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Energy Management for Grid-connected Micro Grid with Renewable Energies and Dispatched Loads

***Abstract**. This paper focused on energy management program for grid-connected micro grid with renewable generation and electric vehicles. The proposed program, including energy purchase and self-scheduling problems, aimed to minimize energy cost based on forecasting of loads, prices and renewable generations and was solved with genetic algorithm and pattern search methods. Furthermore, it adopts the expectation model and Monte Carlo methods to solve the uncertainty problems. Simulation results proved the effectiveness of the proposed program.*

***Streszczenie.** Analizowano zarządzanie energią w sieci typu microgrid. Celem jest minimalizacja kosztów bazująca na przewidywaniu obciążenia. Wykorzystano algorytmy genetyczne oraz metodę Monte Carlo. (**Zarządzanie energią w sieci typu microgrid z rozproszonym obciążeniem i odnawialnymi źródłami energii**)*

Keywords: Energy Management, Micro Grid, Electrical Vehicles, Renewable Energy.
Słowa kluczowe: microgrid, pojazdy elektryczne, energia odnawialna.

Introduction

Micro grid (MG) could work in both isolated and connected with main grid situations. Generally, MGs would be connected with main grid if possible in order to make mutual benefits between distribution generators and main network. MGs connected with power system could reduce their operation cost by participating demand response and increase their reliabilities. Meanwhile, main grid could get extra reserves, demand response resources and more stable loads. Furthermore, grids could accept more renewable energies since the grid-connected micro grid (CMG) could solve the fluctuation problem of renewable energies by themselves at most time.

CMG faces good chances in smart grid environment. The development of smart grid, especially in advanced metering equipment and electrical vehicle (EV), brings lots opportunities for renewable distribute generations, and CMG has been concerned as one of the best methods to integrate those generations into power system [1, 2]. Besides, smart grid would make the power grid much friendlier to end users than it used to be, which means normal users could get more chances to participate daily operation of power system to reduce costs of their electricity consumptions. For example, smart buildings with renewable generations and EVs would be good cases to form a CMG.

To balance demand and supply of power energy economically and reliably is the main task of a power system with any scale and any type. For CMGs with distribute generators, daily scheduling consists of energy procurement and self-scheduling would be one of the key factors to achieve the economical purpose. Significant efforts have made to purchasing problems in electricity market [3-7]. Demand bid of consumers in electricity market could provide benefits for consumers and markets [3], both consumers and markets would reduce their risks though the action. A daily bidding strategy for large consumer through the information gap decision theory has been proposed in article [4], both day-ahead and spot markets had been considered in this research. The authors of it utilized the mean-variance theory to solve the uncertainty problem. The behaviour of other participants was assumed as a function of market distribution to build the model of optimal demand side bidding [5], and the authors adopts the game theory as simulation method. Forecasted electricity price and load of MG are needed for day ahead bidding and dispatching. The uncertainty of electricity price of the market and load of MG could bring risk to both producers and consumers [6]. Demands could be classified to price based load, must-serve load and dispatched load [7]. Equivalently, much attention has paid on power balancing of isolate MGs. A power management model for island MG with diesel generators was built and solved with genetic algorithm for the optimal solution [8]. Mesh adaptive direct search has been utilized to settle the scheduling problem of CMG consisted of multiple generators in article [9], the gas emissions and purchasing costs have been taken into account in the research.

Generally, most attentions focused on energy management of traditional large consumers, such as big companies and factories, and many mathematic methods had been successfully applied in those researches. But studies on energy management for CMGs with renewable generations and dispatched loads are not common. Comparing with traditional consumers, CMGs are more flexible in demand response, and the discharge of DLs or other new applications would provide a new way for consumers to save their bill. So energy management of CMGs needs to solve two more problems than the traditional ones, which are the uncertainties problem of renewable generations and combined optimization of energy purchasing and scheduling of DLs.

