Chapter 7
Energy Management System for Renewable Distributed Generation and Energy Storage

Qiang Yang, Wei Li, Ali Ehsan, Siyang Sun, Ming Cheng, Wei Dong and Weijie Hao

Abstract In recent years, a massive number of inverter-based distributed generations (DGs) and battery-based storage devices have been penetrated in domestic residential areas, and real-time pricing (RTP) schemes of electricity are adopted in many nations. In such context, the residents are able to deploy the domestic energy management system to provide an efficient energy dispatch in advance (e.g. one-day ahead) through appropriate control and scheduling of power loads and energy storage units based on the predicted system operational states. This chapter presents an algorithmic solution to investigate the potential economic benefits of improving matching between domestic DG generation and power loads with explicitly consideration of the real-time pricing information. The proposed energy dispatch solution is evaluated and validated using a set of operational scenarios through numerical simulations. The obtained experimental result clearly demonstrates that the domestic energy can be appropriately controlled to meet the required domestic demand with significantly improved resource utilization efficiency and reduced purchase cost. The robustness of the solution under inaccurate prediction information is also validated considering the presence of inaccurate prediction of RTP and DG generation.

Keywords Distributed generation · Real-time pricing · Demand response
Load control · Energy storage

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Nomenclature

$[\alpha_a, \beta_a]$	Allowable time range of an appliance operation
h	The time that appliance a may operate
x_a^h	Appliance a's on or off condition at time h
m	Number of unschedulable loads
n	Number of schedulable loads
d_a	Operational time period
P_a	Rated power of appliance a
P_{DG}^h	DG power generation at time h
P_{must}^h	Total baseline demand at time h
P_{flexible}^h	Total flexible demand at time h
P_{load}^h	Total loads at time h
$\mathrm{RTP}_j/\mathrm{RTP}_k$	The electricity price at time j or k
c_a^j/c_a^k	Purchased electricity at time j or k
SOC_h	Battery state of charge at time h
$\mathrm{SOC}_{\min}$	Lower limit of battery's SOC
$\mathrm{SOC}_{\max}$	Upper limit of battery's SOC
Q	Battery energy capacity (kWh)
E_{charge}^h	Charged/discharged energy to/from battery
Popsize	The population size of an appliance
pc/pm	Probability of crossover/mutation
gen	The maximum number of iterations
X_a	Appliance a's whole day working status
X_{Chrom}^k	Operational state of schedulable loads
P_{Chrom}^h	Consumed energy at time h
$\left[h_{\mathrm{up}}^{\mathrm{begin}}, h_{\mathrm{up}}^{\mathrm{end}}\right]$	RTP rising stages
$\left[h_{\mathrm{down}}^{\mathrm{begin}}, h_{\mathrm{down}}^{\mathrm{end}}\right]$	RTP falling stages
Buy_h	The electricity to buy from grid at time h
S_+	The area of $P_{\mathrm{DG}}^h > P_{\mathrm{load}}^h$
S_-	The area of $P_{\mathrm{DG}}^h \leq P_{\mathrm{load}}^h$
S	The difference value between S_+ and S_-
$\mathrm{Utilization}_h$	The DG utilization at time h

7.1 Introduction

In recent decades, the quick development and technological advances of distributed energy resources (DER) have driven the penetration of different types of renewable distributed power sources, e.g. photovoltaic (PVs) and wind turbines (WTs), with the small-scale capacities from a few kilowatts (kW) to a number of megawatts (MW). The battery-based energy storage facility becomes increasingly prevalent to be deployed in the scope of households. In fact, the availability of different types of renewable distributed generation (DG) can be considered as a compensated source for power supply from the main power grid in order to meet the domestic electric power demand. In parallel, the dynamic electric pricing scheme, also known as real-time pricing (RTP) scheme, has been used by power utilities as an efficient method to include the end customers into the process of electricity provision and manage their domestic loads to improve the power utilization efficiency as well as the safety of power supply. This mechanism can provide obvious benefit through carrying out appropriate demand side management actions for both power utility and electricity customers. However, it should be noted that the generation intermittency of renewable DGs and dynamical pricing mechanism make the implementation of demand response a non-trivial task [1]. It is always desirable to fully utilize the installed DGs in the households, and thus, the intermittent generation of DGs needs to be fully considered in the household energy management [2, 3]. To address such energy management issue, an efficient demand response solution is demanded to optimally manage the operations of appliances and allocate the domestic loads to the time slots with low costs in accordance to the DG outputs and the up-to-date real-time electricity prices. In such context, the installed domestic energy storage units can well accommodate the randomness of the DG generation and power demand profiles, and in turn improves the global utilization of renewable energy in residential households.

