A hybrid approach for solving Optimum Power Flow problem with IPFC

M.Karthikeyan[#1] , Dr.P.Ajay-D-Vimalraj*[2]
[#1]Research Scholar, PRIST University, Thanjavur, Tamil Nadu
[#1]karthifascinatesyou@gmail.com
[*2]Assistant Professor, EEE Department, Pondicherry Engineering College, Puducherry.
[*2]ajayvimal@yahoo.com

Abstract- In this paper the Bat-Inspired algorithm based hybrid approach, for solving optimum power flow problem in a power system with IPFC, is explained. Here, the bat algorithm develops the different types of generator candidate solutions based on the power balance condition. By using the generator combinations, fuel cost and emission dispatch has been evaluated. From the evaluation results, the most suitable generator candidate solutions are identified. So the fuel cost, emission dispatch and power loss are maintained economically. Then the real power limits of the generators are given as the input of the Artificial Neural Network (ANN). It is trained with the output target which is IPFC injected voltage magnitude and voltage angle. The optimal placement of IPFC depends on the power flow deviation and the combination of the power system buses. Finally the proposed method is applied in the MATLAB/simulink platform and the performance is evaluated by using the comparison at ABC_ANN based OPF with UPFC. The comparison results demonstrate the superiority of the proposed approach and confirm its potential to solve the problem.

Key words: Bat inspired algorithm, OPF, IPFC, Fuel Cost, Emission Dispatch, ABC, ANN

I. INTRODUCTION

The power system consists of a set of connections in which the energy can be transmitted from generators to load. The connection between current and voltage at nodes are signified by it [1]. A combination of several generators, transmission lines, variety of loads and transformers form the network in current power system [2]. The main aim of power system is to provide a dependable power supply with cheapest cost [3]. A coupling of the related power flows resulting in system interactions is formed due to the change of power between different energy carriers [4]. In power system planning and operating tasks, the specific and detailed consistency study is a significant matter [5]. Usually, Power systems have OPF problem, consequently constancy may happen. The original operating conditions of the system and the sternness of the disturbance are the factors on which the constancy depends.

A main problem for power generation in the current generation is the OPF and it is in common non-convex [6]. The OPF is a static nonlinear programming problem which optimizes a certain objective function while satisfying a set of physical and operational constraints [6] [7]. The constraints for OPF include: (i) The AC power flow constraints, (ii) bounds on power generation, (iii) bounds on bus voltage magnitudes, (iv) bounds on line voltage drops, and (v) limits on power transfer on lines [8]. The purpose of a power flow problem is to accomplish the entire voltage angle and magnitude information for every bus in a power system for accurate load and generator's actual power and voltage condition [9]. The main problem of Optimal power flow (OPF) is finding an optimal operating point of a power system that minimizes a suitable cost function such as generation cost or transmission loss on power and voltage variables [10][11].

The power flow complexity may be sub-divided into the well-conditioned case and the ill-conditioned case. In the case of well-conditioned systems, the power flow solution is there with a flat voltage initialization in NR method [12]. Use of the optimal power flow is turning into further important in the deregulated power industry to install the resources optimizations [13]. Regularly, multi-objective OPF problem has been labored out by weighted sum, constraint approach and goal achievement method [14]. More than a few optimization techniques have been executed and employed to work out the OPF problem through, fuzzy emissions constraints, particle swarm optimization, evolutionary algorithm, iterative strategy, genetic algorithm and computational intelligence techniques [15]. In the OPF problem, which discovers out just about all of unreliable variables, such as; power outputs of generators, transformers tap positions, phase shifter angle positions, shunt capacitor /reactor, etc. [16].

At the moment, to find out and categorize dissimilar kinds of OPF events, a number of OPF sustaining methods have been proposed. Different methods are used by the researchers for OPF problem [17]. Interior point techniques, adapted Primal–Dual Logarithmic-Barrier Method, Successive Quadratic Programming Method are in addition employed for improving OPF [18]. Asymptotic numerical method (ANM) is a very proficient method to improve OPF. At present, ANM has been applied with great attainment in a widespread variety of problems mainly in the areas of Continuation Power Flow (CPF), which is a huge impact on the voltage constancy study [19]. A proficient heuristic algorithm is to solve the optimal capacitor placement problem in radial distribution systems [20].

S. Sivasubramani *et al.* has developed a multi-objective harmony search (MOHS) algorithm to produce true and well distributed Pareto optimal solutions for optimal power flow (OPF) problem [21]. Using an algorithm of embedding sensitivity theory in ordinal optimization (STOO), Shieh-Shing Lin *et al.* [22] have achieved a superior sufficient result with smaller objective value and consumed less CPU time than other heuristic techniques. T. Yu *et al.*[23] have developed a novel distributed multi-step learning algorithm based on multi-agent system for working out large-scale multi-objective OPF problem.

