Unit Commitment in Achieving Low Carbon Smart Grid Environment with Virtual Power Plant

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***Abstract*—This paper proposes a novel unit commitment (UC) model under smart grid (SG) environment, which intends to strike a balance pursuing minimum carbon emissions for policy maker, minimum costs for generators and minimum payment bills for consumers. This leads to a multiobjective optimization problem (MOP) which can be solved through the multiobjective immune algorithm (MOIA). Therefore, the energy market scheduling problem considering low carbon smart grid environment can be analysed. The case studies are conducted to demonstrate the proposed model and present the allocation of power generations as well as the daily energy market scheduling results. It has been proved that the penetration of SG contributes to the mitigation of carbon emissions during the peak demand time by around 500 ton/h. It is also suggested that if the policy maker can provide appropriate monetary compensation for the deployment of SG technologies, generators will be encouraged to participate in the SG deployment.**

***Index Terms*—Smart grid (SG), unit commitment (UC), multiobjective optimization (MOP), virtual power plant (VPP), electric vehicle (EV), demand response (DR).**

I. Introduction

The power sector is a major contributor to the greenhouse gas emissions. Since it is closely tied to economic activities, power generation plays a significant role in our everyday life [1]. Additionally, the SG plays a significant role in increasing penetration of distributed resources in demand side. This resources include Distributed generation (DG), electric vehicle (EV), and flexible demand under demand response (DR) programme. Thus, it is necessary to design a virtual power plant to aggregate the capacity of many diverse distributed energy resources and flexible demands [2]. The operation of energy system can be subsequently scheduled balancing supply and demand in real time [3]. This trends requires a more dedicated unit commitment (UC) model to coordinate and optimise the use of distributed resources in both supply and demand sides considering the objective of mitigating of carbon emissions.

With respect to SG technologies, existing studies confirmed the feasibility and significance of DG in managing the balance between supply and demand [4]–[6]. Besides, the SG supports the bidirectional communication between consumers and grids via smart metering systems. It is essential for the deployment of DR, because customers can respond to grids in almost real time. The DR has been noted in studies for supply-demand scheduling [7]–[9]. The EV which is considered as a mobile load is also an important part of SG, because it has the potential to reducing carbon emissions in the transport sector. The cost and carbon emission of EV were investigated in [10], [11] through the use of UC model. Nevertheless, the effects of SG technologies on both generation and consumption levels have barely been studied.

Furthermore, the increasing distributed resources and DR services cause some issues in power systems. These issues include reliability and security of supplies. Virtual Power Plant (VPP) is a powerful platform of aggregating distributed resources, and operating them as a virtual large power plant enabling active participation of distributed resources in the energy market [3].

The SG technologies can encourage the use of the low-carbon resources to replace the conventional power generations. The UC offers an optimal operation point to schedule the energy markets. Normally, the UC model simply focuses on the generation side of power systems [12], [13]. In practice, the policy maker seeks to evaluate the carbon emissions of power systems and make corresponding policies for the minimization of carbon emissions. Considering the emission restrictions, generators seek to minimize their operation costs through the SG technologies. In the meantime, consumers respond to incentive signal and price signal by using SG technologies to minimize their payment bills. Transferring objectives to be constraints [14] and weighted evaluation of each objective [15] are typical approaches to cope with this problem with various dimensions. Nonetheless, it would be more useful to apply multiobjective optimization problem (MOP) into the UC model for the purpose of fairly and reasonably evaluating the interests of both generators and consumers as well as carbon reduction targets. In the UK energy market, for instance, the Department for Business, Energy and Industrial Strategy is responsible for making policies to mitigate the carbon emissions [16]. The Office of Gas and Electricity Markets (Ofgem) concentrates on the aggregated interests of consumers as a whole, including their green house reduction interests [17]. The Big Six Energy Suppliers (British Gas, EDF Energy, E. ON UK, Npower, Scottish Power, SSE) purchase power from wholesale market, before billing consumers for their electricity consumption [18].

Compared with the existing work, this paper has contributions as follows:

- We propose a novel UC model considering not only conventional generation side but also DR as a part of VPP for effectively aggregating distributed resources, thus enabling their participation in the energy market;

- We formulate a MOP by involving policy maker, generators, and consumers, so that the reduction of carbon emissions can be considered into daily energy market scheduling.

The rest of this paper is organized as follows. Section II introduces the model of SG environment in the form of VPP. The UC model and corresponding algorithm are subsequently proposed in Section III. Section IV presents the results of case studies for daily energy market scheduling. Finally, Section V draws the conclusion.

