Multiobjective Optimization for Demand Side Management Program in Smart Grid

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***Abstract*—Demand side management (DSM) plays an important role in smart grid for paving the way to a low-carbon future. In this paper, a hierarchical day-ahead DSM model is proposed, where renewable energy sources are integrated. The proposed model consists of three layers: the utility in the upper layer, the demand response (DR) aggregator in the middle layer, and customers in the lower layer. The utility seeks to minimize the operation cost and give part of the revenue to the DR aggregator as a bonus. The DR aggregator acts as an intermediary, receiving bonus from the utility and giving compensation to customers for modifying their energy usage pattern. The aim of the DR aggregator is to maximize its net benefit. Customers desire to maximize the social welfare, i.e., the received compensation minus the dissatisfactory level. To achieve these objectives, a multiobjective problem is formulated. An artificial immune algorithm is used to solve this problem, leading to a Pareto optimal set. Using a selection criterion, a Pareto optimal solution can be selected, which does not favour any particular participant to ensure the overall fairness. Simulation results confirm the feasibility of the proposed method: The utility can reduce the operation cost and the peak to average ratio; the DR aggregator can make a profit for providing DSM services; and customers can reduce their bill.**

***Index Terms*—Artificial immune algorithm (AIA), demand response (DR) aggregator, demand side management (DSM), multiobjective problem (MOP), pareto optimality, renewable energy sources (RESs), smart grid.**

Nomenclature

$:=$	Assignment operator.
$\alpha,\ \beta$	Compensation coefficient.
μ	Bonus coefficient.
θ	Mutate coefficient.
ε	Dissatisfactory coefficient.
$A(n_c)$	Current antibodies.
$c^0()$	Conventional generation cost without DSM.
$c^1()$	Conventional generation cost with DSM.
$c^{\text{res}()}$	RESs generation cost.
$f()$	Multiobjective problem.
$f_a()$	Objective function for the aggregator.
$f_c()$	Objective function for the customers.
$f_u()$	Objective function for the utility.
f_{bon}	Bonus function.
f_{com}	Compensation function.
f_{dis}	Dissatisfactory function.
f_{fit}	Fitness function.
g_t^c	Power obtained from conventional generators at time slot t.
g_t^{res}	Power obtained from RESs at time slot t.
g_t	Expected power generation at time slot t.
n_c	Current iteration number.
$N_{\max}$	Maximum population size of antibodies.
N_{nom}	Nominal population size of antibodies.
p^*	Selected Pareto optimal solution.
q_f	Electricity price per kWh.
$R(n_c)$	Clone rate.
W	Total consumption of electricity in one day.
x_t^0	Load profile at time slot t without DSM.
x_t^1	Load profile at time slot t with DSM.

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I. Introduction

The threat of climate change has never been more urgent. The speed of the current climate change is faster than it has been previously [1]. To counteract this, renewable energy sources (RESs) therefore, have been added to the agenda. The percentage of energy derived from RESs has risen from 6.7% in 2009 to 24.6% in 2015 [2]. However, these RESs cause intermittent problems due to their inherent characteristics, which makes it difficult to schedule and manage conventional generations for compensating them.

Smart grid can offer a two-way flow of information and a two-way flow of electricity. It includes several parts: smart power generation system, smart substation, smart power distribution network, smart interactive terminals, smart scheduling, smart building electricity, smart city power grid, smart meter, smart appliances, and new types of energy storage system [3], [4]. One

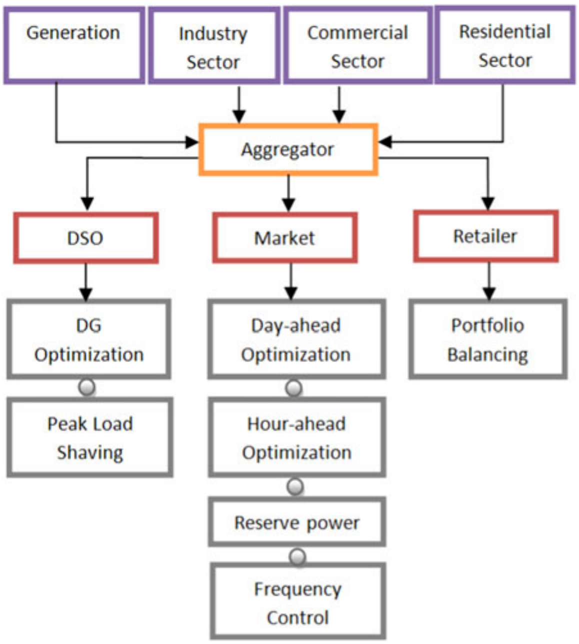

Fig. 1. Functionality of the DR aggregator in a power grid [8].

of the key smart grid technologies is demand side management (DSM) [5].

