

An Efficient Particle Swarm Optimization with Time Varying Acceleration Coefficients to Solve Economic Dispatch Problem with Valve Point Loading

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Abstract This paper proposes a particle swarm optimization approach with time varying acceleration coefficients (TVAC_PSO) for an extensive study of the economic dispatch problem with valve point loading (EDVPL). An optimal short-term thermal generation schedule for 24 time intervals has been presented for the same purpose. In this paper, transmission losses and valve-point loading (VPL) have been considered. The VPL effect results in higher order nonlinearities in the input-output characteristics of a generator. For demonstrating the effectiveness of the proposed method two test systems, first one comprising of three generators and the second one comprising of thirteen generators, have been considered. The performance of the proposed method has been compared with various PSO strategies. The results show that the proposed TVAC_PSO strategy provides comparatively better solutions in terms of total fuel cost as compared to other PSO strategies. Also, the global search capability is enhanced and premature convergence is avoided.

Keywords Economic Dispatch, Particle Swarm Optimization, Time Varying Acceleration Coefficients, Valve Point Loading

1. Introduction

Economic Dispatch (ED) is one of the most important issues in power system operation. The main aim of ED is to minimize the operating cost of units, while satisfying certain constraints [1-3]. Thus, it can be stated that 'the economic dispatch problem is to define the generation level of each plant so that the total cost of generation and transmission is minimum for a prescribed schedule of loads' [1]. Certain conventional methods have been developed in the previous years for solving the ED problem. Some of these methods include lambda-iteration method, direct search method, Newton-Raphson method, efficient method [1,5-7]. In these methods assumption is made that the incremental cost curves of the generators are monotonically increasing piece-wise linear. However, in practical case the cost curves of the generators are highly non-linear and hence, such an assumption may not give accurate results. The nonlinearities in the generator operation are due to valve-point loading effects, prohibited operating zones, etc. [1].

In recent years certain artificial intelligence (AI) techniques such as Fuzzy Logic (FL) [8,9], Artificial Neural

Network (ANN) [10-12], Genetic Algorithm (GA) [13-17], etc. have been successfully applied to the ED problems for units having non-linear cost functions. However, problem faced by FL is its low accuracy and large computational complexity. In ANN adopting an unsuitable sigmoidal function may suffer from excessive numerical iterations, resulting in huge calculations.

GA, which emulates from natural genetic operations, has emerged as a candidate for many optimization problems (including ED) due to its flexibility and efficiency. GA is a stochastic searching algorithm. In some GA applications, certain constraints including network losses and valve-point effects were considered for the practicability of the proposed method. Among these Walters and Sheble [13] presented a GA model for solving the ED problem including valve-point effects. Also Chen and Chang [15] presented a model that included network losses and valve-point effects. For an efficient solution to the ED problem, Chiang [17] and Amjady and Nasiri-Rad [18] presented improved and real-coded GA models respectively that can obtain high quality solutions in lesser time.

Although the GA model has been employed successfully in various optimization problems, recent researches show some difficulties with its implementation. GA shows quiet a large inefficiency when being implemented to objective functions in which the parameters to be optimized are highly correlated [19]. Also premature convergence is another

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problem that reduces its searching capability[20].

Particle swarm optimization(PSO) was developed by Kennedy and Eberhart in 1995 motivated by social behavior of organisms such as fish schooling and bird flocking[21]. It is one of the modern heuristic algorithms and has been found to be efficient and robust in solving non-linear problems[21-23]. The PSO technique can generate high quality solutions taking lesser computational time and providing a faster convergence as compared to other AI techniques[20,24-25,31]. In standard PSO(PSO)[21], particles move around in the search space with the help of two accelerating components. One component, known as the cognitive component, controls the local exploration of the particles, while the second component, known as the social component, guides the global search capability of the particles. Kennedy and Eberhart[21] have shown that a high value of the local component will result in excessive exploration of the particles through the search space while a high value of the social component will result in a premature convergence of the particles. Various researchers[23,26,32-34] have found that the SPSO quickly finds a good local solution but gets stuck to it for rest of the iterations without a further improvement.

