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Hybrid PSO-GSA Applied To Dynamic Economic Dispatch With Prohibited Operating Zones

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Abstract: *This paper proposes a novel and efficient hybrid algorithm based on combining particle swarm optimization (PSO) and gravitational search algorithm (GSA) techniques, called PSO-GSA. The core of this algorithm is to combine the ability of social thinking in PSO with the local search capability of GSA. Many practical constraints of generators such as ramp rate limits, prohibited operating zones, and transmission losses are considered. The new algorithm is implemented for solving the dynamic economic dispatch (DED) problem so as to minimize the total generation cost when considering the linear and non linear constraints. In order to validate of the proposed algorithm, it is applied to two cases with 6-unit and 15-unit power systems for 24-hour time interval, respectively. The results show that the proposed algorithms indeed produce more optimal solution in both cases when compared results of other optimization algorithms reported in literature.*

Keywords: *Dynamic economic dispatch, gravitational search algorithm, particle swarm optimization, prohibited operating zones, ramp rate limits.*

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I. Introduction

In the electric power system, there exit a wide range of problem involving optimization processes. Among of them, the power system scheduling is one of the most important problems in the operation and control. Dynamic economic dispatch (DED) is more realistic dispatch model than economic dispatch as a power system meets demand over several intervals. The objective is to determine the optimum power outputs of all the generating units by minimizing the total fuel cost. The DED schedules the generating outputs of all online units over a time horizon by taking the dynamic constraints of generators into account, whereas the traditional static economic dispatch allocates the outputs of all committed generating units by considering the static behavior of them. The DED problem is an extension of the traditional economic dispatch problem in which the ramp rate limits of the generators are taken into consideration. That makes the DED problem more difficult [1-3]. Regarding the DED problem, there were a number of traditional methods that have been applied to handle this problem such as dynamic programming [4], linear programming [5], and Lagrangian relaxation [6]. Unfortunately, for generating units with non-linear characteristics, such as ramp rate limits, prohibited operating zones, and non-convex cost functions, the conventional methods can hardly to obtain the optimal solution. Furthermore, for a large-scale power system, the conventional methods often oscillate which result in a local minimum solution or a longer solution time. In addition, as a new research, a new algorithm called Brent method was proposed to solve the DED problem and it is applied to determine the optimal lamda [7].

In recent years, evolutionary computation techniques have been developed and proposed so as to solve a wide range of power system problems including DED problem such as genetic algorithm (GA) [8], simulated annealing (SA) [9], differential evolution (DE) [10], artificial bee colony (ABC) algorithm [11], cuckoo search algorithm (CSA) [12], particle swarm optimization (PSO) [13-15], artificial immune system (AIS) [16], and Hopfield neural network (HNN) [17].

PSO is a stochastic algorithm that can be applied to nonlinear optimization problems. PSO has been developed from the simulation of simplified social systems such as bird flocking and fish schooling by Kennedy and Eberhart [18], [19]. The main difficulty classic PSO is its sensitivity to the choice of parameters and they also premature convergence, which might occur when the particle and group best solutions are trapped into local minimums during the search process. One of the recently improved heuristic algorithms is the gravitational search algorithm (GSA) based on the Newton's law of gravity and mass interactions [20]. GSA has been tested to have high quality performance in solving different optimization problems in the literature [20]. The same goal for them is to find the best outcome (global optimum) among all possible inputs. In order to do this, a heuristic algorithm should be equipped with two major characteristics to ensure finding global optimum. These two main characteristics are exploration and exploitation [21].

This paper presents a novel optimization method based on hybrid PSO-GSA algorithm applied to dynamic economic dispatch in a practical power system while considering some nonlinear characteristics of a generator such as the ramp rate limits, prohibited operating zones, and transmission losses. The proposed method is tested for two different test systems and the results are compared with other methods reported in recent literature in order to demonstrate its performance.

