Multiobjective Particle Swarm Optimization with Pollution Control Constraint and FACTS Controller

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Abstract

In this paper an effective method for optimal power flow (OPF) of combined economic and emission dispatch by employing multiobjective particle swarm optimization for a standard IEEE 30 bus test system is presented. The harmful ecological effects caused due to emission of particulate and gaseous pollutants from fossil fuel power plants, can be reduced by proper load allocation among the various generating units. Multiobjective Particle Swarm Optimization is employed for optimization of Fuel cost, Emission and also for minimization total cost which includes economic dispatch and emission component. For improved performance of the power system Static Var Compensator (SVC) is adapted in the IEEE 30 bus system and results for optimization of Combined Economic and Emission Dispatch (CEED) with and without SVC installation are obtained and compared. The limits to carry out PSO has been set on generator real and reactive power outputs, reactive power injection due to capacitor banks, bus voltages and transformer tapings.

1. Introduction

The economic dispatch difficulty has taken an appropriate twist as the public began to worry about environmental situations. The absolute minimum cost is not any more the only condition to be satisfied in the electric power generation and dispatching difficulties. The production of electricity from the fossil fuel discharges various pollutants like Sulfur Oxides (SO_2), and Oxides of Nitrogen (NOx) into the atmosphere. These gaseous pollutants results in harmful effects on human beings and also on plants and animals.

On the other hand, considering only the operation of minimum environmental impact is not practical because of the high production cost of the system. Conversely, to operate the generating system with the lesser production cost will result in higher emission. As a result, economic dispatch, emission dispatch or combined economic and emission dispatch is in some way selected separately or combined together [1]. To determine the suitable solution to this difficulty, an excellent power management approach is set. Various optimization methods like lambda iteration, linear programming, non-linear programming, quadratic programming, interior point technique or even intelligent search techniques (e.g. Genetic Algorithm (GA), Evolutionary Programming (EP), Particle Swarm Optimization (PSO), etc.) are used to overcome several economic dispatch difficulties and also the unit commitment difficulties [2].

The usage of genetic algorithm for economic dispatch difficulties needs a large number of generations if the power generating system has the more number of units. Combined economic and emission dispatch has been emerged in the field of power generation dispatch that concurrently reduce both fuel cost and total emissions. While the emission is reduced the fuel cost may be inappropriately increased or while the fuel cost is reduced the emission may be increased. This difficulty is overcome by creating the objective function and utilizing some optimization methods like PSO and GA.

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling.

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithm (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

Particle Swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position and is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

PSO is a metaheuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics such as PSO do not guarantee an optimal solution is ever found. More specifically, PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and Quasi-Newton methods. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time, etc. To obtain economic load dispatch of a power system, PSO is included in Optimal Power Flow (OPF) technique.

An Optimal Power Flow (OPF) function schedules the power system controls to optimize an objective function while satisfying a set of nonlinear equality and inequality constraints [3]. The equality constraints are the conventional power flow equations; the inequality constraints are the limits on the control and operating variables of the system. Mathematically, the OPF can be formulated as a constrained nonlinear optimization problem.

Optimal scheduling of the operations of electric power systems is a major activity, which turns out to be a large-scale problem when the constraints of the electric network are taken into account.

The OPF problem was defined in the early 1960s as an extension of conventional economic dispatch to determine the optimal settings for control variables in a power network respecting various constraints. OPF is a static constrained nonlinear optimization problem, whose development has closely followed advances in numerical optimization techniques and computer technology. It has since been generalized to include many other problems. Optimization of the electric system with losses represented by the power flow equations was introduced in the 1960s. Since then, significant effort has been spent on achieving faster and robust solution methods that are suited for online implementation, operating practice, and security requirements.

OPF seeks to optimize a certain objective, subject to the network power flow constraints and system and equipment operating limits. Today, any problem that involves the determination of the instantaneous optimal steady state of an electric power system is referred to as an Optimal Power Flow problem. The optimal steady state is attained by adjusting the available controls to minimize an objective function subject to specified operating and security requirements [4,5]. Different classes of OPF problems, designed for special-purpose applications, are created by selecting different functions to be minimized, different sets of controls, and different sets of constraints. All these classes of the OPF problem are subsets of the general problem. Historically, different solution approaches have been developed to solve these different classes of OPF. There are many possible objectives for an OPF. Some commonly implemented objectives are:

-fuel or active power cost optimization,
-active power loss minimization,
-minimum control-shift,
-minimum voltage deviations from unity, and
-minimum number of controls rescheduled.