In order to overcome the above problems, a time varying acceleration coefficient[26] PSO(TVAC_PSO) strategy has been employed in this paper. The TVAC_PSO strategy finds a proper balance between the local and the global component and hence, the problem of premature convergence has been overcome to a much greater extent. The performance of the proposed TVAC_PSO strategy has been compared with SPSO[21], New PSO[27] and Anti-predatory PSO[28]. In order to show the superiority of the TVAC_PSO strategy over other strategies two test systems have been taken. The first test system consists of three generating units[13] while the second test system contains thirteen generating units[30]. A 24-hour short-term thermal generation schedule[4] has been presented for the three generator system with a peak demand of 850 MW to further add to the effectiveness of the proposed strategy.

2. Economic Dispatch with Valve-Point Loading(EDVPL)

The input-output characteristics(or cost functions) of a generator are approximated using quadratic or piece-wise quadratic functions, under the assumption that the incremental cost curves of the units are monotonically increasing piece-wise linear functions. However, real input-output characteristics display higher order nonlinearities and discontinuities due to valve point loading(VPL) in fossil fuel burning plants. The valve-point loading effect has been modeled in as a recurring rectified sinusoidal function[1].

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost functions. The valve-point effects introduce ripples in the heat-rate curves.

Mathematically, ED problem considering VPL[1] is defined as:

$$F(P_{gi}) = a_i P_{gi}^2 + b_i P_{gi} + c_i + |d_i * \sin(e_i * (P_{gimin} - P_{gi}))| \quad (1)$$

Where,

$F(P_{gi})$ is the fuel cost,

P_{gi} is the active power generated,

and a_i, b_i, c_i, d_i, e_i are the fuel cost coefficients of the i_{th} generator.

The objective of the EDVPL problem is to determine the optimal power output P_{gi} of each of the generators for a total load demand of P_D . Total fuel cost F_{total} for NG generators is minimized subject to the equality and the inequality constraints. Hence, the optimization problem can be stated as[1]:

Minimize

$$F_{total} = \sum_{i=1}^{NG} F(P_{gi}) \quad (2)$$

subject to the constraints given as:

a) the equality constraint–

$$\sum_{i=1}^{NG} F(P_{gi}) = P_D + P_L \quad (3.1)$$

b) the inequality constraint–

$$P_{gimin} \leq P_{gi} \leq P_{gimax} \quad (3.2)$$

The total transmission losses P_L is a function of unit power outputs that can be expressed using B-coefficients as[1]

$$P_L = \sum_{i=1}^{NG} P_i \sum_{j=1}^{NG} B_{ij} P_j + \sum_{i=1}^{NG} P_i B_{0i} + B_{00} \quad (4)$$

3. Review of Various PSO Strategies

Since the introduction of the PSO, various PSO based strategies have been successfully applied to deal with the ED problems. Some of the PSO strategies applied to the ED problems are presented briefly in this paper and their performances have been compared with the presented TVAC_PSO strategy.

3.1. Standard PSO(SPSO)

SPSO[21], as an optimization tool, provides a population-based search procedure in which individuals called *particles* change their position(states) with time. In a PSO system, particles fly around in a multi-dimensional search space. During flight, each particle adjusts its position according to its own experience and the experience of neighbouring particles, making use of the best position encountered by it and neighbours. The swarm direction of a particle is defined by the set of particles neighbouring the particle and its history experience. Instead of using evolutionary operation to manipulate the individuals, like in other evolutionary computational algorithms, each individual in PSO flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and its companions flying experience. Let p and v denote a particle's co-ordinate(position) and its corresponding flight speed(velocity) in a search space respectively. Therefore, each i_{th} particle is treated as a volume less particle, represented as $p_i = (p_{i1}, p_{i2}, \dots, p_{id})$ in the d -dimensional space.

The best previous position of the i_{th} particle is recorded and represented as $p_{besti} = (p_{besti1}, p_{besti2}, \dots, p_{bestid})$. The index of the best particle among all the particles is treated as global best particle, is represented as g_{bestd} . The velocity for the i_{th} particle is represented as $v_i = (v_{i1}, v_{i2}, \dots, v_{id})$.

The modified velocity and position of each particle can be calculated using the current velocity and the distance from p_{besti} to g_{bestd} as shown in the following formulas,

$$v_{id}^{(t+1)} = v_{id}^t * w + c_1 * rand() * (p_{bestid}^t - p_{id}^t) + c_2 * Rand() * (g_{bestd}^t - p_{id}^t) \quad (5)$$

$$p_{id}^{(t+1)} = p_{id}^t + v_{id}^{(t+1)} \quad (6)$$

In the above equation, c_1 and c_2 are known as the acceleration coefficients that pull each particle towards the p_{best} and g_{best} positions. $Rand()$ and $rand()$ are the uniform random numbers between [0,1]. The term $rand() * (p_{bestid}^t - p_{id}^t)$ is called the cognitive component. The term $Rand() * (g_{bestd}^t - p_{id}^t)$ is called the social component. w is the inertia weight factor. Low values of acceleration coefficients allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past target regions. Hence, the acceleration constants c_1 and c_2 are often set to be 2.0 according to past experiences.