In the literature, much research effort (e.g. [4–14]) has been carried out to actively address the technical challenge and propose efficient demand side management solutions in the presence of installed domestic generators and battery storage unit. The work in [4] proposed an optimal solution to minimize the cost of electricity purchase from the customers' perspective through minimizing the waiting time of domestic appliances. The peak-to-average ratio of power demand can also be alleviated through considering the RTP tariff together with the inclining block rates (IBRs). For the solution proposed in [5], two different electricity price levels were adopted in IBR, and the electricity price can be switched to the higher price level once the power consumption exceeding the predefined threshold, and hence, the schedulable power demands can be scheduled in an efficient manner. In [6], the domestic appliances are classified into a set of clusters based on the operational characteristics and preferences. Thus, a cluster-based solution was proposed to efficiently schedule and manage the appliances during operation so as to achieve reduced purchased electricity. The theoretical solution based on Lyapunov optimization was proposed in [7] to resolve the time-coupling energy management problem considering the stochastic nature of power demand and DG generation uncertainties. However, the aforementioned solutions have not fully considered the impact of RTP as well as the energy storage on the domestic energy management, and hence, the potential benefit needs to be further investigated. To address such problem, a two-level control architecture considering the installed renewable sources and domestic battery storage devices was proposed (e.g. [8–10]) to integrate the long-term planning and the short-term management functionalities to alleviate the negative impact of prediction inaccuracy of DGs and demands. These two-horizon algorithmic solutions can significantly improve the computational accuracy with reduced computational complexity. The operational states of the network elements, e.g. distributed generators, combined heating and power (CHP) and energy storage system (ESS), were studied and determined periodically to achieve the optimized energy management objectives [11, 12]. In [13], the operational actions of domestic battery devices (e.g. charging and discharging) are modelled and addressed through using a mixed-integer linear programming-based approach in the Vehicle-to-Grid (V2G) context. Also, decentralized battery storage control solution was proposed to manage the ESS operation in the case of the DG generation exceeding an optimized power threshold, so as to reduce the possibilities of over-voltage and protect the lifetime of domestic batteries.

Currently, most of the existing solutions have either not been able to thoroughly investigate the impact and potential benefits of correlative effect among DGs, storage and demand, or not fully included the RTP variability into consideration. On the other hand, the available energy dispatch solutions firmly assumed that the energy dispatch can be determined based on the accurate estimation or prediction of RTP and DG dynamics. As a result, the energy dispatch performance in the presence of prediction inaccuracy still needs to be carefully evaluated and validated. This chapter looks into the aforementioned technical challenges and presents a cost-effective algorithmic solution for demand response in the context of domestic energy management system considering the availability of different forms of renewable generators (e.g. PV panels and wind micro-turbines) and battery-based energy storage units under the condition of RTP. The technical challenges have been comprehensively exploited in our previous studies [15–17]. Most of the solutions were designed merely for the optimal energy management within single household. In fact, due to the limited capacities of installed storage units and variability of household loads and DGs, the utilization efficiency of DGs can be undermined at individual households, e.g. the surplus energy (the overall DG output exceeds demand) cannot be stored at certain times. To address this issue, some notable studies have been carried out to explore the communication and trading between neighbourhoods to improve the DG utilization and reduce the household electricity purchase cost at the residential community level. The methodology for making robust day-ahead operational schedules for controllable residential distributed energy resources based on energy service decision support tool was often developed using a stochastic programming approach formulated for the DER schedulers. On the other hand, the management of dispatchable loads in a residential microgrid was also addressed by decentralized controllers deployed in each household to simultaneously optimize conflicting objectives: minimization of user energy costs and load flattening in an online fashion. However, the operation of such distributed control paradigm can be problematic in large-scale residential community due to inaccurate information update dissemination and prohibitive communication overheads induced from asynchronous communication and distributed coordination scheme.

In summary, the following technical contributions are made: firstly, the work exploits an optimal power demand management approach to schedule the operations of the controllable domestic appliances to the appropriate time slots based on the one-day-ahead predicted domestic DG generation and RTP information; secondly, the energy dispatch by the use of energy storage units is further incorporated into the energy management solution to further optimize the DG utilization efficiency and promote the spatial–temporal matching between generation–demand in households. Consequently, the cost due to power energy purchase from the customer side can be also significantly reduced. In addition, the robustness under various forms of uncertainties of the proposed energy dispatch solution is extensively assessed based on the inaccurate DG generation and RTP information prediction.

The details of the proposed solution and its performance evaluation are described in the following sections. The rest of the chapter is organized as follows. Section 7.2 mathematically formulates the proposed domestic demand response solution in details; In Sect. 7.3, the proposed energy management algorithmic solutions are presented and implemented; Sect. 7.4 presents the numerical results obtained from a set of experiments through examining different operational scenarios. Finally, the conclusions and discussions are provided in Sect. 7.5.

7.2 System Model and Problem Formulation

In this section, the energy management model as well as the proposed demand side management solution considering the availability of different forms of renewable DGs and real-time power electricity pricing is formulated mathematically.

7.2.1 Household Energy System

In this chapter, the small-scale renewable generators installed in the households are a set of solar- and wind-based intermittent power generation sources. These renewable power generators can supply the household power demands together with the electricity purchase from the power utility, if needed (the system installation, reinforcement cost is not explicitly considered). In addition, the installed battery-based energy storage facility can be appropriately managed to control its charging and discharging actions, e.g. absorbs the surplus renewable power generation or under low electricity prices, and supplies the demand upon insufficient energy generation from DGs or high electricity prices. Indeed, the electricity pricing information dynamically changes over time throughout the day and the variability needs to be predicted in advance, e.g. one-day ahead (with the time slot of 30 min) through an offline process based on the historical pricing information and advanced prediction techniques. The prediction methods and techniques are out of the scope and hence are not discussed.

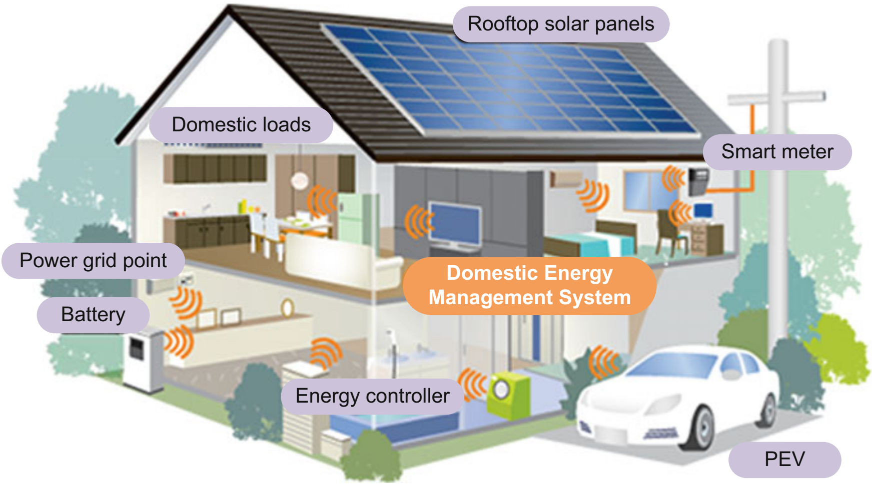

Fig. 7.1 Energy management system in households with small-scale DGs and energy storage

The proposed energy dispatch approach under the inaccurate RTP information and renewable power generation prediction is assessed.