DSM refers to management activities electricity utilities adopt to achieve optimal allocation of resources and improve the efficiency of terminal users [6]. Typically, two approaches are generally used: 1) incentive-based DSM and 2) time-based DSM [7]–[10]. The incentive-based DSM rewards consumers for adjusting the load profile or giving some levels of control over their equipment. It includes direct load control, interruptible service, demand bidding, capacity market program, and ancillary service market. An alternative way is the time-based DSM, in which the electricity price is decided by the generation and demand situations. Several solutions have been proposed, e.g., critical-peak pricing, time-of-use pricing, real time pricing, and peak load reduction credits [11]–[13]. It was proved that both DSM approaches are feasible and thus widely used for the residential sector, commercial sector, and industry sector [14]–[18].

Although the development of DSM has a great future, the application of DSM in residential sector still has many problems. If the generation side directly communicates with customers, there will be numerous information exchanges, which can delay the system response time. Meanwhile, the generation side is designed for large scale. The generation side is not able to negotiate directly with each customer. In this context, an intermediary/representative is needed [19]. An aggregator, as the name implies, bundles a group of customers into a cluster, and therefore becomes an important aspect to the grid. In the U.K., the demand response (DR) aggregator is allowed and supported by the government in the power network. There already exist several DR aggregators in the market, e.g., U.K. Power Reserve Ltd, KiWi Power Ltd, Npower Ltd, and ESP Response Ltd [20]. As shown in Fig. 1, the DR aggregator can bring several benefits into the system: for distribution system operators, it can achieve peak-load shaving and distributed generation (DG) supply optimization; for retailers, it can help with the internal portfolio balancing; for market, it can deliver day-ahead/hour-ahead optimization, frequency control, and power reservation [8].

In [21]–[23], the role of the DR aggregator that balances the generation and demand was studied. When the imbalance occurred, an indirect signal was given in [21], and the DR aggregator solved a quadratic program at each time slot. In [22], customers are willing to modify their consumption profile according to the electricity price. A DR aggregator represented customers to bid energy in the market. In [23], the regulatory, economic, and technical perspectives of critical-peak pricing were examined. The aggregator decided when to employ the critical-peak price. In [21]–[23], the role of the aggregator was involved, but the utility function was not explicit. Only the benefits for the generation side and the customer side were considered, while the benefit for the DR aggregator was neglected. In [19], [24], the DR aggregator was mentioned, the layered structure and biding scheme were used. The model in [19] includes the utility, DR aggregators, and customers. The utility provided rewards to aggregators for providing DR services, and customers would receive monetary compensation for their demand adjustment. In [24], the utility set the target for demand curtailment at a certain time slot. The aggregator tried to achieve this target by providing rewards to customers, aiming to minimize their payment. The customers bid their supply function to the aggregator, aiming to minimize the dissatisfaction. However, in [19], [22], [24], only the conventional generation was considered. In [25]–[27], the hierarchical system was also presented, and the game theory was used to solve the problem. In [25], [26], multiple utilities and a large number of customers were involved. Utilities aimed to maximize the profit, while customers aimed to maximize the individual welfare. A Stackelberg game was established based on that. In [27], the utilities were divided into two types, fossil-fuel based and RES based. The uncertainty of supply was considered. A utility selection program which can minimize customers' costs was proposed. But in [25]–[27], the inconvenience caused by DR program for customers was not detailed.

Although extensive studies of DSM programs have been conducted, there are several gaps for implementing an effective DSM.

1) The DR aggregator has already emerged as an individual unit in the market, but the revenue of it needs to be analyzed to support the underlying power system.
2) For customers, only considering consumption billing is not comprehensive. The quality of electricity service/the satisfactory level should also be included. The consideration of this can promote the active participation of DSM in practical situations.

To tackle these issues, this paper formulates a multiobjective problem (MOP). For maximizing the benefits of all participants, an artificial immune algorithm (AIA) is proposed, leading to a Pareto optimal set. After a selection, a Pareto optimal solution can be obtained, which ensures a fair implementation of DSM program [28]. Overall, the main contributions of this paper are summarized below.

1) The inherent intermittent problems of RES can be addressed by the proposed DSM scheme.

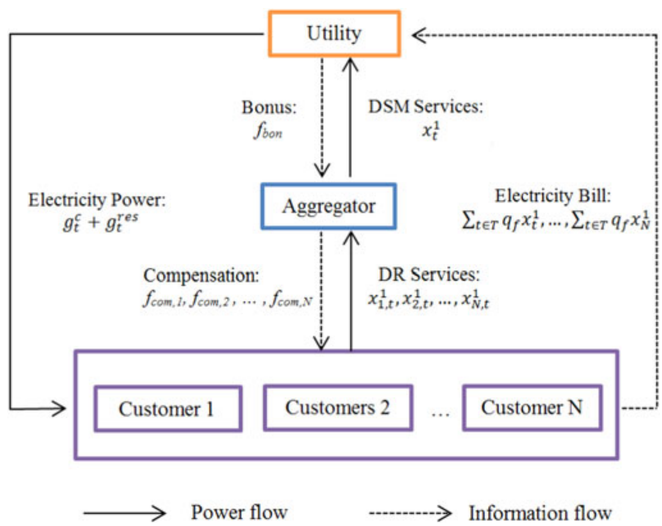

Fig. 2. System operation model.