II. Problem Formulation

The main goal of DED problem is to minimize the total production cost over the operation period, which can be written as follows:

$$\min F_T = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{i,t}(P_{i,t}) = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(a_i P_{i,t}^2 + b_i P_{i,t} + c_i\right) \quad \text{for } i = 1,2,\cdots,N;\ t = 1,2,\ldots,T \tag{1}$$

where $F_{i,t}$ is the fuel cost of unit i at time interval t in \$/hr, a_i, b_i, and c_i are the cost coefficients of generating unit i, $P_{i,t}$ is the real power output of generator unit i at time period t in MW, and N is the number of generators. T is the total number of hours in the operating horizon.

The objective function of the DED problem should be minimized subject to following equality and inequality constraints:

2.1 Active power balance equation

The total power output should be the same as total load demand plus the total line loss.

$$\sum_{i=1}^{N} P_{i,t} = P_{D,t} + P_{L,t} \tag{2}$$

where $P_{D,t}$ and $P_{L,t}$ are the load demand and transmission loss in MW at time interval t, respectively.

The transmission loss $P_{L,t}$ can be expressed by using ***B*** matrix technique and is defined by (3) as,

$$P_{L,t} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{i,t} B_{ij} P_{j,t} + \sum_{i=1}^{n} B_{0i} P_{i,t} + B_{00} \tag{3}$$

where B_{ij}, B_{0i}, and B_{00} are coefficient of transmission loss.

2.2 Minimum and maximum power limits

The real power output of each generator should lie between minimum and maximum limits. The corresponding inequality constraint for each generator is,

$$P_{i,\min} \le P_{i,t} \le P_{i,\max} \tag{4}$$

where $P_{i,\,min}$ and $P_{i,\,max}$ indicates respectively the minimum and maximum limits of the real power output of unit i in MW.

2.3 Ramp rate limits

The actual operating ranges of all generating units are restricted by their corresponding ramp rate limits. The ramp-up and ramp-down constraints can be written as (5) and (6), respectively.

$$P_{i,t} - P_{i,t-1} \le UR_i \tag{5}$$

$$P_{i,t-1} - P_{i,t} \le DR_i \tag{6}$$

where $P_{i,t}$ and $P_{i,t-1}$ are respectively the present and previous the real power outputs. UR_i and DR_i are the ramp-up and ramp-down limits of unit i (in units of MW/time period). Then the ramp rate constraints is expressed as:

$$\max\{P_{i,\min}, P_{i,t-1} - DR_i\} \le P_{i,t} \le \min\{P_{i,\max}, P_{i,t-1} + UR_i\} \tag{7}$$

2.4 Prohibited operating zones

The generating units with prohibited operating zones, there are additional constraints on the unit operating range as follows:

$$P_{i,t} \in \begin{cases} P_{i,\min} \le P_{i,t} \le P_{i,1}^{l} \\ P_{i,k-1}^{u} \le P_{i,t} \le P_{i,k}^{l}, \quad k = 2,3,\ldots,pz_i \\ P_{i,pz_i}^{u} \le P_{i,t} \le P_{i,\max},\ i = 1,2,\ldots,n_{pz} \end{cases} \tag{8}$$

where $P_{i,k}^{l}$ and $P_{i,k}^{u}$ are the lower and upper boundary of prohibited operating zone of unit *i*, respectively. Here, pz_i indicate the number of prohibited zones of unit *i* and n_{pz} is the number of units which have prohibited operating zones.