A large inertia weight factor enhances global exploration while a low inertia weight factor helps in local search. Hence, a suitable selection of inertia weight provides a balance between global and local explorations, thus requiring lesser iterations on average to find a sufficiently optimal solution. As originally developed [23], w often decreases linearly from about 0.9 to 0.4 during a run. In general, the inertia weight w is set according to the following equation,

$$w = w_{max} - [(w_{max} - w_{min}) * It] / (It_{max}) \quad (7)$$

Here w_{max} is the maximum inertia weight, w_{min} is the minimum inertia weight, It is current no. of iterations, It_{max} is maximum no. of iterations.

3.2. New PSO(NPSO)

A new variation in the SPSO by splitting the cognitive component of the SPSO into two different components was proposed by Selvakumar and Thanushkodi [27]. The first component is called good experience component. That is, the particle has a memory about its previously visited best position. This component is exactly the same as the cognitive component of the SPSO. The second component is given the name bad experience component. The bad experience component helps the particle to remember its previously visited worst position. To calculate the new velocity, the bad experience of the particle is also taken into consideration. The new velocity update equation proposed is given by

$$v_{id}^{(t+1)} = v_{id}^t * w + c_{1g} * rand1() * (p_{bestid}^t - p_{id}^t) + c_{1b} * rand2() * (p_{id}^t - p_{worstd}^t) + c_2 * Rand() * (g_{bestd}^t - p_{id}^t) \quad (8)$$

The acceleration coefficients c_{1g} and c_{1b} help the particles to move towards their previous best positions and away from their previous worst positions respectively thereby

increasing the exploration capability. p_{worstd}^t is dimension d of the own worst position of the i_{th} particle until iteration t .

3.3. Anti-predatory PSO(APSO)

Another SPSO variant proposed by Selvakumar and Thanushkodi [28] included an anti-predatory property. The anti-predatory property, which is natural among particles, helps the swarm escape from the predators. This strategy models the predators as the worst result points and the new model is named anti-predatory PSO. The APSO is developed by splitting both the cognitive and the social behaviours of the SPSO. Here, along with the cognitive component, the social component is also split into global good experience and global bad experience components. The velocity update equation of the APSO model is given by

$$v_{id}^{(t+1)} = v_{id}^t * w + c_{1g} * rand1() * (p_{bestid}^t - p_{id}^t) + c_{1b} * rand2() * (p_{id}^t - p_{worstd}^t) + c_{2g} * Rand1() * (g_{bestd}^t - p_{id}^t) + c_{2b} * Rand2() * (p_{id}^t - g_{worstd}^t) \quad (9)$$

Here, g_{worstd}^t is global worst position of member d until iteration t . The acceleration coefficient c_{2g} helps the particles to accelerate towards their previous global best positions and c_{2b} helps the particles to move away from their previous worst positions. By using the bad experiences, particle always by-passes its previous worst positions. Hence, exploration capability is further enhanced.

4. Proposed PSO strategy

4.1. PSO with Time-varying Acceleration Coefficients (TVAC_PSO)

In this paper, the TVAC_PSO [26] strategy has been used to solve the EDVPL problems. Basic purpose of using the time varying acceleration coefficients is to improve the global exploration in the early part of the process and to enhance the convergence of the particles in the later stages of the process. This is done by varying the acceleration coefficients c_1 and c_2 with time in such a manner that the cognitive component reduces and the social component increases as iterations increase. In short, it can be stated that a large cognitive component and a small social component at the beginning of the process help the particles to explore the search space in a better way while a smaller cognitive component and a larger social component at later stages of the process allow the particles to converge to the global optima. The time varying acceleration coefficients are given as [29]:

$$c_1 = (c_{1f} - c_{1i}) * (It/It_{max}) + c_{1i} \quad (10)$$

$$c_2 = (c_{2f} - c_{2i}) * (It/It_{max}) + c_{2i} \quad (11)$$

Where c_{1i} , c_{1f} , c_{2i} and c_{2f} are initial and final values of the cognitive and social acceleration coefficients respectively.