2) The DR aggregator is modelled as an independent participant. The role and the revenue of it are analyzed.
3) For customers, the social welfare is considered. It is presented by the received compensation minus the dissatisfactory level caused by DSM.
4) The U.K. actual daily data of electricity generation and demand from Grid Watch are applied to prove the feasibility and effectiveness of the proposed model.

The rest of this paper is organized as follows. Section II introduces a hierarchical model for the day-ahead market, which includes the utility, the DR aggregator and customers. Section III formulates an MOP, and proposes the AIA and the selection criterion. It can work out a Pareto optimal set and select an optimal solution. Section IV provides a practical case study. Finally, Section V concludes this paper and lists the future research.

II. System Model

In this section, the day-ahead market is considered and a hierarchical framework for grid participants is introduced. This framework can help to define the specific role and goal of each participant. The system operation model is shown in Fig. 2. The utility is at the upper layer to supply electricity; the DR aggregator is at the middle layer to communicate with both the utility and customers; customers are at the lower layer to consume electricity from the utility [19], [24].

A. Role of the Utility

In the day-ahead electricity market, the daily demand of electricity fluctuates with the time according to the customers' behavior. What is more, due to the inherent intermittent character of RESs, the power provided by RESs varies with the external environment conditions, e.g., season, weather, and time period. In order to balance the demand and the supply, the generation side needs to adjust the production, activate the standby power plants, or even purchase power from third parties [29], [30]. The term peak-to-average ratio (PAR) is introduced to describe the stability of the system [31]:

$$\text{PAR} = \frac{\text{Peak Load}}{\text{Average Load}}. \tag{1}$$

The cost of generation consists of two parts: conventional generation cost and maintenance cost of RESs. For the conventional generators, the cost function and the marginal cost are proportional to the total supplied electricity. The marginal cost means the incremental cost of each new unit of production. Thus the cost function $c(\cdot)$ is a strictly convex function, modelled by a quadratic equation in this paper [17], [25], [27], [32]. For RESs, as there is no expense for resources, the cost is mainly due to the maintenance. Thus the cost function $c^{\text{res}}(\cdot)$ is a constant and independent of supplied electricity. (Note: The installation of conventional generators and RESs are not considered in this paper.)

Let q_f denote the selling price of per unit energy. The total consumption for one day is W MWh. For the day-ahead market, the daily generation vectors are $g^c = \{g_t^c : t \in T\}$ for conventional generators and $g^{\text{res}} = \{g_t^{\text{res}} : t \in T\}$ for RESs. The utility aims to maximize the net revenue. Without the use of DSM, the objective of the utility can be given by

$$\max_{g^c, g^{\text{res}}} : \quad \sum_{t\in T} q_f x_t^0 - \left[\sum_{t\in T} c^0(g_t^c) + \sum_{t\in T} c^{\text{res}}(g_t^{\text{res}})\right] \tag{2}$$

$$\begin{aligned} \text{s.t.} : \quad & \sum_{t\in T} g_t^{\text{res}} + \sum_{t\in T} g_t^c \geqslant \sum_{t\in T} x_t^0 \\ & g_{t,\min}^c \leqslant g_t^c \leqslant g_{t,\max}^c \\ & g_{t,\min}^{\text{res}} \leqslant g_t^{\text{res}} \leqslant g_{t,\max}^{\text{res}} \end{aligned} \tag{3}$$

where x_t^0 denotes the aggregated consumption at time slot t before the DSM, c^0 and c^{res} denote the generation cost for conventional generators and RESs before the DSM, respectively. When the DSM is applied to customers, the peak demand and the total generation cost could be reduced to a certain degree. In this paper, the DR aggregator is considered as the operator to implement the DSM. The utility will be willing to share part of the saved cost as bonus to the DR aggregator as an incentive. The bonus can be calculated as [19]

$$f_{\text{bon}} = \Delta c(g_t^c) = \mu \sum_{t\in T} \left[c^0(g_t^c) - c^1(g_t^c)\right] \tag{4}$$

where c^1 denotes the generation cost for conventional generators after the DSM, and $\mu \in [0, 1)$ denotes the bonus coefficient. When $\mu = 0$, it means there is no bonus to the DR aggregator, therefore indicates no DSM is implemented in the system.

Since the total revenue from the customers is fixed, the aim of the utility is to minimize the operational cost. Hence, the objective function of utility becomes

$$\min_{g^c} : \quad f_u(g^c) = \sum_{t\in T} \left[c^1(g_t^c) + \Delta c(g_t^c)\right] \tag{5}$$

$$\begin{aligned} \text{s.t.} : \quad & 0 \leqslant \Delta c(g_t^c), \quad 0 \leqslant \mu < 1 \\ & g_{t,\min}^c \leqslant g_t^c \leqslant g_{t,\max}^c. \end{aligned} \tag{6}$$

The first term of (5) corresponds to the generation cost for conventional generators, and the second term corresponds to the bonus given to the DR aggregator.