III. Meta-Heuristic Optimization

3.1 Overview of particle swarm optimization

The particle swarm optimization (PSO) algorithm is proposed by Kennedy and Eberhart based on the social behavior metaphor. In PSO a potential solution for a problem is considered as a bird without quality and volume, which is called a particle, flying through a D-dimensional space, adjusting its position in search space according to its own experience and its neighbors. In PSO, the *i*-th particle is represented by its position vector x_i in the D-dimensional space and its velocity vector v_i. In each time step *t*, the particles calculate their new velocity then update their position according to equations (10) and (11) respectively.

$$\begin{aligned} v_i^{t+1} = w \times v_i^t + c_1 \times r_1 \times \left(pbest_i - x_i^t\right) + \\ c_2 \times r_2 \times \left(gbest - x_i^t\right) \end{aligned} \tag{9}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{10}$$

$$w = w_{\max} - \left(\frac{(w_{\max} - w_{\min}}{Iter_{\max}} \right) \times Iter \tag{11}$$

where v_i^t is velocity of particle *i* at iteration t, *w* is inertia factor, c_1 and c_2 are accelerating factor, r_1 and r_2 are positive random number between 0 and 1, $pbest_i$ is the best position of particle *i*, *gbest* is the best position of the group, w_{max} and w_{min} are maximum and minimum of inertia factor, $Iter_{max}$ is maximum iteration, *n* is number of particles.

The process of implementing the PSO is as follows:

Step 1: Create an initial population of individual with random positions and velocity within the solution space.

Step 2: For each individual, calculate the value of the fitness function.

Step 3: Compare the fitness of each individual with each *Pbest*. If the current solution is better than its *Pbest*, then replace its *Pbest* by the current solution.

Step 4: Compare the fitness of all individual with *Gbes*t. If the fitness of any individual is better than *Gbest*, then replace *Gbest*.

Step 5: Update the velocity and position of all individual according to (9) and (10).

Step 6: Repeat steps 2-5 until a criterion is met.

3.2 Gravitational search algorithm (GSA)

In this section will be discussed about GSA proposed by E. Rashedi et al in 2009 [20]. The basic physical theory which GSA is inspired from the Newton's theory. This algorithm, which is based on the Newtonian physical law of gravity and law of motion, has great potential to be a breakthrough optimization method. In the GSA, consider a system with *N* agent (mass) in which position of the *i-th* mass is defined as follows:

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^n\right), \quad i = 1,2,\ldots,m \tag{12}$$

where x_i^d is position of the *i-th* mass in the *d-th* dimension and *n* is dimension of the search space. At the specific time *t* a gravitational force from mass *j* acts on mass *i*, and is defined as follows:

$$F_{ij}^d(t) = G(t) \frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon} \left(x_j^d(t) - x_i^d(t)\right) \tag{13}$$

where M_i is the mass of the object *i*, M_j is the mass of the object *j*, *G(t)* is the gravitational constant at time *t*, R_{ij} *(t)* is the Euclidian distance between the two objects *i* and *j*, and *ε* is a small constant.

The total force acting on agent *i* in the dimension *d* is calculated as follows:

$$F_i^d(t) = \sum_{\substack{j=1 \\ j \neq i}}^{m} rand_j F_{ij}^d(t) \tag{14}$$

where $rand_j$ is a random number in the interval [0, 1].

According to the law of motion, the acceleration of the agent *i*, at time *t*, in the *d-th* dimension, $a_i^d(t)$ is given as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{15}$$

Furthermore, the next velocity of an agent is a function of its current velocity added to its current acceleration. Hence, the next position and velocity of an agent can be calculated as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{16}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{17}$$

where $rand_i$ is a uniform random variable in the interval [0, 1].

The gravitational constant, G, is initialized at the beginning and will be decreased with time to control the search accuracy. In other words, G is a function of the initial value (G_0) and time t:

$$G(t) = G(G_0, t) \tag{18}$$

$$G(t) = G_0 e^{-\frac{t}{T}} \tag{19}$$

The masses of the agents are calculated using fitness evaluation. A heavier mass means a more efficient agent. This means that better agents have higher attractions and moves more slowly. Supposing the equality of the gravitational and inertia mass, the values of masses is calculated using the map of fitness. The gravitational and inertial masses are updating by the following equations:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{20}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{m} m_j(t)} \tag{21}$$

where $fit_i(t)$ describes the fitness value of the agent i at time t, and the $best(t)$ and $worst(t)$ in the population respectively indicate the strongest and the weakest agent according to their fitness route. For a minimization problem:

$$best(t) = \min_{j \in [1,\ldots,m]} fit_j(t) \tag{22}$$

$$worst(t) = \max_{j \in [1,\ldots,m]} fit_j(t) \tag{23}$$

The GSA approach for optimization problem can be summarized as follows [20]:

