Enhancement of Power System Stability and Cost Minimization using Fuzzified Improved Particle Swarm Optimization in a Power System

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Abstract—**This paper presents a novel and efficient method for solving the Economic Environmental Dispatch (EED) problem in power systems. The other objectives are Reactive Power Management and voltage stability index of the system and the optimization is done using improved Particle Swarm Optimization (IPSO).which is a novel heuristic optimization algorithm, to improve the searching space and convergence speed of the Conventional PSO (CPSO) algorithm. A suitable and comprehensive fitness function is also introduced to cover the wide operating conditions. All the four objectives are solved individually and the results from the individual optimizations are fuzzified and final trade off solution is obtained. The experimental results show that proposed IPSO method was indeed capable of obtaining higher quality solution. Simulation results for IEEE30 bus network are represented to show the effectiveness of the proposed method.**

Keywords- Improved Particle swarm optimization, IPSO, economic dispatch, emission dispatch, reactive power, voltage stability index, optimization.

I. INTRODUCTION

In traditional economic dispatch the operating cost is reduced by proper allocation of the amount of power generated by different generating units. The primary objective of the ED problem is to determine the optimal combination of power outputs of all generating units so to meet the required demand to at minimum operating cost while satisfying equality and inequality constraints , On the other hand thermal power plants create environmental pollution by emitting toxic gases such as Carbon dioxide(CO_2),Sulphur dioxide(SO_2) and Nitrous oxide(NO_x)

Earlier Economic and Environmental dispatch (EED) was solved by minimising fuel cost[1] considering emission as one of the constraints. The various methods for solving multiobjective EED problem are weight factor approach ,ε-constraint method ,classical Newton–Raphson method, goal programming approach but none of these methods are able to give global optimization .This paper suggests an efficient and reliable improved particle swarm Optimization (IPSO)[2] based solutions for minimum cost and minimum emission.

On the other hand reactive power optimization is also important to improve system stability and power quality. A wide variety of optimization techniques have been applied to solve the reactive power optimization problem such as Newton-Raphson method, linear programming method and successive quadratic programming. The demerit of these methods is, designed for purely continuous variable problem. But these methods are not effective as recent evolutionary computation techniques like Genetic algorithms [3], evaluation programming and evaluation strategy and PSO.In this paper IPSO has been proposed to solve reactive power optimization problem.

A problem related to voltage stability is one of the major concerns in the power system planning and operation. The load growth is one of the causes for increased for increased interest in voltage stability problems. Voltage stability is concerned with the ability of power system to maintain acceptable voltage at all nodes in the system under normal conditions and after being subjected to disturbance. The static voltage method mainly depends on steady state model in the analysis. The other method is dynamic method. The dynamic analysis used for model characterised by nonlinear, differential and algebraic equations which include generator dynamics, tap changing transformers etc. In this paper an analysis of voltage behaviour has been approached using static technique, which is widely used.

In this paper economic dispatch, emission dispatch, reactive power, voltage stability index optimized individually using IPSO and then trade off solution is obtained using fuzzy min-max approach. The IPSO is a population based stochastic optimization technique. In IPSO each potential solution is assigned a randomized velocity and the potential solution is called as particle.

Each particle change their position by flying around a multi dimensional space, adjusts its trajectory towards its own previous best position and the global best position at each step. The advantages of IPSO are easy to implement and provide fast convergence for many optimization problems. IPSO has been successfully applied in many research and application areas.

II. PROBLEM FORMULATION

The objective is to obtain appropriate control actions required to operate power system in an optimized condition while maintaining voltage stability. The problem can be formulated as.

A. Economic Dispatch Optimization sub problem :

The objective of ED problem[4] is to minimize the total generation cost of a power system over some appropriate period, while satisfying various constraints.

