Energy Conversion and Management 74 (2013) 209–222

Contents lists available at SciVerse ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

Efficient energy consumption and operation management in a smart building with microgrid

Di Zhang [a], Nilay Shah [b], Lazaros G. Papageorgiou [a,*]

[a] Centre for Process Systems Engineering, Department of Chemical Engineering, UCL (University College London), Torrington Place, London WC1E 7JE, UK
[b] Centre for Process Systems Engineering, Imperial College London, London SW7 2BY, UK

ARTICLE INFO

Article history:
Received 18 February 2013
Accepted 23 April 2013

Keywords:
Planning/scheduling
Smart building
Microgrid
Mixed integer linear programming
Optimisation
Real-time pricing

ABSTRACT

Microgrid works as a local energy provider for domestic buildings to reduce energy expenses and gas emissions by utilising distributed energy resources (DERs). The rapid advances in computing and communication capabilities enable the concept smart buildings become possible. Most energy-consuming household tasks do not need to be performed at specific times but rather within a preferred time. If these types of tasks can be coordinated among multiple homes so that they do not all occur at the same time yet still satisfy customers' requirement, the energy cost and power peak demand could be reduced. In this paper, the optimal scheduling of smart homes' energy consumption is studied using a mixed integer linear programming (MILP) approach. In order to minimise a 1-day forecasted energy consumption cost, DER operation and electricity-consumption household tasks are scheduled based on real-time electricity pricing, electricity task time window and forecasted renewable energy output. Peak demand charge scheme is also adopted to reduce the peak demand from grid. Two numerical examples on smart buildings of 30 homes and 90 homes with their own microgrid indicate the possibility of cost savings and electricity consumption scheduling peak reduction through the energy consumption and better management of DER operation.

1. Introduction

Due to the increase of energy demand and rising global emissions of greenhouse gases, the current centralised generation system is challenged. The future electricity distribution system will be integrated, intelligent and better known as smart grid, which includes advanced digital metres, distribution automation, communication systems and distributed energy resources. The desired smart grid functionalities include self-healing, optimising asset utilisation and minimising operations and maintenance expenses [1]. Microgrid is a relatively small-scale localised energy network, which includes loads, network control system and a set of distributed energy resources (DERs), such as generators and energy storage devices. A microgrid can operate in either grid connected or islanded mode[1] when there are external faults and/or to gain economic advantage. A microgrid equipped with intelligent elements from smart grid has been adopted to enable the widespread of DERs and demand response programs in distribution systems [2], which is considered as future smart grid. Microgrid has an economic incentive due to avoiding energy purchases during peak periods and creation of carbon benefits through low-carbon/low-pollutant generation and co-production of heat and power, which has higher energy efficiency. It also provides secure and reliable energy supply during serious blackout period as a back-up energy supplying system.

Several studies have considered how to design the capacity of a microgrid system to minimise the annual cost. Comprehensive review of the research on microgrid technology, the current research projects and the relevant standards is given by [3], in which pilot projects and further research are discussed. The optimal choice of the investment and optimisation of run-time operational schedules is presented for commercial-building microgrids in [4], where electrical storage and thermal storage are integrated in Distributed Energy Resources Customer Adoption Model (DER-CAM). Asano et al. [5] develop a methodology to design the number and capacity of each equipment in a microgrid with combined heat and power (CHP) system considering partial load efficiency of a gas engine and its scale economy are considered to minimise the annual cost. A baseline analysis estimating the economic benefits of microgrids is performed by King and Morgan [6], and the examined results indicate that better overall system efficiency and cost savings can be achieved from a good mix of customer types. A computer program that optimises the equipment arrangement of each building linked to a fuel cell network and the path of the hot-water piping network under the cost minimisation objective has also been developed in [7], where operation plan of each piece of equipment

* Corresponding author. Tel.: +44 20 7679 2563.
E-mail address: l.papageorgiou@ucl.ac.uk (L.G. Papageorgiou).

[1] Islanded mode means no electricity can be obtained from grid.