Step 1: Search space identification,
Step 2: Generate initial population between minimum and maximum values,
Step 3: Fitness evaluation of agents,
Step 4: Update $G(t)$, $best(t)$, $worst(t)$ and $M_i(t)$ *for* $i = 1,2,\ldots,m$,
Step 5: Calculation of the total force in different directions,
Step 6: Calculation of acceleration and velocity,
Step 7: Updating agents' position,
Step 8: Repeat step 3 to step 7 until the stop criteria is reached,
Step 9: Stop.

3.3 The hybrid PSO-GSA

A new approach is integrated between PSO and GSA to incorporate social thinking (*gbest*) in PSO with the local search capabilities of GSA. In order to combine these algorithms, the updated velocity of agent i can be calculated as follows:

$$\begin{aligned} V_i(t+1) = w \times V_i(t) + c_1 \times rand_i \times a_i(t) + \\ c_2 \times rand_i \times (gbest - X_i(t)) \end{aligned} \tag{24}$$

where V_i(t) is the velocity of agent i at iteration t, c_j is a weighting factor, w is a weighting function, *rand* is a random number between 0 and 1, a_i(t) is the acceleration of agent i at iteration t, and *gbest* is the best solution so far.

The position of the particles at each iteration updated as follow:

$$X_i(t+1) = X_i(t) + V_i(t) \tag{25}$$

The process of the proposed PSO-GSA algorithm can be summarized as the following steps:

Step 1: Get the data for the system,
Step 2: Generate initial population,
Step 3: Fitness evaluation of agents,
Step 4: Update $G(t)$ and $gbest(t)$,
Step 5: Calculation of the mass of the object, gravitational constant, the total force, and acceleration,
Step 6: Updating agents' velocity and position,

Step 7: Repeat step 3 to step 6 until the stop criteria is reached,
Step 8: Stop.

IV. Simulation Results

To verify the feasibility of the proposed hybrid PSO-GSA method, 6-unit and 15-unit power systems was tested. The generating unit operational constraint, ramp rate limits, prohibited operating zones, and transmission losses are considered. The results obtained from the proposed method were compared in terms of the solution quality and computation efficiency with those reported in the literature. The algorithm was implemented in MATLAB 7.1 on a PC with Pentium IV 3.6 GHz processor and 2 GB RAM. All cases in the simulation, the dispatch horizon is selected as one day with 24 dispatch periods of each one hour. The data employed for the 6-unit and 15-unit power systems can be found from [7, 15, 22], as given in Appendix. During normal operation of the system, the loss coefficients ***B*** with the 100-MVA base is taken from [7, 22] and ***B*** loss coefficients matrix for the sample test systems are given in Appendix.

The PSO-GSA parameters used for the simulation are adopted as follow: c_1 = 0.5, c_2 = 1.5, w = rand[0, 1], α = 20 and G_0 = 100. The population size N and maximum iteration number T are set to 30 and 100, respectively, for all case studies.

Case 1: 6-unit system

The system contains 6-unit power system and the details including cost coefficients, generation limits, ramp rate limits, prohibited operating zones, transmission loss coefficients and forecasted load demand of each interval are presented in the literature [7, 15, 22]. The one day scheduling period is divided into 24 intervals. The optimal dispatch of generating units is determined by the proposed hybrid PSO-GSA technique. The minimum and maximum operating limit of each generating unit is obtained by enforcing the ramp down and ramp up limits of generating unit with the real power dispatch of previous interval. In the scheduling period, respectively the minimum and maximum load demand are 930 MW and 1263 MW. The optimal dispatches of the entire scheduling period are presented in Table I. The results of the proposed hybrid PSO-GSA method are compared with those obtined by the FEP, IFEP, PSO, and HNN from [17] in terms generation cost and computational time as shown in Table II. From the comparison, it is clear that the proposed methodology provides an improvement in the total cost savings.