This paper proposed a daily energy management model for CMGs, with the consideration of multiple renewable generations and DLs [10]. The optimal energy management problem in this paper would integrate purchasing bid and loads dispatching together. The objective of the model is to minimize the total energy costs with the principle of satisfying load demands and some uncertainty forecasting data. CMGs needs to make decisions based on forecasting values of wind speeds, sunshine irradiances, electricity prices and loads, and forecasting accuracies of them would affect the final costs of CMGs [11]. Unlike previous works aimed to improve the forecasting accuracies of these values [12, 13], this paper focused on how to make choices with historical data of those uncertainty inputs by stochastic programming methods.

Generation and Demands Models of CMG

Generally, CMGs would consist of industrial, commercial and residential-alliance users. So CMGs would utilize wind turbines, photovoltaic generators, diesel generators, fuel cells and energies from power market as power sources. In demand side, the growing EVs and other rechargeable appliances are separated with other loads as DLs.

1.1 Photovoltaic Generation

Photovoltaic generators utilize sunshine as the power source to generate electric energies. The output of photovoltaic generator is the function of irradiance and temperature [9].

(1) $$P_{PV} = P_{\max PV} \cdot G_c \Big/ \left[G_{STC} \cdot \left[1 + k(T_c - T_{STC})\right]\right]$$

where: P_{maxPV} – maximum output at standard test condition, G_{STC}, T_{STC} – standard irradiance and temperature, G_C and T_C – current irradiance and temperature, k – temperature coefficient. In this paper, G_{STC} =1000 W/m^2, T_{STC} =25^{o}C.

1.2 Wind Generation

The outputs of wind turbines could be described as a function of wind velocity [12]:

(2) $$\begin{cases} P_w = 0 & V \le V_{ci} \\ P_w = a \cdot V^3 - b \cdot P_r & V_{ci} < V \le V_r \\ P_w = P_r & V_r < V \le V_{co} \\ P_w = 0 & V > V_{co} \end{cases}$$

where: P_r –rated power, V_{ci}, V_r, V_{co} – cut-in, rated, and cut-out wind speeds. The P_r, V_{ci}, V_r, V_{co} in this paper are 15Kw, 3.5m/s, 17.5m/s and 20m/s respectively.

1.3 Diesel Generator

Diesel generators are traditional generators which could be well controlled by operator of MG. The costs of diesel generator, which could be described as follow, are needed by the scheduling model.

(3-a) $$C_{FD}(P_D^t) = Pr_D \cdot \left(a_D + b_D P_D^t + c_D P_D^{t\,2} \right)$$

where: Pr_D – fuel prices, a_D, b_D, c_D –coefficients.

Since the costs of diesel generators are higher than buy energies from energy market at most time, diesel generators would work just in some extreme situations with very small probabilities. For most time, diesel generators just work with the minimum outputs for the sake of reliability. So this paper simplified Equation (3-a) as follow:

(3-b) $$\begin{aligned} & C_{FD}(P_D^t) = C_{FD}(P_{D\min} + P_D^{t\prime}) \\ & = C_{F\min} + \left(b_D + P_{D\min}\right) P_D^{t\prime} + c_D \cdot (P_D^{t\prime})^2 \\ & \approx C_{F\min} + b_D' \cdot P_D^{t\prime} \end{aligned}$$

where: $P_{D\min}$, $C_{F\min}$ – the minimum outputs of diesel generator and its cost at this situation.

Diesel generators the boundary constraint:

(4) $$0 \le P_{D,i}^{t\ \prime} \le P_{D\max,i} - P_{D\min,i} \qquad i = 1, 2 \ldots N_D$$

where: $P_{D\min}$, $P_{D\max}$ – the maximum and minimum outputs of diesel generators.

1.4 Electric Vehicles

The development of smart grid provides some new electric appliances which can keep real time communications between those appliances and controller of grids. In this paper, demands are divided into two types: traditional and dispatched load.

Traditional load (TL) is mainly component by some normal and traditional home and industry appliances. It is a kind of must-serve load which should be satisfied at all times. Although short time prediction for TL has a high accuracy, the uncertainty of TL couldn't be ignored for a MG.

