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Optimal Power Flow Including Facts Devices Using Particle Swarm Algorithm

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ABSTRACT: In this paper a new developed particle swarm algorithm (PSA) for solving the optimal power flow (OPF) problem is presented and tested. The proposed PSA uses three individual different objective functions for the OPF as a single objective optimization. Moreover, FACTs devices have been included in the OPF model to invesitagte their effect on the selected OPF objective functions. An efficient software package is developed using MATLAB based on the PSA. The IEEE-30 bus system is used throughout this work to test the proposed algorithm.

A comparison between results of different objective functions is discussed. The effect of FACTs devices to improve different objective function is demonstrated. The applied FACTs controllers are; Static Var Controllers (SVC) and Thyristor Controlled Series Capacitor (TCSC)

Further objective functions, constraints and/or FACTs devices can be easily added to the developed software package. The proposed algorithm decides the optimal location and size of the specified FACTs devices to optimize the required objective function while satisfying system constraints.

KEYWORDS:particle swarm, optimization, optimal power flow, FACTs, electric power systems

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I. INTRODUCTION

In the past two decades, the problem of optimal power flow (OPF) has received much attention and it has been marked as one of the most operational needs. The OPF problem solution aims to optimize a selected objective function such as fuel cost via optimal adjustment of the power system control variables, while at the same time satisfying various equality and inequality constraints. Generally, the OPF problem is a large-scale highly constrained nonlinear non convex optimization problem.

A wide variety of optimization techniques have been applied to solve the OPF problem. Traditionally, classical optimization methods were used to effectively solve OPF. Recently due to incorporation of FACTs devices and deregulation of a power sector, the traditional concepts and practices of power systems are imposed by an economic market management. So OPF have become complex.

Many researchs have been published using classical optimization method [[1-11]. Generally, nonlinear programming [7,9] based procedures have many drawbacks such as insecure convergence properties and algorithmic complexity. Quadratic programming [2,9] based techniques have some disadvantagesassociated with the piece wise quadratic cost approximation. Newton-based techniques [8,11] have drawback of the convergence characteristics that are sensitive to the initial conditions and they may even fail to converge due to the inappropriate initial conditions. Sequential unconstrained minimization techniques and interior point [5,11] are known to exhibit numerical difficulties when the penalty factors become extremely large.

In past decades, Artificial Intelligence (AI) methods have been emerged which can solve highly complex OPF problems [12-26]. Different techniques have been succeeded to solve the OPF.

Artificial Neural Network (ANN) [14] is an interconnected group of artificial neurons that uses a mathematical model or computational model for information processing based on a connectionist approach to computation. It can provide real-time control for the power system by solving OPF online and the required input data are directly obtained from on-line measurements.

Genetic Algorithm (GA) method [13,14] is evry powerful for solving OPF incorporating FACTs devices. GA is integrated with conventional OPF to select the best control parameters to achieve optimal solution for single or multi objective functions.

Particle Swarm Optimization (PSO)is based on the idea of social behavior of organisms such as animal flocking and fish schooling. It has been applied successfully to solve the OPF [15-19,24].The equality constraint is resolved by reducing the degree of freedom by one at random. Dynamic search-space reduction strategy is devised to accelerate the process. It can find the optimal location, settings, type and number of FACTs devices /to minimize their cost of installation and to improve system load ability for single and multi-type FACTs devices.

S. N. Chaphekar et al. [20], presented a new algorithm for connecting the Microgrid to distribution network and determining the optimal location of Microgrid in the system. In order to locate the optimal placement of Microgrid, the power flow is carried out by considering different penetration ratios of Microgrid.

In [21[, Yun Liu et al., mentioned the drawbacks of power system related to lacks of flexibility and scalability, inaccuracy in load forecast in addition to the penetration of renewable energy increases, which all lead to a relatively long time-scales of secondary and tertiary controls. To avoid these drawbacks, a distributed realtime optimal power flow control strategy is introduced in this paper. With the aid of up-to-date smart grid technologies such as two-way communication and distributed sensor,

Junchao Ma, et al, [22], proposed an efficient power flow sharing and voltage regulation control method based on hierarchical control to minimize the transmission loss of DC micro-grids. Different from the conventional optimal power flow algorithm for the DC grids, the proposed approach needs neither prior knowledge of the grid's conductance matrix nor the load distribution matrix, which means improvement of the expansibility and reduction of the cost.

Yujie Tang et al. [23],developed a real-time algorithm for AC optimal power flow, based on quasi-Newton methods. The algorithm uses second order information to provide suboptimal solutions on a fast timescale, and can be shown to track the optimal power flow solution when the estimated second order information is sufficiently accurate.

