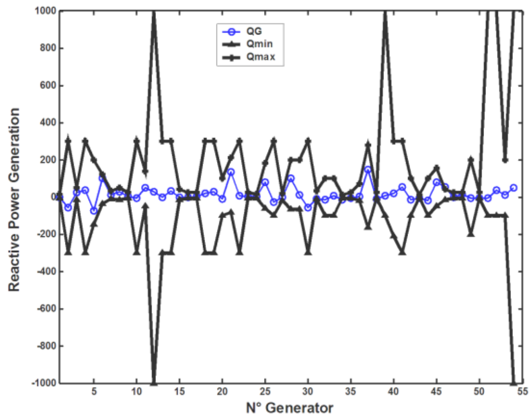

Figure 10: Reactive power generation of IEEE 118-bus electrical network with shunt compensation (Pd=4242 MW).

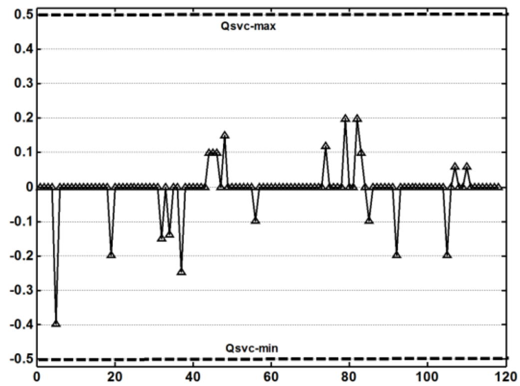

Figure 11. Reactive power compensation based SVC Compensators exchanged withthe IEEE 118-bus electrical network (Pd=4242 MW).

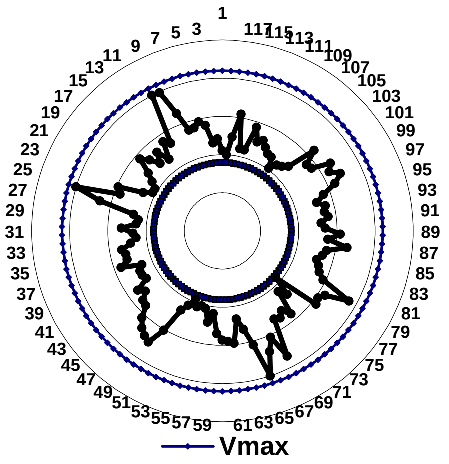

Figure 12. Voltage profiles of IEEE 118-bus electrical network

The convergence values of IEEE 118 bus system on multi objective basis is shown in above figure 13. The variation with real power loss, reactive power loss, voltage profile and fuel cost for the standard IEEE 30 bus system with combined APO with AMO and APO is presented and it shows the importance of utilizing APO with AMO than APO.

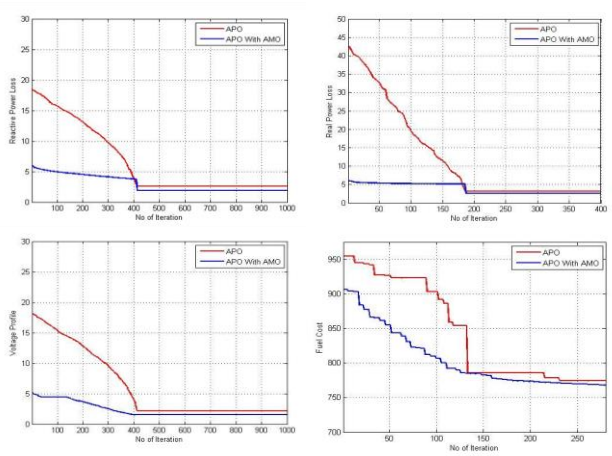

Figure 13: Convergence of IEEE 118 bus system

The comparison Results of proposed method with GA for IEEE 118-Bus in terms of the Minimum Cost and Power Generation is shown in table 7.