DL could be dispatched by the operator of power systems. Compared with TL, it is a new type load in smart grid. It is a good demand response resource for power systems. EVs could be considered as DLs if the charging of them could be control, otherwise they should belong to TLs. EV would be the largest new load in smart grid, lots of researches had carried to study on how manage and utilize the rechargeable character of EVs [11, 13].

Assume that the managements of EVs adopt the battery replaced model in this paper. Under the assumption, all EVs would be DL and could be considered as a whole load. When EVs are introduced to the model as DL, the followed constrains would be involved.

1) Generally, batteries of EVs have large maximum instantaneous charging and discharging power but they could not work long at large power conditions. This paper adopted the average maximum charging and discharging power of batteries as the charging power limits:

(5) $$P_{EV}^{\min} \le P_{EV}^t \le P_{EV}^{\max}$$

where: $P_{EV}^{\min}$, $P_{EV}^{\max}$ – the maximum discharging and charging power of all batteries, P_{EV}^t – the charging or discharging power of all batteries, and $P_{EV}^t > 0$ means charging.

2) Batteries of EVs must satisfy the demand of EVs at any times.

3) Batteries of EVs have the largest and smallest capacity of energy storage. The smallest capacity could be 0 or a proportion of maximum capacity but not negative, because any EV could carry negative energies. The energy storage capacities of batteries at time t could be calculated by following equation:

(6) $$Ca_{EV}(t) = Ca_{EVS} + \sum\nolimits_{i=1}^{t} (P_{EV}^i \cdot \Delta t - N_{need}^i \cdot Ca_{car})$$

(7) $$0 \le Ca_{EV}(t) \le Ca_{\max EV}$$

where: Ca_{EVS}, $Ca_{\max EV}$ – initial, maximum capacity of batteries, Δt – the minimum time interval, N_{need}^i – demand of EVs, Ca_{car} – battery capacity. Since the calculation of $Ca_{EV}(t)$ has already taken demands of EVs into account, Formula (7) contains the third limitation of EVs.

1.5 Energy Storage Component

Energy storage component (ES) is also considered as a mainly part of DL in this paper. Like EVs, ESs also have the energy storage limits, constrains of those components are as follow:

(8) $$Ca_{ES}(t) = Ca_{ESS} + \sum\nolimits_{i=1}^{t} P_{ES}^i \cdot \Delta t$$

(9) $$P_{ES}^{\min} \le P_{ES}^t \le P_{ES}^{\max}$$

(10) $$0 \le Ca_{ES}(t) \le Ca_{\max ES}$$

where: Ca_{ESS}, $Ca_{ES}(t)$ – initial, maximum capacity of ES, P_{ES}^t – charging or discharging power in the time period t, $P_{ES}^{\min}$, $P_{ES}^{\max}$ – maximum discharging and charging power of ES.

Energy Management Model

The objective of the model is to satisfy the demand and minimize the costs of CMG. The costs of CMG include the costs fuel costs of diesel generators and the payment to main grid. The active power balancing constraint of the whole CMG at any time could be described by the following equation:

(11) $$\sum_{i=1}^{N_D} P_{D,i}^t + \sum_{i=1}^{N_W} P_{W,i}^t + \sum_{i=1}^{N_{Pv}} P_{PV,i}^t + P_B^t = P_{ES}^t + P_{EV}^t + P_L^t$$

where: P_B^t – energy procurement of time t.

For most CMGs, the operators could not control P_L^t , $P_{W,i}^t$ and $P_{PV,i}^t$. This means the controllable variables of P_{ES}^t , P_{EV}^t , $P_{D,i}^t$ and P_B^t are not totally independent with each other, the CMG need a slack variable like big grids need a slack bus. Generally, P_{EV}^t must serve the need of EVs, $P_{D,i}^t$ would make high cost and P_{ES}^t have not enough capacities, so P_B^t would be the best choice. So the minimum expected cost could be described as Equation (12) and (13):

(12)
$$\begin{aligned}&\min f(P_{EV}, P_{St}, P_D') \\ &= E\left[\sum_{t=1}^{24}\left(\sum_{i=1}^{N_D}\left(C_{F\min,i} + b_D' \cdot P_{D,i}^{t}{}'\right) + Pr_t \cdot P_B^t\right)\right] \\ &== C_{D,\min} + E\left[\sum_{t=1}^{24}\left[\sum_{i=1}^{N_D} b_D' \cdot P_{D,i}^{t}{}' + Pr_t \cdot P_B^t\right]\right]\end{aligned}$$

