Home Energy Management in Smart Grid with Renewable Energy Resources

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Abstract—In this paper, a real-time optimal appliance usage strategy is proposed based on binary particle swarm algorithm, participated by both energy suppliers and customers, together with renewable resources. With different time-of-use electricity prices, a time table for the appliance operation is derived with the least tariff objective considering the personal habits and characteristics of the appliances. When the demanded power is too high or too low, the supplier will send a feedback signal to ask the customer to stop/delay using some kinds of appliances or to remind that some flexible appliances can be activated or used in order to achieve the 'peak load shifting' effect. Matlab simulation experiments have been implemented to prove the effectiveness of the system.

Keywords—Particle Swarm Optimization; Domestic Appliances; Home Energy Management; Renewable Energy Resources

I. INTRODUCTION

Since the energy crisis and global warming become more and more serious, high-efficiency and energy saving become the world theme for solving the issues. With the economic and social development, smart grid plays an important role in the energy resources reconstruction [8]. As for the electricity suppliers/utility companies, they expect the difference between the peak power and valley power to be suppressed so as to smooth the supply and demand curve, improve power supply efficiency and avoid unnecessary energy waste and reduce environmental pollutions [4][9]. From the end user perspective, time-of-use(TOU) of the electricity and tariff is their mostly concerned. A mechanism is needed to manage their usage of electricity taking into account the interests of electricity suppliers and user side power management [5] to seek an optimum solution.

Many different optimization methods can be used with single objective or multi-objectives for energy management strategy from user side. In paper [12], a game method is adopted to optimize demand side management through real-time pricing for electricity suppliers to provide the best management strategy. However, the customer interest has not been considered in the scheme.

In paper [1], it targets the issue of increasingly difference growth of electricity usage in peak-valley periods. Neural network optimal algorithm is used for industrial users to save the energy and reduce peak-valley difference. An electricity load management model is proposed in [3] for single user or multi users based on linear integer programming, which takes into account renewable energy and distributed battery storage. Mixed linear programming method is applied in paper [11], where the developed mathematical model is used to obtain the least electricity bill objective. Dynamic pricing is considered to be an optimal method satisfying not only the users need but also the minimum tariff [6]. Particle swarm method is used to achieve the minimum exhaustion and economical load assignment so as to improve the energy utilization efficiency and energy conservation and emission reduction [10]. In this paper, a binary particle swarm method is used to optimize the appliances with the minimized tariff objective considering the electrical operating characteristics.

The remainder of the paper is organized as follows. In section II, the system and the details of the binary particle swarm algorithm is described from the user side. A real-time feedback strategy for the appliances usage participated by both the power suppliers and end users are proposed in section III. Simulation experiments are performed to prove the effectiveness of the algorithm in section IV. Renewable energy resources is added in the power supply for further discussion in Section V. Conclusions and future work are given in Section VI.

II. BINARY PARTICLE SWARM OPTIMAL ALGORITHM

A. Description of the System

Due to various characteristics of appliances, i.e., refrigerator, washing machine, there are diverse ways of operation for each type of the appliances. So does the personal habit for each family. Here, one family is regarded as an end user for discussion. One day (24-hour) is partitioned evenly by 24 intervals. From the end-user point of view, an optimal algorithm should be developed with the objective of minimum tariff considering the personal habit and appliance characteristics. Under the time-of-use price circumstances, the least tariff can be obtained via the operational period adjustment for each appliance. A group of $24 \times 1$ metrics with 0,1 elements are used to
describe the appliance working status, where 0 denotes that the appliance is on 'off' status and 1 is 'on' status. Similarly to other swarm intelligence optimization methods, a binary particle swarm method can obtain the optimal solution in N dimension globally. The searching process starts from one solution set, i.e., the system is composed of a swarm of particles. Information sharing mechanism is used in the searching process. Besides, the swarm particle optimization has simple principle and less parameters, which is easy to be realized with fast convergence speed.