The economic dispatch problem is a constrained optimization problem and it can be mathematically expressed as follows

$$Minimize\ F_i = \sum_{i=1}^{n} F_i(P_i) \quad \ldots\ldots (1)$$

F_T= Total cost of generation (Rs/hr)
n = Number of generators
P_i = Real power generation of i^{th} generator
F_i= Fuel cost function of ith generator
The ED problem can be defined as following optimization problem ,[4]the total fuel cost in the system is approximated as a quadratic function of the active power output from the generating units.

$$F_t = Min \sum_{i=1}^{n} a_i + b_i P_i + c_i P_i^2 \quad \ldots . (2)$$

Where a_i,b_i,c_i are fuel cost coefficients of the i^{th} generating units.

Subject to the following:

(a) Equality Constraint:

$$\sum_{i=1}^{n} P_i = P_D + P_L \quad \ldots (3)$$

Where P_D is total system demand(MW)
P_L is total transmission losses in the system(MW)

(b) Inequality Constraint:

$P_{imin} \leq P_i \leq P_{max}$

Where P_{min} is minimum ouput power limit of i^{th} generator(MW)
P_{max} is maximum power output limit of ^{ith} generator(MW)

(c) Network losses:

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} P_i B_{i0} + B_{00} \quad \ldots . (4)$$

Where $B_{ij,}$ B_{OO} ,B_{i0}constants are called B coefficients or loss coefficients.

B. Emission Dispatch Optimization Sub problem:

The emission of pollutants is harmful to all types of life forms, it also causes global warming.

Fossil fuel fired electric power plants use coal, gas or combinations as the primary energy resource .In the emission the most harmful pollutants are sulphur dioxide (SO_2) and nitrous oxides(NO_x). The emission function [5],[6]can be expressed as the sum of all types of emissions such as NO_X, SO_2, particulate materials and thermal radiation with suitable pricing for each pollutant emitted. But in this paper only NO_x is taken into account, since this is more harmful than other pollutants. [10]

The emission dispatch problem for NO_2 can be defined as

$$\min E_n = \sum_{i=1}^{n} a_i + b_i P_i + f_i P_i^{\ 2} \quad \ldots\ldots (5)$$

Where E_n is total NO_x emission release (kg/hr)
a_i ,b_i, c_i are emission coefficients of NO_x of the ith generating unit.
Subject to demand constraints and generating capacity limits

$$\sum_{i=1}^{n} P_i = P_D + P_L \quad \ldots\ldots\ldots\ldots (6)$$

$$P_{imin} \leq P_i \leq P_{imax} \quad \ldots\ldots\ldots\ldots (7)$$

C. Reactive power optimization sub problem:

Reactive Power is very important to power system security and economic operation[7]. It improves voltage profile in the system and decrease system losses. The goal is achieved by proper adjustment of generator voltages, transformer tap settings, reactive power generation of capacitor bank.

The reactive power optimization problem is usually defined as

Minimize P_{loss} = $f(x_1)$

$$Min\ f(x_1) = \sum_{k=1}^{N\,line} P_{loss} = \sum_{i=1}^{N\,bus} \sum_{j=1}^{N\,bus} g_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \quad \ldots\ldots (8)$$

Where
N_{bus} toatal number of busses
g_{ij} is conductance of ij^{th} line

V_i voltage magnitude of i th bus
θ_{ij} is angle difference of ij th line
The reactive power optimization [8],[9] is subjected to following constraints.

(a) Equality Constraints:

These constraints represent load flow equations such as

$$P_i - V_i \sum_{j=1}^{N\,bus} V_j\left(G_{ij}cos\theta_{ij} + B_{ij}sin\theta_{ij}\right) = 0 \quad \ldots.(9)$$

For i=1,2.....N_{bus}

$$Q_i - V_i \sum_{j=1}^{Nbus} V_j\left(G_{ij}sin\theta_{ij} + B_{ij}cos\theta_{ij}\right) = 0 \quad \ldots.(10)$$

For i=1,2,....N_{bus}

(b) Inequality Constraints:

