

PSO BASED DISPATCH OF GENERATION AND LOAD IN RESTRUCTURED POWER SYSTEM

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Abstract: The role of the power system operator or independent system operator in restructured power system is to maintain a balance between the generation and demand. Traditionally, generation rescheduling is carried out in power system to maintain the power balance ignoring the demand side balancing. A PSO based optimization algorithm for dispatch of generation and load (DGL) is proposed in this paper. The dispatchable resources considered are generating units and demands. A framework for DGL is presented which is based on load shifting cost bid by the customer. The operating cost of the power system decreases as the costlier peaking units are off. The proposed algorithm is tested on IEEE 30 bus system, 10, 20, 40, 60, 80 and 100 unit systems. The results validate the efficiency and applicability of the proposed algorithm in deriving economic benefits.

Keywords: Demand Response (DR), Dispatch of Generation and Load (DGL), Unit Commitment (UC), Particle Swarm Optimization (PSO)

1. Introduction

The role of the power system operator or independent system operator in restructured power system is to maintain a balance between generation and demand [1]. Traditionally, generation rescheduling is carried out in power system to maintain the power balance. In day ahead scheduling, usually demand is treated as constant. With the introduction of restructuring and smart grid technology, operators can also use the load adjusting customers to maintain the grid frequency [2].

In any power system, the full generation and transmission capacities are used only a small fraction of time. The reasons are technical and regulatory mechanism in order to provide enough generation capacity to satisfy demand at all time [3]. The consequence is under utilization of peaking units during off-peak hours. This leads to high cost of generation. In order to reduce the generation cost, the power system must utilize the generation and transmission facilities to its optimum.

This can be achieved by flat load profile. Flat load profile is impractical. However, using the load curtailing or load adjustment of large customers, this can be achieved to some extent.

The use of treasury and consumer dependability necessities is linked with cost of reserve and power in deregulated power systems. [4]. Extensive research on demand response programs has been conducted to fully utilize the flexibility of demand-side resources [5]. Demand response programs can reduce electricity prices, improve system reliability, and reduce price volatility. Its performance is measured by peak load reduction and demand elasticity [6]. ISO-NE, PJM operates day ahead real time demand response programs. CAISO market operates voluntary load reduction; investor owned utility curtailment programs [7]. Real time pricing, economics models, emergency demand response, direct load control considering penalties for customers not responding to load discrimination and critical peak pricing is discussed in [8]. An integrated dispatch of Generation and load is formulated [9] that modeled consumption mode switching and load shifting of customer responses. A method of settlement is launched in which the responsive customers load shifting cost is remunerated by the customers those who have not shifted the load. The benefit of this method is the consumers are offered according to their real load shifting [9]. To represent the aggregated response characteristics of customers at a node a decomposition method for the integrated dispatch of generation and load based on nodal equivalent load shifting bidding curve is proposed in [10]. PSO is a population based stochastic optimization technique, initiated by Kennedy and Eberhart and motivated by the behavior of organisms such as bird flocking and fish schooling. It was established by Kennedy and Eberhart [17]. In recent years, PSO algorithm has been successfully employed to solve many optimization problems in power systems such as reactive power optimization [11], transmission expansion planning [12], relieving transmission congestion [13], and optimal placement of multiple distributed generator units and so on [18].

This paper proposes a PSO based optimization algorithm for dispatch of generation and load (DGL). The demands as well as generating units are considered as dispatchable resources. The system operator has the opportunity to optimize both the generation and load simultaneously. The customers who shift the load to improve the system regulation or decommission the peaking unit are given incentives based on load shifting charges. It also creates a healthy competition to incentivize the customers to shift their load. The test systems used for this proposed approach are IEEE -30 bus system, 10, 20, 40, 60, 80 and 100 unit systems. The outcomes validate the efficiency of the proposed approach.

The organization of the paper is as follows. In section 2, the framework of DGL is presented. In section 3, the mathematical formulation of DGL is introduced. Section 4 presents case studies and simulation results of IEEE-30 bus system, 10, 20, 40, 60, 80 and 100 unit systems. Section 5 concludes the paper.

