# A Layered Approach for Enabling Demand Side Management in Smart Grid

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Abstract—Smart grid (SG) represents intelligent technologies used to address the climate change. Demand side management (DSM) is an essential part of the SG. This paper establishes a layered model for the DSM. The model involves three participants: power generators, including renewable energy sources, demand response (DR) aggregator, and consumers. The revenue of the DR aggregator is analyzed. The discomfortable level caused by the DSM is considered for consumers. This model leads to a multiobjective (MO) problem. An MO evolutionary algorithm is used to find the Pareto front, facilitating the selection of a fair solution. Simulation results illustrate the feasibility of the proposed approach.

*Keywords*—Demand side management, demand response aggregator, multiobjective problem, multiobjective evolutionary algorithm, smart grid.

## I. INTRODUCTION

Cimate change is a public concern. To deal with it, the UK government issued the Carbon Plan in December 2011. The plan aims to achieve at least 30% carbon emission reductions by 2020, and 80% by 2050 relative to 1990 level. In the UK, energy supply results in 443 million tons of carbon dioxide emissions [1]. As such, the UK government encourages innovation in lowcarbon technologies for energy markets [2]. Renewable energy sources (RESs) can be one of the choices. More energy is expected to be supplied by the RESs in the grid, such as wind, photovoltaic, and tidal energy. RESs have contributed more than 25% of electricity generation to the UK in the second quarter of 2015, which exceeds that of the coal [3]. But the time-varying nature of RESs causes indeterminacy problems to the electricity supply.

The smart grid (SG) is an intelligent power system that addresses these problems in many aspects. It in-

volves high-speed bidirectional communication network, advanced power equipments, advanced control methods, and advanced decision support systems [4]. Compared to the conventional power grid, SG has six advantages: 1) Because of the strong power grid system and technical support system, it can tolerate different kinds of external disturbances and attacks. The stability of the grid is reinforced and improved; 2) It can obtain a panoramic view of information, and timely discover/foresee the possibility of failure. When a fault happens, the grid can quickly isolate it and realize self-recovery to avoid the blackouts; 3) The control of the grid is more flexible, and can adapt to a large number of distributed power supplies, micro power grids and electric vehicles; 4) Through the modern management technologies, it can greatly improve the efficiency of power equipments and reduce the losses of transmission, making the operations of the grid more economic and efficient; 5) The highly integrated real-time and non-real-time information can show a comprehensive and complete grid operation state, therefore providing decision supports, control schemes and corresponding response plans; 6) By means of the two-way interactive service mode, the utility can obtain consumers' electricity information in detail to provide more value-added services; consumers can acknowledge the real-time status of the power supply ability, power quality and the price, thus exploiting electric equipments [5]. Because of the advantages the SG provides, the UK government had made over £16 billion of investment between 2010 and 2014. From 2014 to 2020, £34 billion investment is forecast to be put in place [6]. The government estimated that smart meters will be installed in every house by 2020.

One important aspect of SG is demand side management (DSM). Electricity demands always fluctuate dramatically in some short time frames. To meet the demand, the system needs to adjust the supply by increasing/decreasing the generation, or adding/curtailing additional resources (e.g., RESs and energy storages

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[7]). Some standby generators may be needed, but they can yield extra costs and lead to system instability. For these reasons, the idea of DSM has emerged. DSM involves combinations of electricity tariffs that are related to the consumption pattern. Through DSM, the system can be better balanced while possessing various benefits [8], e.g., peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shaping.

Two types of DSM programs are often considered: incentive-based program (IBP) and price-based program (PBP) [9] [10]. An IBP directly provides rewards to consumers, while a PBP indirectly uses the price signals to adjust consumers' power consumption. In an IBP, direct load control and interruptible/curtailable service are categorised as classical methods, while emergency service, demand bidding, capacity market and ancillary service market are categorized as market-based methods. In a PBP, price signals are based on the real-time balance of demand and supply and generation costs. Existing price mechanisms include time of use price, critical peak price, extreme day price, and real-time price. Regarding the DSM in the UK, a Short Term Operating Reserve program has been operated by National Grid since 2005. It aims at dealing with the demand shortage and/or plant unavailability. It is a process of gathering various existing onsite standby power generators or promoting the reduction of consumption to offset the extra demand in times of critical need [11].