These constraints represent the system operating constraints. Generator bus voltages(V_{gi}), reactive power generated by capacitor(Q_{ci}), transformer tap setting(t_k), are control variable limits and they are self restricted. Load bus voltages(V_{load}), reactive power generation of generator(Q_{gi}) and line flow limit(S_i) are state variables, whose limits are satisfied by adding a penalty terms in the objective function. These constraints are formulated as

(i) $V_i^{min} \le V_i \le V_i^{max}; i \in N_B$
(ii) $Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}; i \in N_g$
(iii) $Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max}; i \in N_C$.......(11)
(iv) $t_k^{min} \le t_k \le t_k^{max}; i \in N_t$
(v) $S_l^{min} \le S_l \le S_i^{max}; i \in N_l$

Where N_b is number of buses,
N_g is number of generators,
N_c is number of capacitors,
N_t is number of transformer taps,
N_i is number of lines

D. *Voltage stability limit:*

Voltage stability is concerned with the ability of a power system[10],[11] to maintain acceptable voltages at all nodes in the system under normal condition and after being subject to a disturbance .A power system is said to have a situation of voltage instability when a disturbance causes a progressive and uncontrollable decrease in voltage level. Voltage stability index[12] has become an important task for many voltage stability studies. These indices provide reliable information about proximity of voltage instability in a power system. Usually, their values changes between 0 (no load) and 1 (voltage collapse).

The L index[13] describes the stability of the complete system and is given by:

$$Lindex(i) = 1 - \frac{\sum_{i\epsilon N_i} F_{LG}\,(j - no.of\ units, i) * E(i)}{E(j)} \quad \ldots..(12)$$

Where $F_{LG} = -[Y_{LL}]^{-1} * [Y_{LG}]$

$[Y_{LG}(i,j)] = Y_{bus}(n_g+i, j)$ for i=1 to (n-n_g), j=1 to n_g
$[Y_{LL}(i,j)] = Y_{bus}(n_g+i, n_g+j)$ for i , j= 1 to (n-n_g),
n_g is number of generators, n is number of busses

IV. PARTICLE SWARM OPTIMIZATION:

A.CPSO Algorithm:

The CPSO algorithm is a relatively new generation of combinational meta heuristic algorithms, which is fitted for optimizing complex numerical. The fundamental principles of CPSO are adaptability, diverse response, quality, and stability. It has roots in two major component methodologies: (1) evolutionary computation and (2) artificial life such as bird flocking. It lies somewhere in between evolutionary programming and the genetic algorithms. As in evolutionary computation examples, the concept of fitness is employed and candidate solutions to the problem are termed particles or sometimes individuals, each of which adjusts its flying based on the flying experiences of both itself and its companion. The major advantages of PSO are as follows:

(a) The objective function's gradient is not required.
(b) PSO is more flexible and robust in comparison with traditional optimization methods.
(c) PSO ensures the convergence to the optimal solution.
(d) Compared to GA, PSO takes less time for each function evaluation as it does not use many of GA operators like mutation.

CPSO with the random initialization of a swarm of particles in the search space and works on the social behaviour of the particles in the swarm. As a result, it finds the global best solution by simply adjusting the trajectory of each particle towards its own best location and towards the best particle of the swarm at each time step (generation). Though, the trajectory of every particle in the search space is adapted by dynamically altering the position and velocity of every particle, according to its own flying experience and the flying experience of the other particles in the search space. The position and velocity according to the following equations:

$$v_{id}^{t+1} = w \times v_{id}^{t} + c_1 \times r_1 \times (pbest_{id} - x_{id}^{t}) + c_2 \times r_2 \times (gbest_{id} - x_{id}^{t}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

$$x_{id}^{t+1} = x_{id} + v_{id}^{t+1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

Where x_{id}^{t+1} and x_{id} represent the current and previous positions of particle *i*, respectively v_{id}^{t+1} and v_{id} are the current and previous velocities of particle *i*, in the d-dimensional search space at iteration t respectively; $pbest_i$ and $gbest_i$ are the best position found by particle *i*, so far and the best position found by the whole swarm so far, respectively; $\omega \in (0, 1)$ is an inertia weight, which determines how much the previous velocity is preserved; c_1 and c_2 are positive constant parameters called acceleration coefficients; and r_1 and r_2 are two independent random numbers uniformly distributed in the range of [0, 1].