B. Role of the DR Aggregator

The DR aggregator can group a number of individual customers into a cluster for the purpose of carrying more weight in the market. The DR aggregator acts as a mediator between the utility and customers. It undertakes dual responsibilities: on the one hand, ensuring DSM service can be provided to the utility, therefore, obtaining the bonus; on the other hand, guaranteeing there will be a reduction in the electricity bill of customers, encouraging customers to actively participate in a DSM program. By performing the duty, DR aggregator can help with the security and efficiency of the supply.

The DR aggregator tries to adjust the customers' consumption pattern to smooth the peak and follow the generation pattern. The ideal scenario is the demand completely following the generation. Because of the participation of DSM, customers can receive compensation from the DR aggregator for the inconvenience it may cause. The compensation scheme depends on the difference between the aggregated consumption vector $x^1 = \left\{x_t^1 : t \in T\right\}$ and the generation expectation vector $g = \{g_t : t \in T\}$ at time slot t. Suppose the generated power from conventional power plants is a constant value I at each time slot, and the generated power from RESs is time-varying represented by $g^{\text{res}} = \{g_t^{\text{res}} : t \in T\}$, thus, the expected generation vector is $g = \{g_t = I + g_t^{\text{res}} : t \in T\}$. To make demand follow supply, the difference between generation and consumption should be reduced. A compensation function is introduced at that point to promote DSM program and can be modelled by a quadratic equation [19]

$$f_{\text{com}} = \sum_{t \in T} \left[-\alpha \left(x_t^1 - g_t\right)^2 + \beta\right] \tag{7}$$

$$\text{s.t.}: \quad \alpha > 0, \quad \beta > 0 \tag{8}$$

where α and β are compensation coefficients.

The objective of the DR aggregator is to maximize its net payoff. Since the aggregator receives a bonus from the utility and provides compensations to customers, the objective function can be given by

$$\max_{g^c, x^1} : f_a(g^c, x^1) = \sum_{t \in T} \left\{\mu \Delta c(g_t^c) - \left[-\alpha (x_t^1 - g_t)^2 + \beta\right]\right\} \tag{9}$$

$$\begin{aligned} \text{s.t.}: \quad & x_t^1 > 0 \quad \forall t \in T, \quad x_{t,\min} \leqslant x_t^1 \leqslant x_{t,\max}. \\ & g_{t,\min}^c \leqslant g_t^c \leqslant g_{t,\max}^c. \end{aligned} \tag{10}$$

The first term of (9) corresponds to the received bonus from the utility, and the second term corresponds to the compensation to customers.

C. Role of Customers

Typically, the customers' electricity consumption causes a peak demand around 17:00 to 22:00 and a valley demand around 0:00 to 6:00 [33]. As explained before, a group of customers are organized as a cluster. The reference aggregated electricity demand at the time slot t is defined as $x^0 = \left\{x_t^0 : t \in T\right\}$, and the total demand for one day is $\sum_{t \in T} x_t^0 = W$.

Smart meters can provide customers detailed information about their electricity consumption. By equipping them, customers can have a comprehensive understanding of their usage. And customers are assumed to be price-sensitive. With the financial incentive, they are willing to modify their consumption pattern by adjusting deferrable appliances to some extent. After the negotiation with the DR aggregator, the aggregated consumption vector becomes $x^1 = \left\{x_t^1 : t \in T\right\}$. Note that, in order to ensure the basic needs, there is no curtailment in demand, which means $\sum_{t \in T} x_t^1 \geq W$. (Note: The energy conservation approach is not considered in this paper.)

Clearly, DSM would cause inconvenience on customers' daily life. The incurred discomfort should be considered. It depends on the difference between the actual consumption and the reference consumption. As this difference increases, the marginal discomfort also increases. Hence, the dissatisfactory function should be convex and can be modelled by a quadratic equation [19]

$$f_{\text{dis}} = \varepsilon \left(x_t^1 - x_t^0\right)^2 \tag{11}$$

$$\text{s.t.}: \quad \varepsilon > 0, \quad x_{t,\min} \leqslant x_t^1 \leqslant x_{t,\max} \tag{12}$$

where ε is the inelasticity coefficient of demand that characterizes consumers' personal preference. A larger ε means the consumption modification will result in more discomfort, and vice versa. The objective of customers is to maximize their social welfare

$$\max_{x^1} : f_c(x^1) = \sum_{t \in T} \{[-\alpha (x_t^1 - g_t)^2 + \beta] - \varepsilon (x_t^1 - x_t^0)^2\} \tag{13}$$

$$\begin{aligned} \text{s.t.}: \quad & \alpha > 0, \quad \beta > 0, \quad \varepsilon > 0 \\ & x_t^1 > 0 \quad \forall t \in T, \quad \sum_{t \in T} x_t^1 \geqslant W \\ & g_{t,\min}^c \leqslant g_t^c \leqslant g_{t,\max}^c, \quad x_{t,\min} \leqslant x_t^1 \leqslant x_{t,\max}. \end{aligned} \tag{14}$$

The first term of (13) corresponds to the received compensation from the DR aggregator, and the second term corresponds to the dissatisfactory level.