(13) $$P_B^t = P_{ES}^t + P_{EV}^t + P_L^t - \left(P_D^t + P_W^t + P_{PV}^t\right)$$

where: Pr_t – electricity price at time t, N_D – numbers of diesel generators, subscript *i*, *t* – *i*-th generator and time t, $C_{D,\min} = \sum_{t=1}^{24}\sum_{i=1}^{N_D}\left(C_{F\min,i}\right)$ – minimum cost of diesel generators.

Generators and loads have their own limits because their physical characteristics, such as energy capacity and outputs limits, as in Eq.(4)–(10).

3 Solutions

3.1 Mainly Optimization with PS

PS has been used for optimal scheduling problem of power system and been proved very applicably [14]. PS does not require the gradient of objective function, so it could solve problems with discontinuous objective functions. PS has good global search abilities. The procedure of PS was shown in Fig.1, and the details of it were introduced in the following paragraph.

As shown in Fig.1, PS contains axial search and pattern move. The axial search would probe along the direction of every independent variable step by step. The pattern move would make an acceleration of convergence speed based on the result of axial search. The specific steps of PS are as follow:

1) Set the start point $X_0 = \left(x_1^0, x_2^0 \cdots x_n^0\right)$, initial searching step α, count variable k, $l = 0$, the searching start $t_0 = X_0$, the shrinkage factor.., and the termination parameters $\alpha_{\min}$ and $l_{\max}$.

2) Set $e_{k+1} = \left(\underbrace{0,\cdots,}_{k-1}1,\underbrace{0\cdots}_{n-1-k}\right)$, and $t_{k+1}' = t_k + \alpha \cdot e_{k+1}$, and then check the objective values of t_{k+1}' and t_k, if $f(t_k') < f(t_{k-1})$ then make $t_k = t_k'$, go to step 4), otherwise go to Step 3).

3) Set $t_k' = t_k - \alpha \cdot e_k$, and check the objective values of t_{k+1}' and t_k, if $f(t_k') < f(t_{k-1})$ then make $t_k = t_k'$, otherwise make $t_k = t_{k-1}$.

4) Set the count variable k plus 1, and if $k \le n$ go back to Step 2), else go to next step.

5) Set $X_{l+1}' = t_n$, if $X_{l+1}' - X_l = 0$ go to Step 6) and if $X_{l+1}' - X_l \ne 0$ then go to Step 7).

6) Make $\alpha = \beta \cdot \alpha$ and go to step 8).

7) Make $X_{l+1}'' = 2 \cdot X_{l+1}' - X_l$, if $f\left(x_{l+1}''\right) < f\left(x_l\right)$ then set $X_{l+1} = X_{l+1}''$, else set $X_{l+1} = X_{l+1}'$.

8) If $\alpha \le \alpha_{\min}$ or $l \ge l_{\max}$ then stop searching and outputs the X_l as result, otherwise make $k = 0$, $t_0 = X_l$, $l = l+1$ and then go to step 2).