2. Generation and Load Dispatch Framework

This section presents the framework of generation and load dispatch, in which the generation and demand sides are viewed symmetrical and the system operator can schedule the generation and load simultaneously. It consists of two stages, in the first stage, according to the time of use, the customers can change their load profile and a baseline load is determined. If the demand is satisfied by the generation, then the load shifting is not required. In case, if the demand is not met, the load shifting is launched in the second stage [10]. Using the cost minimization principle and the system operator systematizes the load shifting schedule and the load shifting bidding.

2.1. Load shifting cost

The load shifting cost curve expresses the willingness of customers to adjust their load profile block. Load shifting is due to flexible large scale industrial and commercial power consumers like, thermal storage, industrial electric heaters, pumps, smelters, HVACs, refrigerators, potentially programmable thermostats agitators and data centres [14]. The response by these customers towards load shifting tends to change the livelihood of workers and results in extra costs. The extra costs are especially, due to extra operating cost and the compensation is to be provided to the employees. The load shifting cost moreover expresses the costs of customer response. It is closely related to switching ON of the units and hence, it can be considered similar to start-up cost of a generating unit.

Model graph for Load shifting cost for a typical customer is illustrated in Fig 1. Here, the pre-shifting load of customers starts at 5:00. Mostly, customers would prefer consuming electric power as pre-shifting load profile. If the consumer wants to shift their profile one Hour earlier say the consumption starts at 4:00, the load

shifting cost will be \$1000. If the customer shifts their load profile 3 hour earlier it will be \$3000 and similarly, for every hour after 15 will be considered as \$500 per hour and so on.

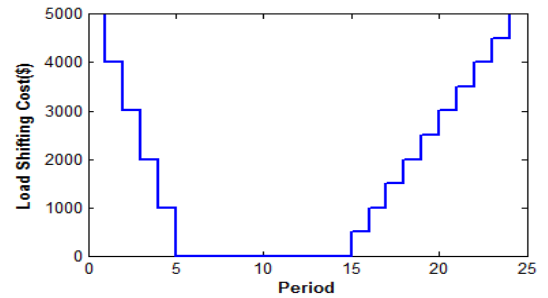


Fig.1. Model graph for load shifting cost

The load shifting cost becomes expensive, as the customer drifts away from the original interval and thus, the payment to be paid for workers become higher. Based on local living standards, equipment maintenance cost and electricity rates, the industrial customers can determine their load shifting cost [8]. For example, if the time window, the customer prefers is 5:00 to 15:00 hours for electricity consumption, then the total load shifting cost for that interval is zero.

2.2. Generation, load dispatch and existing Scenario:

In the existing system, if the time varying prices are high, then the customers voluntarily tend to shift their load from the peak hours to off-peak hours. This is termed as self-response of the customers. In this scenario, there is no competition among the customers.

The meager price difference between the off-peak and peak hours disables the customers in load shifting towards off-peak hours. In this case, the utility must run their peaking unit to satisfy the demand. In the proposed DGL, the customers are given incentive to shift their load based on the load shifting cost. If the customers are willing to shift their load towards off-peak hours, they are not only benefitted from decreased electricity bill, but are also given extra profits for their responsive behaviors. In the second stage, load shifting bidding process is organized by grid operators and based on the load shifting bidding curves of the customers; the load shifting schedules are optimized. This way DGL works by introducing competition among the customers. The customers, those who have not shifted (reluctant to change) their loads, have to pay the load shifting cost to the customers who have shifted their load.

2.3 Review of PSO algorithm

PSO algorithm is a population-based stochastic optimization technique introduced by Kennedy and Eberhart [17]. In recent years, PSO algorithm has been successfully employed to solve many real world

optimization problems. In this algorithm, each particle can be represented by its position and velocity. In a multidimensional search space particles alter their positions by moving around until a relatively unchanged position has been attained. Here particle best is denoted as Pbest and it is defined as the finest location corresponding to the best condition encountered so far by a particle in the search space, whereas global best is denoted as Gbest, defined as the greatest location encountered so far among the entire population in search space. Fitness function can be evaluated for each updated particles by using (1)

$$F = \begin{cases} F_T & \text{if } x \text{ is feasible} \\ f_{\max} + CV & \text{otherwise} \end{cases} \quad (1)$$