Table 7. Results Of The Minimum Cost And Power Generation Compared With Ga For Ieee 118-Bus

Gen	Type	EPGA	GA [19]	Gen	Type	EPGA	GA [19]
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($/hr)t		6347.2	8278.9				
Losses(MW)		106.788	94.305				

From the above figures and comparisons the clear knowledge of the importance of our proposed method is obtained. The simulation results show that the multi objective problem is solved efficiently by using our proposed APO with AMO algorithms than the existing methods. These make us to conclude that the proposed research work will be a better of choice to solve optimal power flow problem with multi objective function.

V. CONCLUSION

This article has presented a novel HMOAPO algorithm and the AMO algorithm to solve the OPF problem in electric power systems. These algorithms are used to optimize multi objective functions simultaneously under the system constraints. The simulation results have proven the high performance of both algorithms for solving the objective function strategy in the standard IEEE 30-bus system. Moreover, the DE algorithm is used to solve multi-objective OPF problems with the help of the fuzzy-based Pareto front method. It can be realized that the proposed APO algorithm-based simulation results are competitive to that of other recent optimization techniques. For an extensive verification, both algorithms are applied to a large power system, i.e., the standard IEEE 118-bus system. The simulation results have supported applicability, potential, and effectiveness of these algorithms.

REFERENCES

[1] M.A. Abido, “Optimal power flow using particle swarm optimization”, International Journal of Electrical Power and Energy Systems, Elsevier, vol. 24, no. 7, pp. 563-71, 2002.
[2] L.L. Lai, J.T. Ma, R. Yokoyama and M. Zhao, “Improved genetic algorithms for optimal power flow under both normal and contingent operation states”, International Journal of electrical power and energy systems, Elsevier, vol. 19, no. 5, pp. 287-92, 1997.
[3] Jason Yuryevich and Kit Po Wong, “Evolutionary Programming Based Optimal Power Flow Algorithm”, IEEE Transactions on power systems, vol. 14, no. 4, pp. 1245-50, 1999.
[4] Q.H. Wu and J.T. Ma, “Power system optimal reactive power dispatch using evolutionary programming”, IEEE transactions on power systems, vol. 10, no. 3, pp. 1243-9, 1995.
[5] P.K. Hota, A.K. Barisal and R. Chakrabarti, “Economic emission load dispatch through fuzzy based bacterial foraging algorithm”, International Journal of electrical power and energy systems, Elsevier, vol. 32, no. 7, pp. 794-803, 2010.
[6] A. Chatterjee, S.P. Ghoshal and V. Mukherjee, “Solution of combined economic and emission dispatch problems of power systems by an opposition-based harmony search algorithm”, International Journal of electrical power and energy systems, Elsevier, vol. 39, no. 1, pp. 9-20, 2012.
[7] D.B. Das and C. Patvardhan, “New multi-objective stochastic search technique for economic load dispatch”, IEEE Proceedings-

Generation, Transmission and Distribution, vol. 145, no. 6, pp. 747-52, 1998.

[8] J. Nanda, Lakshman Hari and M.L. Kothari, “Economic emission load dispatch with line flow constraints using a classical technique”, IEEE Proceedings-Generation, Transmission and Distribution, vol. 141, no. 1, pp. 1-0, 1994.

[9] P.K. Hota, R. Chakrabarti and P.K. Chattopadhyay, “Economic emission load dispatch through an interactive fuzzy satisfying method”, Electric power systems research, Elsevier, vol. 54, no. 3, pp. 151-7, 2000.

[10] S. Titus and A. Ebenezer Jeyakumar, “A Hybrid EP-PSO-SQP Algorithm for Dynamic Dispatch Considering Prohibited Operating Zones”, Electric power components and systems, Taylor Francis, vol. 36, no. 5, pp. 449-67, 2008.

[11] Pathom Attaviriyanupap, Hiroyuki Kita, Eiichi Tanaka and Jun Hasegawa, “A Hybrid EP and SQP for Dynamic Economic Dispatch With Nonsmooth Fuel Cost Function”, IEEE transactions on power systems, vol. 17, no. 2, pp. 411-6, 2002.