Case 2: 15-unit system

The cost coefficients, maximum and minimum generation limits, ramp rate limits, prohibited operating zones, load demand for each interval and the transmission loss coefficients are presented in the literature [7, 15, 22]. The one day scheduling period is considered and the scheduling period is divided into 24 equal intervals. The minimum and maximum load demands of the scheduling period are 2226 and 2970 MW. The results of the proposed hybrid PSO-GSA method are compared with those obtined by the FEP, IFEP, PSO, and HNN from [17] in terms generation cost and computational time as shown in Table II. The comparison clearly indicates that the proposed methodology provides a better schedule than recent reports.

Table I Best solution of the proposed method

Hour	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Cost ($)	Ploss (MW)
1	383.6824	124.6022	206.6448	86.7726	110.4845	50.0000	11419.3331	7.1865
2	380.4720	122.2340	204.2085	84.1053	107.9790	50.0000	11256.6052	6.9987
3	378.7439	120.9590	202.8970	82.6694	106.6294	50.0000	11169.2393	6.8987
4	377.5093	120.0468	201.9618	81.6441	105.6659	50.0000	11106.9451	6.8278
5	378.7437	120.9595	202.8977	82.6693	106.6285	50.0000	11169.2393	6.8987
6	385.6583	126.0645	208.1443	88.4131	112.0232	50.0000	11519.7817	7.3034
7	392.0814	130.8024	213.0172	93.7584	117.0309	50.0000	11847.8631	7.6904
8	400.3206	136.8293	219.2318	100.5863	123.3995	50.8338	12280.6356	8.2012
9	421.5046	152.4959	235.4297	118.4395	139.8703	67.9289	13614.0612	9.6689
10	426.4599	156.1505	239.2104	122.6105	143.7034	71.9029	13929.4373	10.0375
11	437.0024	163.9188	247.2458	131.5020	151.8417	80.3430	14605.4961	10.8537
12	444.0347	169.1111	252.6163	137.4408	157.2695	85.9509	15060.6566	11.4233
13	434.7267	162.2394	245.5132	129.5815	150.0899	78.5232	14459.0018	10.6739
14	447.3548	171.5469	255.1408	140.2409	159.8175	88.5971	15276.0850	11.6980
15	449.8394	173.3806	257.0345	142.3450	161.7322	90.5752	15438.1757	11.9070
16	447.1434	171.3931	254.9748	140.0742	159.6597	88.4351	15262.5975	11.6805
17	441.1456	166.9668	250.4113	134.9880	155.0353	83.6395	14872.8055	11.1866
18	437.2083	164.0730	247.4059	131.6741	152.0030	80.5059	14618.8323	10.8703
19	428.3230	157.5183	240.6211	124.1788	145.1419	73.3952	14048.1599	10.1782
20	414.4876	147.3270	230.0815	112.5320	134.4419	62.2941	13170.3067	9.1641
21	399.8716	137.0079	219.3934	100.7643	123.5656	50.6023	12280.6383	8.2050

22	390.8459	129.8911	212.0797	92.7303	116.0682	50.0000	11784.5776	7.6151
23	388.6220	128.2502	210.3923	90.8802	114.3359	50.0000	11670.8952	7.4806
24	384.9163	125.5144	207.5814	87.8000	111.4473	50.0000	11482.0859	7.2594
Total							**313343.4550**	**217.9075**

Table II Comparison of best costs and computing time for two test systems

Method	Total generation cost ($)		Computing time (s)	
	6-units	15-units	6-units	15-units
FEP [17]	315634	796642	357.58	362.63
IFEP [17]	315993	794832	546.06	574.85
PSO [17]	314782	774131	2.27	3.31
Hybrid HNN [17]	313579	759796	1.52	2.22
Hybrid PSO-GSA	313343.4550	759080.1444	1.30	2.09

