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Multi-agent Technique and Its Application for Economic Load Dispatch

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Abstract: The Economic Load Dispatch (ELD) problem is an important optimization problem in power system and the objective of which is to divide the power demand among generators economically. Being a multi-dimension, discrete, nonlinear constrained numerical optimization problem. The ELD problem has many constraints needed to be satisfied and is hard to be solved. In order to deal with this problem, we present a multi-agents based evolutionary algorithm to deal with the problem of premature convergence and converging slowly. The results have shown that the proposed algorithm can speed up the optimization process and can achieve good solutions.

Key words: Agent, evolutionary computation, economic load dispatch

INTRODUCTION

The Economic Load Distribution problem (ELD) in power system is a key problem, the target of which is to distribute the load and to reduce the total cost under the given constraints. The characteristics of it, discrete, non-convex, nonlinear and high dimension, make it very hard to be efficiently solved for traditional dynamic programming, linear programming and other methods (Holland, 1975; Yuen and Chow, 2009; Walker and Miller, 2008). To deal with this problem, many intelligent optimization algorithms have been used to solve the ELD problem. For example, ant colony algorithm, particle swarm optimization, artificial neural network, genetic algorithm, clone algorithm, differential evolution algorithm, chaos optimization algorithm and so on. With the further development of artificial intelligence and distributed computing, distributed artificial intelligence is becoming a research hotspot which has the features of reactivity, autonomy, social and spontaneity. In fact, Multiple Agent system based on Agent technology can overcome the shortages of single individual Agent and encapsulated them into one system. The characteristics of autonomy, social, non-convex, make it very suitable for solving the ELD problem.

In this study, we propose a multi-agent based optimization method to deal with the ELD problem, in which multi-agent technology was embed in the evolutionary framework. The spontaneity and autonomy feature of it was utilized in local search and the concurrency feature of the framework was used in global search. The algorithm meets the demands of high constraint, nonlinear, high dimension in a power system.

The study is organized as follows. Firstly, we define the mathematical model of the economic load distribution problems. Secondly, we put forward the evolutionary algorithm based on multi-agent technology. Then, we present several corresponding analysis and comparisons. Finally, we conclude the study and list the advantages and disadvantages of the algorithm.

RELATED WORKS

Economic load distribution problem (ELD): Economic Load Distribution problem (ELD) refers to problem on how to appropriately allocate electric loads within different generators with minimized cost and to maximize the profits under the given constraints. The ELD problem is not only a simple security and energy saving issue, but also an issue on how to improve the service life of the power generation assembly.

Statistic results have shown that reasonable distribution can lead to 0.5-1.5% energy saving (Walters and Sheble, 1993). Therefore, it is very important to study the optimization algorithms and the application manner of them. However, due to the constraints, nonlinear, high dimension and other characteristics of ELD problems, traditional optimization algorithms can hardly obtain satisfactory optimization effect.

Characteristics on energy consumption: The characteristics of generators reflect the unit energy consumption in various loads. For coal-fired thermal power unit, this feature is characterized by the function relationship between coal consumption and power load. Energy consumption is the decisive factor for power

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production which directly reflects the production cost of power generation enterprises. So, we make the load-consumption curve as the main object in this study.

Unit energy consumption characteristic curve: Generally speaking, the unit energy consumption characteristic curve was presented by manufacturers or obtained by thermodynamic experiment (Huang *et al*., 2003). However, the curve was decided by many complex factors, such as environment temperature, equipment status, operation mode and so on. Therefore, we usually adopt the method of real-time data fitting to reflect the real performance of the unit and select quadratic polynomial as the fitting function on energy consumption and supply (Jayabarathi, 2003).