Al-Attar Ali Mohamed et al., [24], Proposed a technique inspired by the orientation of moths towards moonlight to solve constrained the OPF problem. The possible solution is represented by position of the light source. The associative learning mechanism with immediate memory and population diversity crossover for Lévy-mutation have been proposed to improve exploitation and exploration ability. This approach is applied to optimize the control variables such as real power generations, load tap changer ratios, bus voltages and shunt capacitance values under several power system constraints.

Dilip P. Ladumor, et al., [25], proposed a passing vehicle search (PVS) algorithm approach discovers the optimal setting of control variables for objective function with satisfying equality and inequality constraints. This approach derived from the passing or overtaking mechanism of vehicles on two lane highway. The overtaking depends on many parameters like oncoming vehicles, acceleration of each vehicle on highway, road, driver skill and weather conditions. They**,** considered three objective function minimization of Fuel cost, minimization of Active power losses and minimization of Reactive power losses. The advantages of this technique compared to other algorithms are less number of parameters and fast rate of convergence

Wei-Jie Liua,et al., [26] considred energy storage units' operational costs and the power price of the main grid in the total costs constraints in addition to the conventional equality and inequality constraints. A fully distributed algorithm based on the alternating direction method of multipliers (ADMM), the projected gradient method and the average consensus is proposed. The proposed algorithm can obtain the optimal output power settings of the energy storage units, distributed generators and the main grid for different demand loads with different initial states.

This work provides a new developed particle swarm algorithm (PSA) to solve different selected objective functions for the OPF problem using MATLAB. The selected objective functions are critical for utility/industrial companies, while satisfying a set of system operating constraints.The proposed algorithm include a model for two FACTs devices; Static Var Controllers (SVC) and Thyristor Controlled Series Capacitor (TCSC). Their effect effects on the the optimum values of the selected objective functions is demonstrated. The IEEE-30 bus system is used throughout this work to test the proposed algorithm.A comparison between results of different objective functions is discussed. Further objective functions, constraints and/or FACTs devices can be easily added to the developed software package in order to study the overall performance of such modifications.The proposed algorithm decides the optimal location and size of the specified FACTs devices minimize the required objective function while satisfying system constraints.

II. OPF PROBLEM FORMULATION

OPF seeks the optimum value for a specified objective function while satisfying sytem and equipment constraints. Different objective functions have been utilized either for single or multi objective optimization. Moreover, numerous constraints have been imposed in the solution algorithms to help providing realistic solutions.

Optimal value of the objective function is reached by optimaly adjusting a set of control (independent) variables in the power system. The set of control variables include the generator real powers, the generator bus voltages, the transformer tap settings, and the reactive power of switchable VAR sources, while the problem dependent variables include the load bus voltages, the generator reactive powers, and the line flows.
Three different objective functions are proposed as follow:

2.1 objective functions
2.1.1 Active Power Loss Minimization (APL)
For N bus system;
Minimizing $PL = \sum_k \sum_j [A_{jk} (P_j P_k + Q_j Q_k) + B_{jk} (Q_j P_k - P_j Q_k)]$ (2.1)
Where j = 1:N; k=1:N , A& B are constants

2.1.2 Reactive Power Reserve Margin Maximization (RPR)
The ultimate goal of the RPR maximization in the OPF is to minimize the reactive power generated and to distribute the reserve among the generators in proportional to their ratings. This can be achieved by simply minimizing the following function:

Minimize $F = \sum_{i=1}^{NG} \frac{Qi - Qmini}{Qmax - Qmini}$ (2.2)

2.1.3 Generation Fuel Cost Minimization (GFC)
The fuel cost of a thermal generating unit can be considred as an essential criterion for economic feasibility. The GFC minimization is formulated as follow:

Minimize (FT) = $\sum_{i=1}^{N_G} F_i(P_{Gi})$ (2.3a)
$F_i (P_{Gi}) = a_i + b_i P_{Gi} + c_i P^2_{Gi}$ (2.3b)
where:
N_G is the number of generators,
a_i ,b, and $c_i$are the quadratic cost coefficients of the ith generator
P_{Gi} is the real power output of the ith generator.

2.2 The Constraints
The OPF constraints are divided into equality and inequality constraints. The equality constraints are active/reactive power equalities in the power flow equations, while the inequality constraints s are the limits on control variables and the operating limits of power system dependent variables including bus voltage constraints, generator active/reactive power constraints,

2.2.1 Equality Constraints:
The power flow equations which require that the net injection of the real and reactive power at each bus to be zero as shown in equation:
P_{Gk}-P_{Dk} = $V_k \sum_{J=1}^{N} [Vj[Gkjcos\ (\delta k - \delta j) + Bkj\ Sin\ (\delta k - \delta j)]]$ (2.4)

$QGk - QDk = Vk \sum_{J=1}^{N} [VjGj\cos(\ k - Sj) + BkjSin\ (\ k - j)]]$ (2.5)
For k=1,2,……………….,N

<u>Where</u>:
P_{GK}, Q_{GK} = active and reactive power generation at bus k
P_{DK}, Q_{DK} = active and reactive power demand at bus k
V_k, δ_k = voltage magnitude and angle at bus k .
G_{KJ}+jB_{Kj} = (k, j) element of the bus admittance matrix.