The velocity and position of each particle are updated by using equations (2) and (3)

$$V_{j,d}^{(k+1)} = wV_{j,d}^k + c_1 \text{rand}_1(Pbest_{j,d}^k - X_{j,d}^k) + c_2 \text{rand}_2(Gbest_{j,d}^k - X_{j,d}^k) \quad (2)$$

$$X_{j,d}^{(k+1)} = X_{j,d}^k + C V_{j,d}^{(k+1)} \quad (3)$$

Where k is the current iteration, $V_{j,d}^k$ is the velocity of the j^{th} particle in the d^{th} dimension at iteration k , $Pbest_{j,d}^k$ is the own best position of particle j in the d^{th} dimension until iteration k , $Gbest_{j,d}^k$ is the best particle in the swarm in the d^{th} dimension at iteration k , c_1 is cognitive component acceleration coefficients and c_2 is social component acceleration coefficients, rand_1 and rand_2 are the random numbers involving 0 and 1 and they are uniformly distributed, $X_{j,d}^k$ j, d, k show the position of particle, dimension and iteration. To supervise the redundant traveling of particles, the velocity of each particle is attained by using (3). It is restricted by their upper and lower limits and it can be specified by

$$V_d^{\min} \leq V_d \leq V_d^{\max} \quad (4)$$

Where V_d^{\max} is the maximum velocity and V_d^{\min} is the minimum velocity in the d^{th} dimension and can be expressed as

$$V_d^{\max} = \frac{(x_d^{\max} - x_d^{\min})}{k} \quad (5)$$

$$V_d^{\min} = -V_d^{\max} \quad (6)$$

Where k is the limit to run the number of space in d^{th} dimension ($k=5$) [15].

In the initialization process, all the individuals in the population are generated randomly within the feasible range. During initialization, the continuous variables of an individual are generated randomly using (7), while the discrete variables are generated randomly using (8).

$$x_{cv} = \text{rand} * (\text{var high} - \text{var low}) + \text{var low} \quad (7)$$

$$x_{dv} = \text{min} + n_k * \Delta s \quad (8)$$

Where x_{cv} and x_{dv} represent the continuous and discrete control variables, high and low are the maximum and minimum values of x_{cv} , min is the minimum value for x_{dv} , n_k is the number of position. The parameter settings for the PSO algorithm are shown in Appendix (A)

2.3.1 PSO based dispatch of generation and load

The DGL flowchart is shown in Fig 2. The steps involved in solving OPF problem using the PSO algorithm are summarized as follows:

1. Define the parameters required for the algorithm and feasible range for the control and dependent variables.
2. Randomly generate the initial population.
3. Evaluate the fitness function for entire population.
4. Repeat step 3 for entire particles in the population until fitness function is evaluated.
5. Estimation of fitness value is the initial Pbest value and Gbest is the best value surrounded by all the Pbest values.
6. Set maximum number of generations and set generation count $i=1$.
7. Update velocity and apply velocity limits.
8. Update position and perform crossover.
9. Fix control variables into the viable range, when they resist inequality constraints; else go to step 10.

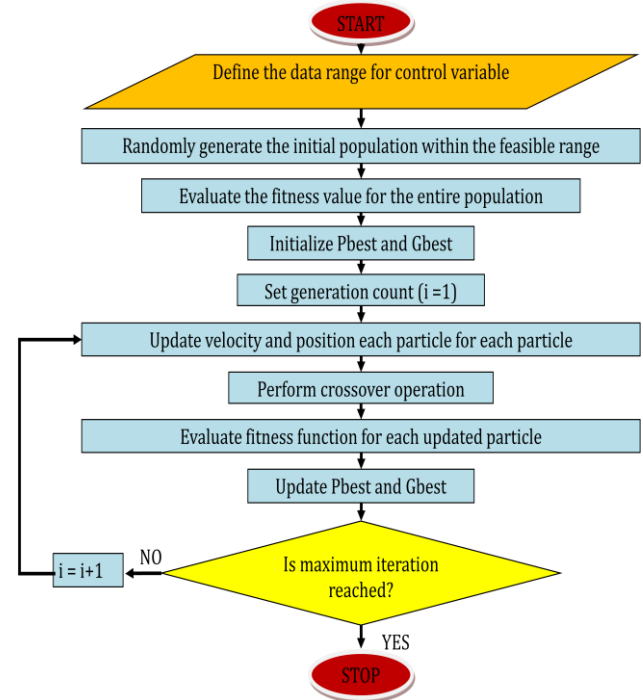


Fig.2. Flowchart for DGL

10. Evaluate fitness function for each updated particle.
11. Update Pbest and Gbest.
12. Increase generation count.

13. Repeat step 7 to step 12 until maximum generation is reached.

2.4 Bidding mechanism

In DGL, the settlement of load shifting cost is a key issue. The consumers are lead to offer according to their actual costs of load shifting. The marginal price of the last scheduled load satisfying the hourly power balance decides the market clearing price for load shifting resources. This settlement attitude is well supported by the explanation and is given below.