When implementing the DSM, the generation side is not likely to communicate with consumers directly. For one reason, there will be numerous information exchanges, which can delay the system response time. For the other reason, the generation side is designed to address a large-scale demand, and the effect of individual's pattern is almost negligible to the system. Therefore, the demand response (DR) emerges as an intermediary between the generation side and consumer side, establishing more efficient communication between both sides [12]. The interactions between the generation side and the DR aggregator are often categorized as two different types: 1) Mutual interaction, where information and predicted demand curve are provided by the generation side in advance. The DR aggregator then acts as a retailer who buys electricity energy in a day-ahead market by biding on the bulk and price of it. 2) Direct interaction, where the generation side announces that a certain amount of power needs to be curtailed in particular time slots. The DR aggregator then attempts to achieve the goal, and if so, the aggregator can be rewarded by the generation side. In the UK, the DR aggregator firms alreadly exist, e.g., Flexitricity, Open Energi, and Kiwi Power. Open Energi works with hospitals, universities, industries, etc. Kiwi Power works with hotels, commercial companies, hospitals, etc. A great potential market is to be expected in the future.

There are a number of studies about DSM and the DR aggregator. DSM has been proved useful for the residential sector, commercial sector, and industry sector [13]-[16]. It has been realized in practice in recent years, supporting many appliances, such as space heating [17], water heaters [18], and electric vehicles [19]. In [12], [14]-[16] and [20], the participation of DR aggregator was emphasized. In [14], the aggregator decided whenever to call the critical peak price to stabilize the system in economic and technical perspectives. In [15], an efficient real-time pricing scheme was proposed, where the Arrow-d'Aspremont-Gerard-Varet (AGV) mechanism was used to ensure the truthfulness of information. Consumers would report the usage plan to the DR aggregator honestly, otherwise would be punished. In [16], once the demand and supply were imbalanced, a signal would be sent to the DR aggregator. Then the DR aggregator would solve a quadratic problem. In [12], the DR aggregator sent bidding information between the generation side and consumers to obtain a Nash equilibrium. In [20], power generators realized curtailment targets, and the DR aggregator facilitated this process by giving rewards to consumers.

While the concepts of DSM and the DR aggregator have been extensively discussed, related approaches in the literature suffer from certain drawbacks. For example, in [17]–[19], the proposed methods need to acknowledge the complete usage of the current and future state; otherwise, the adjustment could not be accomplished. Meanwhile, the safeguard operations for consumers privacy and system security were not discussed. In [14]–[16], the DR aggregators were mentioned as the intermediary, but the revenue of it was not considered. In [13], the electricity bill of consumers was emphasized, but the associated discomfort level was not taken into account. In [12] and [20], only conventional generation was considered.

RESs are more and more important for the electricity generation, but the inherent intermittent characteristic is the major impediment to their development. This paper considers wind turbines as one of the generation methods, and proposes a feasible DSM scheme to eliminate the fluctuation. The DR aggregator is an independent unity in the market, and its benefit cannot be neglected. This paper considers the DR aggregator as an individual, showing its ability to support the business. For consumers, the solely consideration of electricity bill is not enough, and cannot guarantee active participation of the DSM in real-world situations. The discomfort level caused by DSM program needs be added as a factor, represented by a discomfortable function in our paper. The rest of the paper is organized as follows. Section II gives an explanation of the proposed layered model. This model leads to a multiobjective problem (MOP). Section III introduces a multiobjective (MO) evolutionary algorithm to solve the aforementioned MOP. Section IV presents simulation results. Finally, Section V concludes this paper.

## II. MODEL DESCRIPTION

To tackle existing challenges in conventional power grids, a layered model is proposed as shown in Fig. 1. This model can make the system transparent [12]. Generators are at the first layer. The DR aggregator is at the second layer and consumers are at the third layer.

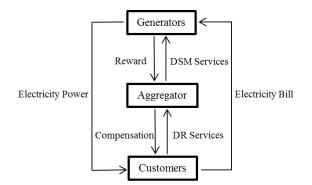


Fig. 1. System operation model.