L.E.S. Pereira *et al.* [24] have proposed interval arithmetic in current injection power flow study to solve power flow problems under both load and line data improbability. They have confirmed that their Methodology was extremely easy and reliable, and meets with a small number of iterations. Xiaoqing Bai *et al.* [25] have proposed a semi definite programming (SDP) method, to solve the optimal power flow problem, in which they reduced the utilization of computer memory and CPU time. Using Particle Swarm Optimization algorithm (PSO), Navid Rezaei. *et al.* [26] has suggested A new strategy to model the Interline Power Flow Controller (IPFC) with the idea of improving the power system dynamic constancy. A. V. Naresh Babu *et al.* [27] have proposed an intelligent search evolution algorithm (ISEA) to minimize the generator fuel cost in optimal power flow (OPF) control with multi-line flexible alternating current transmission systems (FACTS) device which was interline power flow controller (IPFC). E.Gholipour *et al.* [28]. have suggested a novel optimal neuro-based wide area damping controller for the distributed multi functional convertible static compensator (CSC). The bacterial swarm optimization (BSO) algorithm was employed to the adaptive critic design model neural network to get better optimal system recognition.

It has been illustrated by the most recent research works that more than a few methods are functional to work out the most favorable power flow problems. Previously, researchers focused on how to create some practical constraints, such as bus voltage range, generation limits, line transfer capability, possibility constraints, fuel cost environment concerns etc. Genetic Algorithm is applied for working out the optimal power flow problem,. The major disadvantage of GAs is the high CPU execution time and the qualities of the solution decline with practical large scale optimal power flow (OPF) problems. Goal Attainment technique and weighted sum method are followed for the problem of OPF. To accomplish an optimal solution the above mentioned techniques need several steps and necessitate much computational time. Hence the optimal power flow problem is not upholded successively. Moreover, the Sensitivity Theory in Ordinal Optimization (STOO) is functional for working out OPF problem. However this technique is only suitable for smaller objective value of OPF problem; it is not suitable for the larger objective value of OPF. In this paper, Bat-Inspired algorithm based hybrid strategy for working out OPF problem in a power system with IPFC is proposed, tested and recommended.

II. MATHEMATICAL MODEL OF IPFC

The IPFC can be regarded as the combination of several static synchronous series compensators (SSSCs) via a common DC voltage link [29]. The SSSC is the one of the voltage source converter (VSC), which is based on the FACTS device. Here, two VSC's are connected via the DC link capacitor C_{dc}. The voltage source inverters are connected between the buses with the help of series transformer. The VSC injects the sinusoidal voltage magnitude (V^{se}) and the voltage angle (θ^{se}) and depending on these line parameters, the IPFC not only regulate the bus voltage but also transfer the active power among the transmission lines. So the OPF can be maintained in the system. The IPFC installation in the power system and the structure is described in the following figure 1. The power flow equations of the IPFC have been described in the following.

A. Power flow equation of i^{th} bus

The real and reactive power injected at the i^{th} bus is given in the following equations (1) and (2).

$$P_{inj,i} = \sum_{n=j,k} V_i V_{inj}^{se} b_{inj} \sin(\theta_i - \theta_{inj}^{se}) \tag{1}$$

$$Q_{inj,i} = -\sum_{n=j,k} V_i V_{inj}^{se} b_{inj} \cos(\theta_i - \theta_{inj}^{se}) \tag{2}$$

Where, $P_{inj,i}$ and $Q_{inj,i}$ are the active and reactive power injected at the i^{th} bus, V_i and θ_i are the voltage magnitude and angle of the i^{th} bus, V_{inj}^{se} and θ_{inj}^{se} are the voltage and corresponding angle injected in the i^{th} bus. Similarly the real and reactive power flow in the n^{th} buses has been calculated, which is given in the following section.

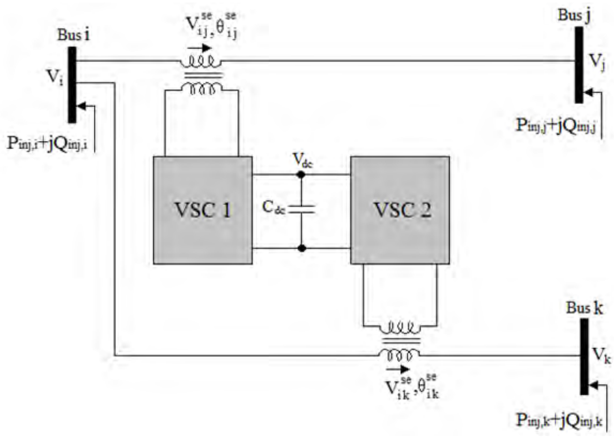

Figure.1: Structure of the IPFC

B. Power flow equation of n^{th} *bus*

The real and reactive power injected at the bus is given in the following equations (3) and (4).

$$P_{inj,n} = -V_n V_{inj}^{se} b_{in} \sin(\theta_n - \theta_{inn}^{se}) \tag{3}$$

$$Q_{inj,n} = V_n V_{inj}^{se} b_{in} \cos(\theta_n - \theta_{inn}^{se}) \tag{4}$$

Where, $n = j,k$, $P_{inj,n}$ and $Q_{inj,n}$ are the active and reactive power injected at the n^{th} bus, V_n and θ_n are the voltage magnitude and angle of the n^{th} bus, V_{inn}^{se} and θ_{inn}^{se} are the voltage and corresponding angle injected in the n^{th} bus. The injected voltage and angle is the control parameters of the IPFC. So, to maintain the OPF of the system, optimally predict the control parameters of the IPFC devices. The objective function of the proposed method is briefly described as follows.