B. The Proposed IPSO Algorithm:

Although CPSO has shown some important advances by providing high speed of convergence in specific problems; however it does exhibits some shortages. It sometimes is easy to be trapped in local optimum, and the convergence rate decreased considerably in the later period of evolution; when reaching a near optimal solution, the algorithm stops optimizing, and thus the achieved accuracy of algorithm is limited [11]. Several modifications have been proposed in literature to improve the performance of CPSO. Most of them are from one of the four categories: swarm topology [7-8], diversity maintenance [11-12], combination with auxiliary operations [13-14], and adaptive PSO.

Adaptation is the most promising category in PSO. Many approaches are attempted to improve the performance of CPSO by adaption of inertia weight. Empirical studies of PSO with inertia weight have shown that a relatively large inertia weight have more global search ability while a relatively small inertia weight results in a faster convergence. Consequently, the inertia weight decreases as a linear or nonlinear function of iterative generation [11-12]. In addition to efficiently control the local search and convergence to the global optimum solution, time-varying acceleration coefficients were proposed in addition to the time-varying inertia weight factor [`12]. Since the search process of PSO is nonlinear and highly complicated, linearly and nonlinearly decreasing inertia weight and acceleration coefficients with no feedback taken from the global optimum fitness cannot truly reflect the actual search process. In fact, if the global fitness is large, the particles are far away from the optimum point. Hence, a big velocity is needed to globally search the solution space and so the inertia weight and acceleration coefficients must be larger values.

Motivated by the aforementioned, in this paper, the inertia weight and acceleration coefficients are set as a function of global optimum fitness during search process of PSO, the inertia weight and accelerate coefficients are big since it still needs globally explore the search space to give the algorithm a better ability to rapidly search and move out of the local optima. Conversely, these parameters decrease fast to facilitate finer local explorations since global optimum solution reaches a near optimum. The most important advantages of the proposed algorithm are algorithm. Based on this, two modifications are incorporated into the CPSO algorithm that prevents local convergence and provides excellent quality of final result. In this case, these parameters dynamically change according to the rate of global fitness improvement as follows:

$$c_i = 1 + 1/\left[1 + exp\left(-\beta \times F(G_t)\right)^{\alpha}\right] \text{..(15)}$$

$$w = 1/\left[1 + exp\left(-\beta \times F(G_t)\right)^{\alpha}\right] \text{.........(16)}$$

where $F(G_t)$ is the fitness of global optimum in t-th iteration. The parameters α and β need to be predefined. The value of β can be set to the inverse of the value of global optimum fitness in the first iteration, i.e. β =1/ $F(G1)$). Through the study of the nonlinear modulation parameter α and β reasonable set of choice for this parameter is derived within the range (1, 2). Moreover, under the assumption and definition above, it can be concluded that $0.5 \leq \omega < 1$, $1.5 \leq c1 < 2$ and $1.5 \leq c2 < 2$. Considering Equations (15) and (16), it is obvious that the bigger global fitness requires the bigger inertia weight and the bigger accelerate coefficients, and vice versa. Therefore, until the fitness of global optimum does not improve significantly to achieve faster convergence speed and better solution accuracy with minimum incremental computational burden [12].

In 1995, [14] Kennedy and Eberhert first proposed the IPSO method, inspired by social behaviour of organisms such as fish schooling and bird flocking. It is a population based stochastic optimization technique. In a IPSO the potential solution called particles, fly around in a multi-dimensional search space. The individual particles move towards the position of their own previous best performance and their neighbours best performance .In this process it searches optima by updating iterations. In every iteration ,each particle is updated by following two 'best'values . The first one is best solution it has achieved so far, this is called 'pbest'. Another value is the best value obtained so far by any particle in the population. This value is called global best , "gbest".