The domestic appliances can be classified into three categories. The 1st group is the appliances that their working time cannot be shiftable with determined working period, such as refrigerator that has to be powered in 24 hours. The 2nd group includes shiftable appliances, i.e., washing machine and dish washer. Although their working time can be shiftable, they have to be worked continuously without being interrupted otherwise more electricity bills will be generated. The 3rd type is those that can be switched on and off at any time, such as humidifier, air-conditioner and electrical charging system.

Suppose \( x_i (i \in R) \) denote the \( i \)th domestic appliance. \( T_i \) is the plan table to represent \( n \) possibilities for the appliance \( x_i \) per day. The elements are composed of '0' and '1'. For instance, \( x_i \) belongs to the 1st category, and there is only one possibility in the time table, i.e., \( T_i \in 24 \times 1 \). If \( x_i \) belongs to the 2nd category with continuous working hour \( 1 < m_i < 24 \), there are \((24 - m_i)\) possibilities in the 24-hour time slots, i.e., \( T_i \in (24 \times (24 - m_i)) \). For example,

\[
m_i = 2, \text{then } T_i = \begin{pmatrix}
1 & 0 & 0 & \cdots & 0 \\
1 & 1 & 0 & \cdots & 0 \\
0 & 1 & 1 & \cdots & 0 \\
0 & \cdots & \cdots & \cdots & 0 \\
0 & 0 & 0 & \cdots & 0
\end{pmatrix}
\]

the 3rd category and it should satisfy the whole power requirement \( H_i \). Then the time table can be designed based on the appliance power and whole power requirement. Suppose the working hour for this appliance \( t_i \leq 24 \), thus there are \( C_{24}^d \) possibilities, i.e., \( T_i \) with \( C_{24}^d \times 24 \) dimension. Let the time-of-use \( L = (L_1, L_2, L_3, \ldots, L_{24}) \) denote the electricity prices per day in 24 time slots. According to the working matrix \( T_i \) of each appliance \( x_i (i \in R) \), \( n \) schemes of the power matrix \( P_{in} \) can be obtained. Only one scheme will be selected each time for the user to satisfy the minimum tariff expectation.

### B. A binary particle swarm optimization algorithm

Study shows that birds often abruptly change their directions, i.e., spreading, aggregating during their flights. Although their immediate flight behaviours are unpredictable, they keep consistency as a whole and each individual maintains optimum distance to the other individuals. Through research on similar behaviours of biological populations, a social information sharing mechanism exists in the swarms, which is the origin of the particle swarm optimization (PSO) algorithm.

When PSO algorithm is used to solve optimal issues, the solution is to seek the best position to the objective, which is called ‘particle’. Each particle can fly freely in D-dimensional space. Four factors should be discussed in the optimized procedure: the current position \( X_i \) of each particle, the current speed \( V_i \) of each particle, the best searched position \( P_i \), the global best position of all particles \( P_g \). The current speed \( V_i \) decides the direction and distance of its flight. \( P_i \) and \( P_g \) are all determined by an evaluation function \( f \) (the function to be optimized).

Therefore, in D-dimensional solution space, each particle will update themselves by tracking two "extremes" \( P_i \) and \( P_g \) in each iteration. Assuming particle \( i = (1, 2, \ldots, M) \) is in the D-dimensional space, \( M \) particles are composed of a population, then \( X_i = (x_{i1}, x_{i2}, \cdots, x_{iD}) \), \( V_i = (v_{i1}, v_{i2}, \cdots, v_{iD}) \), \( P_i = (p_{i1}, p_{i2}, \cdots, p_{iD}) \) and \( P_g = (p_{g1}, p_{g2}, \cdots, p_{gD}) \) denotes the position of each particle, speed of each particle, current optimized position and global optimized position of the group, respectively. The binary particle swarm law of each particle will be updated in '0' or '1' values according to the following formula velocity and position:

\[
v_{id} = \omega v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{1}
\]

\[
x_{id} = \begin{cases}
0 & r \geq 1/(1 + exp(-v_{id})) \\
1 & r \geq 1/(1 + exp(-v_{id}))
\end{cases} \tag{2}
\]

where \( d \in (1, 2, \cdots, D) \) denotes the space dimension, \( \omega \) is the inertia coefficient; \( c_1 \) and \( c_2 \) are the learning factors; \( r_1, r_2 \) and \( r \) are the random numbers in the range of \([0, 1]\).