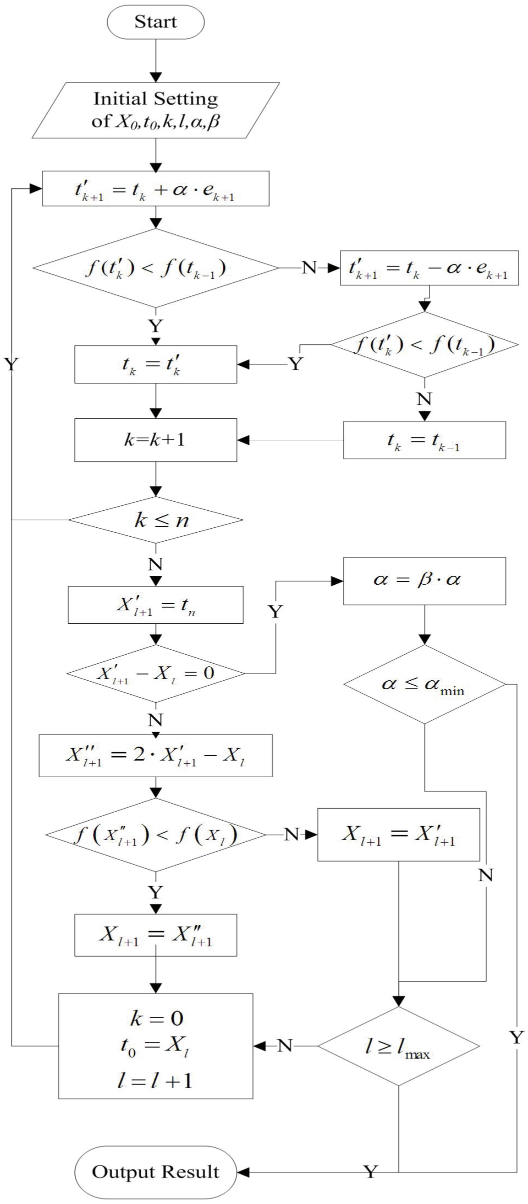

Fig. 1. Flow Chat of PS

As shown in Fig.1, PS needs a start point, which would have a decisive effect on the search process and finally result especially when the problem has many independent variables.

This paper adopts GA as the start point provider for PS. GA starts seeking with a random population of individuals, but it faced the problem of converging too early or falling into a local optimum for the population has low creativity when individuals are similar with each other, which is hardly avoided at the late stage of GA. Generally, PS has a good performance at the late stage when the searching point is near the optimum point while GA has a good performance at the initial stage when the population has large diversity. So this paper utilized GA to find a start point for PS to combine their advantages together.

3.2 Settlement of Uncertainty Cost with Expectation theory and Monte Carlo Method

Forecasting values of wind speeds, sunshine irradiances, electricity prices and loads are needed by the scheduling model, and P_B^t would resolve the uncertainty problem of them form the view of power balance. However, the change of P_B^t would affect the real cost, in other words, the system cost was also an uncertainty value when making decisions, and the forecasting accuracy would affect the final costs of CMGs.

Generally, prediction errors of a forecasting program would follow a fixed distribution. So all uncertainty inputs are random variables with the expectation of forecasting value, and their fluctuation rages were decided by the distribution of forecasting errors. According to the expectation theory, the program aimed to find a scheduling plan that could make the best overall performances in all possible cases, which means the objective function would be the expected value of system cost. So with the consideration of uncertainty of those inputs, the objective function is as follow:

$$\min f = E\left[f(P_{EV}, P_{St}, P_D') \right]$$

$$= \int F(Pr, P_W, P_{PV}, L) \bullet f(P_{EV}, P_{St}, P_D')_{Pr, P_W, P_{PV}, P_L} \qquad \text{(14-a)}$$

$$= \sum_{j=1}^{N} \left[Po_j \bullet \sum_{t=1}^{24} \left[\sum_{i=1}^{N_D} b_D' \cdot P_{D,i}^t{}' + Pr_t \cdot P_{Bt} \right]_{Pr_j, P_{W,j}, P_{PV,j}, P_{Lj}} \right]$$

where: $F(Pr, P_W, P_{PV}, L)$ – joint probability distribution function of daily prices, outputs of wind and photovoltaic generations and loads, $f(P_B, P_{EV}, P_{St}, P_D)_{Pr, P_W, P_{PV}, L}$ – system cost with the scheduling plan under condition of Pr, P_W, P_{PV}, L, Po_j –probability of the combination of Pr_j, $P_{W,j}$, $P_{PV,j}$, L_j.