Let V_i and P_i represents particle coordinates its corresponding flight speed(velocity) and particle position in a search space respectively. The position of each agent is represented by XY-axis position and the velocity is expressed by V_x (the velocity of X-axis) and V_y (the velocity of Y-axis). Modification of the agent position is realized by the position and velocity information. . The modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation.

$$V_i^{k+1} = w * V_i^k + C_1 * rand()_1 * \left(pbest_i - P_i^k\right) + C_2 * rand()_2 * \left(gbest_i - S_i^K\right) \text{....(17)}$$

$$P_i^{k+1} = P_I^K + V_i^{k+1} \quad \text{......(18)}$$

Where V_i^{k+1}: velocity of particle i at iteration k+1

V_i^k: velocity of particle i at iteration k

P_i^{k+1} : position of particle i at iteration k+1

P_1^k : position of particle i at iteration k

C_1 : constant weighing factor for *pbest*

C_2 : constant weighing factor for *gbest*

$rand()_1, rand_2$:random value in range [0,1]

i : number of particles 1,2...n

w: inertia weight

Initialize the swarm in an *M*-dimensional space // *M* is the number of system parameters

DO
// fitness evaluation and updating global memories
Evaluate fitness of particles, then:
FOR *i* = 1 to number of particles
IF *f* (*Xi*) < *f* (*Pi*) THEN *Pi* = *Xi* , *f* (*Pi*) = *f* (*Xi*)
IF *f* (*Xi*) < *f* (*G*) THEN *G* = *Xi* , *f* (*G*) = *f* (*Xi*)
END FOR
// inertia weight and acceleration coefficients calculation
Calculate ω using Equation (16)
Calculate *c*1 and *c*2 using Equation (15)
// updating velocity and positions of particles
Calculate new velocity of the particles using Equation (17)
Calculate new position of the particles using Equation (18)
UNTIL stop criteria is satisfied.

V. FUZZY MIN-MAX APPROACH:

To obtain the compromise set of four objectives ,fuzzified optimization method[15] is used. Our aim is to minimize $G(x)=\{G_1(x_1), G_2(x_2), G_3(x_3), G_4(x_4)\}$ while satisfying the equality and inequality constraints.

Where $G_1(x_1)$ is fuel cost minimization sub problem, $G_2(x_2)$ is emission minimization sub problem, $G_3(x_3)$ is loss minimization sub problem, $G_4(x_4)$ is index maximization sub problem.

Let $F_1(X_i)$ be the fuel cost in \$/hr for i^{th} control vector. $F_2(X_i)$ be the losses in P.U for i^{th} control vector$F_3(X_i)$ be the Stability index for i^{th} control vector$F_4(X_i)$ be the Emission release in kg/hr for i^{th} control vector

Let the individual optimal control vectors for the sub problems be X_1*, X_2*, X_3*, X_4* respectively. We have to find out a global optimal control vector X *such that

$$F_1\Big|_{X_1^*} \le F_1\Big|_{X^*} \le F_1\Big|_{(X_2^*, X_3^*, X_4^*)}$$

$$F_2\Big|_{X_2^*} \le F_2\Big|_{X^*} \le F_3\Big|_{(X_1^*, X_3^*, X_4^*)}$$

$$F_3\Big|_{X_3^*} \le F_3\Big|_{X^*} \le F_3\Big|_{(X_1^*, X_2^*, X_4^*)}$$

$$F_4\Big|_{X_4^*} \le F_4\Big|_{X^*} \le F_4\Big|_{(X_1^*, X_2^*, X_3^*)}$$

The imprecise or fuzzy goal of the DM for each of the objective functions is quantified by defining their corresponding membership functions μ_i as a strictly monotonically decreasing function with respect to the objective function f where i=1 to 4. In case of a minimization problem,

μ_i=0 or tends to zero, if $f_i > f_i^{max}$ and

μ_i = 1 or tends to 1, if $f_i < f_i^{min}$.

where f_i^{max} and f_i^{min} are the unacceptable and desirable level for respectively. In our proposed approach we have considered a simple linear membership function for f_i because none of the objectives have very strict limits.