To improve the precision, we divide the output range into several intervals and descript each of them with a quadratic function:

$$Bi=\begin{cases}\alpha_{i1}P_i^2+\beta_{i1}P_i+\gamma_{i1} & P_i^{min}\le P_i\le P_{i1}\\ \alpha_{i2}P_i^2+\beta_{i2}P_i+\gamma_{i2} & P_{i1}^{min}\le P_i\le P_{i2}\\ \dots & \dots\\ \alpha_{ik}P_i^2+\beta_{ik}P_i+\gamma_{ik} & P_{i(k-1)}^{min}\le P_i\le P_i^{max}\end{cases}\tag{1}$$

Let P_i^{min} be the minimum output power of the i th units, P_i^{max} be the maximum output power of the i th units, α_{i1}, β_{i1}, γ_{i1}, α_{i2}, β_{i2}, $\gamma_{i2}\dots$, α_{ik}, β_{ik}, γ_{ik} be the energy characteristic parameters of the i th units. The unit energy consumption function can be expressed as:

$$F=\sum_{i=1}^{Ng}F_i(P_i)=\sum_{i=1}^{Ng}(\alpha_iP_i^2+\beta_iP_i+\gamma_i)\tag{2}$$

Among them, F is the total cost of the given system, N_g is the total number of generators, P_i is the ith generator active power; $F_i(P_i)$ is the consumption characteristics of the i th generator. α_i, β_i, γ_i is the consumption characteristic parameters on the i th generator.

Constraints:

- **Operating constraints:** Let $P_i^{min}$and P_i^{mAX},be the lower and higher active power limits of the generator i, P_i be the output of generator i. The operating constraints of the generators can be expressed by:

$$P_i^{min}\le P_i\le P_i^{mAX},\ i=1,2,\dots,Ng\tag{3}$$

- **Climbing constraints:** Let P_i^{t-1} be the active power in time t-1, UR_i and DR_i be the allowable maximum rising and falling values of generator i:

$$\max(P_i^{min}, P_i^{t-1}-DR_i)\le P_i\le \min(P_i^{min}, P_i^{t-1}-DR_i)\tag{4}$$

- **Operating range constraints:** Let $P_{i,k}^{pz}$ and $P'^{pz}_{i,k}$ be the the upper and lower bounds for generator I, the operating range linit can be expressed by:

$$P_i\le P_{i,k}^{pz}\text{ and }P_i\ge P'^{pz}_{i,k}\tag{5}$$

- **Power balance constraints:** Let P_L be the total load of the system, P_S be the network loss, then:

$$\sum_{i=1}^{Ng}P_i=P_L+P_s\tag{6}$$

- Network loss:

$$\sum_{i=1}^{Ng}P_i=P_L+P_s\tag{7}$$

Network loss P_S is a function of active power, topological structure and parameters of transmission. When the coverage is very large or the load density is very lower, the network loss can reach 20-30%. If use B-coefficient method to calculate the network loss, we can get the relationship:

$$Ps=P^TBP+P^TB_0+B_{00}\tag{8}$$

Among them, $P=(P_1, P_2,\dots, P_{Ng})^T$ be the active power column vector, P^T be the transpose of P. $B\epsilon R^{Ng\times Ng}$, $B_0\epsilon R^{Ng}$, $B_{00}\epsilon R$ is the network loss, also known as the B-coefficient.

Objective function: The objective function can be expressed by:

$$\min F=\sum_{i=1}^{Ng}F_i(P_i)+\sum_{i=1}^{Ng}E_i=\sum_{i=1}^{Ng}(\alpha_iP_i^2+\beta_iP_i+\gamma_i+E_i)$$

$$\text{st } P_i^{min}\le P_i\le P_i^{mAX},\ i=1,2,\dots,Ng$$
$$\max(P_i^{min}, P_i^{t-1}-DR_i)\le P_i\le\min(P_i^{min}, P_i^{t-1}-DR_i),$$
$$i=1,2,\dots,Ng$$
$$P_i\le P_{i,k}^{pz}\text{ and }P_i\ge P'^{pz}_{i,k},\ i=1,2,\dots,Ng$$

$$\sum_{i=1}^{Ng}P_i=P_L+P_s\tag{9}$$

MULTI-AGENT BASED ELD ALGORITHM

The optimization goal of the Economic Load Distribution (ELD) problem in power system is to search a reasonable distribution method to meet the demands of minimum cost, load and constraints. Swarm intelligence is a new appeared computing technology applied in power system, but it can find good solutions in both discrete solution space and continuous solution space. So, it has gradually become a hotspot in research of power economic load.