C. Objective function

This section describes the objective function of the proposed method, which should minimize the fuel cost, emission dispatch and IPFC installation cost. It helps to maintain the OPF of the system without violating the equality and inequality constraints of the power system. The objective function can be described in the following equation (5).

$$\Phi = Minimize \ \{C_{FC}(t,x), C_{ED}(t,x), C_{IPFC}(t,x)\} \tag{5}$$

Where, fuel cost

$$C_{FC}(t,x) = \sum_{i=1}^{NG} (a_i + b_i P_{G_i} + c_i P_{G_i}^2) \ \$/hr$$

Emission dispatch $C_{ED}(t,x) = \sum_{i=1}^{NG} (\alpha_i P_{G_i}^2 + \beta_i P_{G_i} + \gamma_i)\, Kg/hr$

IPFC installation cost [32] $C_{IPFC}(t,x) = C_{IPFC}^{A} + C_{IPFC}^{B}$

$$C_{IPFC}^{A} = 0.00015 S_i^2 - 0.01345 S_i + 94.11 \ \$/KVAR$$

$C_{IPFC}^{B} = 0.00015 S_j^2 - 0.01345 S_j + 94.11 \ \$/KVAR$ With, a_i, b_i and c_i are the fuel cost coefficients of the i^{th} generator unit, α_i, β_i and γ_i are the emission coefficients and P_{G_i} is the real power generated from i^{th} generator unit, which should be lying between $P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max}$, $S_i = |Q_{i2}| - |Q_{i1}|$ and $S_j = |Q_{j2}| - |Q_{j1}|$ are the cost functions for converters connected in bus i and bus j respectively, Q_{i1} and Q_{i2} are the reactive power flows in line i at before and after installing IPFC, Q_{j1} and Q_{j2} are the reactive power flows in line j at before and after installing IPFC, The above objective function is subjected to the equality and inequality constraints of the power system . The bat inspired algorithm to optimize the generator real power is briefly explained in the following section

D. Bat inspired algorithm to optimize the generator real power

The bat- inspired algorithm is an optimization algorithm, which is derived from the echolocation behavior of micro-bats with varying pulse rates of emission and loudness[30]. This section describes the determination of the generator real power limits based on the power balance condition. Here, the different types of generator candidate solutions are developed according to the power balance condition. In each generator candidate solutions fuel cost and emission dispatch has been identified. From that, the minimized fuel cost, emission dispatch and power loss generator candidate solution is attained. The generators real power limits are once assigned to the generators, the OPF of the system can be maintained by the IPFC. The algorithmic steps to find the generator real power limit are described in the following.

Steps to find the generator generation limits

Step 1: Input micro-bats (B_i) population is randomly generated, i.e., IEEE standard benchmark system generators possible candidate solutions, which should satisfy the power balance condition. The each micro-bat has the velocity vector (v_i) and position vector (x_i), which is described in the following equation (6).

$$B_i = \begin{bmatrix} (v_{11}, x_{11})^{b1} & (v_{12}, x_{12})^{b2} & \dots & (v_{1n}, x_{1n})^{bn} \\ (v_{21}, x_{22})^{b1} & (v_{22}, x_{22})^{b2} & \dots & (v_{2n}, x_{2n})^{bn} \\ \vdots & \vdots & & \vdots \\ (v_{m1}, x_{m1})^{b1} & (v_{m2}, x_{m2})^{b2} & \dots & (v_{mn}, x_{mn})^{bn} \end{bmatrix} \tag{6}$$

Step 2: To assign the echolocation parameters, the micro-bat populations are incorporated with the echolocation parameters like frequency (f_i), pulse rate (r_i) and the loudness parameters (l_i). These parameters are non-negative real values with the following ranges.

$$f_{\min} \le f_i \le f_{\max} \tag{7}$$

$$r_{\min} \le r_i \le r_{\max} \tag{8}$$

$$l_{\min} \le l_i \le l_{\max} \tag{9}$$

Here, we assign the frequency range $f_{\min} = 0$ and $f_{\max} = 1$, the pulse rate minimum value $r_{\min} = 0.5$ is and the loudness maximum value is $l_{\max} = 1$. The remaining values are determined by the following equation (10).

$$l_{\min} = \frac{1}{\sqrt{n_{\sec}}} \text{ and } r_{\max} = 1 - \frac{1}{n_d} \le 1 \tag{10}$$

Where, $n_{\sec}$ is the number of sections in the discrete set used for sizing the design variable and n_d is the number of discrete design variables.