2.2.2 Inequality Constraints:
The necessary inequality constraints needed for the OPF implementation are:
- Bus Voltage Magnitude Constraints. .

$V i_{min} \leq V i \leq V i_{max}$ (2.6)
- Active/reactive power generation constraints for all units

$P_{gi\text{-}min} \leq P_{gi} \leq P_{gi\text{-}max}$ (2.7)
$Q_{gi\text{-}min} \leq Q_{gi} \leq Q_{gi\text{-}max}$ (2.8)

- Reactive Power Source Capacity Constraints:

All capacitors are restricted by lower and upper reactive power limit as

$q_{ci\text{-}min} \leq q_{ci} \leq q_{ci\text{-}max}$ (2.9)

$q_{ci} = q_{ci\text{-}min} + N_{ci} * \Delta q_{ci}$ (2.10)

- Transformer Tap Position Constraints

The magnitude of the load tap changer is a discrete variable since the tap is changing with a certain increment. This increment depends on the size of the specified transformer.

$T_{i\text{-}min} \leq T_i \leq T_{i\text{-}max}$ (2.11)
$T_i = T_{i\text{-}min} + N_{Ti} * \Delta T_i$ (2.12)

- Line Thermal Limit Constraints for all Transmission Lines:

$$|S_i| \leq S_{i\,max}$$ (2.13)

Where
S_i :the complex power flow at line i
S_{imax}.: the maximum complex power flow at line

2.3 FACTs devices Models

In this paper two FACTs devices Static VAR Compensation (SVC) and Thyresitor Controlled Seris Capacitor (TCSC) are implemented in the OPF model in the Y_{bus} matrix. The following sections describe the applied models for FACTs devices.

(a) (b

Fig. (2.1) FACTs devices models

2.3.1 SVC Model

The SVC can be operated at both inductive and capacitive compensation. It is modeled as an ideal reactive power injection at bus i, . The injected power at bus i is [Fig.(2.1-a)]:

$Q_i = Q_{svc}$; (2.14)

2.3.2 TCSC Model

A thyristor-controlled series compensator is composed of a series capacitance which has a parallel branch including a thyristor-controlled reactor. The benefits of TCSC are seen in its ability to control the amount of compensation of a transmission line, and in its ability to operate in different modes. The TCSC can serve as the capacitive or inductive compensation respectively by modifying the reactance of the transmission line. In this work, the reactance of the transmission line is adjusted by TCSC directly. The rated value of TCSC is a function of the reactance of the transmission line [Fig.(2.1-b)], Where the TCSC is located:

$Xu = X_{line} + X_{TCSC}$, (2.15)
$X_{TCSC} = r_{tcsc}. X_{line}$ (2.16)

Where X_{Line} is the reactance of the transmission line and r_{tcsc} is the coefficient which represents the compensation degree of TCSC. To avoid overcompensation, the working range of the TCSC is between -0.7X_{Line} and 0.2 X_{Line}

III. PARTICLE SWARM OPTIMIZATION ALGORITHM FOR OPF

3.1Overview

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr.kennedy and Dr.Eberhart in 1995, inspired by social behavior of bird flocking or fish schooling [15]. In PSO the potential solution, called particles, fly through the problem space by following the current optimum particles.

In PSO algorithms, particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has beenencountered, or until computational limitations are exceeded. Each particle keeps track of its coordinates in the problem space, which are associated with the best solution, fitness, it has achieved so far [16-18]. The fitness value is also stored. This value is called pbestanother 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 Ibest. When a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest.The concept of the PSO consists of, at each time step, changing the velocity of (accelerating) each particle toward its pbest and Ibest locations (local version of PSO).

3.2 Major Steps Of The Proposed PSA For OPF

The major steps of the proposed PSA are summariezed as:

1. Read system data (lines, buses, generation, cost data)
2. Select the control variables according to the case study (with or without FACTs)
3. Generate random particles (control parameters for OPF)
4. Calculate the Ybus
5. Solve Power Flow for each particle
6. Calculate the objective function for each particle
7. Check for constraints violation and modify the objective function accordingly
8. Apply the PSO for local and global best solution.
9. Check for stopping criterion. If satisfied go to step 11; otherwise go to step 10
10. Update the velocities and positions of particles, go to step 4
11. Print results

IV. OPF RESULTS WITHOUT FACTS DEVICES

In this section results of solving the OPF problem using the PSA are presented. The three objective functions presented in Sec. 3 are individually applied as a single objective function optimization to the IEEE-30 bus system. Different case studies are tested to show the capabilities of the implemented algorithm. The values of the three objective functions; Active Power Loss (APL), Reactive Power Reverse (RPR) and Generation Fuel Cost (GFC) are calculated before applying the PSA and considered as the base case. In optimizing each objective function other two objective function are calculated to be compared with the base case.