V. Conclusion

This paper has presented a novel approach based on hybrid PSO-GSA for solving DED problem. The test systems used to validate the proposed method considered most of the practical aspects of the all thermal generation systems such as ramp rate limits, prohibited operating zones, and transmission losses. The effectiveness of the proposed method is illustrated by using a 6-unit and 15-unit power systems and compared with the results obtained from other method. It is evident from the comparison that the proposed method provides better results than other methods in terms of minimum production cost and computation time.

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APPENDIX

Table A Generating unit capacity and coefficients (6-unit system)

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a_i ($/MW^2)	b_i ($/MW)	c_i ($)
1	100	500	0.0070	7.0	240
2	50	200	0.0095	10.0	200
3	80	300	0.0090	8.5	220
4	50	150	0.0090	11.0	200
5	50	200	0.0080	10.5	220
6	50	120	0.0075	12.0	190

Table B Ramp-rate limits and prohibited operating zones of generating units (6-unit system)

Unit	P_i^0	UR_i (MW/h)	DR_i (MW/h)	Prohibited zones (MW)
1	440	80	120	[210 – 240] [350 – 380]
2	170	50	90	[90 – 110] [140 – 160]
3	200	65	100	[150 – 170] [210 – 240]
4	150	50	90	[80 – 90] [110 – 120]
5	190	50	90	[90 – 110] [140 – 150]
6	110	50	90	[75 – 85] [100 – 105]

Table C Load demand for 24 hours (6-unit system)

Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)
1	955	7	989	13	1190	19	1159
2	942	8	1023	14	1251	20	1092
3	935	9	1126	15	1263	21	1023
4	930	10	1150	16	1250	22	984
5	935	11	1201	17	1221	23	975
6	963	12	1235	18	1202	24	960

Transmission loss coefficient for 6-unit system,

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_{0i} = 1.0e^{-3} * [-0.3908 \quad -0.1297 \quad 0.7047 \quad 0.0591 \quad 0.2161 \quad -0.6635]$$

$$B_{00} = 0.0056$$

Table D Generating unit data for 15-unit system

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a_i ($/MW^2)	b_i ($/MW)	c_i ($)	UR_i (MW/h)	DR_i (MW/h)	P_i^0
1	150	455	0.000299	10.1	671	80	120	400
2	150	455	0.000183	10.2	574	80	120	360
3	20	130	0.001126	8.8	374	130	130	105
4	20	130	0.001126	8.8	374	130	130	100
5	150	470	0.000205	10.4	461	80	120	190
6	135	460	0.000301	10.1	630	80	120	400
7	135	465	0.000364	9.8	548	80	120	350
8	60	300	0.000338	11.2	227	65	100	95
9	25	162	0.000807	11.2	173	60	100	105
10	25	160	0.001203	10.7	175	60	100	110
11	20	80	0.003586	10.2	186	80	80	60
12	20	80	0.005513	9.9	230	80	80	40
13	25	85	0.000371	13.1	225	80	80	30
14	15	55	0.001929	12.1	309	55	55	20
15	15	55	0.004447	12.4	323	55	55	20

Table E Prohibited zones of generating units for 15-unit system

Unit	Prohibited zones (MW)
2	[185 – 225] [305 – 335] [420 – 450]
5	[180 – 200] [305 – 335] [390 – 420]
6	[230 – 255] [365 – 395] [430 – 455]
12	[30 – 40] [55 – 65]

Table F Load demand for 24 hours (15-unit system)

Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)
1	2236	7	2331	13	2780	19	2651
2	2215	8	2443	14	2830	20	2584
3	2226	9	2651	15	2953	21	2432
4	2236	10	2728	16	2950	22	2312
5	2298	11	2783	17	2902	23	2261
6	2316	12	2785	18	2803	24	2254

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