4.2. Algorithm for TVAC_PSO

The sequential steps of the proposed TVAC_PSO strategy are given below.

Step1: Representation of the swarm- Since the decision variables of the economic dispatch problem are the real power generations, they are used to form the swarm. The set of real power output(P_g) of all the generators is represented as the position of the particle in the swarm. For a system with NG generators, the particle position is represented as a vector of length NG . If there are NP particles in the swarm, the complete swarm is represented as a matrix as shown below:

$$\text{Swarm} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1NG} \\ P_{21} & P_{22} & \dots & P_{2NG} \\ \vdots & \vdots & \ddots & \vdots \\ P_{NP1} & P_{NP2} & \dots & P_{NPNG} \end{bmatrix}$$

Where P_{ij} is the j th position component of particle i and it represents the real power generation of generator j of the possible solution i .

Step2: Initialization of the swarm- The particles of the swarm are initialized randomly according to the limit of each generating unit. These initial particles must be feasible candidate solutions that must satisfy the operating constraints.

Step3: Evaluation of objective function- In order to satisfy the equality constraint(3), a generator is arbitrarily selected as a dependent generator(P_{dep}) whose generation is calculated as given below:

$$P_{dep} = (P_D) - \begin{cases} P_L - \sum_{i=1, i \neq dep}^{NG} P_{gi}; & \text{if } P_L \neq 0 \\ \sum_{i=1, i \neq dep}^{NG} P_{gi}; & \text{if } P_L = 0 \end{cases} \quad (12.1) \quad (P_D) - \sum_{i=1, i \neq dep}^{NG} P_{gi}; \quad \text{if } P_L = 0 \quad (12.2)$$

If the output of the dependent generator violates its lower limit, its output is set equal to its lower limit and if it violates its upper limit, its output is set equal to its upper limit. An output between the lower and upper limit is automatically acceptable.

The operating cost of individual generating unit is calculated using(1) and hence the total operating cost can be calculated using(2).

Step4: Initialization of best positions- In the PSO strategy, the particle's best position, p_{bestid} and global best position, g_{bestd} are the key factors. The position with minimum objective function value is the particle's best position. The best position out of all the p_{bestid} is taken as g_{bestd} .

Step5: Movement of the particles- Particles in the swarm are accelerated to new positions by adding new velocities to their current positions. The new velocity is calculated using the equation:

$$v_{id}^{(t+1)} = v_{id}^t * w + ((c_{1f} - c_{1i}) * (It/It_{max}) + c_{1i}) * rand() * (p_{bestid}^t - p_{id}^t) + ((c_{2f} - c_{2i}) * (It/It_{max}) + c_{2i}) * Rand() * (g_{bestd}^t - p_{id}^t) \quad (13)$$

The positions of the particles are updated using(6).

Step6: Updating the best positions- If the evaluation value of each particle is better than previous p_{bestid} , the current value is set to p_{bestid} . If the best p_{bestid} is better than g_{bestd} , this new value is set as g_{bestd} . An objective function value at g_{bestd} is set as F_{best} .

Step7: Stopping criterion- If the number of iterations

reaches the maximum than the process is stopped and F_{best} is the minimum generation cost of the economic dispatch problem. Otherwise, the above process is repeated from step2.

5. Test Systems and Results

In order to show the superiority of the TVAC_PSO strategy over other PSO strategies discussed before, two test systems have been taken into consideration. The first test system consists of three generating units[13] with a load demand of 850 MW. The second test system has been taken from[30] which consist of 13 generating units with a load demand of 1800 MW. In this paper following parameters have been used for different PSO strategies: For NPSO, $c_{1g} = 1.6$, $c_{1b} = 0.4$ and $c_2 = 2$ [27] have been used. For APSO, $c_{1g} = 1.6$, $c_{1b} = 0.4$, $c_{2g} = 1.8$ and $c_{2b} = 0.2$ [28] have been adopted. For TVAC_PSO, [26] suggests that the values for c_1 should vary from 2.5 to 0.5 and from 0.5 to 2.5 in case of c_2 for best results.

Case1: Three-Generator system

For this system a population size of 20 has been taken with maximum number of iterations as 200. Losses have also been calculated using the loss coefficients given in[13] by using equation(4). Power generation of each generator, generating cost and losses corresponding to different PSO strategies have been shown in table 1. Convergence characteristics of each PSO model are shown in figure 1.