2.4.1. Type 1 Customer: Willing to shift the load

The marginal cost of shifting the load reduces, if the customer bids below their actual cost of load shifting. If this customer is chooses to move the load, the financial recompense for their actual cost of load adjustment is not met. Similarly, if the customer bids at a high price, they have to pay the customers who are willing to shift their load. Hence, sensible customer's willingness to shift the load on the basis of real load shifting cost is appropriate.

2.4.2 Type 2 Customer: Not willing to shift the load

If the customer bids with a high price or a low price than their real load shifting cost, they will suffer a loss, as proper economic compensation cannot cover their real load shifting cost, even though the customer may not show willingness. Hence, even when the customer is reluctant to shift the load, the bidding on the basis of real load shifting cost is appropriate. Thus, the proposed mechanism behaves like an "invisible hand" that guides the market participants to behave rationally. This also allows a healthy competition among the customers and it is necessary for practical implementation.

3. Mathematical formulation of generation and load dispatch

The mathematical formulation of DGL is similar to the standard UC problem formulation.

3.1. Objective functions

The objective function of system operator is to minimize the total fuel cost (including the generating cost and start up cost in the generation side and the load shifting cost in the demand side). The DGL function can be expressed as follows.

$$F = FC_T + SU_T + LSC_T \quad (9)$$

Where F is Total generation cost (\$), FC_T is Total fuel cost (\$), SU_T is Total unit start up cost (\$), LSC_T is Load shifting cost (\$), and T is the number of time intervals. FC_T is calculated for every hour (T), and the sum of the hourly fuel cost is found by economically dispatching the

load demand to the operating units. Start-up cost is expressed as a function in which, the number of hours the unit has been shut down is considered. The function is exponential for cooling and linear for banking. The shutdown cost is considered as a fixed cost for each turned OFF unit. The load shifting costs on the demand side and the generating costs and start up costs on the generation side can be synchronized directly and efficiently. So, power system can be functioned in a more cost-effective manner. The various constraints on the system, which should be fulfilled through the optimization process, are power generation-load balance, minimum up time & down time, operating constraints etc [16]. A simplified time-dependent start-up cost is given as follows.

$$\text{Start-up cost} = \begin{cases} \text{hot start cost} & \text{if down - time} \leq \text{cold start hours} \\ \text{cold start cost} & \text{otherwise} \end{cases}$$

For every unit, shut down cost is taken as zero.

3.2. Constraints on generating units and load

3.2.1. Inflexible demand

The bulk of loads in a practical power system is inflexible in nature. This specifies that the load is insensitive to the electrical energy cost. Thus, the demand is considered constant. Hence, this is parallel to generating units with fixed output power by bodily bonding agreements.

3.2.2. Minimum up time

The minimum up time is the time in which the unit is started (ON) once it should run for certain numbers of hours, called minimum up time, before permit it to turn-off.

3.2.3. Maximum down time

The most equipment of the customer needs cooling time, which is given by the maximum down time constraints.

3.2.4. Minimum/Maximum power limits

The electric devices have their own power ratings and these limits on their operating range can be given as

$$P_{imin} \leq P_t^i \leq P_{imax}$$

Where P_{imin} and P_{imax} is minimum/maximum limits of power

3.2.5. Fixed load Profile constraints

The load profile as well as production procedure is fixed for most of the industrial customers. Thus, the customers can shift the entire load profile for few hours later or earlier.