4.1 Active Power Loss Minimization (APL)

The PSA is applied to the APL objective function. A dramatical reduction of 2.898 MW in APL is achieved which about 47.63 % lower than the base case, i.e. the case without optimization. Both RPR & GFC are increased (Table (4.1)). Appendix A presents detailed results for this case.

Table 4.1 IEEE 30-Bus Active Power Loss Minimization (APL)

Objective Function	Base case	PSA
APL	5.5339	**2.8980**
RPR	3.6424	3.9392
GFC	901.16	967.18

4.2 Reactive Power Reserve Margin Maximization (RPR)

It is noted that maximizing the RPR leads to a very high increasing of APL while the GFC is slighly increased (Table (4.2). On the otherhand, increasing the RPR reduces the required generator reactive power capacity rating, which reduces the capital cost that’s mean the two effects should be consider togther to find the optimum decsion.

Table 4.2 IEEE 30-Bus Reactive Power Reserve Margin Maximization (RPR)

Objective Function	Base case	PSA
APL	5.5339	11.0063
RPR	3.6424	**5.0296**
GFC	901.16	915.98

4.3 Generation Fuel Cost Minimization (GFC)

Minimization 0f GFC increases the APL by 57.6% while RPR improved slightly (Table (4.3)).

Table 4.3 IEEE 30-Bus Generation Fuel Cost Minimization (GFC)

Objective Function	Base case	PSA
APL	5.5339	8.7180
RPR	3.6424	3.6883
GFC	901.16	**799.21**

Table 4.4: A Comparison with GFC Minimization Algorithms

Literature	Method	Min. GFC
[6]	Linear programming	806.84
[12]	Genetic Algorithm	800.805
[10]	Gradient Algorithm	804.583
[17]	PSO Algorithm	799.98
Our work	Current paper	**799.21**

Comparing between different optimization techniques and our proposed PSA for GFC minimization showed that our proposed algorithm achieves better value than other published methods for IEEE-30 bus sytem (Table 4.4)

Table (4.5) shows a comparison between results of applying different objective functions for solving OPF problem with the base case of power flow without optimization.

Table (4.5) Comparisons of all OPF Objective functions

	APL	RPR	GFC
Base case	5.5339	3.6424	901.16
Cas1 Min. APL	**2.898**	3.9392	967.18
Cas2 Max. RPR	11.0063	**5.0296**	915.98
Cas3 Min. GFC	8.7180	3.6883	**799.21**

Case (1), the minimization of APL was considered. It is clear that minimizing this objective function has improved (RPR), while increase the GFC. It is concluded that APL is highly correlated with GFC.

In case (2), RPR is maximized. It is obvious that APL is improved while the GFC become worst.

In case (3) GFC is minimized. It is was discovered that APL is the worest while the RPR is slightly changed. It is concluded that GFC is highly correlated with the APL.

V. OPF RESULTS INCLUDING FACTS DEVICES

The implementation of FACTs devices in the proposed PSA for the OPF problem is considered in the modifications of the bus admittance matrix, consequently influences the system overall performance. Two selected FACTs devices (SVC and TCSC) are applied individually and together. Moreover, the number of FACTs devices and sizes are randomly selected. However to limit the search a sepecified maximum number of FACTs devices tried are 2, 5 and 10. The proposed PSA is designed to find the optimal location and size of the applied FACTs for each objective function.

The following scenarios are applied for the three studied objective functions:

- PSA with SVC only (2 , 5 and 10 devices)
- PSA with TCSC only (2 , 5 and 10 devices)
- PSA with both SVC &TCSC (2 , 5 and 10 of both devices)

5.1 Minimization Of Active Power Transmission Loss (APL)

5.1.1 SVC results

Ressults including 2,5 and 10 SVCs are presented in Table (5.1).

Table (5.1) IEEE 30-Bus System with APL minimization using**SVC only**

Objective Function	Objective Function Value		
	(2SVC)	**(5SVC)**	**(10SVC)**
APL	**3.0965**	**3.0965**	**2.9398**
(RPR)	3.5487	3.5487	4.0597
GFC	967.65	967.65	967.28

5.1.2 TCSC results

Rresults including 2,5 and 10 TCSCs are presented in Table(5.2).

Table (5.2) IEEE 30-Bus System with APL minimization using TCSC only

Objective Function	Objective FunctionValue		
	(2-TCSC)	**(5-TCSC)**	**(10-TCSC)**
APL	**3.0995**	**3.0995**	**3.0995**
(RPR)	3.5361	3.5490	3.5486
GFC	967.66	967.65	967.65

5.1.3 SVC & TCSC results

Results including 2,5 and 10 SVC&TCSCs are presented in Table (5.3).Appendix B presents detailed results for APL with SVC and TCSC.