II. System Model

This Section describes the deployment of SG, in which DR, DG, and EV are regarded as elemental components of SG. The demand aggregator is a medium facilitating communication between system operators and consumers [19]. This is because the scattered consumers have limited negotiation power in the energy market. The system operator also faces the challenge of managing the DR, DG, and EV.

A. Demand Response

The advance of smart meter enables bidirectional communication between consumers and grids [20]. Building on this, the DR can be realised through incentive signal and price signal [21]. The demand aggregator is capable of gathering scattered DR resources through contracts with operators. As a consequence, DR can be conceptualised to a single unit. The cost of DR can be modelled to be a quadratic function [22]:

$$C(DR_t) = a_{DR}DR_t^2 + b_{DR}DR_t + c_{DR} \tag{1}$$

where $C(DR_t)$ is the total cost of DR at time t, DR_t is the aggregated power of DR at time t, and a_{DR}, b_{DR}, and c_{DR} are cost coefficients of DR unit. Considering the interests of consumers, there is a constraint for maximal level of DR:

$$DR_t \leq DR_t^{max} \tag{2}$$

where DR_t^{max} is the power limit of DR.

Meanwhile, the deployment of DR may cause inconvenience of consumers due to the deviation from the original consumption, which can be modelled by a dissatisfaction function $V(DR_t)$ [23]:

$$V(DR_t) = d \cdot DR_t^2, d \geq 0 \tag{3}$$

where d is the inelasticity parameter of payment bills. Through this dissatisfaction function, the inconvenience caused by DR can be transferred to the increases of payment bills for customers.

B. Distributed Generation

Similarly, the aggregator is also responsible for gathering DGs and selling extra power of grid-connected DG back to grids. This paper focuses on the dispatchable DG which can be sold back to grids. The cost function of dispatchable DG is:

$$C(DG_t) = a_{DG}DG_t^2 + b_{DG}DG_t + c_{DG} \tag{4}$$

where $C(DG_t)$ is the total cost function of DG at time t, DG_t is the power of DG which will be sold back to grids by consumers at time t, and a_{DG}, b_{DG}, and c_{DG} are cost coefficients of DG unit. There exists a limit of DG output:

$$DG_t \leq DG_t^{max} \tag{5}$$

where DG_t^{max} is the power limit of DG.

C. Electric Vehicle

SG supports a fundamental platform for the interactions between power systems and EV users [24]. The EV can be directly charged through power grids. It is possible to treat the charging of EV batteries as an additional load [25], so that it will be included into the electricity demand paid by consumers. The extra electricity of EV can be sold back to grids through the aggregator by signing contract with system operators. The cost function of EV can be modelled as (6), since the marginal cost increases when EVs draw more power from the power grid [26].

$$C(EV_t) = a_{EV}EV_t^2 + b_{EV}EV_t + c_{EV} \tag{6}$$

where $C(EV_t)$ is the total cost function of EV at time t, EV_t is the EV power which will be sold back to grids, and a_{EV}, b_{EV}, and c_{EV} are cost coefficients of EV units. The constraints of EV include:

$$EV_t \leq EV_t^{max} \tag{7}$$

where EV_t^{max} is the upper limit of EV power which can be sold back to grids considering the safe operation.

D. Virtual Power Plant

The aforementioned DR, DG, and EV can be conceptualised as a VPP which is a necessary infrastructure to coordinate each element inside [27]. The VPP can dispatch and optimise these resources to support power system operations. In addition to DR, DG, and EV, the Energy Storage (ES) is another instrumental component of VPP. The behaviour of storages can be modelled as:

$$-(ES_t^{min} - SoC_{t-1}) \leq ES_t \leq ES_t^{max} - SoC_{t-1} \tag{8}$$

$$SoC_{t-1} - SoC_t \leq R_{Dch} \tag{9}$$

$$SoC_t - SoC_{t-1} \leq R_{ch} \tag{10}$$

where ES_t is charged/discharged capacity of ES at hour t, ES_t^{min} and ES_t^{max} are minimum and maximum capacities of ES, respectively, SoC_t is state of charge of ES at hour t, and R_{ch} and R_{Dch} are maximum charge and discharge rates of ES. Hence, the cost function of ES can be modelled as:

$$C(ES_t) = A \cdot |ES_t| + B \tag{11}$$

where $C(P_{ES_t})$ is operation cost function of ES, and A and B are cost coefficients of ES.