Figure 7.1 schematically presents the power energy management system at the household level in the presence of installed renewable DGs, including rooftop solar panels and wind turbines, the domestic Li-ion battery-based energy storage units and different types of appliances in household, e.g. washing machine, air conditioner. The household customers can be informed with the real-time pricing information through the smart metre. Specifically, the components, including the renewable power generation sources, storage units and the domestic appliances, are interconnected with the energy hardware controller through the available home area communication networks. The operations of the controllable domestic appliances can be managed through the energy dispatch algorithm which is operated in the household energy controller.

In this work, the appliance operations in the residential households can be classified into three different types, i.e. the baseline loads, unschedulable (uninterruptible) loads and schedulable (interruptible) loads, discussed as follows:

- The baseline load is considered not schedulable and hence required to be immediately supplied according to the resident's need.
- The unschedulable load refers to the domestic appliances that the operation cannot be interrupted once started;
- Interruptible load refers to the domestic appliances that the operation state can be manipulated at any time. This type of power loads is considered controllable and can be flexibly scheduled based on the adopted load management strategies whilst meeting their operational constraints as follows:

$$\begin{cases} \alpha_a \le h \le \beta_a, \quad a = 1, \ldots, m+n \\ x_a^h = \{0, 1\} \\ \beta_a - \alpha_a \ge d_a \\ \sum\limits_{h=\alpha_a}^{\beta_a} x_a^h \times P_a = P_a \times d_a \end{cases} \tag{7.1}$$

7.2.1.1 Optimal Dispatch Problem Formulation

The primary objective of the proposed power demand management solution is to minimize the mismatching between the renewable power generation and power demand over the day. This can be realized by allocating the operations of the schedulable domestic appliances into certain time slots (30 min/slot). Once the available DG generation is fully utilized, the surplus loads, if any, need to be supplied by the power grid. In this case, the operation of appliances can be further scheduled to the time slots with low electricity prices so as to reduce the electricity bills. Consequently, such load management can be effectively formulated as a optimization problem with multiple operational objectives with the following mathematical expressions:

$$\begin{aligned} &\min \begin{cases} \sum\limits_{h=1}^{48} \left| P_{\mathrm{DG}}^h - P_{\mathrm{must}}^h - \sum\limits_{a=1}^{m+n} x_a^h \cdot P_a \right| \\ 0.5 \times c_a^j \times \mathrm{RTP}_j + 0.5 \times c_a^k \times \mathrm{RTP}_k \end{cases} \\ &\text{s.t.} \quad j \in \left\{ h \middle| \, P_{\mathrm{DG}}^h < P_{\mathrm{must}}^h + P_{\mathrm{flexible}}^h, x_a^h = 1, \; h = 1, \ldots, 48 \right\} \\ &k \in \left\{ h \middle| \, x_a^h = 0, \; h = [\alpha_a, \beta_a] \right\} \\ &c_a^j = \begin{cases} 0, \; P_{\mathrm{DG}}^j \ge P_{\mathrm{must}}^j + P_{\mathrm{flexible}}^j - P_a \\ P_{\mathrm{must}}^j + P_{\mathrm{flexible}}^j - P_a - P_{\mathrm{DG}}^j, \; P_{\mathrm{DG}}^j < P_{\mathrm{must}}^j + P_{\mathrm{flexible}}^j - P_a \end{cases} \\ &c_a^k = \begin{cases} 0, \; P_{DG}^k \ge P_{\mathrm{must}}^k + P_{\mathrm{flexible}}^k + P_a \\ P_{\mathrm{must}}^k + P_{\mathrm{flexible}}^k + P_a - P_{\mathrm{DG}}^k, \; P_{\mathrm{DG}}^k < P_{\mathrm{must}}^k + P_{\mathrm{flexible}}^k + P_a \end{cases} \end{aligned} \tag{7.2}$$

In (7.2), the appliance a is selected to be allocated from time j to time k according to manage the household demand based on RTP, and hence to reduce the overall purchased electricity.

Following to the implementation of the power demand management utilizing the renewable DG power generation and real-time electricity prices, the battery-based storage devices adopted in the residential households can be considered as either the electric demand or power generators through charging action (in the case of sufficient DG generation or low RTP) and discharging (in the case of insufficient DG generation or high RTP) actions. In the proposed solution, through the incorporation of battery-based storage units into the energy dispatch, the utilization efficiency of stochastic DGs can be promoted and the electricity purchase cost can be minimized. The charge/discharge pattern can be managed in the proposed energy dispatch solution such that the distributed power generation can be allocated to the time slots over a day with insufficient generation.