Step 3: Evaluate the objective function of the initial populations; the required objective function is described in the following equation (11).

$$\Phi = \text{Minimize } \left\{ C_{FC}(t, x), C_{ED}(t, x) \right\} \tag{11}$$

Step 4: Store the current population and increase the iteration count as t+1, i.e., iteration t = t+1.

Step 5: The current population of generators candidate solutions are randomly updated based on the frequency and the velocity. Initially the frequency can be evaluated, which is described in the following equation (12).

$$f_i^t = f_{\min} + (f_{\max} - f_{\min}) u_i \tag{12}$$

Where, the random number of values, which is selected from 0 to 1, then the frequency is applied into the velocity equation, which can be described in the following equation (13).

$$v_i^t = round\ [v_i^{t-1} + (X_i^{t-1} - X_\Psi) u_i] \tag{13}$$

Where, v_i^t and v_i^{t-1} are the velocity vectors of the micro-bats at the time steps t and $t-1$, X_i^t and X_i^{t-1} are the position vectors of the micro-bats at time steps t and $t-1$, X_Ψ is the current global best solution. Here after the local search is performed in the randomly selected population, which is described in the following equation (14).

$$x_i^t = x_i^{t-1} + \xi_{i,j} l_{avg}^t \tag{14}$$

Where, $\xi_{i,j}$ is a random number between -1 and 1, l_{avg}^t is the average value of loudness at time step t.

Step 6: Find the fitness of the new micro-bats population using the equation (11). After evaluation, the micro-bats echolocation parameters are updated for better moving of the micro-bats, which can be described in the following equation (15).

$$l_i^{'} = a.l_i \;\; and \;\; r_i^{t+1} = r_{\max}[1-\exp(\gamma t)] \tag{15}$$

Where, $l_i^{'}$ and l_i are the previous and updated values of the loudness, r^{t+1} is the pulse rate of the micro-bats in time step , a and γ are the adaptation parameters of the loudness and pulse rate.

Step 7: Find the best micro-bats, which satisfies the objective function (11).

Step 8: The steps 4 to 7 is continued until the termination criteria is attained.

Once the process is finished, the algorithm is ready to give the accurate generator candidate solutions based on the minimization of the fuel cost, emission dispatch and power loss. The selected real power settings are applied to the generator; so the OPF of the system is maintained by the IPFC. The power flow parameters of the IPFC depends on the injected voltage magnitude and angle. Here, the injected voltage magnitude and the voltage angle of the IPFC can be determined by the ANN.

E. IPFC power flow parameters determination by using ANN

The ANN is the training and testing algorithm, which is the inspiration model of human brain. It doesn't need any mathematical model for prediction. Many real time applications are used in the ANN such as stock market prediction, travelling salesman's problem and miscellaneous applications. The ANN contains three layers, i.e., input layer, hidden layer and output layer. Here, the ANN is trained with the IPFC injected voltage magnitude and voltage angle based on optimal generation of the generators. During the testing time, the ANN provides the required voltage angle and magnitude of the IPFC. The well-known back propagation algorithm is used for the training process of the ANN.

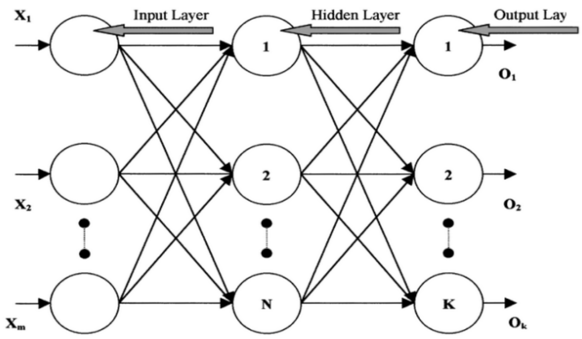

Figure.2: Structure of feed forward neural network

The inputs of the network are denoted as x_1, x_2 *and* x_m, the output of the network are denoted as o_1, o_2 *and* o_k. The weights of the network from input layer to hidden layer is denoted as V_{11}, V_{22}, …V_{1n} and V_{pn} respectively. Then, the weights between hidden and output layer is denoted asW_{11}, W_{22}, W_{1n} and W_{mp} respectively. The network is trained by back propagation training algorithm. The back-propagation algorithm is one of the most famous algorithm to train a feed forward network [31]. The back propagation training algorithm is divided into two phases that are named as propagation and weight update.

Back propagation learning algorithm steps:

(1) The input and hidden layer, hidden and output layer weights of the neural network are initialized randomly.
(2) Learning the network according to the input and the corresponding target.
(3) Calculate the back propagation error of the target o_1, o_2 *and* o_k.

$$\left.\begin{aligned} BP_{error}^{1} &= o_{1}^{NN(tar)} - o_{1}^{NN(out)} \\ BP_{error}^{2} &= o_{2}^{NN(tar)} - o_{2}^{NN(out)} \\ BP_{error}^{k} &= o_{k}^{NN(tar)} - o_{k}^{NN(out)} \end{aligned}\right\} \tag{16}$$

Where, $o_k^{NN(tar)}$ is the network target of the k^{th} node and $o_k^{NN(out)}$ is the current output of the network.