2. Problem Formulation

The standard OPF problem can be formulated as a constrained optimization problem mathematically as follows:

$$\begin{aligned} &\text{minimize} && f(x) \\ &\text{subjected to} && g(x) = 0 \\ & && h(x) \leq 0 \end{aligned} \qquad (1)$$

where $f(x)$ is the objective function, $g(x)$ represents the equality constraints, $h(x)$ represents the inequality constraints and x is the vector of the control variables such as generator real power Pg, generator voltages Vg, transformer tap setting T, and reactive generations of VAR sources Qc. Therefore, x can be expressed as

$$x^T = [Pg_1, Pg_2, \dots \ Pg_{ng}, Vg_1, Vg_2, \dots \ Vg_{ng}, T_1, T_2, \dots \ T_{nt}, Qc_1, Qc_2, \dots \ Qc_{nc}] \qquad (2)$$

where ng is the number of generator buses, nt is the number of transformer branches and nc is the number of shunt compensators.

The essence of the optimal power flow problem resides in reducing the objective function and simultaneously satisfying the load flow equations (equality constraints) without violating the inequality constraints.

3. Objective Function

3.1 Economic objective function

The most commonly used objective in the OPF problem formulation is the minimization of the total operation cost of the fuel consumed for producing electric power within a schedule time interval (one hour). The individual costs of each generating unit is assumed to be function, only, of real power generation and are represented by quadratic curves of second order. The objective function for the entire power system can then be expressed as the sum of the quadratic cost model at each generator.

$$F_{ec}(x) = \sum_{i=1}^{ng}(a_i + b_i Pg_i + c_i Pg_i^2) \quad \$/h \qquad (3)$$

where a_i, b_i and c_i are the cost coefficients of generator at bus i .

3.2 Emission objective function

The emission control cost results from the requirement for power utilities to reduce their pollutant levels below the annual emission allowances assigned for the affected fossil units. The total emission can be reduced by minimizing the three major pollutants: oxides of nitrogen (NOx), oxides of sulphur (SOx) and carbon dioxide (CO_2). The objective function that minimizes the total emissions can be expressed in a linear equation as the sum of all the three pollutants resulting from generator real power Pg_i.

In this study, Nitrogen-Oxide (NOx) emission is taken as the index from the viewpoint of environment conservation. The amount of NOx emission is given as a function of generator output (in Ton/hr), that is, the sum of quadratic and exponential functions.

$$F_E = \sum_{i=1}^{ng}(a_i + b_i Pg_i + c_i Pg_i^2 + d_i \exp(e_i Pg_i)) \quad \text{Ton/hr} \qquad (4)$$

where a_i, b_i, c_i,$d_i$and e_i are the coefficients of generator emission characteristic.

The pollution control cost (in \$/h) can be obtained by assigning a cost factor to the pollution level expressed as

$$F_{pc} = wF_E \quad \$/h \qquad (5)$$

where w is the emission control cost factor in \$/Ton.

3.3 Total objective function

The economic dispatch and emission dispatch are considerably different. The economic dispatch reduces the total fuel cost (operating cost) of the system at an increased rate of NOx. On the other hand emission dispatch reduces the total emission from the system by an increase in the system operating cost. Therefore it is necessary to find out an operating point, that strikes a balance between cost and emission. This is achieved by combined economic and emission dispatch (CEED).

The CEED problem can be formulated as,

$$\text{minimize } f(F_{ec}, F_E) \qquad (6)$$

subject to demand constraint and generating capacity limits.

The above mentioned multi-objective optimization problem can be converted to a single objective optimization problem by introducing the emission control cost factor w, as follows,

$$\text{minimize} \quad F = F_{ec} + wF_E \qquad (7)$$

4. Types of constraints

4.1 Equality Constraints

The equality constraints are the power flow equations describing bus injected active and reactive powers of the $i\ th$ bus[6].