III. Methodology

In this section, an MOP is formulated for maximizing the benefits of all participants. An AIA is then proposed to solve the problem. To stabilize the normal operations of the electricity market, it is important to maintain the fairness among all participants.

A. Formulation

To maintain fairness, three objectives are considered. The objective of utility is to minimize the operation cost, i.e., the generation cost plus the bonus to the DR aggregator. The objective of the DR aggregator is to maximize the net income, i.e., the bonus from the utility minus compensation to customers. The objective of customers is to maximize the social welfare, i.e., the compensation from the DR aggregator minus the dissatisfactory level. By considering the day-ahead market, the resultant MOP can be formulated as

$$\min_{g^c} : \quad f_u(g^c) = \sum_{t \in T} \left[c^1(g_t^c) + \mu \Delta c(g_t^c) \right] \tag{15}$$

$$\min_{g^c, x^1} : \; -f_a(g^c, x^1) = \sum_{t \in T} \left[-\mu \Delta c(g_t^c) - \alpha \left(x_t^1 - g_t \right)^2 + \beta \right] \tag{16}$$

$$\min_{x^1} ; \; -f_c(x^1) = \sum_{t \in T} \left[\alpha \left(x_t^1 - g_t \right)^2 - \beta + \varepsilon \left(x_t^1 - x_t^0 \right)^2 \right] \tag{17}$$

$$\text{s.t.} : \quad x_t^1 > 0 \quad \forall t \in T, \quad \sum_{t \in T} x_t^1 \geqslant W$$

$$f_a(g^c, x^1) > 0, \quad f_c(x^1) > 0$$

$$g_{t,\min}^c \leqslant g_t^c \leqslant g_{t,\max}^c, \quad x_{t,\min} \leqslant x_t^1 \leqslant x_{t,\max} \tag{18}$$

which is solved hourly. To ensure that all the constraints can be strictly followed, an additional objective $f_r(x)$ is introduced to simplify (18)

$$f_r(g^c, x^1) = \sum \Bigg[\max(-f_a(g^c, x^1), 0) + \max\left(W - \sum_{t \in T} x_t^1, 0 \right) + \max\left(-f_c(x^1), 0\right) + \max\left(-x_t^1, 0\right) \Bigg]. \tag{19}$$

The constraints in (18) hold true if and only if $f_r(x) = 0$. Using (19), the resulting MOP can be written as

$$\min_{g^c, x^1} : f(x^1) = \left[f_u(g^c), \; -f_a(g^c, x^1), \; -f_c(x^1), \; f_r(g^c, x^1) \right]. \tag{20}$$

If the MOP is feasible, there should be a possible consumption schedule satisfying all the requirements. To address the process, Pareto optimality is used [28].

Definition 1 (Pareto Optimality): A state of allocation procedure, in which it is impossible to improve one participant's situation without making at least one participant's situation worse.

Definition 2 (Pareto Dominance): For a strategy set with H as the objective function, each vector in the set means a possible strategy. For two different vectors u and k, k is Pareto dominated by u if and only if $H(u)_i \leq H(k)_i$ holds true for all i and at least one inequality exists, where i is the ith element of objective vector. It means the strategy u can make at least one participant better than the strategy k without making anyone worse.

Definition 3 (Pareto Optimal Solution): A strategy p is a Pareto optimal solution if p is feasible and there are no other strategies can dominate it.

Definition 4 (Pareto Optimal Set): The collection of Pareto optimal solutions is termed a Pareto Optimal Set.

Definition 5 (Pareto Front (PF): When plotted in the objective space, the image of Pareto Optimal set is termed Pareto Front.