(4) The current output of the network is determined by following them,

$$\left.\begin{aligned} o_{1}^{NN(out)} &= \alpha_1 + \sum_{n=1}^{N} w_{1n}\, o_{1}^{NN}(n) \\ o_{2}^{NN(out)} &= \alpha_2 + \sum_{n=1}^{N} w_{2n}\, o_{2}^{NN}(n) \\ o_{k}^{NN(out)} &= \alpha_k + \sum_{n=1}^{N} w_{kn}\, o_{k}^{NN}(n) \end{aligned}\right\} \tag{17}$$

Where, α_1, α_2 and α_k are the bias function of the node $1, 2\, and\, k$ respectively.

$$\left.\begin{aligned} o_{1}^{NN}(n) &= \frac{1}{1+\exp(-w_{1n}o_1 - w_{2n}o_2)} \\ o_{2}^{NN}(n) &= \frac{1}{1+\exp(-w_{2n}o_2 - w_{kn}o_k)} \\ o_{k}^{NN}(n) &= \frac{1}{1+\exp(-w_{kn}o_k - w_{1n}o_1)} \end{aligned}\right\} \tag{18}$$

(5) The new weights of the each neurons of the network is updated by $w_{new} = w_{old} + \Delta w$. Here, w_{new} is the new weight, w_{old} is the previous weight and Δw is the change of weight of each output. The change of weight is determined by follow,

$$\left.\begin{aligned} \Delta w_1 &= \delta . o_1 . BP_{error}^{1} \\ \Delta w_2 &= \delta . o_2 . BP_{error}^{2} \\ \Delta w_k &= \delta . o_k . BP_{error}^{k} \end{aligned}\right\} \tag{19}$$

Where, δ is the learning rate (0.2 to 0.5).

(6) Repeat the above steps till the BP_{error} gets minimized $BP_{error} < 0.1$.

Once the neural network training process is completed, the network is trained well for identifying the injected voltage and voltage angle of the input. Based on the output of the network, the IPFC voltage and voltage angle is injected. After connecting the IPFC, the load flow analysis was applied. Here, the Newton Raphson load flow algorithm is used for analyzing the power flow solution. Then, the fuel cost, emission, IPFC installation cost and power loss are determined. Then the operational structure of the proposed method is described in the figure 3.

Here, the generator optimum combinations are identified by the bat inspired algorithm based technique on the power balance condition; so it minimize the fuel cost, emission dispatch, power loss and IPFC installation cost. Also, depending on the power flow deviation and the combination of the power system buses, the optimal location of the IPFC has been evaluated. Then the IPFC power flow parameters are obtained from the ANN technique, i.e., the optimal injected voltage magnitude and voltage angle.

III RESULTS AND DISCUSSIONS

The proposed hybrid model is implemented in the MATLAB 7.10.0 (R2012a) platform. The numerical results of the proposed hybrid method is presented and discussed in this section. The effectiveness of our proposed hybrid model is evaluated by comparing other technique. Here, the hybrid technique is applied to the IEEE standard bench mark system, i.e., IEEE 30 bus system. The structure of the IEEE 30 bus system is described in the figure 4. The IEEE 30 bus system consists of six generator bus (1,2,6,13,22 and 27), 21 load bus and 41 transmission lines. The Newton-Raphson (N-R) load flow analysis technique is used to evaluate the power flow of the IEEE 30 bus system. By using N-R method bus data like voltage magnitude, voltage angle, real and reactive power flow is evaluated and the corresponding line data and line losses are considered as a standard data [33]. The selected generators combinations are mainly depended on the fuel cost and emission dispatch, which can be calculated by using the fuel cost and emission dispatch coefficients. The generator bus fuel cost and emission dispatch coefficients are illustrated in the table 1. The comparison of voltage magnitude and voltage angle is also shown in table 2.