The calculation of the above objective function would be time consuming, which would bring extra difficulty for optimal search and make the program inefficient. For simplification, this paper adopts the following approximate:

$$\min\left[E\left[f(P_B, P_{EV}, P_{St}, P_D') \right] \right]$$

$$= \min E\left[\sum_{t=1}^{24} \left[\sum_{i=1}^{N_D} (b_D' \cdot P_{D,i}^t{}') + Pr_t \cdot P_{Bt} \right]_{Pr, P_W, P_{PV}, P_L} \right] \qquad \text{(14-b)}$$

$$\approx E\left[\min \sum_{t=1}^{24} \left[\sum_{i=1}^{N_D} (b_D' \cdot P_{D,i}^t{}') + Pr_t \cdot P_{Bt} \right]_{Pr, P_W, P_{PV}, P_L} \right]$$

$$= f(\overline{P}_{B\min}, \overline{P}_{EV\min}, \overline{P}_{St\min}, \overline{P}_{D\min})$$

where: $\overline{P}_{B\min}, \overline{P}_{EV\min}, \overline{P}_{St\min}, \overline{P}_{D\min}$ – the mean value of the best scheduling plans of every combination of Pr_j, $P_{W,j}$, $P_{PV,j}$, L_j.

In order to develop a model that match different forecasting models, this paper assumed that they are independent with each other and utilized Monte Carlo method to settle the uncertainty as following steps.

1) Get distribution functions of forecasting errors of all uncertainty inputs from historical data of them. Take the forecasting error of loads Er_L as example, assuming the number of all historical data is N_L, the distribution function of Er_L is as follow:

$$F(x) = N_x / N_L \qquad (15)$$

where: N_x – number of Er_L which is smaller than x.

2) A random forecasting load could be generated based on the distribution function, the forecasting value P_L^t and a random number ε between 0 and 1. First the simulation algorithm needs to find the corresponding Er_L by $F(Er_L) = \varepsilon$, and then the random forecasting value could calculated as :

$$P_{Lj} = P_L \cdot (1 - Er_L) \qquad (16)$$

Utilize the same method for other forecasting values to generate random values. A group data could be obtained after this procedure.

3) Take optimal solution based on the values obtained from Step 3) to get the optimal bidding and scheduling strategy Rs_j, which includes bidding information and outputs of generators and scheduling of DLs.

4) Iterate Step 2) and 3) m times. Use the mean value as the final result.

Based on the above description, the integral process of the energy management program for CMGs was shown in Fig.2.

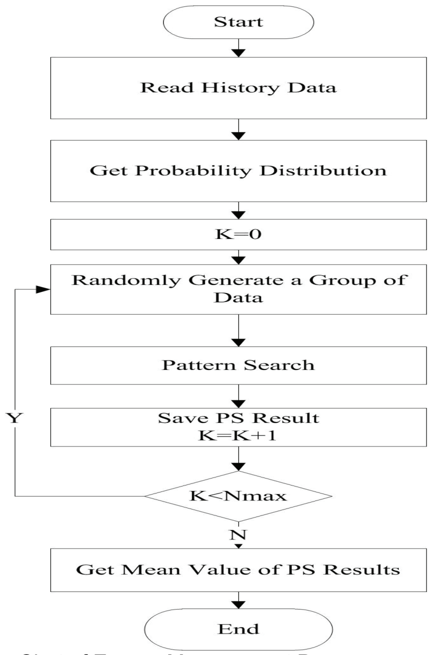

Fig. 2. Flow Chat of Energy Management Program

Numerical Simulation

This paper takes a smart building with renewable generators as a CMG model. A BF-V700 type diesel generator, with a rating power of 505Kw is equipped by the CMG system. The a_D, b_D and c_D are 8.88, 0.312, 0.0001.

Assume EVs in the CMG are with the maximum charging power of batteries for 25Kw and capacity of 75Kwh, and number of them is 100. Assume 50% of EVs need replace their batteries every day, and the replacements centralize at 8 am and 6 pm at when residents of the building go out for work and back home. The energy storage instrument used in the CMG is with a capacity of 150Kwh and a rating power of 50Kw.

In order to verify the effectiveness of simulations, this paper carried simulations based on three days' prices respectively. Fig.2 shows prices of three days of April, 2010, PJM. Since this paper didn't do the forecasting job, assume the distribution of forecasting errors of prices follows the N(0.1,0.2) distribution.