This can be effectively implemented through minimizing the difference between the generated renewable power energy, domestic power load, and charging and discharging of battery throughout the day, expressed as follows:

$$
\begin{aligned}
&\min \sum_{h=1}^{48} \left|(P_{\mathrm{DG}}^{h} - P_{\mathrm{load}}^{h}) \times 0.5 - (\mathrm{SOC}_{h} - \mathrm{SOC}_{h-1}) \cdot Q\right| \\
&\text{s.t.}\quad P_{\mathrm{load}}^{h} = P_{\mathrm{must}}^{h} + P_{\mathrm{flexible}}^{h} \\
&E_{\mathrm{charge}}^{h} = \begin{cases} \text{if } P_{\mathrm{DG}}^{h} > P_{\mathrm{load}}^{h}: \\ \min\left\{(P_{\mathrm{DG}}^{h} - P_{\mathrm{load}}^{h}) \times 0.5, (\mathrm{SOC}_{\max} - \mathrm{SOC}_{h-1}) \cdot Q\right\} \\ \text{else if } P_{\mathrm{DG}}^{h} < P_{\mathrm{load}}^{h}: \\ \max\left\{(P_{\mathrm{DG}}^{h} - P_{\mathrm{load}}^{h}) \times 0.5, (\mathrm{SOC}_{\min} - \mathrm{SOC}_{h-1}) \cdot Q\right\} \end{cases} \\
&\mathrm{SOC}_{h} = \mathrm{SOC}_{h-1} + \frac{E_{\mathrm{charge}}^{h}}{Q} \\
&\mathrm{SOC}_{h} \in \left[\mathrm{SOC}_{\min}, \mathrm{SOC}_{\max}\right]
\end{aligned}
\tag{7.3}
$$

In such formulation, the status of charge (SOC) of the Li-ion battery is constrained within the range of 20 and 90% in this study to guarantee its operation whilst protecting its lifetime [18]. Based on the recognition of mismatch between the renewable power generation and electric demand in household, the appropriate Li-ion battery capacity can be determined based on the selection criterion adopted in many studies (e.g. [19]) and the current capacity standards available in the market to guarantee that the battery state of charge within the expected range [14].

7.3 Optimal Domestic Energy Management Solution Under RTP

Here, the proposed energy management solution and designed dispatch algorithm are presented and discussed in details. The proposed demand side management solution is designed to be carried out and implemented in two levels, i.e. DG- and RTP-based load management and storage-based energy dispatch.

- DG- and RTP-based load management: it can arrange the schedulable household appliances to operate at the appropriate time slots throughout the day so as to achieve optimal match between the renewable DG generation and the power demands with the minimized the purchased electricity based on the RTP information;
- Battery-based energy dispatch: once the load management is carried out, the control actions can be further taken to manage the charging and discharging states of the battery-based storage in accordance with the electricity pricing information to optimize the DG utilization whilst minimizing the residential electricity bills as well as meeting the domestic power demand.

7.3.1 DG- and RTP-Based Load Management

This chapter adopts the well-known genetic algorithm (GA) to address the optimal allocation of schedulable power loads to match the appliance operation to the dynamic DG power generation. This is realized by shifting certain loads to be operated in the time slots with low electricity prices according to (7.2) by determination of the best-fit set of domestic appliances. The detailed GA algorithmic solution for DG-RTP-based load management is implemented and can be described in pseudo-codes as follows.

Algorithm 1 DG and RTP based load control

Require: P_{DG}^{h}, P_{must}^{h}, P_a, α_a, β_a, d_a, RTP

Initialize $Popsize = N$, $X_a = [x_a^1, x_a^2, \cdots, x_a^{48}]_{N\times 48}$ using (1), pc, pm, gen

Form $X_{Chrom}^{k} = [X_1^{1\times 48}; \cdots; X_m^{1\times 48}; \cdots; X_{m+n}^{1\times 48}]_{(m+n)\times 48}$, $k \in 1, \cdots, N$,
  $P_{Chrom}^{k} = X_{Chrom\,(a)}^{k} \times P_a$

FOR $t \leftarrow 1$ to gen **DO**

Calculate fitness $Objvalue(t) = \sum_{h=1}^{48} | P_{DG}^{h} - P_{must}^{h} - \sum_{a=1}^{m+n} P_{Chrom}^{a\times h} |$ and select $X_{Chrom}(t)$ using the roulette method

IF $rand(0,1) < pc$ and appliance a is uninterruptible

  Allocates the time slots $[h_a^{start}, h_a^{end}]$ of $X_a^{1\times 48}$ in X_{Chrom}^{i} to the left or right side within $[\alpha_a, \beta_a]$

ELSEIF $rand(0,1) < pc$ and appliance a is interruptible

  Cross the $X_a^{1\times 48}$ of X_{Chrom}^{i} and X_{Chrom}^{i+1} at a random position

END IF

IF $rand(0,1) < pm$

  Choose the appliance a to do mutation and insure $sum(X_a^{1\times 48}) = d_a$

END IF

  Select $X_{Chrom}(t)$ with the minimum $Objvalue\,(t)$, update X_{Chrom} and P_{Chrom}

END FOR

  Calculate the purchasing power and cost by DG-based control, labeled as $BuyElec$ and $BestCost$, respectively.

FOR $j \leftarrow 1$ to 48

IF $BuyElec\,(j) > 0$

  Choose appliance $a \in \{a \mid x_a^j = 1, a \in 1, \cdots, m+n\}$ and calculate c_a^j // using (2)

IF appliance a is uninterruptible

  FOR $k \leftarrow \alpha_a$ to $\beta_a - d_a + 1$

    Calculate c_a^k and $Cost$ when a is shifted to $[k, k + d_a - 1]$, update $BestCost = \min\{Cost, BestCost\}$ and P_{Chrom}

  END FOR

ELSEIF appliance a is interruptible

  FOR $k \in \{k \mid x_a^j = 1, x_a^k = 0, \alpha_a \le k \le \beta_a\}$

    Calculate c_a^k and $Cost$, update $BestCost$ and P_{Chrom}

  END FOR

END IF

END IF

END FOR

Based on the execution of Algorithm 1, X_{Chrom} denotes the obtained final operational status of all domestic schedulable loads, where digital "1" indicates the corresponding appliance's ON condition and "0" indicates its OFF status, and P_{Chrom} indicates its consumption every 30 min over the day.