In order to manage the household appliances via binary PSO algorithm, here, assume \( D = 24, M = 40, c_1 = c_2 = 2, \omega = 0.9 \), the maximum iteration time is 2000, the fitness function is \( L \times X_i \) (TOU price × particle position). Thus the control of the appliances in the 2nd and 3rd categories can be optimized via PSO based on their inherent characteristics. 40 particles are updated in 2000 times to seek the minimum solution, where the fitness function \( L \times X_i \) is regarded as the fitness value and \( P_i, P_g \) are computed at the same time which are brought to the next iteration till the process completion. The diagram of the calculation procedure is depicted in Fig.1.

First of all, the appliances are classified into 3 groups. The appliances included in the 2nd and 3rd categories are used for particle swarm optimization. The optimal position of the appliances are obtained at the final calculation procedure.
III. REAL-TIME FEEDBACK ENERGY MANAGEMENT STRATEGY FROM USER SIDE

In practice, the electricity end users can be divided into three groups: commercial users, industrial users and domestic users. Traditional peak periods include \((9 \sim 12, 19 \sim 22)h\) and valley period is between \((24 \sim 8)h\) per day, which is caused by the production and living activities. In the above section, binary particle swarm algorithm is used to obtain the least tariff. Theoretically, this method can realize the peak shaving and load shifting function with good performance, where the time shiftable appliances can be operated during night with less bills generation. However, the behaviours of the end-users with huge population possesses quite a certain uncertainties or the submitted working timetable of the appliances share a great degree of similarity, which would cause another peak electricity usage. So a real-time feedback electricity management strategy is needed participated by both the end-users and electricity suppliers to adjust the working scheme, which is shown in Fig.2.

In Fig.2, \(S_r\) is the required real-time electricity, \(S_{ave}\) is the averaged peak value, \(S_{max}\) is the maximum power value and \(S_{min}\) is the minimum valley power. There are only two states for the appliances in the real-time plan table for management: ‘0’ and ‘1’. The ‘1’ status contains two meanings: postponed activation optimization and asking activation optimization. In the ‘0’ state, the user submits his/her plan table. When the power suppliers find the demand over/under threshold, further adjustment will be adopted. If the real-time monitoring power \(S_r \geq 60\% \times S_{max}\), then the postponed activation will be triggered to decrease the real-time demand power \(S_r\). On the contrary, if \(S_r \leq 60\% \times S_{max}\), the optimization stops. When \(S_r \leq 120\% \times S_{min}\), the asking for activation step will be implemented to increase the real-time power consumption. The optimization will be stopped while \(S_r = S_{ave}(\Delta = 10\%S_{ave})\). The delayed and invited appliances will be ordered according to their power magnitudes, i.e., higher power with higher priority for simplicity. Moreover, in order to protect the benefits of the clients, the TOU prices of the appliances in the postponed list should be kept the same as that before entering the list. Through the allocation and management, the electricity usage efficiency can be improved, load shifting can be achieved and the contradiction between supply and demand can be reduced greatly.

IV. SIMULATION EXPERIMENTS

Matlab simulation tool is used to verify the proposed algorithm. Suppose there are twelve appliances in one family, as shown in Table I.