#### A. Generators

The conventional power generation uses fossil fuels, like coal, oil and gas, as primary resources. These resources are limited and will be exhausted some day. The output power by these sources are predictable and easy to control. But during the process of power generation, these sources produce a large amount of carbon emission and waste, which has a negative impact on the environment. By contrast, renewable generation uses RESs as primary resources. These sources are clean and sustainable, which are preferable to the system. But the output power by these RESs is intermittent and susceptible to many external conditions.

On the basis of the different sources, the generation cost can be calculated in two ways. For conventional generation, the cost function is assumed to be convex. As the output power increases, the cost and marginal cost should also increase. We use t to denote the time index, and  $g_t$  and  $c_g(\cdot)$  to denote the conventional generation output power and cost, respectively. For renewable generation, the cost function is assumed to be fixed. It means the cost is independent of the output power. The main cost comes from the installation and maintenance. We use  $r_t$  and  $C_r$  to denote the renewable generation output power and cost, respectively.  $C_r$  is assumed to be a constant. The total generation cost function  $f_{cost}$ can be expressed as

$$f_{cost} = \sum_{t \in T} [c_g(g_t) + C_r] \tag{1}$$

s.t. 
$$g_{t,min} \leqslant g_t \leqslant g_{t,max}$$
. (2)

The aim of generators is to minimize the generation cost to satisfy the demand as much as possible. The DSM can help modify consumers' power consumption therefore to obtain a relatively flat pattern. In this situation, generators can reduce the generation cost. To reward contribution of the DR aggregator in this process, generators will give part of the DSM gain to the DR aggregator. We use  $g'_t$  to denote the ouput power from conventional generations after DSM. The reward can be calculated as

s

$$f_{reward} = \alpha \Delta c_g(g_t) = \alpha \sum_{t \in T} [c_g(g_t) - c_g(g_t')] \quad (3)$$

where  $\alpha$  is the reward coefficient and  $\alpha \in [0, 1]$ . Therefore, the objective function for generators becomes

$$\min_{g'_{t}} \quad f_{1}(g'_{t}) = \sum_{t \in T} [c_{g}(g_{t}') + C_{r} + \alpha \Delta c_{g}(g_{t})] \quad (4)$$

s.t. 
$$0 \leq \alpha \leq 1$$
,  $\sum_{t \in T} g'_t = \sum_{t \in T} g_t$ , (5)  
 $g'_{t,min} \leq g'_t \leq g'_{t,max}$ .

#### B. DR aggregator

The DR aggregator operates in the market as an individual unit. It can facilitate the DSM by bundling separated consumers into a group. On one hand, it provides the DSM service to generators and receives reward from generators; on the other hand, it persuades consumers to be involved in the DSM and compensates consumers for any induced discomfort. The compensation is related to the generator' expected output power and consumers' demand. The ideal situation for generators is that demand follows generation rather than the contrary. The best case for conventional generators is to produce a constant amount of electricity. It indicates a relatively stable system, and no need to activate standby power generators. We use G to denote this constant output power, and use  $d_t$  and  $d'_t$  to denote consumers' demand before and after DSM, respectively. The compensation function is assumed to be concave. As the difference between generators' expected output power and consumers' demand increases, the corresponding compensation should decrease. The compensation function can be written as

$$f_{comp} = \sum_{t \in T} \left[ -\beta \left( d'_t - G - r_t \right)^2 + \gamma \right]$$
(6)

s.t. 
$$\beta, \gamma > 0$$
 (7)

where  $\beta$  and  $\gamma$  are compensation coefficients.

The aim of the DR aggregator is to maximize the net income, pertaining to the received reward from generators and the given compensation to consumers. Therefore, the objective function for the DR aggregator becomes

$$\max_{g_{t},d_{t}^{'}} f_{2}(g_{t},d_{t}^{'}) = \sum_{t \in T} \{ \alpha \Delta c_{g}(g_{t}) - [-\beta(d_{t}^{'} - G - r_{t})^{2} + \gamma] \}$$
(8)

s.t. 
$$d'_{t} > 0, \ g'_{t,min} \leq g'_{t} \leq g'_{t,max}, \ \beta, \gamma > 0.$$
 (9)