Table 1. Optimal results for 3 generator system including losses($P_D = 850$ MW)

Power output(MW)	SPSO	NPSO	APSO	TVAC_PSO
P1	399.3723	399.8393	400.4504	399.1669
P2	325.7694	326.5124	326.1388	326.8991
P3	150.6753	149.4418	149.1996	149.7331
Losses(MW)	25.8170	25.7936	25.7890	25.7991
Cost(\$/hr)	8453.6077	8449.3794	8443.5561	8440.7647

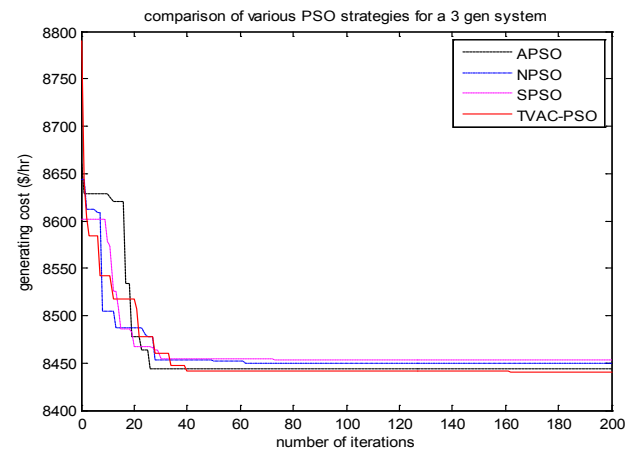


Figure 1. Convergence characteristics of different PSO strategies(3-generator system)

Table 2. Optimal results for 13 generator system excluding losses($P_D=1800$ MW)

Power output(MW)	SPSO	NPSO	APSO	TVAC_PSO
P1	538.5587	538.5042	539.1930	628.3185
P2	149.5459	298.7765	297.6252	223.5256
P3	224.3200	301.2419	312.2458	298.4228
P4	154.8511	60.0310	60.0280	60.0000
P5	109.8372	60.0000	60.0000	60.0000
P6	109.2508	60.0000	60.0000	60.0000
P7	60.0000	60.0120	60.0000	60.0000
P8	60.0000	60.0000	60.0000	60.1560
P9	60.0000	106.4773	160.7820	159.5771
P10	113.0114	40.1120	40.1050	40.0000
P11	73.2248	40.0000	40.0000	40.0000
P12	92.3999	55.2250	55.0210	55.0000
P13	55.0000	119.6200	55.0000	55.0000
Cost(\$/hr)	18156.0423	18133.1781	18105.7977	17989.0048

Table 3. Short-term thermal generation scheduling for case 1(Peak Demand= 850 MW)

Time interval	Demand(MW)	P1(MW)	P2(MW)	P3(MW)	Generation Cost(\$/hr)	Losses(MW)
1	490	299.4235	165.8151	50.0000	5299.7132	23.8842
2	493	299.3172	167.5672	50.0000	5301.74552	23.8843
3	495	299.4662	169.4179	50.0003	5302.2856	23.8844
4	499	299.4661	173.1361	50.2878	5308.0231	23.8900
5	506	299.4662	180.0012	50.4255	5410.2912	23.8929
6	513	299.4676	187.4176	50.0000	5524.1834	23.8852
7	537	299.4662	174.7272	87.4010	5731.8712	24.5944
8	588	299.4662	175.3221	138.7424	6186.6227	25.5710
9	605	299.6675	181.3801	149.7331	6303.0091	25.7808
10	651	299.7988	177.9412	200.0000	6724.9173	26.7400
11	699	399.1993	175.7951	149.7962	7093.7716	25.7962
12	755	399.2602	182.4889	200.0000	7685.5134	26.7491
13	793	399.1993	262.4881	157.2503	8077.7387	25.9377
14	812	399.4145	324.7318	112.9521	8186.1096	25.0984
15	831	399.1993	312.8684	149.7303	8399.4645	25.7979
16	850	399.1669	326.8991	149.7331	8440.7647	25.7991
17	824	399.1407	251.6786	199.9326	8229.0647	26.7519
18	756	306.7987	325.2584	149.7331	7650.0912	25.7901
19	809	399.1993	323.1519	111.7237	8161.6756	25.0749
20	688	298.5953	314.3775	99.8666	7047.5423	24.8393
21	625	299.8796	250.4649	99.4834	6407.7079	24.8279
22	540	299.4893	173.9640	91.2135	5737.5865	24.6668
23	495	299.4662	169.4179	50.0003	5302.2534	23.8844
24	490	299.4235	165.1851	50.0000	5299.7175	23.8842

Case2: Thirteen-Generator system

For this system population size has been taken as 30 and maximum number of iterations as 200. Losses have been neglected for this case. Power generation of each unit and

generating cost are shown in table 2. Corresponding convergence characteristics are shown in figure 2.