<table>
<thead>
<tr>
<th>Appliances</th>
<th>x1</th>
<th>x2</th>
<th>x3</th>
<th>x4</th>
<th>x5</th>
<th>x6</th>
<th>x7</th>
<th>x8</th>
<th>x9</th>
<th>x10</th>
<th>x11</th>
<th>x12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td>Usage</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Since the refrigerator \(x_1\) belongs to the 1st type, therefore only one working-time table is obtained with \((24 \times 1)\) matrix, \(T_1 = [1, 1, 1, \cdots, 1]’\). So does the matrices \(T_2\) and \(T_3\) of the \(x_2\) and \(x_3\). The washing machine, heating water and washing machine, \(x_4\), \(x_5\) and \(x_6\), belong to the 2nd category, which have 24 operational possibilities and the time tables are with \((24 \times 24)\) dimension. The electric vehicle charger \(x_7\) belongs to the 3rd category with 8 working hours and the humidifier \(x_8\) has a 6-hour working period. For the computation simplicity, \([x_9, x_{10}, x_{11}, x_{12}]\) are assumed having 1-hour working period. Fig.3 shows one randomly selected power distribution. The total power distribution of all appliances is depicted in Fig.4, where the TOU prices \(L = [0.8, 0.8, 0.8, 0.5, 0.5, 0.5, 0.8, 0.8, 0.8, 0.8, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]¥\) (Chinese Unit¥).
### Table I

**The Category of the Appliances and Their Characteristics**

<table>
<thead>
<tr>
<th>Type</th>
<th>Residential appliances</th>
<th>Characteristics and requirement</th>
</tr>
</thead>
</table>
| 1\(^{st}\) | Refrigerator \(x_1\) | 24 hour working time  
Power: 0.12 kw/h |
| 1\(^{st}\) | TV \(x_2\) | Working time: [20:00-22:00]  
Power output: 0.15kw/h |
| 1\(^{st}\) | Electric frying pot \(x_3\) | Working time: [18:00-20:00]  
Power output: 2kw/h |
| 2\(^{nd}\) | Washing machine \(x_4\) | Continuous 2 working hours  
Power output: 1 kw/h |
| 2\(^{nd}\) | Heating water \(x_5\) | Continuous 2 working hours  
Power output: 1.5 kw/h |
| 2\(^{nd}\) | Dish washer \(x_6\) | Continuous 2 working hours  
Power output: 0.8 kw/h |
| 3\(^{rd}\) | EV Charger \(x_7\) | Power rating: 4kw  
Power output: 0.5 kw/h |
| 3\(^{rd}\) | Humidifier \(x_8\) | Power rating: 0.8kw  
Power output: 0.14 kw/h |
| 3\(^{rd}\) | Ovens \(x_9\) | Power rating: 0.8kw  
Power output: 0.15 kw/h |
| 3\(^{rd}\) | Vacuum cleaners \(x_{10}\) | Power rating: 0.6kw  
Power output: 0.11 kw/h |
| 3\(^{rd}\) | Heating \(x_{11}\) | Power rating: 0.5kw  
Power output: 0.12 kw/h |
| 3\(^{rd}\) | Rice cookers \(x_{12}\) | Power rating: 0.6kw  
Power output: 0.13 kw/h |

As for the 12 appliances, the working matrix for each appliance is developed. Since the working program of the appliances has a great freedom to be chosen, there is still some difference in the obtained results even with 5000 iteration time during the calculation. Fig.3 and Fig.4 are the results of one randomly selected scheme. The peak periods of the electricity curve are in [17:00-18:00]h and [20:00-22:00]h, which are also the peak load periods of the grid. The price for the adoption of this scheme is ¥48.56 Yuan. If such a scheme is adopted, it would increase the power requirement in these periods, which would further increase the difference between peak and valley load values resulting in waste of energy resources and environmental pollution. Besides, more electricity bills will be generated for the end-users.