## C. Consumers

We assume consumers are price-sensitive, which means their electricity consumption can be influenced by market prices. We also assume a flat price for the per kWh electricity and there is no conservation for consumption after DSM. This means the market price only varies with the compensation that comes from DR aggregator. Having financial compensation, consumers are willing to participate in the DSM program. They would adjust their consumption patterns to a certain extent according to the command of the DR aggregator. Because this process would cause inconvenience to consumers, a function is introduced to quantify the associated discomfort. The discomfortable function is assumed to be convex. As the difference between the demand before the DSM and the demand after the DSM increases, the corresponding discomfortable level should increase. The compensation function can be written as

$$f_{dis} = \lambda \left( d_t - d_t^{'} \right)^2 \tag{10}$$

s.t. 
$$\sum_{t \in T} d'_t = \sum_{t \in T} d_t$$
(11)

where  $\lambda$  is the discomfortable coefficient for consumers. Every consumer has their unique consumption habit, therefore a different coefficient.

The aim of consumers is to maximize the net profit, pertaining to the received compensation from the DR aggregator and the corresponding discomfortable caused by DSM. Therefore, the objective function for consumers becomes

$$\max_{d'_{t}} f_{3}(d'_{t}) = \sum_{t \in T} \left[-\beta \left(d'_{t} - G - r_{t}\right)^{2} + \gamma - \lambda \left(d_{t} - d'_{t}\right)^{2}\right]$$
(12)

s.t. 
$$\sum_{t\in T} d'_t = \sum_{t\in T} d_t, \quad \beta, \ \gamma > 0.$$
 (13)

## III. METHODOLOGY

The objectives described by (4), (8), and (12) lead to an MOP. We consider three objectives: minimize generation costs for generators; maximize the net income for the DR aggregator; and maximize the net profit for consumers. An MO evolutionary algorithm is modified from [21] to solve this problem. An approximate Pareto front can be obtained in the end. To introduce the algorithm, Pareto terminology is introduced first.

**Pareto domination:** A point is Pareto dominated if there exists one point that can provide better performance to at least one objective without hurting any other objectives. A point is nondomiated if it is not dominated by other points.

**Pareto front:** The image of all nondominated solutions through the mapping of objective functions is termed the Pareto front.

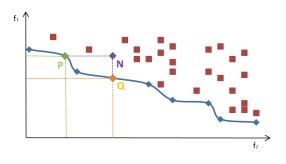


Fig. 2. Example of a Pareto front.

Fig. 2 shows an example of the Pareto front of a minimization problem. In Fig. 2, all points are assumed to be feasible. Point N is dominated by point P and point Q. With the same value of  $f_1$ , point P can provide a smaller value of  $f_2$  than point N. Similarly, with the same value of  $f_2$ , point Q can provide a smaller value of  $f_1$  than point N. For points P and Q, they are not dominated by others. A Pareto front can then be obtained by connecting all the nondominated points.

To solve the previously mentioned MOP, we propose an MO evolutionary algorithm described in Fig. 3. Descriptions of the pseudo code are presented as follows.

Step 1: Randomly generate solutions  $S(0) = (s_0^1, s_0^2, ..., s_0^n)$  from interval  $[s_{min}, s_{max}]$ .

**Input**: Objective functions, initial solution size n, and maximum iteration time  $t_{max}$ .

Step 1) Initialization: Generate a group of solutions to form S(0).

Step 2) Selection: Remove dominated solutions from S(0).

Let t = 0.

While  $t \leq t_{max}$ 

Step 3) Diversification: Apply gene operations to S(t).

Step 4) Selection: Remove infeasible points and dominated solutions from S(t).

# Let t := t + 1.

## End While

**Output**: The solution that does not favor any particular objectives.

Fig. 3. Pseudo code of the proposed MO evolutionary algorithm.

Step 2: Remove dominated individuals from S(0). Let t = 0.

Step 3: To obtain a diversified solution group, the gene operations, normally mutation and crossover, are applied to solutions in S(t).

Step 4: Remove infeasible and dominated solutions from S(t). Let t := t + 1.

Stopping criterion: Repeat Steps 3 and 4 until the current iteration time t reaches the maximum iteration time  $t_{max}$ .