7.3.2 Battery-Based Energy Storage Dispatch

Through the load management process described above, the operations of the domestic schedulable appliances are appropriately organized so as to improve the generation–demand matching at the domestic level. As a result, the purchased electricity is reduced. Indeed, the potentials to reduce the electricity purchase cost can be further exploited through properly manage the energy charging and discharging behaviours of the household energy storage device in accordance with the dynamics of the DG power generation, electric demand and real-time pricing information. Thus, this section examines the impact of utilizing the Li-ion battery as storage to further optimize the performance of the demand side response under real-time electricity prices. The algorithmic solution of battery-based energy dispatch can be described in pseudo-codes as follows.

Algorithm 2 Battery storage based scheduling

Require: P_{DG}^{h} , $P_{load}^{h}=\sum_{a=1}^{m+n} P_{Chrom}^{h}$, RTP

1: Initialize $SOC_{\min}$, $SOC_{\max}$, $SOC_{h=1}$, Q

2: Divide the working time into $\left[h_{up}^{begin}, h_{up}^{end}\right]$ and $\left[h_{down}^{begin}, h_{down}^{end}\right]$

3: **FOR** $h \leftarrow h_{down}^{begin}$ to h_{down}^{end} **DO**

4: Calculate E_{charge}^{h} and SOC_h using (3), update the power to buy for loads $Buy_h = \max\left\{(P_{DG}^{h} - P_{load}^{h})\times 0.5 - E_{charge}^{h}, 0\right\}$

5: **END FOR**

6: **FOR** $h \leftarrow h_{up}^{begin}$ to h_{up}^{end} **DO**

7: Calculate S_+ , S_- , $S = S_+ - S_-$, E_{charge}^{h} , SOC_h //using (3)

8: **IF** $P_{DG}^{h} > P_{load}^{h}$ and $h \in h_{up}^{begin}$

9: **IF** $S < 0$

10: Update $Buy_h = \min\left\{-S, (SOC_{\max} - SOC_h)\cdot Q - S_+\right\}$ for battery, $E_{charge}^{h} = (P_{DG}^{h} - P_{load}^{h})\times 0.5 + Buy_h$, and SOC_h at time $h \in h_{up}^{begin}$

11: **WHILE** $(SOC_{\max} - SOC_h)\cdot Q < S_- - (P_{load}^{h} - P_{DG}^{h})\times 0.5$, $h \in P_{DG}^{h} < P_{load}^{h}$

12: Update $E_{charge}^{h} = 0$, SOC_h and $Buy_h = (P_{load}^{h} - P_{DG}^{h})\times 0.5$

13: **END WHILE**

14: **END IF**

15: **ELSEIF** $P_{DG}^{h} < P_{load}^{h}$ and $h \in h_{up}^{begin}$

16: **IF** $(SOC_h - SOC_{\min})\cdot Q > S_-$

17: Calculate E_{charge}^{h} and SOC_h //using (3)

18: **ELSE**

19: Update $Buy_h = (P_{load}^{h} - P_{DG}^{h})\times 0.5 + E_{charge}^{h}$ for loads and battery, $E_{charge}^{h} = S_- - (SOC_h - SOC_{\min})\cdot Q - (P_{load}^{h} - P_{DG}^{h})\times 0.5$ and SOC_h at time $h \in h_{up}^{begin}$, follow Step11 to 13 afterwards

20: **END IF**

21: **END IF**

22: **END FOR**

The incorporation of battery storage-based scheduling into the demand side management process can further optimize the energy dispatch performance. The battery installed at household can be optimally controlled for their charging/discharging states under different system conditions. Thus, the domestic energy can be appropriately dispatched to meet the domestic power demand and make the best use of the available DG generation, whilst achieving the minimized cost of electricity purchase.

7.4 Simulation Experiment and Numerical Result

In this section, the effectiveness of the proposed energy dispatch solution is extensively assessed through examine different operational scenarios through simulation experiments. The obtained experimental result clearly demonstrates and confirms the effectiveness and benefits of the suggested domestic energy dispatch and management solution.

7.4.1 Simulation Parameters

In simulations, it is considered that the maximum number of schedulable domestic appliances is 30, including both schedulable and unschedulable household appliances. The operational characteristics and constraints of the studied domestic appliances are described in Table 7.1. Here, the appliances with (*) indicate that the appliance is uninterruptible. In reality, the operational pattern of appliances can be diverse in time intervals, durations and power ratings according to the appliance types and preferences.

In all simulations, it is considered that a period of 30 min is set as a time slot, i.e. in total 48 time slots over a day. The RTP information and baseline load profile are adopted from AEMO [20]. The capacity of the installed DGs is obtained by scaling down the typical PV and wind generators [21, 22], ranging from 0 to 5 kW, as depicted in Fig. 7.2.

Here, the performance of the proposed demand response solution is assessed through a comparative study by evaluating four different operational scenarios. The details can be found in Table 7.2.