Table 5.3 IEEE 30-Bus system with APL minimization using SVC&TCSC

Objective Function	Objective Function Value		
	2SVC& 2TCSC	**5SVC& 5TCSC**	**10SVC &10TCSC**
APL	**3.0965**	**3.0965**	**2.9377**
(RPR)	3.5487	3.5487	4.0650
GFC	967.65	967.65	967.28

Table (5.4) shows comparison between the objective function value APL without and with FACTs devices. It is clear that when using TCSC and SVC together the losses is the lowest due to supplying the system with proper values of reactive power at the proper location, which results in decreasing the currents in lines and consequently the losses.

Table (5.4) Comparison of APL minimization for different FACTs devices

Base case		5.5339
	Without FACTs	2.9890
PSO	SVC	2.9398
	TCSC	3.0995
	SVC&TCSC	**2.9377**

5.2 Reactive Power Reserve Margin Maximization (RPR)

5.2.1 SVC results

Results including 2,5 and 10 SVCs are presented. Tables (5.5) show control variables and objective functions values for all cases respectively.

Table (5.5) IEEE 30-Bus System with RPR maximization using SVC only

Objective Function	Objective Function Value		
	(2-SVC)	**(5-SVC)**	**(10-SVC)**
APL			
(RPR)	12.4490	12.5163	13.1730
GFC	**4.8293**	**4.9405**	**4.9989**
	941.47	935.21	864.71

5.2.2 TCSC results

Results including 2,5 and 10 TCSCs are presented in Table (5.6).

Table(5.6) IEEE 30-Bus System with RPR maximization using TCSC only

Objective Function	Objective Function Value		
	2TCSC	**5TCSC**	**(10TCSC**
APL	12.5480	12.5274	12.9073
(RPR)	**4.7527**	**4.7535**	**4.7548**
GFC	988.83	990.49	983.76

5.2.3 SVC & TCSC results

Results including 2, 5 and 10 SVC&TCSCs are presented in Table (5.7).

Table(5.7) IEEE 30-Bus System with RPR maximization using SVC & TCSC

Objective Function	Objective Function Value		
	2SVC& 2TCSC	**5SVC& 5TCSC**	**10SVC& 10TCSC**
APL	12.7810	12.8086	10.4528
(RPR)	**4.8414**	**4.9259**	**5.0115**
GFC	939.58	911.27	917.72

Table (5.8) shows comparison between the objective function value (reactive power reserve margin maxization) without and with FACTS devices. It is clear that when using TCSC and SVC together the losses is the lowest due to supplying the system with proper values of reactive power at the proper location, which results in decreasing the currents in lines and consequently the losses.

Table (5.8) comparison of with RPR maximization for different FACTs devices

Base case		3.6424
	Without FACTs	5.0296
PSO	SVC	4.9989
	TCSC	4.7548
	SVC&TCSC	**5.0115**

5.3 Minimization of Generation Fuel Cost GFC)

5.3.1 SVC results

Results including 2,5 and 10 SVCs are presented in Table(5.9)

Table (5.9) IEEE 30-Bus System with GFC minimization using SVC only

Objective Function	Objective Function Value		
	(2-SVC)	(5-SVC)	(10-SVC)
APL	8.7893	8.7498	8.6897
(RPR)	3.3775	3.5682	3.7273
GFC	**799.71**	**799.50**	**799.37**

5.3.2 TCSC results

Results including 2,5 and 10 TCSCs are presented inTable (5.10).

Table (5.10) IEEE 30-Bus System with GFC minimization using TCSC only

Objective Function	Objective Function Value		
	(2-TCSC)	(5-TCSC)	(10-TCSC)
APL	8.8647	8.8635	8.8639
(RPR)	3.2562	3.2572	3.2577
GFC	**799.91**	**799.90**	**799.90**

5.3.3 SVC & TCSC results

Results including 2, 5 and 10 SVC&TCSCs are presented in Table (5.11).

Table (5.11) IEEE 30-Bus System with GFC minimization using SVC & TCSC

Objective Function	Objective Function Value		
	2SVC & 2TCSC	**5SVC& 5TCSC**	**10SVC& 10TCSC**
APL	8.8119	8.7275	8.7413
(RPR)	3.4420	3.6673	3.8275
GFC	**799.73**	**799.46**	**799.36**

Table (5.12) shows comparison between the objective function value (generation fuel cost) without and with FACTSdevices. It is obvious that when using TCSC and SVC together the generation cost is the lowest.

Table (5.12) comparison of GFC minimization for different FACTs devices

Base case		901.16
	Without FACTs	799.21
PSO	SVC	799.37
	TCSC	799.91
	SVC&TCSC	799.36

VI. CONCLUSIONS

This paper provides a new developed algorithm to solve the OPF problem considering three different objective functions and a set of practical constraints. An efficient software package is developed with MATLAB based on the Particle Swarm Optimization (PSO) technique.