Output criterion: A fair solution can be selected according to

$$s^{\star} = \arg \max_{s \in S(t_{max})} \min_{i=1,2,3} \frac{f_{i,max} - f_i(s)}{f_{i,max} - f_{i,min}}$$
(14)

This solution can maximize the minimum improvement in all dimensions.

#### **IV. NUMERICAL RESULTS**

This section presents our numerical results to justify the proposed MO approach. We divided one day into 12 time slots. For customers, we assumed 20% of electricity demand can be adjusted in different time slots. For RESs, 100 wind turbines were considered. The output power  $r_t$  generated from wind turbines can be calculated from the wind speed according to the experimental equation [22]

$$r_t = \frac{1}{2}\pi r^2 \rho v_t^3 C_p \tag{15}$$

where r is the blade length,  $\rho$  is the air density,  $v_t$  is the wind speed and  $C_p$  is the performance coefficient. Table I lists other model parameters.

TABLE I Model Parameters

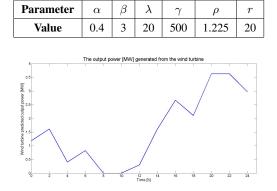


Fig. 4. Example of the output power [MW] generated from the wind turbine.

Fig. 4 shows an example of the output power generated from the wind turbine. It fluctuates dramatically during one day, and there is no pattern to follow. A number of factors, e.g., air pressure, temperature, jet streams, humidity, Rossby waves, weather and season, can influence the wind speed and, therefore, influence the output power.

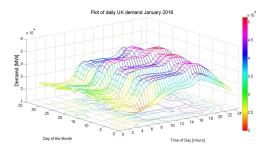


Fig. 5. Daily electricity in the UK, January 2016.

Fig. 5 shows daily electricity demand in the UK, January 2016 [23]. Generally, there is a peak demand from 5 pm to 12 pm, and a valley demand from 12 pm to 6 am. We chose two different days, Jan. 1st (a holiday) and Jan. 29th (a normal working day), as test subjects and applied the proposed approach.

Fig. 6 and Fig. 7 show the optimized load profile and referenced load profile on Jan. 1st and Jan. 29th in the UK, respectively. On both dates, the load profiles present a relatively flat pattern. The optimized demand increases during the off-peak time, while the optimized demand decreases during the peak time. On Jan. 1st, after the optimization, the valley demand increases from  $2.336^{*}10^{4}$  MW to  $2.474*10^{4}$  MW, and the peak demand decreases from  $3.641^{*}10^{4}$  MW to  $3.421^{*}10^{4}$  MW. The peak-to-average ratio can be reduced by approximately

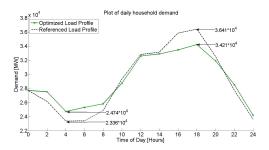


Fig. 6. Optimized load profile on January 1st, 2016.

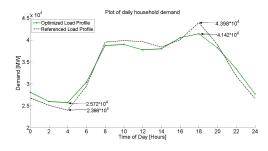


Fig. 7. Optimized load profile on January 29th, 2016.

6.4%. Generation cost can be reduced from £11.213 million to £11.134 million. The DR aggregator can have a net income of £11542. Customers can save £3711 for the electricity bill. On Jan. 29th, after the optimization, the valley demand increases from  $2.398*10^4$  MW to  $2.572*10^4$  MW, and the peak demand decreases from  $4.398*10^4$  MW to  $4.142*10^4$  MW. The peak-to-average ratio can be reduced by approximately 6.1%. Generation cost can be reduced from £15.779 million to £15.65 million. The DR aggregator can have a net income of £20537. Customers can save £4670 for the electricity bill. These results fully embody the aim of the proposed DSM program.

#### V. CONCLUSION

This paper discussed the MO optimization for the DSM. First, an overview of the smart grid, DSM and the DR aggregator was given. A layered model was then proposed, involving the generators, DR aggregator, and consumers. Compared to existing studies, the RESs were considered and the DR aggregator was modelled as an individual unit. Through the use of proposed MO evolutionary algorithm, a Pareto front was obtained. After that, a Pareto optimal solution was selected. Our numerical results illustrated the effectiveness of the proposed model and approach to load profile adjustment.

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