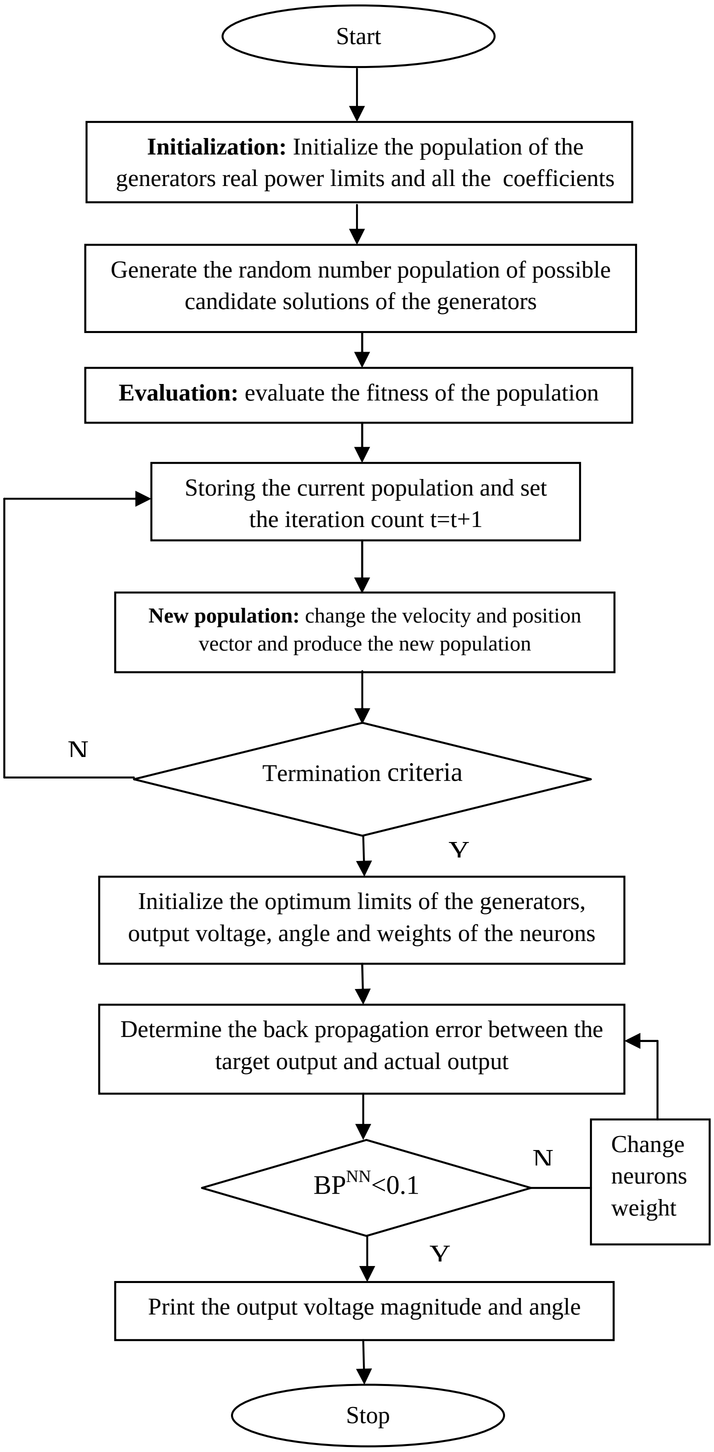

Figure.3: Algorithm for Proposed Method

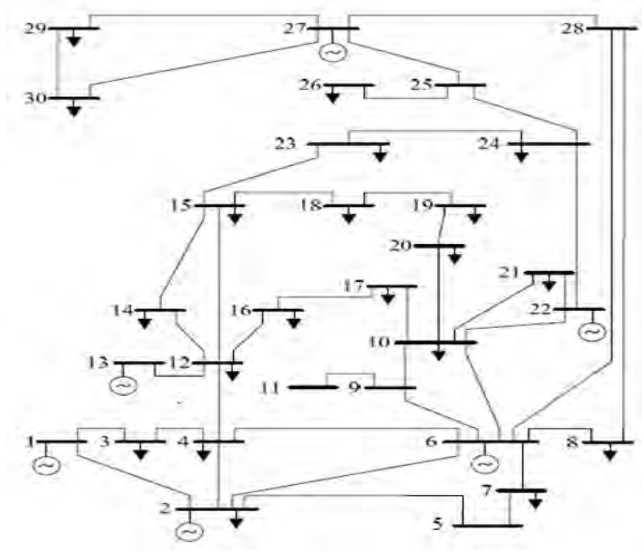

Figure.4: Structure of the IEEE 30 bus system

TABLE 1
Fuel cost and Emission coefficient.

Generator bus number	Fuel cost coefficient			Emission coefficient		
	a_i	b_i	c_i	α_i	β_i	γ_i
1	0	2	0.0038	0.0126	-1.1	22.983
2	0	1.75	0.0175	0.02	-0.1	25.313
6	0	1	0.0625	0.027	-0.01	25.505
13	0	3.25	0.0083	0.0291	-0.005	24.9
22	0	3	0.025	0.029	-0.004	24.7
27	0	3	0.025	0.0271	-0.00055	25.3