The active and reactive power injections at ith bus are defined in the following equation:

$$P_i = Pg_i - Pd_i = \sum_{j=1}^{nb} V_i V_j (g_{ij} Cos\theta_{ij} + b_{ij} Sin\theta_{ij}) \qquad (8)$$

$$Q_i = Qg_i - Qd_i = \sum_{j=1}^{nb} V_i V_j (g_{ij} Cos\theta_{ij} - b_{ij} Sin\theta_{ij}) \qquad (9)$$

where Qg_i is the reactive power generation at bus i; Pd_i, Qd_i are the real and reactive power demands at bus i; V_i,V_j, the voltage magnitude at bus i, j, respectively; θ_{ij} is the admittance angle, b_{ij} and g_{ij} are the real and imaginary parts of the admittance and nb is the total number of buses.

4.2 Inequality Constraints

The inequality constraints of the OPF reflect the limits on physical devices in the power system as well as the limits created to ensure system security.

The inequality constraints on the problem variables considered include:

- Upper and lower bounds on the active generations at generator buses
  $Pg_i^{min} \le Pg_i \le Pg_i^{max}$, $i = 1\ to\ ng$.
- Upper and lower bounds on the reactive generations at generator buses
  $Qg_i^{min} \le Qg_i \le Qg_i^{max}$, $i = 1\ to\ ng$
- reactive power injections due to capacitor banks
  $Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i = 1, \ldots, cs$
- Upper and lower bounds on the voltage magnitudes at all the buses.

$$V_i^{min} \le V_i \le V_i^{max}, \quad i = 1\ to\ nb.$$

- Upper and lower bounds on the tap changes of linear tap changing transformers

$$T_i^{min} \le T_i \le T_i^{max}, \quad i = 1\ to\ nb.$$

- Voltage stability index:

$$L_j \le L_j^{max}, \quad j=1,\dots,NL$$

- SVC susceptance constraint:

$$B_{SVC}^{min} \le B_{SVC} \le B_{SVC}^{max}$$

- transmission lines loading

$$S_i \le S_i^{\max}, i = 1, \dots, nl$$

5. Particle Swarm Optimization in Optimal Power Flow

5.1 Search Mechanism of PSO:

Each particle moves from the current position to the next one according to the present fitness function values. Generally, the fitness function is same the objective functions. The local best of other particles in the population should be changed if the present fitness function value is better than the previous. Repeat the new searching points until the maximum number of generations reached. 100 generations are set in this paper as the stopping criteria.

Each particle keeps track of its coordinates in the problem space, which are associated with the best solution, fitness, it has achieved so far. The fitness value is also stored. This value is called pbest. Another best value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called local best (lbest). When a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest.

The inertia weight parameter is considered important for the convergence of the algorithm. It controls the impact of previous history of velocities on the current velocities of particles and hence regulates the local and global exploration capabilities of the particles. A large inertia weight facilitates exploration, i.e., searching newer areas while a small value tends to facilitate exploitation, i.e., a finer searching of current search area. The value of the inertia weight parameter is normally kept between 0.4 and 0.9. Thus, the choice of inertia weight should be carefully made.

Each position and velocity in the N dimensional space such as position $X_i = (x_{i1}, x_{i2}, x_{i3}, \dots \dots x_{in})$and velocity $V_i = (v_{i1}, v_{i2}, v_{i3}, \dots \dots v_{in})$Each particle is then flown over the search space in order its flying velocity and direction according to its own flying experience as well as that of its neighbors. Positions of the particles (tentative solutions) are evaluated at the end of every iteration relative to an objective or fitness value. Particles are assumed to retain memory of the best positions they have achieved in course of flying and share this information among the rest.