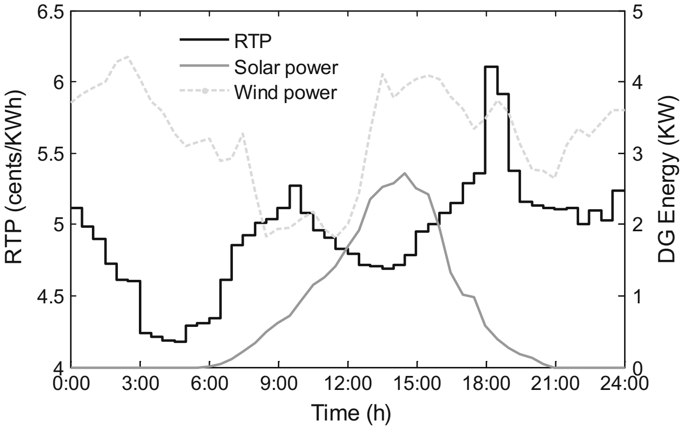

Fig. 7.2 RTP and DG generation profile [15]

Table 7.1 Parameters of schedulable domestic appliances in simulations

Domestic appliance	$\alpha_a \sim \beta_a$	Operational during (h)	Power rating (kW)
Dish washer[a]	08:00–12:00 20:00–23:00	1.5	0.73
Rice cooker[a]	06:00–08:00 18:00–20:00	1	0.8
Washing machine[a]	06:00–09:00 17:00–20:00	2	0.38
Humidifier	00:00–09:00 14:00–20:00	4	0.15
Laundry drier	09:00–12:00 20:00–23:00	2 1.5	1.26
Floor cleaning robot	06:00–12:00 08:00–18:00 20:00–23:30	3 2.5 1.5	0.74 0.7 0.64
Water heater	04:30–08:30 16:00–20:00 20:00–24:00	3 2 3	1.64 1.85 1.64
Electric kettle	06:00–07:30 16:00–19:00 20:00–23:00	0.5	1.5
Air conditioner	00:00–08:00 16:00–24:00 00:00–08:00 18:00–24:00	3 4 4 4	1 1.1
Electric radiator	12:00–17:00	2.5	2
Pool pump	07:00–18:00	4	1.8
Water pump	06:00–15:00	6	1.6
Oil press	09:00–18:00	3.5	0.35
Floor waxing	14:00–18:00	3	0.42
Electric oven	13:00-18:00	2	1.3
PHEV	00:00–08:00	3.5	2.4

[a]Appliance

Table 7.2 Simulation scenarios of different energy dispatch strategies

Evaluated scenario	Load control	Battery-based dispatch
A	×	×
B	×	
C	●	×
D	●	●

- Scenario A: in this case, no optimal energy dispatch is taken; the appliances can operate without any scheduling as long as meeting the operational constraints;
- Scenario B: The battery is installed in the household, and the battery-based storage dispatch (i.e. algorithm 2) is adopted without any load management;
- Scenario C: the optimal DG-RTP-based load management is used to manage the operation of the schedulable appliances (i.e. algorithm 1);
- Scenario D: both the DG-RTP-based load management and the battery storage-based energy dispatch (i.e. algorithm 1 and algorithm 2) are adopted.

7.4.2 Energy Dispatch Performance Assessment

The proposed demand response algorithmic approach is extensively evaluated from three different aspects: the matching performance between the power supply from renewable power generation sources and storage and power loads, utilization efficiency of DG generation and the resident's electricity purchase cost.

The DG generation utilization efficiency is another important aspect to the residents to evaluate their investment on DG installation within households. The DG utilization at any time slot over a day can be described through two conditions as follows:

$$\text{Utilization}_h = \begin{cases} P^h_{\text{load}} + \max\left\{E^h_{\text{charge}}, 0\right\}, & P^h_{\text{DG}} > P^h_{\text{load}} \\ P^h_{\text{DG}}, & P^h_{\text{DG}} \leq P^h_{\text{load}} \end{cases}, \quad h \in 1, \ldots, 48 \tag{7.4}$$

Figure 7.3 demonstrates the performance of power supply–demand matching of four different operational scenarios in simulations. The numerical result of power supply (shadow area) and power demand (solid line) is plotted over a day (00:00–24:00), respectively, in a polar coordination. The detailed explanation and discussion of the simulation results are provided as follows:

Figure 7.3a clearly demonstrates significant mismatch between the distributed generation in household and the power demand. For example, during the period of 6:00–12:00, the demand far outweighs the DG supply, but a large portion of the DG power generation is seriously underutilized from 0:00–6:00 and 12:00–17:00. Based on the observation of supply–demand mismatch indicated by scenario A, the 12 V–600 Ah Li-ion battery with the capacity of 7.2 kWh is adopted in the evaluation scenario B in this work.

Figure 7.3b clearly indicates that the matching performance between power demand and generation can be significantly improved through temporal–spatial arrangement of the generated power energy, e.g. battery charging to absorb the surplus renewable DG generation (12:00–17:00), and discharge to supply loads in the case of insufficient DG generation. In this case, the DG generation utilization efficiency is improved, and hence, the electricity purchase cost is reduced to 36.4 cents.