Three different objective functions APL, RPR and GFC are applied to the IEEE-30 bus sytem. Comparison between results of the three objective functions shows the superiority of the obtained results over the published work for the same system.

The effect of applying different FACTs devices to improve objective function values is demonetrated. The proposed algorithm decides the optimal number, location and size of the specified FACTs devices to achieve optimal objective function value while satisfying system constraints.

Results for the first objective function (APL minimization) show when applying FACTs devices the value of active power losses is decreasing dramatically with the increase of FACTs devices number SVC, TCSC or both. It is clear that the losses is the lowest when using free number of FACTs and the algorithm determine the proper umber, location, and size of FACTs devices.

Results for the second objective function (RPR maximization) show the improvement of the margin with increasing the number of FACTs devices.

Results for the third objective function (GFC minimization) show that the values of objective functions are improving slightly which shows that the effect of FACTs on fuel cost is not as much as other objective functions.

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Appendix A: Detailed results for GFC minimization without FATCs devices.

Table A.1EEE 30-Bus results (Min. GFC without FACTs)

Bus No.	V (p.u.)	Delta (degree)	Pd (MW)	Qd (MVAR)	Pg (MW)	Qg (MVAR)
1	1.1000	0.0000	0.0000	0.0000	177.5353	-17.2515
2	1.0874	-3.3693	21.7000	12.7000	48.8154	20.1482
3	1.0610	-9.5750	94.2000	19.0000	21.2331	26.8238
4	1.0689	-7.6432	30.0000	30.0000	20.6060	34.1280
5	1.1000	-8.1648	0.0000	0.0000	11.9281	14.2302
6	1.0999	-9.4436	0.0000	0.0000	12.0000	19.9167
7	1.0579	-8.7502	22.8000	10.9000	0.0000	0.0000
8	1.0746	-6.3536	7.6000	1.6000	0.0000	0.0000
9	1.0733	-9.3689	0.0000	0.0000	0.0000	0.0000
10	1.0702	-11.0953	5.8000	2.0000	0.0000	0.0000
11	1.0800	-5.2922	2.4000	1.2000	0.0000	0.0000
12	1.0747	-10.2579	11.2000	7.5000	0.0000	0.0000
13	1.0681	-7.3631	0.0000	0.0000	0.0000	0.0000
14	1.0650	-11.1841	6.2000	1.6000	0.0000	0.0000
15	1.0647	-11.4410	8.2000	2.5000	0.0000	0.0000
16	1.0664	-10.8953	3.5000	1.8000	0.0000	0.0000
17	1.0649	-11.2582	9.0000	5.8000	0.0000	0.0000
18	1.0569	-12.0287	3.2000	0.9000	0.0000	0.0000
19	1.0553	-12.1962	9.5000	3.4000	0.0000	0.0000
20	1.0597	-12.0124	2.2000	0.7000	0.0000	0.0000
21	1.0614	-11.5987	17.5000	11.2000	0.0000	0.0000
22	1.0619	-11.5865	0.0000	0.0000	0.0000	0.0000
23	1.0624	-11.9986	3.2000	1.6000	0.0000	0.0000
24	1.0547	-12.0786	8.7000	6.7000	0.0000	0.0000
25	1.0586	-11.8999	0.0000	0.0000	0.0000	0.0000
26	1.0417	-12.2869	3.5000	2.3000	0.0000	0.0000
27	1.0693	-11.5422	0.0000	0.0000	0.0000	0.0000
28	1.0645	-7.8264	0.0000	0.0000	0.0000	0.0000
29	1.0533	-12.7451	2.4000	0.9000	0.0000	0.0000
30	1.0411	-13.5127	10.6000	1.9000	0.0000	0.0000

Table A.2Control Variables (Min GFC without FACTs)

Control Variable	Optimal Value
VB(1)	1.1000
VB(2)	1.0874
VB(3)	1.0610
VB(4)	1.0689
VB(5)	1.1000

VB(6)	1.0999
PG(2)	0.4882
PG(3)	0.2123
PG(4)	0.2061
PG(5)	0.1193
PG(6)	0.1200
TCL(11)	1.0125
TCL(12)	0.9375
TCL(15)	1.0250
TCL(36)	0.9750
QC(10)	0.0150
QC(12)	0.0200
QC(15)	0.0450
QC(17)	0.0200
QC(20)	0.0300
QC(21)	0.0450
QC(23)	0.0500
QC(24)	0.0350
QC(29)	0.0100