TABLE 2
Comparison of voltage magnitude and voltage angle

Bus No.	IPFC injected voltage magnitude and voltage angle		UPFC injected voltage magnitude and voltage angle			
			ABC_ANN		NR-method	
	Voltage in p.u.	Angle in degree	Voltage in p.u.	Angle in degree	Voltage in p.u.	Angle in degree
1	1.0600	0	1.0600	0.0000	1.0600	0.0000
2	1.0331	-3.686	1.0430	-2.8044	1.0330	-3.6081
3	1.0227	-5.1125	1.0244	-3.8362	1.0228	-4.9889
4	1.0135	-6.2709	1.0155	-4.6817	1.0136	-6.1169
5	1.0045	-11.6703	1.0094	-10.1653	1.0044	-11.5389
6	1.0100	-7.5521	1.0100	-5.4785	1.0100	-7.3632
7	0.9999	-9.7711	1.0020	-7.9272	0.9999	-9.6045
8	1.0102	-8.2555	1.0103	-6.1647	1.0103	-8.0582
9	1.0459	-9.5136	1.0457	-7.3657	1.0458	-9.2535
10	1.0369	-10.5466	1.0364	-8.3601	1.0367	-10.2492
11	1.0772	-9.5136	1.0770	-7.3657	1.0771	-9.2535
12	1.0574	-9.2608	1.0565	-7.6343	1.0572	-9.0214
13	1.0711	-7.4188	1.0710	-6.1454	1.0710	-7.1792
14	1.0416	-10.2231	1.0405	-8.4905	1.0414	-9.9688
15	1.0355	-10.3639	1.0351	-8.5203	1.0355	-10.0942
16	1.0413	-10.070	1.0408	-8.2105	1.0411	-9.8065
17	1.0328	-10.6105	1.0324	-8.5232	1.0326	-10.3234

18	1.0238	-11.1275	1.0233	-9.1644	1.0236	-10.8482
19	1.0211	-11.395	1.0195	-9.3551	1.0198	-11.1050
20	1.0234	-11.237	1.0230	-9.1638	1.0232	-10.9488
21	1.0228	-10.9113	1.0225	-8.7378	1.0228	-10.5951
22	1.0352	-10.0386	1.0300	-7.4656	1.0300	-9.6655
23	1.0229	-10.8684	1.0226	-8.6992	1.0229	-10.5463
24	1.0151	-10.7059	1.0155	-8.1414	1.0158	-10.2432
25	1.0043	-10.4009	1.0068	-7.3492	1.0069	-9.5967
26	0.9863	-10.8318	0.9889	-7.7779	0.9890	-10.0252
27	1.0100	-9.5513	1.0100	-6.5952	1.0100	-8.9337
28	1.0092	7.9111	1.0096	-5.7390	1.0094	-7.6744
29	0.9899	-10.8144	0.9899	-7.8583	0.9899	-10.1968
30	0.9782	-11.7218	0.9782	-8.7657	0.9782	-11.1042

TABLE 3

The power loss, fuel cost and emission using ABC_ANN

UPFC connected bus	Power loss (MW)	Fuel cost ($/hr)	Emission (Kg/hr)
2-3	8.4197	723.4103	309.2178
5-6	9.1681	497.4753	207.7048
6-8	9.6427	709.3847	305.2213
9-10	8.9303	622.8654	243.4336
12-13	8.6038	597.209	250.5799
18-19	9.0287	670.7175	284.8097
10-21	9.2015	702.2233	291.0308
22-23	8.5548	743.3521	329.4189
27-30	9.5826	509.228	208.6349
8-28	8.375	676.3555	282.9007

TABLE 4

The cost base parameters and power loss using proposed method

IPFC connected bus	Power loss (MW)	Fuel cost ($/hr)	Emission (Kg/hr)	installation cost ($/KVAR)
4-6-12	9.147	469.4539	197.7677	187.7349
9-10-12	8.4065	648.5164	342.829	188.1109
6-7-8	8.4682	415.3417	193.0046	187.7796
12-13-14	8.8925	480.6366	249.0489	188.0787
6-9-10	7.754	464.9617	194.2943	187.7826
10-17-21	7.7657	467.5636	271.2989	188.0945
12-14-16	8.4832	462.7592	199.7029	187.8370
9-11-10	8.7307	594.3031	311.6019	188.1051
10-21-22	9.3827	478.8761	246.4444	187.9165
6-8-9	7.397	451.8083	337.7967	187.8354

The proposed method's first stage or bat inspired algorithm determines the IEEE 30 bus system generators optimum combinations based on the power balance condition. In each combination, the fuel cost, emission dispatch and power loss has been identified. From the data, the minimized fuel cost and power loss generator combinations are attained. The selected generator optimum real power limit is applied to the ANN, which determines the IPFC injected voltage magnitude and voltage angle. The IPFC injected voltage and the angle is compared with the ABC_ANN based OPF with UPFC and N-R method, which is given in the table 2. Then the ABC_ANN based OPF with UPFC connected with different buses, the power loss, fuel cost and emission dispatch has been mentioned in the table 3. Similarly the OPF based on our proposed method, IEEE 30 bus system cost base parameters, power loss, IPFC connected buses are illustrated in the table 4. Depending on these results the average cost base parameters by using different kind of FACTS devices are calculated and illustrated in the table 5.