The collective best positions of all the particles taken together is termed as the global best position given as $gbest = (gb_1, gb_2, gb_3, \dots \dots gb_n)$and the best position achieved by the individual particle is termed as the local best or position best and for the i_{th}particle given as $pbest = (p_{i1}, p_{i2}, p_{i3}, \dots \dots p_{in})$ .Particles use both of these information to update their positions and velocities as given in the following equations:

$$v_i^{(t+1)} = w_i . v_i^{(t)} + c_1 . r_1 . (x_{gbest}^{(t)} - x_i^{(t)}) + c_2 . r_2 . (x_{ipbest}^{(t)} - x_i^{(t)}) \quad (10)$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (11)$$

where:

t : pointer of iterations (generations).
w_i: inertia weight factor.
c_1, c_2 : acceleration constant.
r_1, r_2 : uniform random value in the range (0,1).
$v_i^{(t)}$: velocity of particle i at iteration t.
$x_i^{(t)}$: current position of particle i at iteration t
$x_{ipbest}^{(t)}$: previous best position of particle i at iteration t.
$x_{gbest}^{(t)}$: best position among all individuals in the population at iteration t.
$v_i^{(t+1)}$: new velocity of particle i.
$x_i^{(t+1)}$: new position of particle i..

PSO applied to optimal power flow

The objective is to minimize the objective function of the OPF defined by (7), taking into account the equality constraints and the inequality constraints.

The cost function implemented in PSO is defined as:

$$F(x) = \left[\sum_{i=1}^{ng} (a_i + b_i Pg_i + c_i Pg_i^2)\right] + w . \left[\sum_{i=1}^{ng} (a_i + b_i Pg_i + c_i Pg_i^2 + d_i \exp(e_i Pg_i))\right] \quad \$/h \quad (12)$$

To minimize F is equivalent to getting a maximum fitness value in the searching process. The particle that has lower cost function should be assigned a larger fitness value.

The objective of OPF can be changed to maximization of fitness correspondingly as follows:

$$\text{maximize} \quad fitness = 1/F \quad (13)$$

In this method only the inequality constraints on active powers are handled in the cost function. The other inequality constraints are scheduled in the load flow process. Because the essence of this idea is that the inequality constraints are partitioned in two types of constraints, active constraints that effect directly the objective function are checked using the PSO-OPF procedure and the reactive constraints are updating using an efficient Newton-Raphson Load flow (NR) procedure.

Our objective is to search (Pg_i) set in their admissible limits to achieve the optimization problem of OPF. At initialization phase, (Pg_i) is selected randomly between Pg_i^{min} and Pg_i^{max} .

After the search goal is achieved, or an allowable generation is attained by the PSO algorithm. It is required to performing a load flow solution in order to make fine adjustments on the optimum values obtained from the PSO-OPF procedure. This will provide updated voltages, angles and points out generators having exceeded reactive limits. To determine reactive powers of all generators and to determine active power that should be supplied by slack generator taking into account the different reactive constraints, it requires a fast and robust load flow program with best convergence properties[7,8]. The developed load flow process is based on the NR algorithm.

5.2 Optimal setting of PSO parameters in OPF case

The role of the inertia weight w_i, in equation(10), is considered critical for the PSO's convergence behavior. The inertia weight is employed to control the impact of the previous history of velocities on the current velocity. In this way, the parameter w_i regulates the trade-off between the global (wide-ranging) and local (nearby) exploration abilities of the swarm. A large inertia weight facilitates global exploration (searching new areas); while a small one tends to facilitate local exploration, i.e. fine-tuning the current search area. A suitable value for the inertia weight w_i usually provides balance between global and local exploration abilities and consequently results in a reduction of the number of iterations required to locate optimum solution. Initially inertia weight was constant. However, experimental results indicated that it is better to initially set the inertia to a large value in order to promote global exploration of search space, and gradually decreased it to get more refined solutions. The parameters c_1 and c_2 in equation (10) are not critical for PSO's convergence. However, proper fine-tuning may result in faster convergence and alleviation of local minima. The random numbers (r_1, r_2) are used to maintain the diversity of the population, and they are uniformly distributed in the range (0, 1).

PSO algorithm application to OPF

5.3 PSO Algorithm

The PSO algorithm applied to OPF can be described in the following steps:

Step 1: Input parameters of system, and specify the lower and upper boundaries of each control variable.

Step 2: The particles are randomly generated between the maximum and minimum operating limits of the generators.

Step 3: Calculate the value of each particle using objective function.

Step 4: Evaluate the fitness value of objective function of each particle using (13). x_{ibest} is set as the i th particle's initial position; x_{gbest} is set as the best one of x_{ibest} . The current evolution is t =1.

Step 5: Initialize learning factors c_1, c_2, inertia weight w_i and the initial velocity v_1.