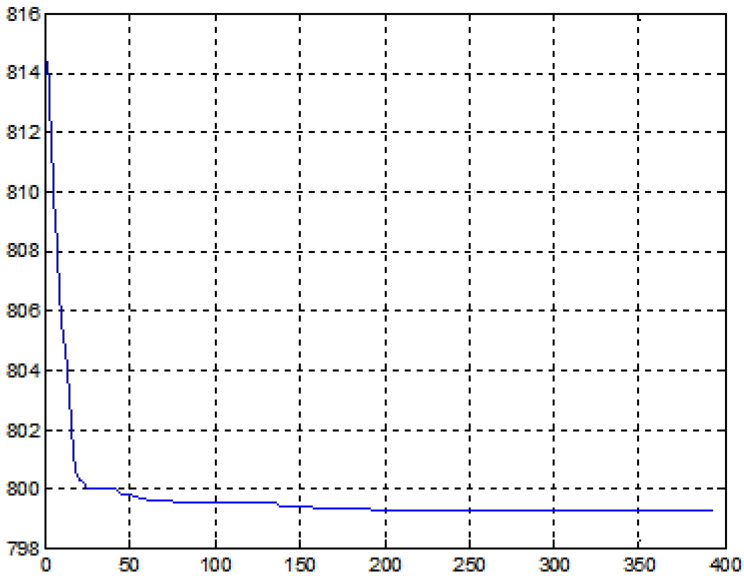

Fig. (A.1) Minimizing of GFC using the PSO without FACTs

Table A.3 IEEE 30-Bus Line Flow and Losses ((Min GFC without FACTs)

Line No.	From Bus	To Bus	Line Flow From (p.u.)	Line Flow To (p.u.)	Line Loss (p.u.)
1	1	2	118.3286 - 14.9531i	-116.0850 + 15.3566i	2.2437 + 0.4035i
2	1	11	59.2067 - 2.2984i	-57.8972 + 2.8159i	1.3095 + 0.5176i
3	2	8	34.2529 - 4.5251i	-33.6847 + 1.9563i	0.5683 - 2.5687i
4	11	8	55.4972 - 4.0159i	-55.1472 + 4.0459i	0.3500 + 0.0299i
5	2	3	63.5467 + 0.2866i	-61.9316 + 1.6749i	1.6151 + 1.9615i
6	2	13	45.4008 - 3.6700i	-44.3869 + 2.4023i	1.0139 - 1.2677i
7	8	13	49.7468 + 2.6244i	-49.4908 - 2.7667i	0.2560 - 0.1423i
8	3	7	-11.0353 + 6.1489i	11.1068 - 8.2583i	0.0715 - 2.1093i
9	13	7	34.1818 + 1.5653i	-33.9068 - 2.6417i	0.2750 - 1.0765i

10	13	4	11.7379 - 5.9446i	-11.7203 + 4.9787i	0.0176 - 0.9659i
11	13	9	19.5321 - 9.2463i	-19.5321 + 10.0977i	-0.0000 + 0.8515i
12	13	10	12.5459 + 12.8516i	-12.5459 - 11.2795i	0.0000 + 1.5721i
13	9	5	-11.9281 - 13.6375i	11.9281 + 14.2302i	0.0000 + 0.5927i
14	9	10	31.4603 + 3.5398i	-31.4603 - 2.5828i	0.0000 + 0.9570i
15	8	12	31.4851 - 10.2266i	-31.4851 + 12.6560i	0.0000 + 2.4294i
16	12	6	-12.0000 - 19.2910i	12.0000 + 19.9167i	0.0000 + 0.6257i
17	12	14	7.4859 + 0.5327i	-7.4259 - 0.4079i	0.0600 + 0.1248i
18	12	15	17.8066 - 0.6100i	-17.6247 + 0.9684i	0.1820 + 0.3584i
19	12	16	6.9926 + 1.2124i	-6.9514 - 1.1257i	0.0412 + 0.0867i
20	14	15	1.2259 - 1.1921i	-1.2202 + 1.1973i	0.0057 + 0.0051i
21	16	17	3.4514 - 0.6743i	-3.4424 + 0.6952i	0.0090 + 0.0209i
22	15	18	5.7711 + 0.9970i	-5.7387 - 0.9309i	0.0324 + 0.0661i
23	18	19	2.5387 + 0.0309i	-2.5350 - 0.0234i	0.0037 + 0.0075i
24	19	20	-6.9650 - 3.3766i	6.9833 + 3.4131i	0.0183 + 0.0366i
25	10	20	9.2546 + 1.2724i	-9.1833 - 1.1131i	0.0713 + 0.1592i
26	10	17	5.5722 + 4.5333i	-5.5576 - 4.4952i	0.0146 + 0.0381i
27	10	21	15.7906 + 5.3093i	-15.7063 - 5.1278i	0.0843 + 0.1815i
28	10	22	7.5888 + 2.2473i	-7.5490 - 2.1653i	0.0398 + 0.0820i
29	21	22	-1.7937 - 1.5722i	1.7943 + 1.5734i	0.0006 + 0.0012i
30	15	23	4.8738 - 1.1627i	-4.8516 + 1.2074i	0.0221 + 0.0447i
31	22	24	5.7547 + 0.5919i	-5.7206 - 0.5388i	0.0341 + 0.0531i
32	23	24	1.6516 + 2.1926i	-1.6428 - 2.1745i	0.0088 + 0.0180i
33	24	25	-1.3366 - 0.4866i	1.3401 + 0.4926i	0.0034 + 0.0060i
34	25	26	3.5411 + 2.3614i	-3.5000 - 2.3000i	0.0411 + 0.0614i
35	25	27	-4.8812 - 2.8541i	4.9124 + 2.9136i	0.0312 + 0.0595i
36	28	27	18.1639 + 6.4878i	-18.1639 - 5.1879i	0.0000 + 1.3000i
37	27	29	6.1811 + 0.9212i	-6.1060 - 0.7793i	0.0751 + 0.1418i
38	27	30	7.0705 + 1.3531i	-6.9254 - 1.0799i	0.1451 + 0.2731i
39	29	30	3.7060 + 0.8793i	-3.6746 - 0.8201i	0.0314 + 0.0593i
40	4	28	2.3262 - 0.8507i	-2.3218 - 4.0056i	0.0044 - 4.8563i
41	13	28	15.8800 + 1.1384i	-15.8421 - 2.4822i	0.0379 - 1.3439i