Definitions: As a distributed intelligence calculation model, the Agent model is initially used in controlling the complexity of distributed computing and overcoming the limitations of man-machine interface. Many researcher looked on it as a software entity which has the abilities of perception and can interact with other entities in the system. The typical characteristics of them contain:

- Agent usually lives in a particular environment
- Agent has the capability to perceive the local environment around itself
- Agent has the autonomy capability to control their actions without external intervention and to independently complete several specific tasks
- Agent can perceive the change of environment and moves freely according to it

Actions: In the optimization progress, each agent will show some specific behaviors according to the changes of the environment. For example, communication, self-replicating, diffusion and other actions can be triggered by the changing external environment.

Marking: When an agent finds a point p in the solution space, the fitness function of it is higher than that of others in the current population, the agent will be activated and put the solution into its memory bank. Otherwise, the agent abandons the point.

Definition 1 (Activity): Let $A(p_i)$ be the activity of agent p_i, the value of it can be expressed by:

$$A(p_i) = 1 \text{ if Fitness}(p_i) > \text{Fitness}_{average}(P) = 0 \text{ otherwise} \quad (10)$$

Self-replicating: If an agent p_i found a point, at which the fitness value of it is little higher than the average of the current population, the agent will copy N_i offsprings and each of the offsprings will be given the same integer energy E. In fact, the self-replicating behavior of agents expands the local search ability of the algorithm. The value of N_i is determined by the formula below:

$$N_i = Q \times A(p_i) \times \text{Fitness}(p_i)/\text{Fitness}_{average}(P) \quad (10)$$

```
Method:

Initialize M = Ø, P, generationCount = 0
While generationCount <maxGeneration do
    While P ≠ θ do
        For all current pi∈P do
        Calculate the fitness values of pi
        If fitness(pi) > fitness_average(P) then
            Reproduce offspring { pi^(j+1)}
            Diffuse {pi^(j+1)}
        Else
            P←P-pi
        Endif
        If A(pi) = 0 then
            P←P-pi
        Endif
        Endfor
        generationCount = generationCount+1
    Endwhile
Endwhile
```

Fig. 1: Procedure of the proposed algorithm

Spreading: Within the solution space, agents keeps on searching for the best solutions. If a solution found conflicts with the constraints, the agent will spread into the neighbor area and the energy of it will be minus by 1, until 0:

$$E_{pi} = E_{pi}-1 \quad (11)$$

Death: When the activity degree $A(p_i)$ of agent p_i declined to 0 or their energy of it was reduced to 0, the agent will die and exit the searching progress for the optimal solution.

Multi-agent based ELD algorithm: The procedure of the algorithm can be presented by Fig. 1.

SIMULATION RESULTS

Here, we have conducted several experiments on a 3.0 GHz Pentium PC with 512 MB of memory running with Microsoft Windows XP to measure the performance of the proposed approach.

Thermal units and 6 buses system: The B coefficient for the 100 WM system is:

$$\begin{aligned} B_{ij} &= \begin{bmatrix} 0.06760 & 0.00953 & -0.00507 \\ 0.00953 & 0.0520 & 0.00901 \\ -0.00507 & 0.00953 & 0.02940 \end{bmatrix} \\ B_0 &= \begin{bmatrix} -0.07660 \\ -0.00342 \\ 0.01890 \end{bmatrix} \\ B_{00} &= 0.040357 \end{aligned} \quad (8)$$

Table 1: Consumption curve coefficient and active power limit of 3 thermal units and 6 buses system

Unit	α_i	β_i	γ_i	P^{min}_i	P^{max}_i
1	0.00156	7.92	561	100	600
2	0.00194	7.85	310	100	400
3	0.00482	7.97	78	50	200

Table 2: Comparisons between different algorithms

Algorithms	P1	P2	P3	¥Pi	Ps	[illegible]
MA-ELD	299.46	171.87	99.85	571.18	71.18	5735.73
[Tang]	299.46	172.00	98.84	570.30	70.24	5735.93
[Wang]	299.46	171.49	99.86	570.81	71.11	5735.84
[Hou]	299.46	171.93	99.84	571.23	71.22	5735.74
[Mao]	299.16	174.42	99.56	573.14	71.72	5736.40