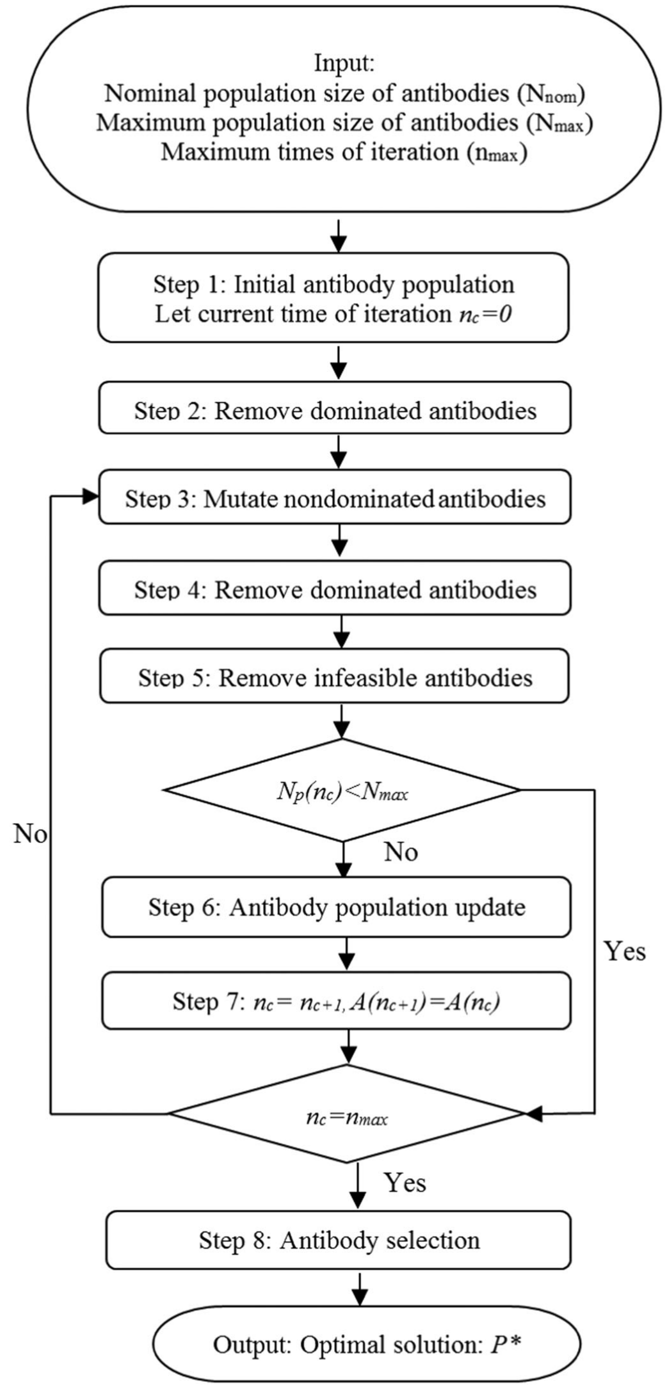

Fig. 3. Flowchart of the AIA algorithm.

B. Algorithm

To attain the Pareto Optimal Set for MOP, the AIA can be used [28], [34], [35]. The AIA is a global search method that uses an iterative process. Compared to traditional search algorithms, AIA is easy to use, robust, and suitable for parallel processing. In using the AIA, the terminology antibody is used to describe a point in the decision variable space.

Fig. 3 shows the flowchart of the AIA algorithm used to solve the MOP in (20). The antibody p represents the decision variables x^1 in the MOP. A group of antibodies are first randomly generated over the interval $[P_{\min}, P_{\max}]$ following the uniform distribution, where $P_{\min}$ and $P_{\max}$ are the minimum and maximum value of the decision variable, respectively. Dominated antibodies are removed gradually. Next, gene operation is applied to the nondominated antibodies. The antibodies then mutate in order to produce a diversified population. The dominated antibodies are removed as well. After that, the condition $f_r(p) = 0$ is used to eliminate the infeasible antibodies. If the population size is still too large, the antibody population update operation will be adopted till the population size reduces to N_{nom}. The above process repeats until the maximum number of iteration is reached. At this stage, a Pareto frontier is obtained. According to the selection criterion, the most fit antibody is chosen as the output, which can maximize the minimum improvement in all dimensions. This solution will maintain fairness, and does not favour any particular participants. Detailed search steps are described as follows.

Step 1: Generate the initial population of antibodies randomly. Let $n_c = 0$ and

$$A(0) = \{p_1, p_2, p_3, \ldots p_{\text{nom}}\} \tag{21}$$

where p_i is a random vector from $[P_{\min}, P_{\max}]$.

Step 2: Remove dominated antibodies and maintain the nondominated antibodies.

Step 3: Mutate the remaining nondominated antibodies. The current population is

$$A(n_c) = \{p_1, p_2, p_3, \ldots p(n_c)\} \tag{22}$$

The current population size is $N_P(n_c) = \|A(n_c)\|$. Define the clone rate as

$$R(n_c) = \left\lfloor \frac{N_{\max}}{N_p(n_c)} \right\rfloor \tag{23}$$

where $\lfloor . \rfloor$ is a floor function. The clone and mutation operation is implemented to each element p in the set A, according to the equation

$$p_i^j = \theta p_i + (1-\theta) p_i^{'} \tag{24}$$

where θ is randomly chosen from $[0, 1]$, and $p_i^{'}$ is a random vector belonging to $[P_{\min}, P_{\max}]$. Through the mutation, a new set of antibodies is produced

$$C = \left\{p_1^1, p_1^2, \ldots, p_1^{R(n_c)-1}\right\} \cup \left\{p_2^1, p_2^2, \ldots, p_2^{R(n_c)-1}\right\} \\ \cup \ldots \cup \left\{p_{N_p(n_c)}^1, p_{N_p(n_c)}^2, \ldots, p_{N_p(n_c)}^{R(n_c)-1}\right\}. \tag{25}$$

Let $A(n_c) := A(n_c) \cup C$.

Step 4: Repeat Step 2, and remove the dominated antibodies from the new population.

Step 5: The remaining antibodies are all nondominated, but not all of them are feasible. The antibodies with $f_r(p) > 0$ are not applicable for the MOP formulated in this paper. The antibodies with the largest $f_r(p)$ will be first removed. If $f_r(p_1) > f_r(p_2) > 0$, then p_1 is removed first. The process continues until the condition $f_r(p) = 0$ holds true for all antibodies.