Appendix B: Results for APL minimization with FATCs.

B-1: APL minimization with 10 SVC devices

Table (B.1) control variables with 10 SVC

Control Variable	**Optimal Value**
VB(1)	1.1000
VB(2)	1.1000
VB(3)	1.0825
VB(4)	1.0891
VB(5)	1.1000
VB(6)	1.1000
PG(2)	0.8000
PG(3)	0.5000
PG(4)	0.3500
PG(5)	0.3000
PG(6)	0.4000
TCL(11)	1.0125
TCL(12)	0.9000
TCL(15)	0.9875
TCL(36)	0.9875
QC(10)	0.0000
QC(12)	0.0000
QC(15)	0.0000

QC(17)	0.0000
QC(20)	0.0000
QC(21)	0.0000
QC(23)	0.0000
QC(24)	0.0000
QC(29)	0.0000
SVC(7)	0.0250
SVC(8)	0.0300
SVC(9)	0.0300
SVC(11)	0.0500
SVC(14)	0.0050
SVC(16)	0.0450
SVC(18)	0.0450
SVC(19)	0.0450
SVC(26)	0.0350
SVC(30)	0.0400

B-2: APL minimization with 10 TCSC

Table (B.2) control variables with 10 TCSC

Control Variable	Optimal Value
VB(1)	1.1000
VB(2)	1.0979
VB(3)	1.0802
VB(4)	1.0880
VB(5)	1.1000
VB(6)	1.1000
PG(2)	0.8000
PG(3)	0.5000
PG(4)	0.3500
PG(5)	0.3000
PG(6)	0.4000
TCL(11)	1.0375
TCL(12)	0.9000
TCL(15)	1.0250
TCL(36)	0.9875
QC(10)	0.0000
QC(12)	0.0000
QC(15)	0.0000
QC(17)	0.0000

B-3: APL minimization with 10SVC & 10TCSC

Table (B.3) control variables with 10SVC & 10TCSC

Control Variable	Optimal Value
VB(1)	1.1000
VB(2)	1.0972
VB(3)	1.0797
VB(4)	1.0869
VB(5)	1.1000
VB(6)	1.1000
PG(2)	0.8000
PG(3)	0.5000

PG(4)	0.3500
PG(5)	0.3000
PG(6)	0.4000
TCL(11)	1.0000
TCL(12)	0.9000
TCL(15)	0.9750
TCL(36)	0.9750
QC(10)	0.0000
QC(12)	0.0000
QC(15)	0.0000
QC(17)	0.0000
QC(20)	0.0000
QC(21)	0.0000
QC(23)	0.0000
QC(24)	0.0000
QC(29)	0.0000
RTCSC(17)	0.0000
RTCSC(22)	-0.0121
RTCSC(25)	-0.1680
RTCSC(32)	-0.0365
RTCSC(33)	-0.1376
RTCSC(34)	-0.2000
RTCSC(35)	-0.1486
RTCSC(37)	-0.1112
RTCSC(38)	-0.0959
RTCSC(39)	-0.0795
SVC(7)	0.0450
SVC(8)	0.0450
SVC(9)	0.0250
SVC(11)	0.0200
SVC(14)	0.0400
SVC(16)	0.0250
SVC(18)	0.0300
SVC(19)	0.0300
SVC(26)	0.0400
SVC(30)	0.0150

QC(20)	0.0000
QC(21)	0.0000
QC(23)	0.0000
QC(24)	0.0000
QC(29)	0.0000

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