The installed capacities of photovoltaic generations and wind generations are 50Kw and 500Kw. The irradiation date and temperature are showed in Fig.3(a) and Fig.3(b).. The used wind speed date is showed in Fig. 4. Fig. 5 shows the real loads and 5 groups of random TLs based on the real ones.

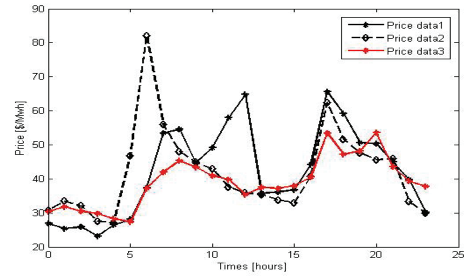

Fig.2 Daily prices data.

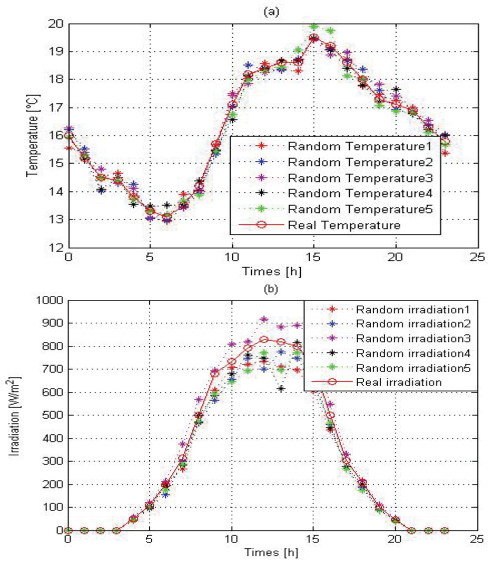

Fig. 3. (a) Daily temperature data. (b) Daily irradiation data

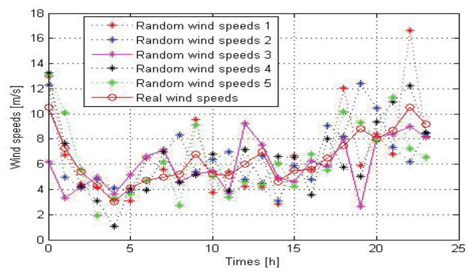

Fig. 4. Daily wind speeds data.

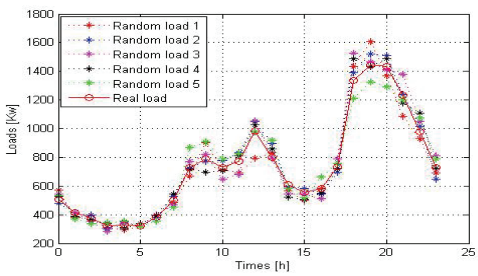

Fig. 5. Daily Loads data of the CMG

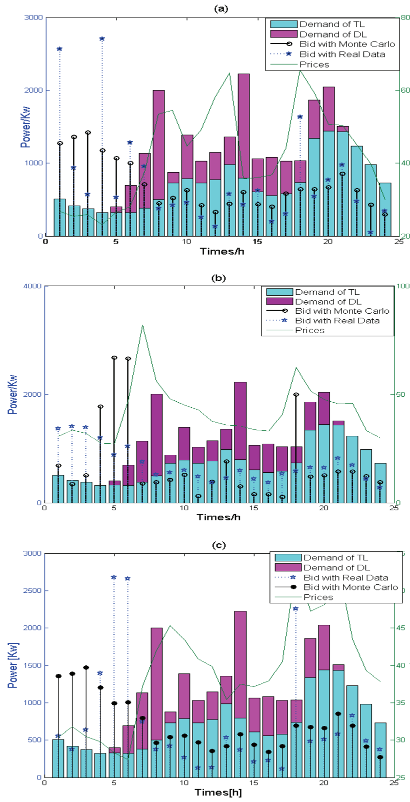

Fig. 6. Bidding strategy of the CMG based on prices of the different days. (a) Based the first day's prices. (b) Based on the second day's prices. (c) Based on the third day's prices.