Step 6: Modify the velocity v of each particle according to (10).

Step 7: Modify the position of each particle according to (11). If a particle violates its position limits in any dimension, set its position at proper limits. Calculate each particle's new fitness; if it is better than the previous x_{gbest} , the current value is set to be x_{gbest} .

Step 8: To each particles of the population, employ the Newton-Raphson method to calculate power flow and the transmission loss.

Step 9: Update the time counter $t = t + 1$.

Step 10: If one of the stopping criteria is satisfied then go to step 11. Otherwise go to step 6.

Step 11: The particle that generates the latest p_{gbest} is the global optimum.

6. Power Flow Including Facts Controllers

FACTS controllers narrow the gap between the non-controlled and the controlled power system mode of operation, by providing additional degrees of freedom to control power flows and voltages at key locations of the network. Key objectives of the technology are: to increase transmission capacity allowing secure loading of the transmission lines up to their thermal capacities; to enable better utilization of available generation; and to contain outages from spreading to wider areas.

In order to determine the effectiveness of this new generation of power systems controllers on a network-wide basis, it has become necessary to upgrade most of the analysis tools on which power engineers rely to plan and to operate their systems. For the purpose of steady-state network assessment, power flow solutions are probably the most popular kind of computer-based calculations carried out by planning and operation engineers. The reliable solution of power flows in real-life transmission and distribution networks is not a trivial matter and, over the years, owing to its very practical nature, many calculation methods have been put forward to solve this problem. Among them, Newton–Raphson type methods, with their strong convergence characteristics, have proved the most successful and have been embraced by industry.

6.1 Static Var Compensator (SVC)

Conventional and advanced power flow models of SVCs are presented in this section. The advanced models depart from the conventional generator-type representation of the SVC and are based instead on the variable shunt susceptance concept. In the latter case, the SVC state variables are combined with the nodal voltage magnitudes and angles of the network in a single frame of reference for unified, iterative solutions using the Newton–Raphson method [9].

6.2 Shunt Variable Susceptance Model

In practice the SVC can be seen as an adjustable reactance with either firing-angle limits or reactance limits. The equivalent circuit shown in Figure 1 is used to derive the SVC nonlinear power equations and the linearized equations required by Newton's method.

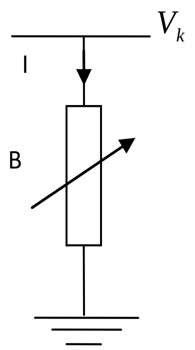

Figure 1: Variable Shunt Susceptance

With reference to Figure 1, the current drawn by the SVC is

$$I_{SVC} = jB_{SVC}V_k \qquad (17)$$

and the reactive power drawn by the SVC, which is also the reactive power injected at bus k, is

$$Q_{SVC} = Q_k = -V_k^2 B_{SVC} \qquad (18)$$

The linearized equation is given by Equation (19), where the equivalent susceptance B_{SVC} is taken to be the state variable:

$$\begin{bmatrix} \Delta P_k \\ \Delta Q_k \end{bmatrix}^{(i)} = \begin{bmatrix} 0 & 0 \\ 0 & Q_k \end{bmatrix}^{(i)} \begin{bmatrix} \Delta\theta_k \\ \Delta B_{SVC}/B_{SVC} \end{bmatrix}^{(i)} \qquad (19)$$

At the end of iteration (i), the variable shunt susceptance B_{SVC} is updated according to

$$B_{SVC}^{(i)} = B_{SVC}^{(i-1)} + \left(\frac{\Delta B_{SVC}}{B_{SVC}}\right)^{(i)} B_{SVC}^{(i-1)} \qquad (20)$$

The changing susceptance represents the total SVC susceptance necessary to maintain the nodal voltage magnitude at the specified value.

In the present work the SVC is located at 26th bus as the voltage deviation at that bus is maximum.