Table.1 IEEE-30 bus system fuel cost and generation schedule for 24 hour before load shifting

Hour	1	2	3	4	5	6	7	8	9	10	11	12
FC _T (\$)	38538	35434	32361	35434	33274	33883	27799	30840	33883	36986	40091	49418
Hour	13	14	15	16	17	18	19	20	21	22	23	24
FC _T (\$)	52539	55663	65046	68352	65046	58788	52539	40091	41644	43198	49418	43198
Total cost(\$)=1024925												

Unit No	Power Generation (MW)																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	80	80	75	80	78	80	60	70	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
2	45	35	30	35	30	30	30	30	30	40	50	80	80	80	80	80	80	80	80	50	55	60	80	60
3	0	0	0	0	0	0	0	0	0	0	0	0	10	20	50	50	50	30	10	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0
5	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
6	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30

4. Results and Discussion

The proposed method is performed in IEEE 30-bus system, 10, 20, 40, 60, 80 and 100 unit systems to demonstrate the economic benefits and effectiveness. A demand schedule of 24 hour is chosen. MATLAB program is written for solving the PSO based DGL problem. The results were obtained using an Intel i3-3217U CPU @ 1.80 GHz processor, 4GB RAM. The following case studies are considered for analysing the effect of dispatch of generation and load.

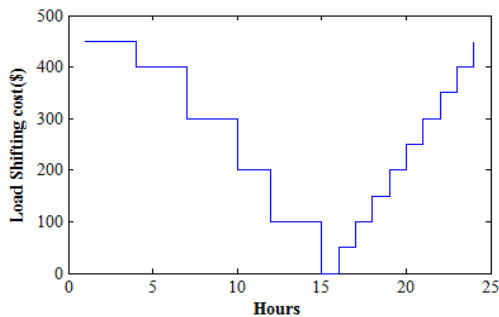


Fig.3. Graph for Load shifting cost

4.1. Case 1: IEEE 30-bus system

The IEEE 30-bus system has 41 lines, 6 generators, 4 transformers with tap setting and 9 capacitor banks [19]. The cost data and load data are given in Appendix (B & C). In this system, for simplicity it is assumed that there is

one load shifting customer and others are considered as inflexible. The load shifting cost of customer 1 for 10MW block is shown in Fig 3.

The proposed PSO based DGL is applied in the IEEE 30 bus system. The results of power generation schedule and fuel cost for 24 hours before load shifting is shown in Table 1. The total operating cost of the system before load shifting for 24 hour is \$ 1024925. From the Table 1, it is seen that at the 16th hour, all the units are switched ON and so peak demand occurs in that hour. In DGL, part of the peak load is moved towards off-peak period. Now, a load of 10 MW from 16th hour is shifted to unit 1 at the 7th hour.

The total operating cost of 7th, 16th, 17th and 18th hour schedule after load shifting for IEEE- 30 bus is given in Table 2. In the 16th hour instead of turning ON of unit 4 to meet 10 MW demand, this load is shifted to the 7th hour in unit 1. This load of 10 MW can be met by unit 1 itself. There is a shifting of load 9 hours earlier. Because of this load shifting the generation cost changes. Comparison of before and after load shifting is shown in Table 3. It is clear that the difference in total cost of before and after load shifting is \$4819. So after load shifting the generation cost is reduced by \$4819. This indicates that the cost of generation can be reduced by shifting the load.

Table 2 IEEE 30 Bus after load shifting

Hr	Power Generation of units(MW)						LSC _T (\$)	FC _T (\$)
	P1	P2	P3	P4	P5	P6		
7	70	30	0	0	30	30	450	30840
16	80	80	50	0	30	30		65046
17	80	80	50	0	30	30		65046
18	80	80	30	0	30	30		58788

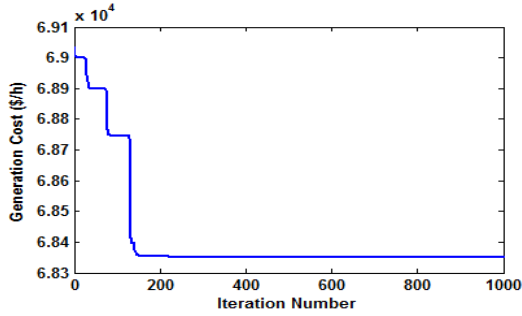


Fig.4. Characteristic of IEEE 30 bus system

Therefore, it is economically feasible. The convergence characteristic of IEEE-30 bus system for 16th hour is given in Fig 4.