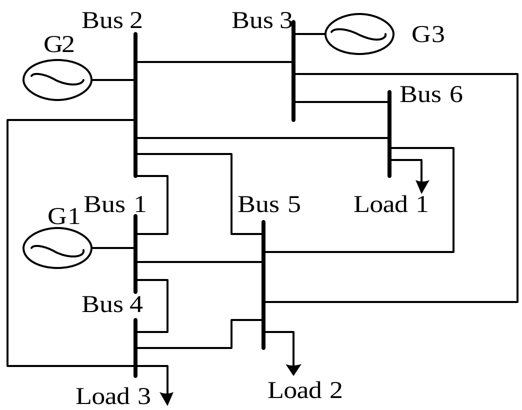

Fig. 2: Thermal units and 6 buses system (IEEE)

Considering the total load (500 Mw) and the network loss, we optimized the 3 thermal units and 6 buses system with proposed multi-agent based ELD algorithm. This can be seen from Fig. 2 and Table 1. After 100 generations of running, we compared the obtained results and the optimal results reported by Tang and Li (2000), Wang *et al*. (2005), Hou *et al*. (2003) and Mao *et al*. (2005). Both of them were listed in Table 2.

From Table.2, we can see that the optimal result in literatures is 5735.74 h. However, the optimal result found by the proposed multi-agent based ELD algorithm is 5735.73 h. In fact, the optimization results found by these algorithms were very similar. The main differences were the adjustments of the active power of the three generators. Since, the multi-agent based algorithm can effectively deal with the multi-constraint and high-dimension optimization problem, the algorithm can found the optimal solution and was more suitable for ELD problem. In this study, the optimization results of the maximum, minimum and average values, respectively 5832.08, 5735.73, 5762.15.

Thermal units system: The B coefficient for the 100 WM system is:

Table 3: Consumption curve coefficient and active power limit of 6 thermal units system

Unit	α_i	β_i	γ_i	P^{min}_i	P^{max}_i
1	0.0070	7.0	240	100	500
2	0.0095	10.0	200	50	200
3	0.0090	8.5	220	80	300
4	0.0090	11.0	200	50	150
5	0.0080	10.5	220	50	200
6	0.0075	12.0	190	50	120

Table 4: Climbing constraints and operating ranges in IEEE 6 thermal units system

Unit	P^0_i	UR_i	DR_i	Rrohibited none
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 5: Comparisons between different algorithms (P_L = 1264 Mw)

	Mult-agent	[Lee]	[Leandro]	[Selvakumar]	[Panigrahi]
P1	446.3360	474.8066	458.2904	446.9600	446.6685
P2	172.7721	178.6363	1680518	173.3944	173.1555
P3	265.4870	262.2089	262.5175	262.3430	262.8259
P4	139.3814	134.2826	139.0604	139.5120	143.4686
P5	165.7911	151.9039	178.3936	164.7089	163.9139
P6	85.6850	74.1812	69.3416	89.0162	85.3437
ΣPi	1275.4526	1276.03	1275.655	1275.94	1275.3764
Ps	12.45	13.0217	12.6550	12.9361	12.4216
Objects	15443.16	15459	15448	15450	15443.57

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

$$B_0 = \begin{bmatrix} -0.0003908 \\ -0.0001297 \\ 0.0007047 \\ 0.0000591 \\ 0.0002161 \\ -0.0006635 \end{bmatrix}$$

$$B_{00} = 0.0056$$

From Table 3-5, we can see that the optimal results of maximum, minimum and average values within 100 generations running were 15454, 15443.16 and 15447. Comparing with the results reported in conference15-19, the active power of the 3th, 5th generators found by the proposed algorithm were higher than that of (Gaing, 2003) and the active power of the 2th, 4th generators were lower than that.