7. IEEE 30 bus system Data

Table 1: Power generation limits and cost coefficients of IEEE 30-bus system

Bus	Pg_{min}	Pg_{max}	a_1 ($/hr)	b_1 ($/hr)	c_1 ($/hr)
01	0.5	2.0	37.5	200	0
02	0.2	0.8	175	175	0
03	0.15	0.5	625	100	0
04	0.1	0.35	83	325	0
05	0.1	0.3	250	300	0
06	0.12	0.4	250	300	0

Table 2: Pollution coefficients for IEEE 30-bus system

Bus	a ton/hr $*10^{-2}$	b ton/hr $*10^{-2}$	c ton/hr $*10^{-2}$	d ton/hr $*10^{-4}$	e
1	4.091	-5.554	6.490	2.00	2.857
2	2.543	-6.047	5.638	5.00	3.333
3	4.258	-5.094	4.586	0.01	8.000
4	5.326	-3.550	3.380	20.00	2.000
5	4.258	-5.094	4.586	0.01	8.000
6	6.131	-5.555	5.151	10.00	6.667

Table 3: Parameters and their values taken

Parameter	Value taken
Emission control cost factor, *w*	550.66 $/ton
total load demand	2.834 p.u
no. of generations	100
no. of particles	6
population size	50
Cognitive constant, c_1	2
Social constant, c_2	2
No. of SVCs	1

8. Results & Graphs

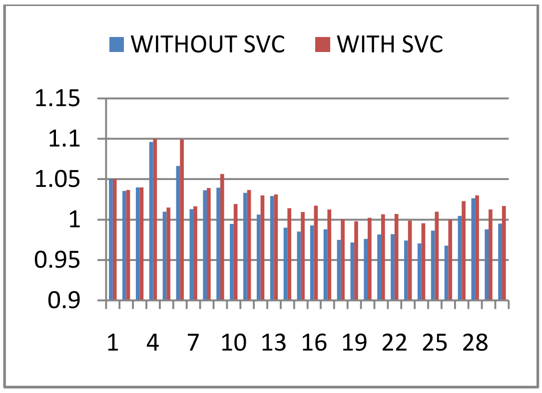

Figure 2: Voltage profile of IEEE 30 bus system with and without SVC for CEED optimization

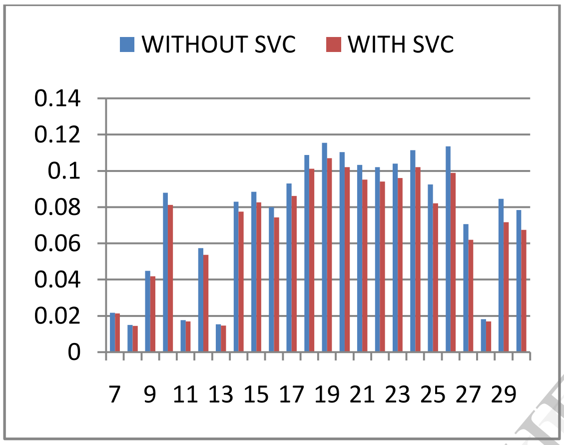

Figure 3: Voltage stability index of IEEE 30 bus system with and without SVC for CEED optimization

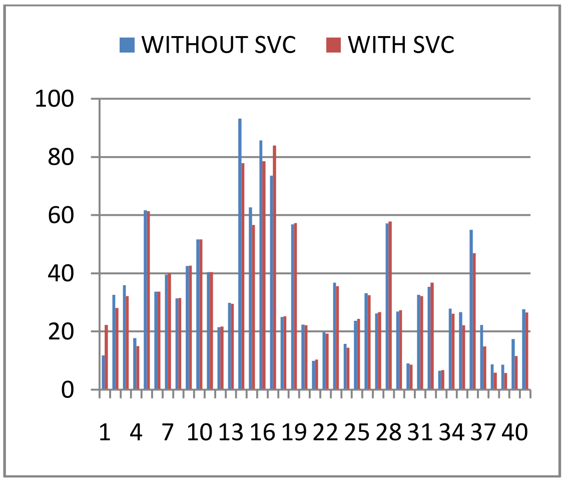

Figure 4: MVA loading of IEEE 30 bus system with and without SVC for CEED optimization

On installation of SVC, from fig 2, 3 and 4 it can be observed that on installing Shunt Var Compensator (SVC) at 26th bus the voltage profile improved to 1p.u and also voltage levels at all other buses improved; the stability index approached further closer to zero and finally, the MVA loading on transmission lines is observed to decrease at almost all the buses on installation of SVC.