The membership function can be defined as

$$\mu_i = \begin{cases} 0 & F_i > F_{imax} \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_{imin} \le F_i \le F_{imax} \\ 1 & F_i < F_{imin} \end{cases} \quad .....(16)$$

Using Eq. (16) the membership functions can be formulated as

Membership function for Fuel cost **:**

$$\mu_1 = \begin{cases} 0 & F_1 > F_{1max} \\ \dfrac{F_1^{max} - F_1(X)}{F_1^{max} - F_1^{min}} & F_{1min} \le F_1 \le F_{1max} \\ 1 & F_1 < F_{1min} \end{cases} \quad ...(17)$$

Membership function for emission release

$$\mu_2 = \begin{cases} 0 & F_2 > F_{2max} \\ \dfrac{F_2^{max} - F_2(X)}{F_2^{max} - F_2^{min}} & F_{2min} \le F_2 \le F_{2max} \\ 1 & F_2 < F_{2min} \end{cases} \quad ....(18)$$

Membership function for losses

$$\mu_3 = \begin{cases} 0 & F_3 > F_{3max} \\ \dfrac{F_3^{max} - F_3(X)}{F_3^{max} - F_3^{min}} & F_{3min} \le F_3 \le F_{3max} \\ 1 & F_3 < F_{3min} \end{cases} \quad ......(19)$$

Membership function for stability index

$$\mu_4 = \begin{cases} 0 & F_4 > F_{4max} \\ \dfrac{F_4^{max} - F_4(X)}{F_4^{max} - F_4^{min}} & F_{4min} \le F_4 \le F_{4max} \\ 1 & F_4 < F_{4min} \end{cases} \quad ....(20)$$

The maximum degree of overall satisfaction can be achieved by maximizing a scalar $\lambda=\min(\mu_1, \mu_2, \mu_3. \mu_4)$

VI TEST RESULTS AND DISCUSSIONS:

An algorithm have been developed to get the final trade-off solution for the four different sub problems i.e. fuel cost, emission ,losses and stability index minimization using Fuzzified multiobjective PSO. The solution is tested on IEEE 30 bus system.

The generator data of IEEE 30 bus system and cost and emissions coefficients are given below in table 1 and 2

unit	P_i (min) MW	P_i (max) MW	a_i	b_i	c_i
1	50	200	0.00375	2.00	0
2	20	80	0.01750	1.75	0
5	15	50	0.06250	1.00	0
8	10	35	0.00834	3.25	0
11	10	30	0.02500	3.00	0
13	12	40	0.02500	3.00	0

Table 1: Fuel Cost Coefficients

Unit	Q_i (min) MW	Q_i (max) MW	α_i	β_i	γ_i
1	-20	250	0.0126	-1.100	22.983
2	-20	100	0.0200	-0.1000	22.313
5	-15	80	0.0270	-0.1000	25.505
8	-15	60	0.0291	-0.0050	24.900
11	-10	50	0.0291	-0.0400	24.700
13	-15	60	0.0271	-0.0055	25.300

Table2: Emission Coefficients

Each sub problem run for 25 times independently and the values of four factors considered at minimum value at each sub problem over 25 independent runs are determined. These values for all sub problems and final trade off solution for IEEE30 bus are given in Table3.

The established population size is 60and the maximum number of iterations are 10.The number of units is 6 in this algorithm

Optimization Problem(Final Trade off solution)	**Fuel Cost ($/hr)**	**Losses (MW)**	**Stability Index**	**Emission (kg/hr)**
CPSO	926.20	4.6347	0.26645	242.14
IPSO	918.184	4.5621	0.24634	237.42

Table 3:Results of various sub problems and final trade off solution for IEEE 30 bus system.