[12] Amita Mahor, Vishnu Prasad and Saroj Rangnekar, “Economic dispatch using particle swarm optimization: A review”, Reviewable and Sustainable energy reviews, Elsevier, vol. 13, no. 8, pp. 2134-41, 2009.

[13] Tahir Nadeem Malik, Azzam ul Asar, Mudasser F. Wyne and Shakil Akhtar, “A new hybrid approach for the solution of nonconvex economic dispatch problem with valve-point effects”, Electric power systems research, Elsevier, vol. 80, no. 9, pp. 1128-36, 2010.

[14] Po-Hung Chen and Hong-Chan Chang, “Large-scale economic dispatch by genetic algorithm”, IEEE transactions on power systems, vol. 10, no. 4, pp. 1919-26, 1995.

[15] Anastasios G. Bakirtzis, Pandel N. Biskas, Christoforos E. Zoumas and Vasilios Petridis, “Optimal Power Flow by Enhanced Genetic Algorithm”, IEEE transactions on power systems, vol. 17, no. 2, pp. 229-36, 2002.

[16] M. Basu, “Hybridization of Artificial Immune Systems and Sequential Quadratic Programming for Dynamic Economic Dispatch”, Electric power components and systems, Taylor and francis, vol. 37, no. 9, pp. 1036-45, 2009.

[17] V. Ravikumar Pandi and Bijaya Ketan Panigrahi, “Dynamic economic load dispatch using hybrid swarm intelligence based harmony search algorithm”, Expert systems with applications, vol. 38, no. 7, pp. 8509-14, 2011.

[18] Shanhe Jiang, Zhicheng and Yanxia Shen, “A novel hybrid particle swarm optimization and gravitational search algorithm for solving economic emission load dispatch problems with various practical constraints”, International Journal of Electrical Power & Energy Systems, Elsevier, vol. 55, pp. 628-44, 2014.

[19] Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay, “Hybrid Differential Evolution with Biogeography-Based Optimization for Solution of Economic Load Dispatch”, IEEE transactions on power systems, vol. 25, no. 4, pp. 1955-64, 2010.

[20] Jiejin Cai, Qiong Li, Lixiang Li, Haipeng Peng and Yixian Yang, “A hybrid CPSO–SQP method for economic dispatch considering the valve-point effects”, Energy Conversion and Management, Elsevier, vol. 53, no. 1, pp. 175-81, 2012.

[21] Behnam Mohammadi-Ivatloo, Abbas Rabiee and Alireza Soroudi, “Nonconvex Dynamic Economic Power Dispatch Problems Solution Using Hybrid Immune-Genetic Algorithm”, IEEE Systems Journal, vol. 7, no. 4, pp. 777-85, 2013.

[22] K. Vaisakh, P. Praveena, S. Rama Mohana Rao and Kala Meah, “Solving dynamic economic dispatch problem with security constraints using bacterial foraging PSO-DE algorithm”, International Journal of electrical power and energy systems, Elsevier, vol. 39, no. 1, pp. 56-67, 2012.

[23] Spears DF, Kerr W, Kerr W, Hettiarachchi S. An overview of physicomimetics. Lect Notes Comput Sci–State Art Ser 2005; 3324:84–97

[24] Xie LP, Zeng JC. A global optimization based on physicmimetics framework. In: Proceedings of the first ACM/SIGEVO summit on genetic and evolutionary computation. New York, USA; June, 2009. p. 609–16

[25] Xie L, Zeng J, Cui Z. Using artificial physics to solve global optimization problems. In: 8th IEEE International Conference on Cognitive Informatics (ICCI). Kowloon, Hong Kong; June 2009. p. 502–8

[26] Xie LP, Zeng JC. The performance analysis of artificial physics optimization algorithm driven by different virtual forces. ICIC Express Lett 2010; 4(1):239–44

[27] Xie L, Zeng J. An extended artificial physics optimization algorithm for global optimization problems. In: IEEE fourth International Conference on Innovative Computing, Information and Control (ICICIC). Kaohsiung, Taiwan. p. 881–4.