Table 4: Comparison of results obtained for economic, emission and CEED optimization

Parameter	Optimization of		
	Fuel Cost	Emission	CEED
Total cost ($/hr)	999.9080	979.1398	965.7238
Fuel cost ($/hr)	800.1297	845.1430	816.7049
Emission (ton/hr)	0.3629	0.2433	0.2706

Table 5: Comparison of Results Obtained for CEED optimization without and with SVC

Parameter	Without SVC	With SVC
Total cost ($/hr)	965.7238	965.3164
Fuel cost($/hr)	816.7049	818.1669
Emission(ton/hr)	0.2706	0.2672

Table 6: Comparison of performance parameters obtained in CEED optimization without and with SVC

Parameter	Without FACTS	With SVC
PG1	1.3206	1.2978
PG2	0.5781	0.5873
PG3	0.2487	0.2515
PG4	0.3000	0.3000
PG5	0.2434	0.2535
PG6	0.2030	0.2015
VG1	1.0500	1.0500
VG2	1.0446	1.0443
VG3	1.0321	1.0296
VG4	1.0995	1.1000
VG5	1.0166	1.0166
VG6	1.0644	1.0986
Tap - 1	0.9687	0.9523
Tap - 2	1.0550	1.0141
Tap - 3	1.0673	1.0637
Tap - 4	0.9739	0.9928
Q_{C10}	0.0692	0.0576
Q_{C12}	0.0850	0.0776
Q_{C15}	0.0000	0.0076
Q_{C17}	0.0219	0.0145
Q_{C20}	0.0052	0.0022
Q_{C21}	0.0000	0.0000
Q_{C22}	0.0000	0.0007
Q_{C23}	0.0000	0.0019
Q_{C29}	0.0249	0.0053
L_{jmax}	0.1155	0.107

Real power loss(pu)	0.0598	0.0574

9. Conclusion & Future scope

In this paper the fuel cost and emission are combined into a single function and the load dispatch for minimum of the total objective function are obtained. SVC is installed in the IEEE 30 bus system and the stabilized voltages and reduction MVA loading of the transmission lines has been observed. PSO technique is employed as it possesses advantages of modelling flexibility, sure and fast convergence, less computational time over other heuristic methods. Further this work can be extended over to other FACTS devices.

10. References

[1]Tarek Bouktir, Rafik Labdani and Linda Slimani, 'Economic Power Dispatch of Power System with pollution control using Multiobjective Particle Swarm Optimization', published in University of Sharjah Journal of Pure & Applied sciences Volume 4, No.2.

[2]A.Momoh, M.E. El-Hawary and R.Adapa,A (1999). Review of Selected Optimal Power Flow Literature to 1993 PartII: Nonlinear and Quadratic Programming Approaches, IEEE Trans. Power Syst., Vol. 14 (1) (pp. 96-104).

[3]M.Haneault F.D.Galiana, (1991). A survey of the optimal power flow literature.

[4]A.Momoh, M.E. El-Hawary and R.Adapa, (1999). A Review of Selected Optimal Power Literature to 1993 PartII: Newton, Linear Programming and Interior Points Methods, IEEE Trans. Power Syst., Vol.14 (1) (pp. 105-111).

[5]H.W.Dommel, W.F.Tinney, (1968). Optimal power flow solutions, IEEE Trans. on apparatus and systems, Vol.PAS-87 (10) (PP.1866-1876).

[6]K.Y.Lee, Y.M.Park, and J.L.Ortiz, (1985). A United Approach to Optimal Real and Reactive Power Dispatch, IEEE Trans. Power Syst., Vol. PAS-104 (pp. 1147-1153).

[7]M.Sasson, (1969). Non-linear Programming Solutions for load flow, minimum loss, and economic dispatching problems, IEEE Trans. Power Syst., Vol. PAS-88 (4) (pp. 399-409).

[8]T.Bouktir, M.Belkacemi, K.Zehar, (2000). Optimal power flow using modified gradient method, In:Proc. of ICEL'2000, U.S.T.O, Algeria, Vol.02 (pp. 436-442).

[9]Enrique Acha, Claudio R. Fuerte-Esquivel, Hugo Ambriz-Pe´rez, Ce´sar Angeles-Camacho,FACTS - Modeling and Simulation in Power Networks, (2004).

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