The below figures shows convergence characteristic of fuel costing, emission, stability index and reactive power for IPSO

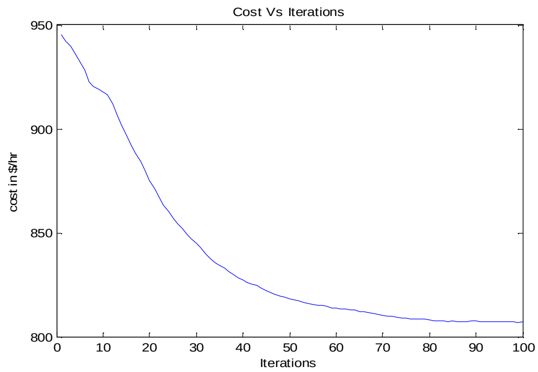

Fig 1: optimization of fuel cost

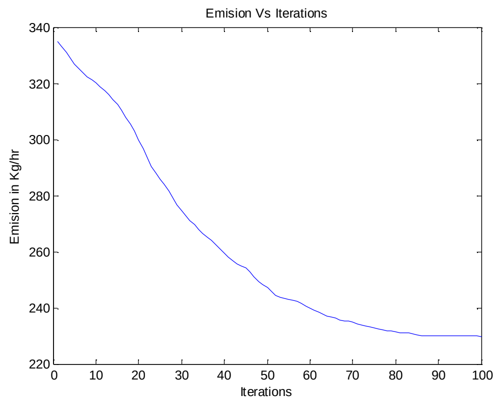

Fig 2: Optimization of emission dispatch

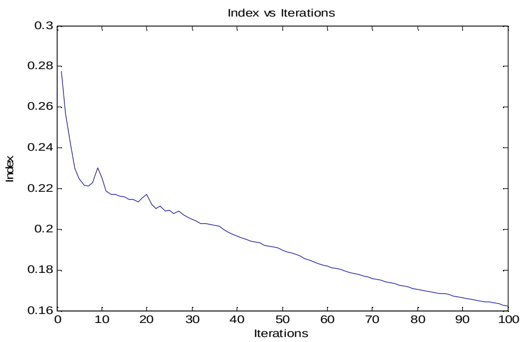

Fig 3: optimization of line index

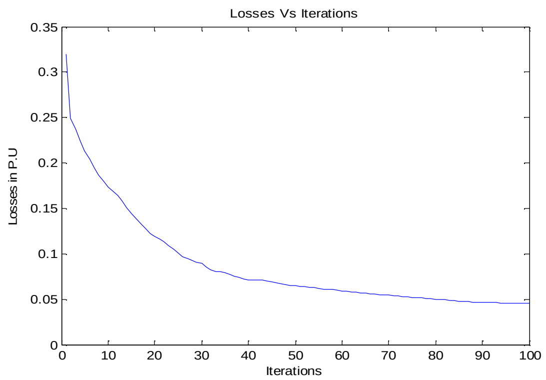

fig: 4 optimization of losses

The below figure shows fuzzified IPSO

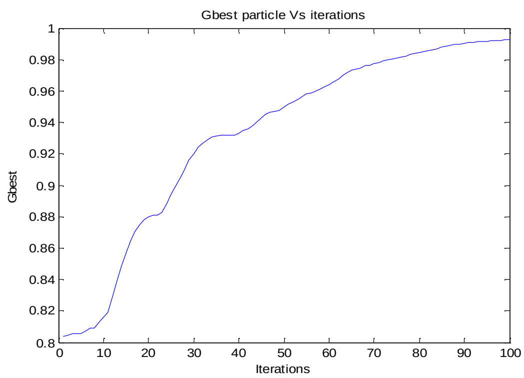

Fig 5: Gbest vs Iterations

VII. CONCLUSION:

This paper presents an approach to solve multi objective problem which aims at minimizing fuel cost, real power loss, emission release and improving stability index of the system. This proposed IPSO was utilized to find the optimize parameters of objective function for different scenarios by minimizing the fitness function. Using the proposed algorithm, the optimization problem can be reduced appropriately. The main advantage of proposed algorithm is to achieve faster convergence speed whereas the appropriate performance of system at different loading conditions was guaranteed. Simulation results demonstrated the effectiveness of developed technique. We have successfully implemented IPSO solution for economic dispatch problem. The algorithm is tested on IEEE30 bus system. The four objectives are solved individually and the results from these individual optimizations are fuzzified and final trade off solution is obtained.

IX. REFFERENCES

[1] T.Thakur, Kanik Sem, Sumedha Saini, and Sudhanshu Sharma "A Particle Swarm Optimization Solution to NO**2** and SO**2** Emissions for Environmentally Constrained Economic Dispatch Problem", IEEE PES Transmission and Distribution Conference and Exposition Latin America, Venezuela ,pp.1-5 ,2006.

[2] M. R. AlRashidi, M. E. El-Hawary, "A Survey of Particle Swarm Optimization Applications in Electric Power Systems" IEEE Trans. On Evolutionary Computation Vol.13, No. 4, pp913-918, August 2009.