Case 2: 10 Unit system

The proposed PSO based DGL is applied in 10 unit system. The system data are taken from [16]. The total operating cost of the system before load shifting for 24 hour is \$550933. For 24 hour time schedule startup costs, operation cost, generation supplying the load and unit on/off schedule before load shifting are given in Table 4. The computation time of 25 run is 5964.339 seconds for the period of 24 hour time schedule. In this system three customers are willing to shift their loads. Here, the original schedule of demand for the hours 20th, 21st and 22nd hours are 1200 MW, 1300 MW and 1100 MW, respectively.

In this system, there are three load shifting customers, while the others are considered as inflexible. The reduced demands from the original load of 25 MW from 20th hour, 25 MW from 21st hour and 30 MW from 22nd hour are reallocated to 15th hour and 23rd hour. Consequently, the changes in demand for the hours 20, 21 and 22 are 1175 MW, 1275 MW and 1070 MW, respectively. The loads of 25 MW, 25 MW and 30 MW are shifted from hours 20, 21 and 22 to hours 15 and 23. Now, the demands for the hours 15 and 23 become 1225 MW and 955 MW. Moreover, the compensation of 25 MW and 55 MW is provided in the hours 15 and 23, respectively. Table 5 shows the before and after load

Table 3 IEEE 30 Bus before and after load shifting

Cost	Before Load Shifting	After Load Shifting
Operating cost(\$)	219989	219720
Startup cost(\$)	21200	16200
Load shifting cost (\$)	0	450
Total Cost(\$)	241189	235920
Benefit(\$)		4819

shifting demand values. The load shifting cost for 25MW shift from the hour 20th to 15th hour is \$500 (i.e., the customer is asked to shift their load 5 hours earlier. From Fig 3, the cost is \$200 per 10MW shift, $LSC = 200 \times 2.5 = \$500$). Similarly, for shifting 25MW and 30MW, the

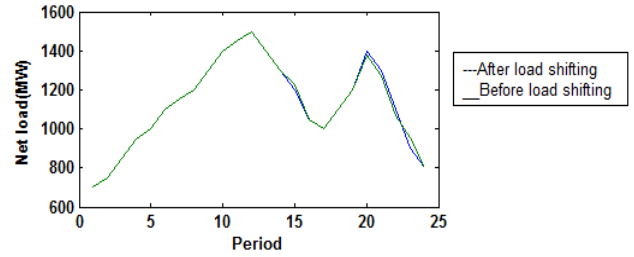


Fig.5. Net load comparisons for 10 unit system

$LSC = \$275$ (\$125 + \$150). This specifies that 5th unit is not committed in 22nd hr and hence start up cost is not added in that hour. As a result, after load shifting total cost of 24 hour schedule is reduced. The total operating cost of 24 hour schedule for after load shifting is \$541634. The operating cost for after load shifting of 15th and 23rd is depicted in Table 6. Table 7 represents the comparison of scheduling results before and after Load shifting for 10 Unit systems. The difference in operating cost of before load shifting and after load shifting is \$3184. This indicates that the cost is reduced by shifting the load from peak hours to off-peak hours.

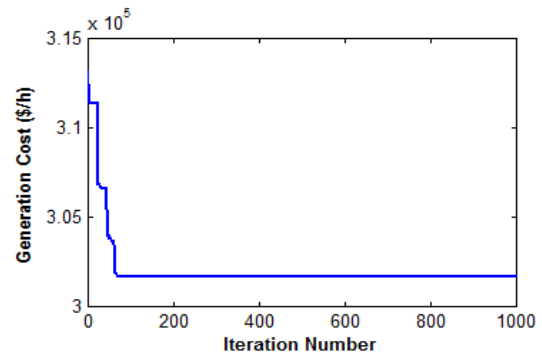


Fig.6 Convergence characteristics of 10 unit system

The PSO algorithm is normally obtained for numerous generations and may need an essential size of populations for convergence to obtain an optimal solution. The Net load comparisons for 10 unit system before and after load shifting are exposed in Fig.5. The convergence characteristic of 10 unit system is shown in Fig.6. For DGL, a portion of the crest load transfers to the off-peak

period and valley period. The flexible customers change their load profile few hours earlier. Hence, in DGL, the expensive generators are not required to start up and accordingly the total cost is reduced for 24 hour time schedule. This cost reduction depends on the customer's load shifting costs and operating cost of peak units.