Step 6: After Step 4 and Step 5, if the population size is still larger than the nominal size, the antibody population update procedure needs to be applied to normalize the antibodies. For a crowded region, a fitness value is allocated to antibodies

$$f_{\text{fit}}(p_n) = \sum_{j=1}^{J} \frac{F(p_n)_j - F(p_{n-1})_j}{F_j^{n_c,\text{up}} - F_j^{n_c,\text{low}}} \tag{26}$$

where J is the number of objectives, $F_j^{n_c,\text{up}} = \max_{p \in A(n_c)} F(p)_j$ and $F_j^{n_c,\text{low}} = \min_{p \in A(n_c)} F(p)_j$.

The antibody with the smallest fitness value will be first removed. If $f_{\text{fit}}(p_1) > f_{\text{fit}}(p_2)$, then p_2 is removed first. The procedure stops when the current population size is no large than the nominal size. It is noted that this procedure will not be carried out for the extreme vectors in $F(P)$, where extreme vector means at least one element in this vector reaches its extreme value, i.e., $F(p')$ is an extreme vector if there exists j such that $F(p')_j = \max_{p \in A(n_c)} F(p)_j$ or $\min_{p \in A(n_c)} F(p)_j$.

Step 7: Let $n_c = n_c + 1$ and $A(n_c + 1) = A(n_c)$. Repeat Step 3 to Step 7, until $n_c = n_{\max}$.

Step 8: As the iteration counter n_c increases gradually, $A(n_c)$ forms a Pareto frontier. All the vectors in it are possible solutions to $F(P)$. A solution that can maximize the minimum improvement in all dimensions is selected as the output. This output can guarantee the fairness among all the participants rather than giving advantage to one particular participant. The criterion can be written as

$$P^{\star} = \arg \max_{p \in A(n_{\max})} \min_{j=1\ldots J} \frac{F_j^{\text{up}} - F(p)_j}{F_J^{\text{up}} - F_j^{\text{low}}} \tag{27}$$

where $F_j^{\text{up}} = \max_{p \in A(n_{\max})} F(p)_j$ and $F_j^{\text{low}} = \min_{p \in A(n_{\max})} F(p)_j$.

IV. Simulation Results

In this section, a practical case study is presented. The modelled system consists of one utility with 2500 wind turbines, one aggregator and one cluster of customers. The utility comprises 2500 wind turbines with the rating of 2.75 MW. In the day-head market, a calendar day is equally divided into 24 time slots, i.e., $T = 24$. The UK actual daily data from Grid Watch is fed into the model. The U.K. average electricity price 0.18 £/kWh is applied. For conventional generators, the cost function is given as

$$c(g_t^c) = 5(g_t^c)^2 + 400 g_t^c + 100\ \pounds/\text{GWh}. \tag{28}$$

For RESs, wind power is considered. The wind speed v_t in m/s can be predicted in advance. The relationship between the output power z_t in MW and v_t is set as [36]

$$z_t = \sigma(\tau, \psi) \frac{\rho S}{2} v_t^3 \tag{29}$$

where the performance coefficient $\sigma(\tau, \psi)$ can be calculated from experiential arithmetic, based on the blade tip speed ratio τ and blade pitch angle ψ. The air density and swept area are set as $\rho = 1.225$ kg/m^3 and $S = 1257$ m^3. The rated wind speed and maximum wind speed are specified as: $v_{\text{rate}} = 15$ m/s and

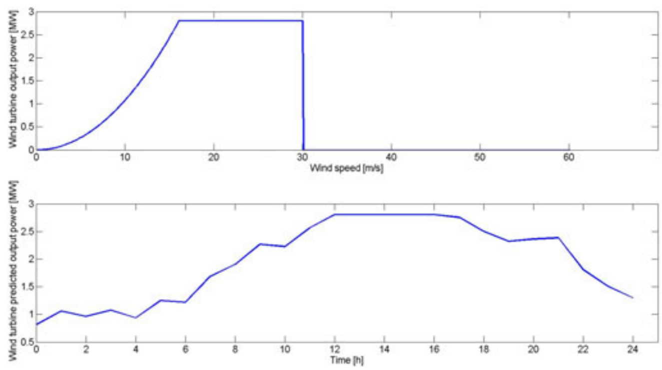

Fig. 4. Wind turbine output performance.

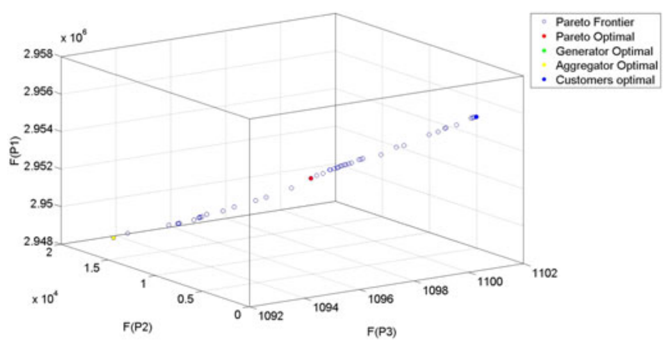

Fig. 5. Example of Pareto Frontier.