[3] Wen Zhang, Yutian Liu, "Reactive Power Optimization based on PSO in a Practical Power System" IEE Power society engineering general meeting ,Vol.1, pp.239-243, 2004.

[4] Zwe-Lee Gaing, "Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints", IEEE Tans. on Power Syst., Vol 18, No. 3, pp 1187- 1195, Aug. 2003.

[5] J.H.Talaq,F.El-Hawary,andM.E.El-Hawary, "A Summary of Environmental/Economic Dispatch algorithms," IEEE Trans. Power Syst., Vol. 9, pp. 1508–1516, Aug. 1994.

[6] A. Immanuel Selva Kumar, K. Dhanushkodi, J. Jaya Kumar, C. Kumar Charlie Paul, "Particle Swarm Optimization Solution to Emission and Economic Dispatch Problem", IEEE TENCON , Vol.1, pp.435-439, 2003.

[7] Iba K. 'Reactive power optimization by genetic algorithms', IEEE Trans on power systems, Vol.9, No.2, pp.685-692 ,May 1994.

[8] Wu Q.H. and Ma J. T. 'Power system optimal reactive power dispatch using Evolutionary programming 'IEEE Trans on Power Systems,Vol.10 ,pp.1243-1249,1995.

[9] Bhagwan Das, Patvardhan C. 'A New Hybrid Evolutionary Strategy for Reactive Power Dispatch', Electric Power Research, Vol.65. pp.83-90, 2003.

[10] Papiya Dutta, A.K.Sinha- IIT Kharagpur Professor, "Environmental Economic Dispatch constrained by voltage stability using PSO", IEE ICIT, pp.1879-1884, 2006.

[11] J.C. Chow, R. Fischl and H. Yan **“**On the Evaluation of Voltage Collapse Criteria**”** IEEE Transaction on power systems., Vol.5, pp. 612-620, May 1990

[12] PA Lof T, Smed G, Andersson**,** “Fast Calculation of Voltage Stability Index” IEEE Transactions on Power Systems**,** Vol. 7, No.1 pp.54-64, February 1992.

[13] Claudia Reis, F.P. Maciel Barbosa” A Comparison of Voltage Stability Indices,” IEEE MELECON 2006, pp. 1007-1010,May 2006.

[14] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in Proc. IEEE Int. Conf. Neural Networks (ICNN’95),Perth, Australia, vol 4,pp.1942-1948, 1995.

[15] Y.H. Song, G.S. Wang, P.V. Wang, A.T. Johns, “Environmental/economic dispatch using fuzzy logic controlled genetic algorithms”, IEE Proceedings of Generation, Transmission, Distribution, vol. 144, no. 4, pp.377–382, 1997.

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