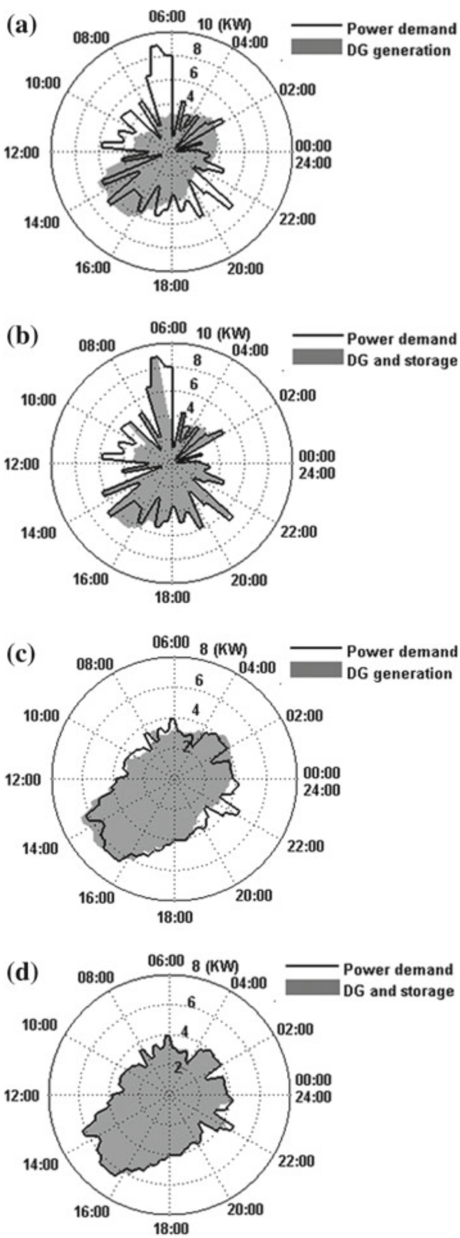

Fig. 7.3 Energy dispatch performance of generation–demand matching within households **a** scenario A; **b** scenario B; **c** scenario C; **d** scenario D [15]

The purchased electricity is used to supply the required load demand the installed battery.

Figure 7.3c presents the numerical simulation result in the case that only DG-RTP load management is used. The result indicates that the load management can well arrange the operational patterns to match the power generation from DGs under real-time electricity prices. It can be seen that the matching performance between power supply (from DGs and battery) and the domestic loads in scenario C is significantly improved in comparison with the performance in scenario A (Fig. 7.3a). In addition, the required capacity of the installed battery can be reduced, which leads to a cost reduction in installation.

Finally, it is assumed that the Li-ion battery (12 V–220 Ah, 2.64 kWh) is adopted in this evaluated case; the proposed demand response solution for domestic energy management is evaluated assuming that both DG-RTP and battery-based dispatch are adopted. In Fig. 7.3d, the presented numerical result clearly shows that the presented solution can cope with the stochastic generation of DGs, varied power loads and RTP information, and reach the optimal matching performance between the power supply and household demand. This leads to obvious benefit that the electricity purchase cost is reduced to 4.0 cents over the day in this simulated scenario.

In Fig. 7.4, the energy dispatch performance for four evaluated scenarios is compared in terms of the DG energy utilization efficiency. The adopted Li-ion batteries for the scenarios considering storage units (i.e. scenario B and D) are with the same specification (i.e. 12 V–600 Ah and 12 V–220 Ah).

In Fig. 7.4a, the result shows that the DG power generation cannot be efficiently utilized and the average utilization efficiency is about 80.67%. This is mainly because that the operations of all appliances cannot be optimally scheduled without appropriate load management and battery storage. With the installation of domestic battery-based storage unit, the average energy utilization efficiency of installed DG power generation is improved to 93.32% throughout the day, as illustrated in Fig. 7.4b. It can be seen that unutilized DG power generation still exists at certain time slots in the case of low domestic power loads. In Fig. 7.4c, it shows that the average DG utilization efficiency can be further improved to 96.09% by allocating the domestic appliances in accordance with the DG generation pattern based on load management. By combining the battery-based storage dispatch with the DG-RTP energy dispatch, the utilization efficiency of all DG power generation can reach up to 99.39%, as indicated in Fig. 7.4d. These results directly demonstrate the effectiveness and benefit of installation of energy storage units and load management to improve the global utilization efficiency of renewable power generation.

Finally, the performance of the proposed domestic energy dispatch solution is further assessed in terms of the electricity purchase cost through simulation experiments. This evaluation adopts 3-month statistics of RTP information and DG power generation during March to May, 2014. In Fig. 7.5, the daily electricity purchase cost over 90 days is presented for the proposed household energy dispatch solution (i.e. scenario IV). The result is provided against another two operational scenarios (scenario A and C), and the electricity purchase cost in 50th and 95th percentile is calculated. The simulation result from this comparative study shows that, the 50th and 95th percentiles of the daily electricity cost are significantly reduced to 14.8 and 8.5 cents, respectively, through adopting the suggested demand response solution in comparison with scenario A. As a result, the resident can save up to 8626.1 cents for electricity purchase cost over the simulated period.

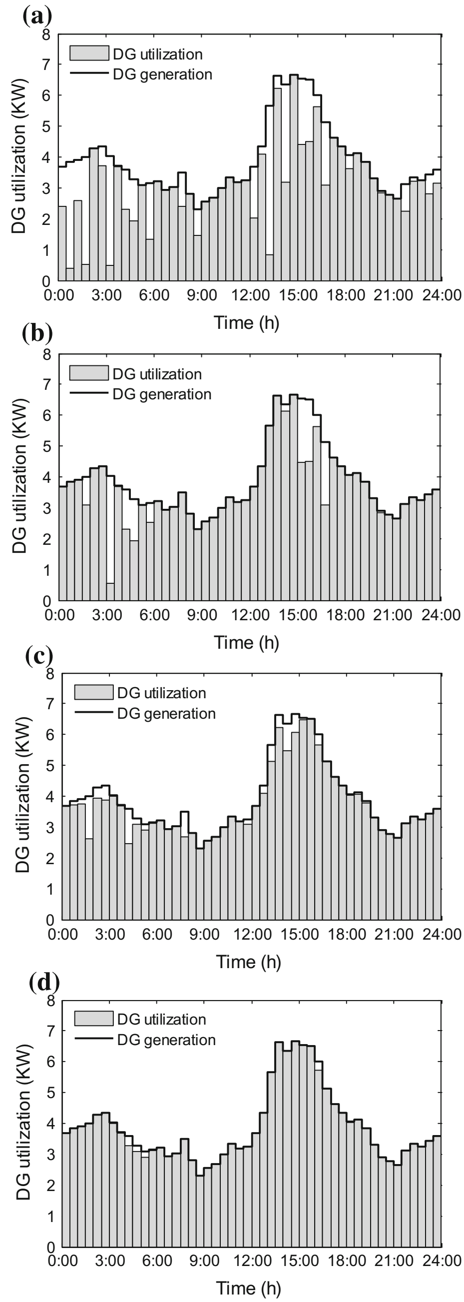

Fig. 7.4 DG utilization efficiency **a** scenario A; **b** scenario B; **c** scenario C; **d** scenario D [15]