III. Multiobjective Problem Framework

A. Objective of Generators

The optimization problem of generation cost is described as operation cost for power generation presented in (12) [15] with additional costs caused by the deployment of SG presented in (1), (4), and (6).

$$C(P_{i,t}) = a_i P_{i,t}^2 + b_i P_{i,t} + c_i \tag{12}$$

where $C(P_{i,t})$ is the generation cost of ith power generator at time t, $P_{i,t}$ is the power output of ith generator, and a_i, b_i, and c_i are cost coefficients of generator i. Therefore, the generation costs optimization problem can be modelled as follow.
Objective of generators (min costs) :

$$\begin{aligned}\min_{P_{i,t},DR_t,DG_t,EV_t,ES_t} \{ &\sum_{i=1}^{n}[C(P_{i,t}) + SUC_i + SDC_i] + \\ &C(DR_t) + C(DG_t) + \\ &C(EV_t) + C(ES_t)\}\end{aligned} \tag{13}$$

where SUC_i and SDC_i are start up and shut down costs of ith power plant.

B. Objective of Policy Maker

The carbon emissions of conventional power plant can be modelled using second order polynomial function [28]:

$$E(P_{i,t}) = \alpha_i P_{i,t}^2 + \beta_i P_{i,t} + \gamma_i \tag{14}$$

With the objective of minimizing the total carbon emissions, the optimization problem of policy maker can be described as follow.
Objective of policy maker (min carbon emissions) :

$$\min_{P_{i,t}} \{\sum_{i=1}^{n} E(P_{i,t})\} \tag{15}$$

It is worth mentioning that the carbon emissions in VPP are not taken into consideration during the optimisation process, since these emissions are irrelevant to the operational process. The carbon emissions in VPP will be evaluated through carbon emission factors [29], based on the life cycle analysis.

C. Objective of Consumers

The objective of customers is described as the payment of electricity consumption with incurred dissatisfaction due to the DR subtracting monetary compensation of carbon reduction from policy maker. Since a higher level of DR contributes to a more significant effect of carbon emissions reduction, the variations of monetary compensation M with the effects of carbon reduction due to DR $E(DR_t)$ can be modelled as a linear increasing function since the amount of compensation increases as the effect of carbon reduction increases.

$$M(DR_t) = \delta \cdot E(DR_t) \tag{16}$$

where δ is the carbon compensation rate. $E(DR_t)$ can be calculated according to (14). Considering the dissatisfaction function of DR presented in (3), the optimization problem of consumers can be described as follow.
Objective of consumers (min payment bills) :

$$\begin{aligned}\min_{P_{i,t},DR_t,DG_t,EV_t,ES_t} \{&(D_t - DR_t - DG_t - EV_t)p_e \\ &- M(DR_t) + V(DR_t)\}\end{aligned} \tag{17}$$

where D_t is the original load demand at time t, and p_e is the average electricity price.

D. Constraints

In addition to the aforementioned constraints in (2), (5), and (7), there are three common constraints in the UC model including power balance constraint, limitations of power output, and ramp rate constraint [30].

1) Power Balance Constraint:

$$\sum_{i=1}^{n} P_{i,t} + P_{ch_t} - \eta P_{Dch_t} = D_t - DR_t - DG_t - EV_t \tag{18}$$

where P_{ch_t} and P_{Dch_t} are power charged and discharged into ES at hour t, and η is efficiency of ES.

2) Power Output Constraint:

$$P_{i,t}^{min} \leq P_{i,t} \leq P_{i,t}^{max} \tag{19}$$

where $P_{i,t}^{min}$ and $P_{i,t}^{max}$ are the minimum and maximum power generations of generator i.

3) Ramp Rate Constraint:

$$-R_i^{down} \leq P_{i,t} - P_{i,t-1} \leq R_i^{up} \tag{20}$$

where R_i^{down} and R_i^{up} denote the ramp-down and ramp-up rates of ith generator.

E. Algorithm

The proposed objectives of generators, consumers, and policy maker form a MOP. The multiobjective immune algorithm (MOIA) [31] is adopted to solve this problem for the purpose of obtaining Pareto front (PF). MOIA (See Algorithm1)is a global searching algorithm with robust computational capability. The PF is the image of the Pareto optimal set which contains the set of all Pareto optimal solutions. A point in the decision variable space is a Pareto optimal (PO) solution if it is feasible and no other points dominate it [31]. Examples of PF and PO are shown in Fig. 1. Therefore, the terminology antibody is selected to illustrate a point in the decision variable space.