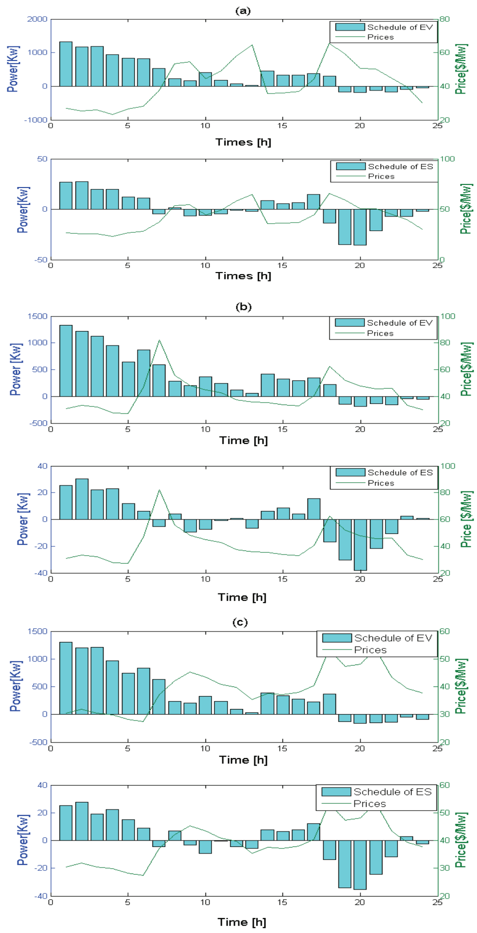

Fig. 7. Scheduling strategy of the CMG's DLs based on prices of the first day. (a) Scheduling of EVs. (b) Scheduling of ESs. (c) Scheduling of all DLs.

According to the simulation results in Fig,6 and Fig,7, CMGs with DLs could well response to electricity prices to save system costs, which could show the effectiveness of the proposed energy management program. To response electricity prices smartly would be benefit for both CMG and main grids. For CMG, demand responses could save energy costs. For main grids, prices would be high when system loads are relatively large, and system reserve might in a low capacity at the same time. So the fluctuation of loads would affect electricity prices and system reliability. However, the demand responses of CMG could help it to make a stable state of loads, which could enhance both economic and reliability of power system.

From Fig.7, although EVs and ESs are both DLs, the charging statements of them are not synchronization. This is because the EVs need serve for demands of consumers and the ESs need not.

Table.1 shows costs of the CMG under different assumptions of EVs. Cost 1 stands for the assumption that charging and discharging of EVs could be scheduled. Cost 2 stands for the assumption that charging of EVs could be scheduled but could not discharge to the system. The results showed that discharged of EVs for a smart building could save system cost by 5% to 25% in different prices.

Table 1. Costs of the building under different conditions

Prices data	Cost 1($)	Cost 2($)
Prices data 1	618.7	811.2
Prices data 2	642.2	844.9
Prices data 3	637.2	670.9

Conclusion

Electric power system would develop towards the direction of being kindly and open to end users under the concept and framework of smart grid. Meanwhile, with the technology maturation and cost reduction of renewable generations and DLs, more and more residential and commercial buildings are equipping them in both urban and rural. Under the above backgrounds, most residents and companies would face the problem of smartly arranging the schedule of DLs and energy purchase in the near future.

This paper proposed an energy management program from the view of CMG. For detail, consumers with renewable generations and DLs are all considered as CMGs, which would include most residential and commercial buildings and factories in smart grid. The proposed energy management program solved the daily purchasing and self-scheduling problems of CMGs with GA and PS method. With the consideration of uncertainty of prices, loads and outputs of renewable generations, the proposed algorithm took the expect cost of CMG as objective function and adopted Monte Carlo methods to simulate those uncertainties. Outputs of the program would contain purchase and self-scheduling information of the CMG. A simulation example involving a smart building was carried at last, and simulation results showed the effectiveness of the proposed program. Through the results, CMGs could save their costs by arranging the charging of DLs when the prices are relatively high and discharging at the opposite situation. That means they would buy more energy form main grids at power adequate time and would reduce energy purchase or discharge to main grid at power shortage time, which would better for both economic and reliability of power system.

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