The effectiveness of the proposed TVAC_PSO strategy has been demonstrated with the help of the above two test

systems. The optimal generation costs for the three-generator system and the thirteen-generator system using TVAC_PSO are \$ 8440.7647 per hour (shown in bold in table 1) and \$ 17989.0048 per hour (shown in bold in table 2) respectively which are lower as compared to the other PSO strategies discussed. The cost convergence characteristics for the three-generator system and the thirteen-generator system have been shown in figures 1 and 2 respectively. From these it can be easily deduced that the proposed TVAC_PSO strategy is better as compared to other PSO strategies. The TVAC_PSO strategy for the three-generator system has been used for finding the optimal short-term generation schedule for 24 time intervals each of 1 hour [4] with a peak demand of 850 MW. The optimal generation schedule has been shown in table 3. Load profile during 24 time intervals is shown in figure 3.

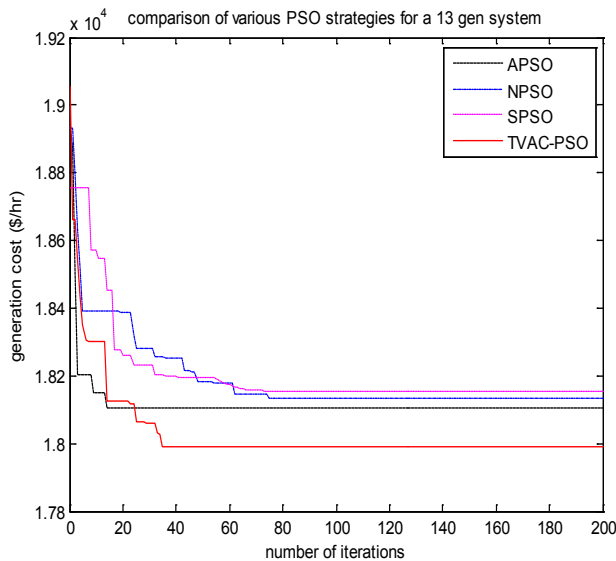


Figure 2. Convergence characteristics of different PSO strategies (13-generator system)

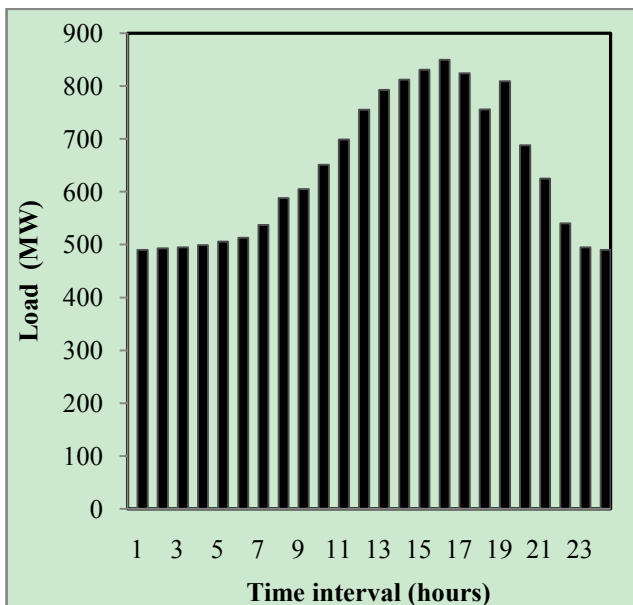


Figure 3. Load profile during 24 time intervals (each of 1 hour)

6. Conclusions

In this paper, the TVAC_PSO strategy has been applied to EDVPL problems. A 24-hour short-term thermal generation scheduling has been presented to further add to the effectiveness of the proposed strategy. The performance of this strategy has been compared with SPSO, NPSO and APSO. Two standard test systems have been used for comparison. It has been found that by using the time varying acceleration coefficients better results are obtained in respect with the generation cost. The TVAC help in avoiding the premature convergence and thus providing a stable convergence. The TVAC_PSO strategy outperforms other PSO strategies, particularly for EDVPL problems, in terms of solution quality, stable convergence and stability.

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