IV. Case Studies

In order to demonstrate the performance of the proposed UC model, case studies have been conducted on the IEEE 30-bus system by replacing the original system data with the scaled down UK daily power generation and consumption in proportion. The IEEE 30-bus system consists of 6 generators, 41 branches, and 21 nodes carrying loads [32]. The cost and emission coefficients of generators are obtained from

Algorithm 1

Input: Objective functions: (13), (15), and (17); initial solution size n; maximum iteration time: t_{max}.

1: Generate a group of antibodies as initial population to represent the power dispatch over constraints (2), (5), (7), (18), (19), and (20):
$A(0) = \{P_{i,t}, DR_t, DG_t, EV_t, ES_t\}$

2: Remove dominated antibodies and remain nondominated antibodies.

3: Perform mutation operation over the remaining nondominated antibodies to produce a set of antibodies.

4: **repeat**

5: Remove dominated antibodies.

6: Evaluate the remaining antibodies through satisfying the constraints and remove infeasible antibodies.

7: **if** The population size is larger than the nominal size **then**

8: Update to normalize the antibodies

9: **end if**

10: **until** The maximum iteration time is reached.

Output: A solution which is able to maximize the minimum improvement in all dimensions is selected.

[14]. The cost coefficients of SG technologies are obtained from [22]. The percentage of DG is set according to the UK present DG penetration rate [33]. The upper limit of DR is assumed 5% of demand in each hour. The emissions of DG and DR are assessed through life cycle analysis [29]. The carbon compensation rate 18 $\pounds/ton$ is selected according to the UK current value [34]. The parameters in simulation of ES behaviours are based on [35].

The optimization results at $4h$ is selected as an example (See Fig. 1) to illustrate the interactions among three objectives during the process of evaluating the optimal solution. It is clear that the PO is located in the centre of the PF geographically, which indicates that the adopted MOIA is able to obtain a fair scheduling solution without sacrificing the interest of any objective.

Fig. 2 presents the allocation of scheduling power for generators by solving the MOP in each hour. The total contributions of SG technologies including DR, DG, and EV are also presented in the reduction of total demand. It can be seen that the deployment of SG technologies results in the reduction of total demand by around 10 MW through selling back to grids or DR, which contributes to the supply-demand balance in SG environment. Furthermore, the SG in the form of VPP can support the total demand economically and environmental friendly due to zero or near-zero emissions during the operational process. It is especially for the peak-time, when the marginal cost of power generation increases dramatically.

The allocated power of SG technologies in the form of VPP is shown in Fig. 3. The 5% DR contributes to a majority portion of total power output in VPP. Nevertheless, due to the increasing penetrations of DG and EV, they are expected to

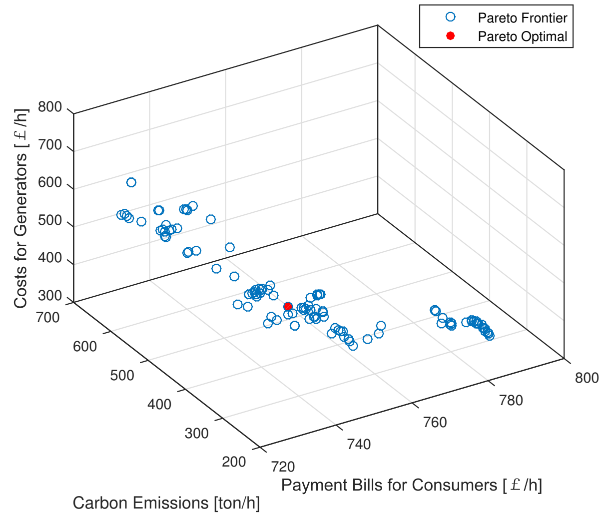

Fig. 1. Example of possible scheduling solutions at 4 h.

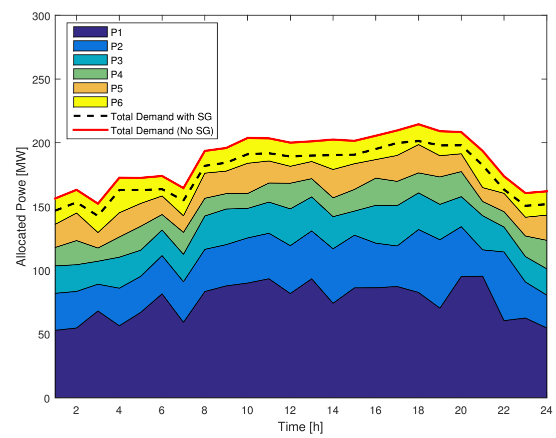

Fig. 2. Optimized power allocation on supply side.

play significant roles in demand side management. Besides, from this significant amount of VPP output, it is worth mentioning that SG environment provides great opportunities for aggregators to gather the scattered consumers, EV users, and DG serving on negotiation between system operator and consumers.