Thermal units system: The B coefficient for the 100 WM system is:

Table 6: Consumption curve coefficient and active power limit of 15 thermal units system

Unit	α_i	β_i	γ_i	P^{min}_i	P^{max}_i	P^0_i	UR_i	DR_i	Rrohibited none
1	0.000299	10.1	671	150	455	400	80	120	
2	0.000183	10.2	574	150	455	300	80	120	[185, 255], [305, 335], [420, 450]
3	0.001126	8.8	374	20	130	105	130	130	
4	0.001126	8.8	374	20	130	100	130	130	
5	0.000205	10.4	461	150	470	90	80	120	[180, 200], [305, 335], [390, 420]
6	0.000301	10.1	630	135	460	400	80	120	[230, 255], [365, 395], [430, 455]
7	0.000364	9.8	548	135	465	350	80	120	
8	0.000338	11.2	227	60	300	95	65	100	
9	0.000807	11.2	173	25	162	105	60	100	
10	0.001203	10.7	175	25	160	110	60	100	
11	0.003586	10.2	186	20	80	60	80	80	
12	0.005513	9.9	230	20	80	40	80	80	[30, 40], [55, 65]
13	0.000371	13.1	225	25	85	30	80	80	
14	0.001929	12.1	309	15	55	20	55	55	
15	0.004447	12.4	323	15	55	20	55	55	

$$B_{ij} = \begin{bmatrix}
0.0014 & 0.0012 & 0.0007 & -0.0001 & -0.0003 & -0.0001 & -0.0001 & -0.0001 & -0.0003 & -0.0005 & -0.0003 & -0.0002 & 0.0004 & 0.0003 & -0.0001 \\
0.0012 & 0.0015 & 0.0013 & 0.0000 & -0.0005 & -0.0002 & 0.0000 & 0.0001 & -0.0002 & -0.0004 & -0.0004 & 0.0000 & 0.0004 & 0.0010 & -0.0002 \\
0.0007 & 0.0013 & 0.0076 & -0.0001 & -0.0013 & -0.0009 & -0.0001 & 0.0000 & -0.0008 & -0.0012 & -0.0017 & 0.0000 & -0.0026 & 0.0111 & -0.0028 \\
-0.0001 & 0.0000 & -0.0001 & 0.0034 & -0.0007 & -0.0004 & 0.0011 & 0.0005 & 0.0029 & 0.0032 & -0.0011 & 0.0000 & 0.0001 & 0.0001 & -0.0026 \\
-0.0003 & -0.0005 & -0.0013 & -0.0007 & 0.0090 & 0.0014 & -0.0003 & -0.0012 & -0.0010 & -0.0013 & 0.0007 & -0.0002 & -0.0002 & -0.0024 & -0.0003 \\
-0.0001 & -0.0002 & -0.0009 & -0.0004 & 0.0014 & 0.0016 & 0.0000 & -0.0006 & -0.0005 & -0.0008 & 0.0011 & -0.0001 & -0.0002 & -0.0017 & 0.0003 \\
-0.0001 & 0.0000 & -0.0001 & 0.0011 & -0.0003 & 0.0000 & 0.0015 & 0.0017 & 0.0015 & 0.0009 & -0.0005 & 0.0007 & 0.0000 & -0.0002 & -0.0008 \\
-0.0001 & 0.0001 & 0.0000 & 0.0005 & -0.0012 & -0.0006 & 0.0017 & 0.0168 & 0.0082 & 0.0079 & -0.0023 & -0.0036 & 0.0001 & 0.0005 & -0.0078 \\
-0.0003 & -0.0002 & -0.0008 & 0.0029 & -0.0010 & -0.0005 & 0.0015 & 0.0082 & 0.0129 & 0.0116 & -0.0021 & -0.0025 & 0.0007 & -0.0012 & -0.0072 \\
-0.0005 & -0.0004 & -0.0012 & 0.0032 & -0.0013 & -0.0008 & 0.0009 & 0.0079 & 0.0116 & 0.0200 & -0.0027 & -0.0034 & 0.0009 & -0.0011 & -0.0088 \\
-0.0003 & -0.0004 & -0.0017 & -0.0011 & 0.0007 & 0.0011 & -0.0005 & -0.0023 & -0.0021 & -0.0027 & 0.0140 & 0.0001 & 0.0004 & -0.0038 & 0.0168 \\
-0.0002 & 0.0000 & 0.0000 & 0.0000 & -0.0002 & -0.0001 & 0.0007 & -0.0036 & -0.0025 & -0.0034 & 0.0001 & 0.0054 & -0.0001 & -0.0004 & 0.0028 \\
0.0004 & 0.0004 & -0.0026 & 0.0001 & -0.0002 & -0.0002 & 0.0000 & 0.0001 & 0.0007 & 0.0009 & 0.0004 & -0.0001 & 0.0103 & -0.0101 & 0.0028 \\
0.0003 & 0.0010 & 0.0111 & 0.0001 & -0.0024 & 0.0017 & -0.0002 & 0.0005 & -0.0012 & -0.0011 & -0.0038 & -0.0004 & -0.0101 & 0.0578 & -0.0094 \\
-0.0001 & -0.0002 & -0.0028 & -0.0026 & -0.0003 & -0.0003 & -0.0008 & -0.0078 & -0.0072 & -0.0088 & 0.0168 & 0.0028 & 0.0028 & -0.0094 & 0.01283
\end{bmatrix}$$