The binary particle swarm optimization strategy described in Section II is used to optimize the operation of appliances in the 2\(^{nd}\) and 3\(^{rd}\) categories. The parameter settings are: \(D = 24\), \(M = 40\), \(c_1 = c_2 = 2\), \(\omega = 0.9\), and the fitness function is \(L \times X_i\). 40 particles are iterated in 2000 times in the procedure. Fig. 5 shows the electrical power distribution of the appliances, and the total electrical power distribution is depicted in Fig.6. As it is shown, the electricity usage peak periods are at [2:00-9:00]h and [17:00-18:00]h, which are the low load periods in the grid. The generated tariff with this scheme is ¥27.92 Yuan. If this program is adopted by the users, load shifting can be achieved with less tariff.

With the binary PSO algorithm participation for the appliances (see Fig. 5 and Fig. 6), the real-time feedback
energy management strategy will be used if too much similarities in working time table of the users submitted. If the power suppliers find out \( S_r \geq 60\% \times S_{\text{max}} \) at 4am, the activation of appliance \( x_5 \) will be postponed. If the current power is still \( \geq 60\% \times S_{\text{max}} \), then appliance \( x_7 \) is stopped. The appliance \( x_5 \) will be restored operation till \( S_r \leq 120\% \times S_{\text{min}} \). If the total power is still \( \leq S_{\text{min}} \), \( x_7 \) can be back on status.

V. RENEWABLE ENERGY RESOURCES INVOLVED ALGORITHM

Renewable energy resources are gradually entering in the power supply industry. Here, Photovoltaic (PV) power generator is used as an example. It is a renewable generation system which uses the solar battery to transfer the sun radiation to electricity. The system capacity is influenced by the radiation amount (weather), panel installation direction, panel area and transfer efficiency. The power generation capacity of a typical PV station is shown in Fig.7, where the power output \( f(x) \) can be expressed as [7]:

\[
f(x) = 10 \times \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right)
\]

where \( x \) is the time, \( f(x) \) is the output power from the PV station at \( x \) time.

As shown in Fig.8, curve 1 is the electricity load distribution without photovoltaic solar power and optimal energy management. It is a traditional power supply load distribution, where [1~5am] period is the valley load and the power demand increases significantly after 6am and a peak electricity consumption is reached in the 10 to 12am. There is less variation during 13~18pm. The highest electricity demand is formed between 18~22pm. A suddenly drop occurs after 22pm. The least value of the curve is 5Mw and peak value is 12.5Mw, which means a great difference between peak and valley period. It could cause a huge waste of resources and low power utilization.

Curve 2 in Fig.8 is the traditional power supply load distribution with a solar power supply. It can be seen that there is a significant drop in the period of 6~18pm compared to curve 1 and the least value is achieved at 13pm. The reason is that the generated photovoltaic solar energy (normally 6~18pm) has been added in the grid, which reduces the electricity demand from the traditional energy resources. Although the electricity load can be smoothed or adjusted during the daytime, peak period still exist in the night. Energy management strategy should then be used to remove the peak electricity demand.

The binary PSO algorithm and real-time feedback mechanism proposed in the paper is used for further optimization. In one community, there are 20000 families and their domestic appliances are shown in Table I. The optimized load distribution is shown in Fig.9 with 600 families participated in the optimization program. Therefore, the load curve after optimization is used to modify curve 2 (the appliances from \( x_4 \sim x_{12} \) in traditional usage) in valley period, which forms curve 3 (with optimization of loads of the appliances \( x_4 \sim x_{12} \)) in Fig.8. The trough curve is 5.65Mw and the peak value is 10.85Mw, which has smaller difference. If more families participate the optimized energy management strategy, the curve 3 would be much flat and peak shaving function can be achieved with better performance.

VI. CONCLUSIONS

In this paper, an optimal home energy management strategy is proposed via binary particle swarm algorithm considering both the interests of the power suppliers and end-users. It can satisfy the requirement of least tariff from
the user side and the demand of power reduction or shifting, so that the peak load shaving can be achieved.

Further research will explore the possibility to seek the least tariff and power requirement for the benefits of both electricity suppliers and end-users in more paretical ways.

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