Table.4 10 Unit system operating cost and 24 hour generation schedule for before load shifting

Hr	Operation Cost(\$)	SU _T	Total Cost(\$)	Unit Schedule										Generation Schedule										
1	13683	0	13683	1	1	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	
2	14554	0	14554	1	1	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	
3	16302	0	16302	1	1	0	0	0	0	0	0	0	0	455	395	0	0	0	0	0	0	0	0	
4	19262	2220	21482	1	1	1	1	0	0	0	0	0	0	455	235	130	130	0	0	0	0	0	0	
5	20133	0	20133	1	1	1	1	0	0	0	0	0	0	455	285	130	130	0	0	0	0	0	0	
6	21879	0	21879	1	1	1	1	0	0	0	0	0	0	455	385	130	130	0	0	0	0	0	0	
7	23262	1800	25062	1	1	1	1	1	0	0	0	0	0	455	410	130	130	25	0	0	0	0	0	
8	24150	0	24150	1	1	1	1	1	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	
9	26184	0	26184	1	1	1	1	1	0	0	0	0	0	455	455	130	130	130	0	0	0	0	0	
10	29133	920	30053	1	1	1	1	1	1	1	1	0	0	455	455	130	130	162	33	25	10	0	0	
11	30325	0	30325	1	1	1	1	1	1	1	1	1	0	0	455	455	130	130	162	80	28	10	0	0
12	32375	60	32435	1	1	1	1	1	1	1	1	1	0	455	455	130	130	162	80	68	10	10	0	
13	28442	0	28442	1	1	1	1	1	1	1	1	0	0	0	455	455	130	130	162	43	25	0	0	0
14	25689	0	25689	1	1	1	1	1	1	1	0	0	0	0	455	455	130	130	110	20	0	0	0	0
15	23706	0	23706	1	1	1	1	1	1	1	0	0	0	0	455	440	130	130	25	20	0	0	0	0
16	20614	0	20614	1	1	1	1	1	1	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0
17	19742	0	19742	1	1	1	1	1	1	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0
18	21487	0	21487	1	1	1	1	1	1	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0
19	23706	340	24046	1	1	1	1	1	1	1	0	0	0	0	455	440	130	130	25	20	0	0	0	0
20	28442	520	28962	1	1	1	1	1	1	1	1	0	0	0	455	455	130	130	162	43	25	0	0	0
21	25342	0	25342	1	1	1	1	1	1	0	0	0	0	0	455	455	130	130	25	20	25	0	0	0
22	25239	0	25239	1	1	1	0	1	0	0	0	0	0	0	455	455	130	130	0	0	30	0	0	0
23	16895	0	16895	1	1	1	0	0	0	0	0	0	0	0	455	315	130	0	0	0	0	0	0	0
24	14527	0	14527	1	1	0	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0
Total cost(\$)	545073	5860	550933																					

TABLE 5 10 Unit system demand values

Before load shifting		After load shifting		Change of value
Hour	Load	Hr	Load	
20	1200	20	1175	-25
21	1300	21	1275	-25
22	1100	22	1070	-30
15	1200	15	1225	25
23	900	23	955	55(25+30)

Table 6 10 Unit system after load shifting

Hr	Power Generation units(MW)						FC _T (\$)	SU _T (\$)	LSC _T (\$)
	P1	P2	P3	P4	P5	P6			
15	455	455	130	130	35	20	25068	0	500
23	455	340	130	0	0	0	18232	0	125
23	455	345	130	0	0	0	18319	0	150

Case 3: For the rest of the cases

The proposed PSO based DGL is applied to the rest of the cases. For instance, to perform the problem on 20 unit system the initial 10 units are duplicated and the load is multiplied by 2. The problem data were chosen properly for the problems with more units [16]. General scrutiny of compare demand, supply and price real time data in [20].

To validate the proposed PSO based DGL algorithm, it is subjected to different unit system ranging from 10, 20, 40, 60, 80 and 100 unit systems. In this work, the PSO result of 10 unit system alone is explored and the statistical analysis of other system is given for other test systems. The test runs made for each problem set for every hour is 25. This avoids deceptive effects, owing to the stochastic character of PSO. Every run is accomplished at the similar generation limit, though the number of variables increases with the number of units. A run is considered successful, when the total operating cost of DGL is less than that of without load shifting cost.