TABLE 5
Comparison of the average power loss, fuel cost and emission dispatch

FACTS devices	**Power loss (MW)**	**Fuel cost ($/hr)**	**Emission (Kg/hr)**
UPFC[33]	8.950	645.22	271.295
IPFC	8.42	493.422	254.378

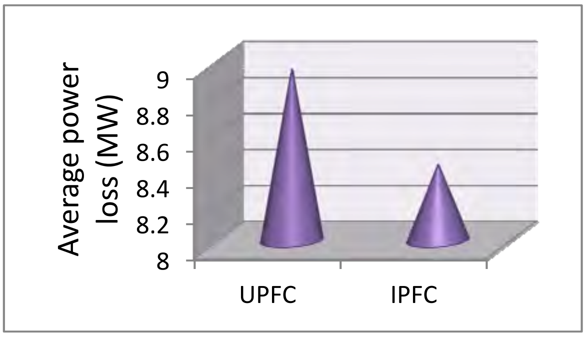

Figure.5: Comparison of power loss

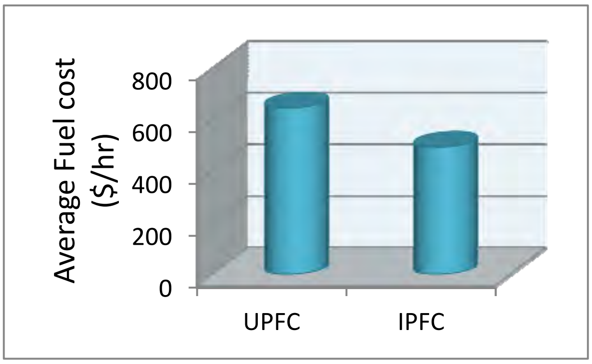

Figure.6: Comparison of fuel cost

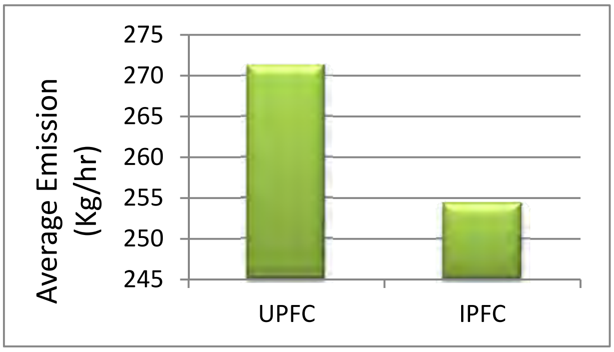

Figure.7: Comparison of Emission dispatch

The comparison of average power loss, fuel cost and emission dispatch using different FACTS devices is described in the figure 5, 6 and 7 respectively. Here, we can understand ABC_ANN based OPF with UPFC has 8.95 MW average power losses, which is not effective when compared to our proposed method. Our proposed method contains 8.42MW average power loss, also the proposed method has reduced average cost base parameters, i.e., average fuel cost 493.422$/hr and average emission dispatch is 271.295 Kg/hr, when compared to the ABC_ANN based OPF with UPFC. From the results we finalized that our proposed method is the well effective method to maintain the OPF of the system and is competent over the other techniques.

IV CONCLUSION

In this paper bat-inspired algorithm based hybrid approach for solving OPF in power system with IPFC was proposed. Then the proposed hybrid technique is applied to the IEEE 30 bus system and the numerical results were analyzed. The generator optimum real power limits are optimized by the bat inspired algorithm and the fuel cost, emission dispatch, IPFC installation cost and power loss were analyzed. The IPFC injected voltage magnitude and voltage angle is predicted from the ANN. The proposed hybrid technique result analysis are used for the performance evaluation. Here, the proposed hybrid technique results are compared with the ABC_ANN based OPF with UPFC. From the comparative analysis the proposed method is effectively maintained by the OPF in power system by economically maintaining the fuel cost, emission dispatch and real power loss of the system. When comparing with other techniques, the proposed hybrid method with IPFC is the well effective method to maintain OPF in power system.

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AUTHOR PROFILE

M.Karthikeyan, is a Research Scholar in PRIST University, Thanjavur, and working as an Assistant Professor, Department of Electrical and Electronics Engineering, Kongunadu College of Engineering and Technology, Tholurpatti, Trichy District, India. He is a life member of ISTE and member in Institution of Engineers(India). His research interests include Power System Control and Study of FACTS Devices. Email: karthifascinatesyou@gmail.com

Dr.P.Ajay-D-Vimal Raj received the B.E. degree from Madras University in 1998, M.E. degree from Faculty of Engineering, Anamalai University, Tamil Nadu, India, in 1999, and the Ph.D. degree from Pondicherry Engineering College, Pondicherry University, Pondicherry, in 2008. Currently he is Assistant Professor in the Department of Electrical and Electronics Engineering, Pondicherry Engineering College, Pondicherry University, Pondicherry, India.. Dr. Raj is a life member of the Institution of Engineers (India), life member of Indian Society of Technical Education (India), life member of Society of Power Engineers (India) and member of IEEE (USA). He has published more papers in national/international journals and conference proceedings. His research interests include power system control in renewable energy systems and conventional power systems, power system optimization, analysis of power quality issues, and application of artificial intelligence techniques in power systems. Email: ajayvimal@yahoo.com