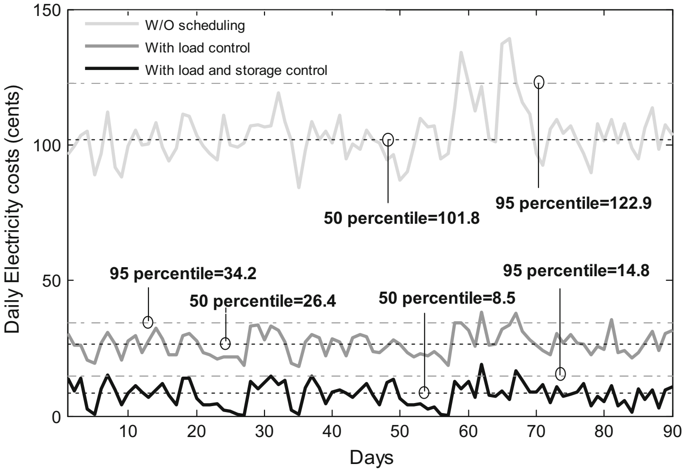

Fig. 7.5 Average daily electricity purchase cost (with vs. w/o) proposed energy dispatch solution [15]

7.4.3 *Energy Dispatch Performance Under Uncertainties*

It should be noted that the numerical results obtained from the previous section are based on the assumption that the prediction of RTP and power demand accurately. However, the renewable power generation from the installed generators, e.g. PV- and wind-based generators, as well as the real-time electricity prices are stochastic in nature which can be hardly to be accurately predicted. Such non-deterministic characteristics and randomness can significantly degrade the performance of the energy dispatch solution. Thus, the impact of such uncertainties needs to be assessed and analysed through quantitative study. In this section, the performance of the energy dispatch solution is further assessed based on the assumption that the accuracy of RTP and DG power output prediction is within the error range of (−10% to +10%) [23].

As the proposed energy dispatch solution is designed to make dispatch decision one-day ahead in advance based on the prediction of DG generation and RTP information, the actual operation can deviate from the optimality due to the prediction errors. In such case, it is often required to purchase electricity from the power utility so as to supply the household power demand. Figure 7.6 shows the performance of the design energy management solution through examining the power supply against the household demand over a day. The utilization efficiency of DG power generation is examined using the actual RTP data, and the average efficiency reaches 97.47%. This implies that it is 1.92% less than the optimality in terms of utilization efficiency, and the purchase cost is 355% higher than the optimal value in this simulated case. The daily electricity purchase costs over 90 days are also calculated based on the prediction one-day ahead and actual information on the day, respectively (50th and

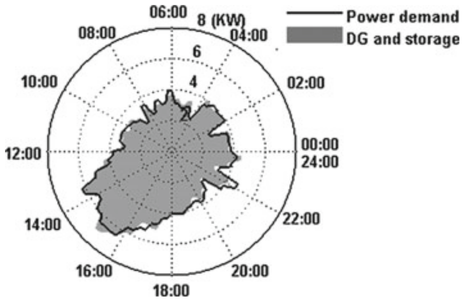

Fig. 7.6 Power supply–demand matching performance under RTP and DG uncertainties [15]

95th percentile). As we expected, the electricity purchase cost in the presence of prediction inaccuracy is higher than that calculated using the prediction of RTP and DG power generation. It still can outperform other simulated operational scenarios. This performance assessment quantifies the impact of the prediction inaccuracy of RTP information and DG power generation on the energy dispatch performance. The numerical result indicates that the proposed solution can perform well under different uncertainties as well as generation and electric pricing prediction inaccuracy.

7.5 Conclusions and Remarks

In this chapter, an optimal domestic energy dispatch solution is presented as a demand response tool to coordinate the domestic DGs, battery-based storage and appliances. In details, the investigated case considers the availability of renewable distributed generators, e.g. solar and wind, as well as Li-ion battery-based energy storage devices in the real-time pricing context. The proposed-algorithmic solution implements the energy management at the domestic level which combines the household load management, and battery storage-based energy dispatch can match the domestic power demands in an optimal way to the power supply at the domestic level whilst promoting the utilization of DG resources and electricity purchase cost reduction. The proposed algorithmic solution has been assessed extensively based on simulation experiments through comparative studies. The robustness of the solution is also evaluated considering prediction errors. The obtained numerical result demonstrated that the proposed domestic demand response solution can appropriately control the domestic appliances- and battery-based storage unit to meet the required power load with significantly improved resource utilization efficiency and reduced purchase cost. The suggested solution can also provide certain degree of robustness under condition of inaccurate RTP and DG generation prediction. A number of research directions are considered worth further exploited based on the observation of this study. The advanced prediction tools and the error correction methods need to be explored to improve the prediction accuracy of DG generation and RTP, to guarantee the performance of the proposed solution; on the other hand, the potential benefit as well as the cost-benefit analysis of multiple coordinated domestic energy management systems needs to be further exploited.

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