The simulation results up to 100 unit systems are shown in Table 8. It is clear that the proposed algorithm gives better solution for greater system like more than 60 units. The operating cost, average cost, worst cost, best cost and CPU execution time are found for all the test units for 24 hour schedule. The degree of PSO execution with the total units committed is shown in Fig.7 and it proves that the execution time of PSO boost up with the number of units to be committed.

Table 7 10 Unit system comparison results

Cost	Before Load Shifting	After Load Shifting
Operating cost(\$)	545073	541634
Startup cost(\$)	5860	5340
LSC (\$)	0	775
Total Cost(\$)	550933	547749
Benefit(\$)		3184

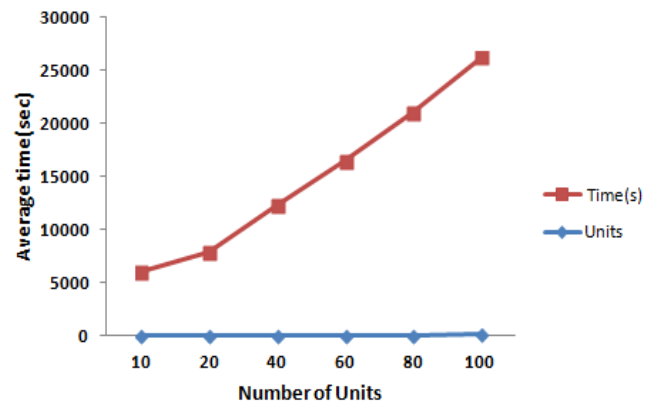


Fig.7 Execution time of PSO with number of units

Table 8 Simulation results up to 100-unit systems

Units	Operating Cost(\$)	Best Cost(\$)	Worst Cost(\$)	Average Cost(\$)	Average time(s)
10	559410	559410	569788	560128	5964.339493
20	1112515	1112515	1131637	1118656	7846.176581
40	2345114	2345114	2355787	2347431	12279.54147
60	3734997	3734997	3736357	3735503	16457.52195
80	6492200	6492200	6492200	6492200	20985.36403
100	6318430	6318430	6318430	6318430	26141.85217

5.Conclusion

This paper presents a novel approach to reduce the operating cost of power system by using DGL optimized by PSO. In DGL, the willingness of the customers is expressed using load shifting cost and it also guides the customer to shift their load profile to off-peak hours. This utilized mechanism acts like an invisible hand in which non-responsive customers pay the responsive customers according to their real load shifting cost. Thus, commitment of expensive units at off-peak hours is avoided. The operating cost is reduced by shifting the load towards off-peak hours and it also requires only few on/off commitment of generating units. Here, the test systems used are IEEE-30 bus system, 10, 20, 40, 60, 80 and 100 unit systems and it yields economic benefits. The operating, best, worst and average costs for a power system using DGL is evaluated for various test systems by using PSO. This proposed algorithm provides better convergence and it gives optimum solution with complete state enumeration. The disadvantage of PSO algorithm is that it takes more execution time for larger units. Thus, DGL is a feasible selection for managing the demand in power system.

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Appendix: B

IEEE-30 Bus System (DGL)

Unit	P_{\max}	P_{\min}	a	b	c	UT(h)	UD(h)	Start up cost(\$)
Unit 1	80	30	302.79	40	0.01	12	12	8000
Unit 2	80	30	309.61	40	0.01	12	12	8000
Unit 3	50	20	312.05	40	0.01	3	3	5000
Unit 4	50	20	330.52	40	0.01	3	3	5000
Unit 5	30	0	0	40	0.01	1	1	100
Unit 6	30	0	0	40	0.01	1	1	100

Appendix: C

Load data for IEEE-30 Bus System

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load	185	175	165	175	168	170	150	160	170	180	190	220
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load	230	240	270	280	270	250	230	190	195	200	220	200

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Appendix A. Parameter settings for PSO

Parameter	Setting
W_{\max}	0.9
W_{\min}	0.4
c_{1i}, c_{2f}	2.5
c_{1f}, c_{2i}	0.2
C_r	0.6
No. of iterations	1000
Trial runs	25
Population size N_p	60