Fig. 4 presents the comparison of optimized objectives for generators, policy maker, and consumers between PO and partial optimal solution in PF which only considers their own objective during the process of evaluating the optimized solution. Through compromising with other two objectives, the optimal results of payment bills for consumers keep almost unchanged, whereas the carbon emissions and operation costs for generators show slight increases considering the interests of other objectives. Moreover, the peak-time (from $8h$ to $18h$) shows obvious increases in three objectives. It is particularly for the carbon emissions, for which the amount in peak time decreases by around 500 ton/h. This is because the peak-

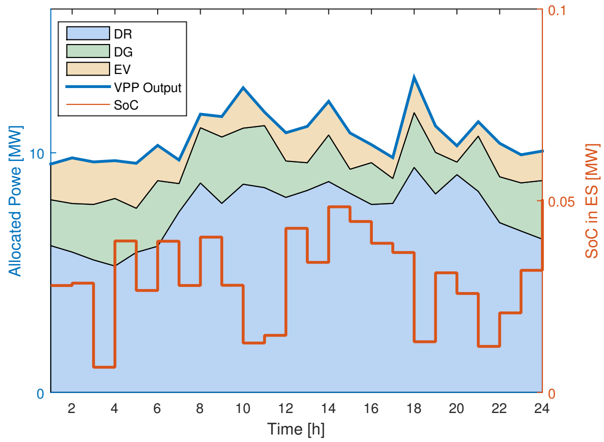

Fig. 3. Optimized power allocation in VPP.

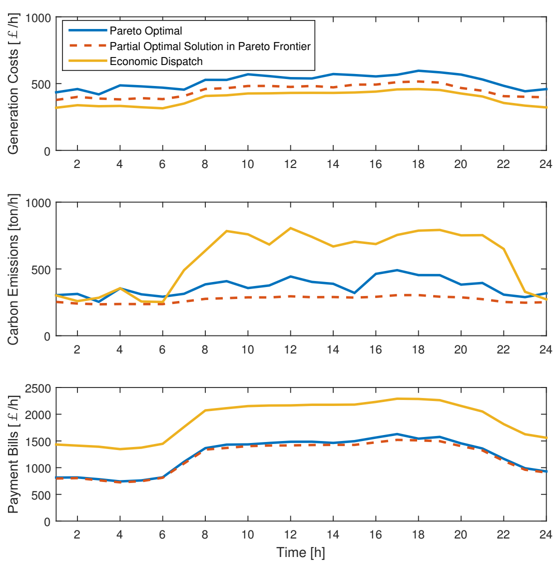

Fig. 4. The comparison of optimized objectives.

time demand is the primary driving factor for total emissions. Therefore, it indicates the necessary to deploy low carbon SG to replace the conventional generations.

Additionally, the economic dispatch is a classic generation dispatch approach, in which the generators with the lowest cost will be triggered first [36]. The interests of carbon emissions and payment bills for consumers are also not considered in economic dispatch. Compared with conventional economic dispatch without the penetration of SG, it is noted that the carbon emissions in peak time will be dramatically reduced with the UC scheduling. The Payment bills will also decrease because of the carbon compensations and the power sold back to grids in SG environment. The operation costs slightly increase by around 100 $\pounds/h$ for the purpose of SG deployment, which means that the generators sacrifice their own interests to contribute to the carbon reduction and SG deployment. If this scarification can be compensated by policy maker, there will be an incentive for generators to involve in the SG environment.

V. Conclusion

This paper develops a UC model for SG technologies including DR, DG, and EV in the form of VPP. The UC optimization problem fairly schedules the energy market considering carbon emissions, operation costs, and payment bills which do not share the same dimension in energy markets. This MOP is subsequently solved by MOIA.

Case studies demonstrate that the proposed model is capable of scheduling daily optimized energy market. The penetration of SG contributes to the balance between supply and demand. Under the circumstances of SG, carbon emissions during peak-time can be reduced by replacing the conventional generations with demand-side resources. If further policy is able to compensate the costs of generators, this UC will be a promising model for energy market scheduling.

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