$v_{\max} = 30$ m/s. When $v_t > v_{\max}$, $v_t = 0$, since the extreme fast speed will produce an undesirable large moment on the blade, which may damage the wind turbine, the turbine will be forced to stop for safety. When $v_{\text{rate}} < v_t < v_{\max}$, $v_t = v_{\text{rate}}$, since the turbine is already fully operated when the wind speed reaches the rated speed. Even with a faster wind speed, the turbine is not able to generate more power. Fig. 4(a) shows the statement above, and Fig. 4(b) shows the predicted wind power output g_{res} for the day-ahead market. The electricity generated from wind turbines will be consumed first. The remaining electricity demand will be satisfied by the conventional power generators.

For the utility, the bonus coefficient $\mu = 0.7$ in (3) has been set, indicating 70% of the DSM gain will be given to the DR aggregator. For the DR aggregator, the compensation strategy is defined as

$$f_{\text{com}} = \sum_{t \in T} [-0.01(x_t^1 - g_t)^2 + 30]. \tag{30}$$

For customers, it is assumed 20% of the load profile can be deferred with $x_{t,\max} = 1.2x_t$ and $x_{t,\min} = 0.8x_t$. The dissatisfactory function is given by

$$f_{\text{dis}} = 0.01(x_t^1 - x_t^0)^2. \tag{31}$$

Using the AIA, the Approximate Pareto Front (APF) for the day-ahead market model can be generated. Fig. 5 gives an example of the APF. It illustrates the interaction between three objectives. For a solution p, if an arbitrary element yields an extreme objective value $F(p)_j = F_j^{\text{up}}$ or $F(p)_j = F(p)_j^{\text{low}}$, it means this solution advantages a particular participant. To ensure the fairness, an optimal solution p^* can be chosen based on the APF by using (27), which can maximize the minimum improvement in all dimensions. As shown in Fig. 5, the selected optimal solution p^* is located in the centre of the APF graphically. It proves that through the proposed multiobjective approach, a fair design can be obtained.

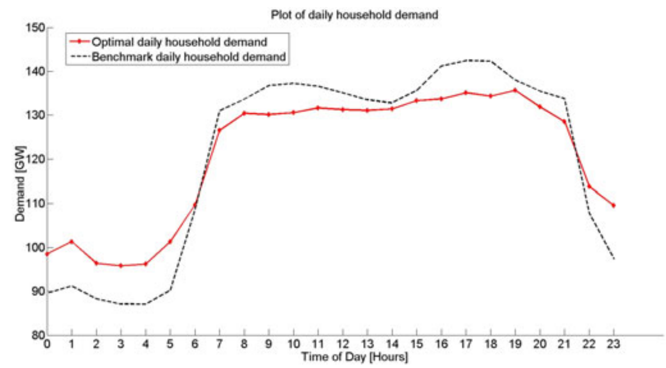

Fig. 6. Optimized usage pattern for the day-ahead market.

TABLE I

COMPARISON OF THE REFERENCE LOAD PROFILE AND THE OPTIMAL LOAD PROFILE IN THE U.K., MAY 5, 2017

	Reference Load Profile	Optimized Load Profile
Total (GWh)	2892	2898
Average (GW)	120.5	120.8
PAR	1.182	1.119
Generation Cost (£)	2956774	2951090
Bonus to DR aggregator (£)	–	12632
Compensation to Customers (£)	–	620

Fig. 6 shows the optimized load profile and the reference load profile in the U.K. for the selected day, May 5, 2017. It is clearly shown that after the optimization, during the off-peak time (i.e., 0:00–6:00), the demand increases. While during the peak-time (i.e., 17:00–22:00), the demand decreases. The utility, DR aggregator, and customers can benefit from using the proposed multiobjective DSM. The detailed information can be found in Table I.

For that day, the utility can save £ 5684 for the generation cost. The PAR is reduced about 5.33%, from 1.182 to 1.119. By providing the DSM, the DR aggregator can make a profit of £ 12632. For customers, the electricity bill can be cut down by £ 620 in total.

V. CONCLUSION

This paper proposed a multiobjective optimization approach for enabling DSM program. A hierarchical framework was studied, which consists of the utility, the DR aggregator, and customers. The role of the DR aggregator was defined as an intermediary communicating with both the utility and customers. The modelled system led to a MOP, which can be solved by the AIA. Through the proposed AIA, a Pareto frontier can be obtained. After that, a Pareto optimal solution was selected that maximizes the minimum improvement in all dimensions. The simulation results showed that all the participants can benefit from the proposed design: the utility can reduce the generation cost; the DR aggregator can make profit by providing DR service; customers can save money on their bill. For future research, the focus will be on two research topics. The first topic is to develop a fair allocation mechanism among the customers that meets their needs. The second topic is related to a feasible information exchange method that can protect customers' privacy.

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