$$B_0 = \begin{bmatrix} -0.0001 \\ -0.0002 \\ 0.0028 \\ -0.0001 \\ 0.0001 \\ -0.0003 \\ -0.0002 \\ -0.0002 \\ 0.0006 \\ 0.0039 \\ -0.0017 \\ 0 \\ -0.0032 \\ 0.0067 \\ -0.0064 \end{bmatrix}$$

$B_{00} = 0.0055$

Table 7: Comparisons between different algorithms (P_L = 1264 Mw)

	Mult-agent	[Lee]	[Leandro]	[Selvakumar]	[Panigrahi]
P1	441.3220	439.1162	415.3108	441.1587	455.00
P2	450.3371	407.9727	359.7206	409.5873	380.01
P3	121.5470	119.6324	104.4250	117.2983	130.00
P4	106.7377	129.9925	74.9853	131.2577	126.52
P5	251.9124	151.0681	380.2844	151.0108	170.01
P6	456.1550	459.9978	426.7902	466.2579	460.00
P7	456.4349	425.5601	341.3164	423.3678	428.28
P8	73.3490	98.5699	124.7867	99.948	60.00
P9	31.8775	113.4936	133.1445	110.684	25.00
P10	67.8675	101.1142	89.2567	100.2286	159.78
P11	62.8634	33.9116	60.0572	32.0573	80.00
P12	75.7523	79.9583	49.9998	78.8147	80.00
P13	27.2753	25.0042	38.7713	23.5683	33.70
P14	16.2453	41.4140	41.9425	40.2581	55.00
P15	17.1226	35.6140	22.6445	36.9061	15.00
ΣPi	2656.80	2662.4	2668.4	2662.04	2658.32
Ps	26.88	32.4306	38.2782	32.4075	28.36
Fitness value	32634	32858	33113	32854	32742.77

Considering the network loss, prohibited operating range, total load(2630 MW) and climbing constraint (Table 6), we implemented the proposed power load optimization algorithm for 50 generations, compared the optimal results appeared in reports of (Gaing, 2003; Coelho and Mariani, 2007; Panigrahi *et al*., 2007; Selvakumar and Thanushkodi, 2007; Panigrahi *et al*., 2008) and then, listed them in Table 7.

From Table 7, we can see that the optimal results of maximum, minimum and average values within 100 generations running were 32806, 32634 and 32791. Comparing with the results reported in (Gaing, 2003; Coelho and Mariani, 2007; Panigrahi *et al*., 2007; Selvakumar and Thanushkodi, 2007; Panigrahi *et al*., 2008), the active power of the 2th, 5th, 8th generators found by the proposed algorithm were higher than that of (Coelho and Mariani, 2007) and the active power of the 4th, 10th, 11th, 14th generators were lower than that. The others were very similar.

CONCLUSION

From the above two groups of experiments we can see that due to the introduction of autonomous agents, the flexibility and adaptability of the algorithm were clearly increased so as to a better performance. With the increasing of the quantity and the complexity of the optimization goal, the proposed algorithm will further show the advantages of it.

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