0196-8904/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.enconman.2013.04.038

is considered. Bagherian and Tafreshi [8] present energy management systems and optimal scheduling of microgrid. The optimal decisions, including the use of generators for power and heat production, storage system scheduling, proper load management and local grid power selling and purchasing for next day, are determined by maximising the profit. A generalised formulation to determine the optimal strategy and cost optimisation scheme for a microgrid is shown in [9], accounting for emission cost, start-up costs, operation cost and maintenance costs. Optimal economic operation scheduling of a microgrid in an isolated load area is obtained by mixed integer linear programming (MILP) model in [10], and a Virtual Power Producer (VPP) is used to operate the generation units optimally and the methodology is applied to a real microgrid case study. A short-term DER management methodology in smart grids is presented by [11], which involves as short as 5 min ahead scheduling and the previously obtained schedule is rescheduled accordingly. A Genetic Algorithm (GA) approach is used for optimisation. Hawkes and Leach [12] present a linear programming (LP) model to minimise the cost for the high level system design and corresponding unit commitment of generators and storages within a microgrid. Compared with centralised generation, the sensitivity analysis of results to variations in energy prices indicates a microgrid can offer an economic proposition. This model can provide both the optimal capacities of candidate technologies and the operating schedule.

As the energy consumption by buildings represents 30–40% of the world's primary energy consumption [13], smart planning of energy supply to buildings is important to conserve energy and protect the environment. Basic actions to improve energy efficiency in commercial buildings in operation are presented in [14]. Domestic energy consumption depends on the dwelling physical properties, such as location, design and construction, as well as appliances' efficiency and occupants' behaviour. By changing the living behaviour itself, there can be 10–30% energy consumption reduction [15]. More importantly, the liberalisation of electricity markets results in electricity hourly or half-hourly prices and real-time electricity prices encourage consumers to get involved in searching for optimal power consumption way to save their energy costs [16].

This paper considers a smart residential building with its own microgrid, DER and automation system. Smart building is becoming more attractive and viable in the building industry while meeting both desires of comfort and energy savings. The idea of the smart home originated from the concept of home automation, which provides some common benefits to the end users, including lower energy costs, provision of comfort, security and home-based health care and assistance to elderly or disabled users [17]. Smart homes with automation operations are becoming capable along with the technology development, where heating or lighting can be controlled according to the presence of customers [18]. Particle swarm optimisation (PSO) algorithm is applied to the load balancing problem in smart homes in [19], where the optimal distribution of energy resources is determined by an adapted version of the Binary PSO. A method based on LP techniques is proposed for economic evaluation of microgrids from the consumer's point of view in [20]. Operation of distributed generators and energy storage systems are optimised and power interruption costs together with additional expenses to construct the microgrid itself are involved. Some work has also been done to achieve the energy conservation and management perspectives. A multi-agent system for energy resource scheduling of an islanded power system with microgrid is proposed by [21], with an objective to manage the resources efficiently and obtain the minimum operation cost while satisfying the internal demand. A dynamic decision model is presented by [22] to optimise energy flows in a green building with a hybrid energy system, which involves different renewable energy sources. A fuzzy controller is developed and the Man Machine Interface is integrated with Building Energy Management systems to improve the indoor environmental conditions with minimum energy needs [23]. While in [24], an MILP model is developed for scheduling operations in microgrids connected to the national grid to analyse potential policies. A linear diversity constraint is introduced to maintain diversity in the generation of electricity from multiple resources on the production schedule. An energy management and warning system for resident has been proposed for energy saving in [25], which monitors the power usage and warns the users when the power usage is getting close to the monthly prescribed energy usage levels. The electric power dispatch optimisation problem is solved by the genetic algorithm approach by [26], the proposed model determines the optimum operation of a microgrid for residential application under environmental and economic concerns. However, these scheduling optimisation models only consider operation scheduling based on given energy profile rather than scheduling the energy demand.

Scheduling tasks subject to limited resources is a well known problem in many areas of the process industry and other fields, but there are differences when considering the scheduling of electrical appliances. Different time representations and mathematical models for process scheduling problems are summarised in [27]. Four time representations are presented with strengthened formulations which are compared in different scheduling problems. While short-term and medium-term scheduling of a large-scale industrial continuous plant is addressed in [28]. A systematic framework is proposed there and applied on an industrial continuous plant to utilise the main units efficiently. Maravelias and Sung [29] reviewed the integration of production planning and scheduling problem, while key concepts and advantages/disadvantages of different modelling methods are presented. Sun and Huang [30] reviewed energy optimisation methods for energy management in smart homes, such as fuzzy logics, neural network and evolutionary approaches. Hybrid intelligent control systems for generating control rules is recommended for further study and works considering scheduling of appliance operation time are also included. An MILP based smart residential appliance scheduling framework is proposed in [31], where electricity is solely bought from grid and the tariff is known 24 h in advance. Another work for scheduling the operation of smart appliances is presented by [32], where the savings from energy is maximised by shifting domestic loads with real-time pricing. A peak-load shaving online scheduling framework is proposed by [33], and the power consumption scheduling is developed in a systematic manner by introducing a generic appliance model. Scheduling of both energy generation and loads has been studied for single smart home in recent works. The operation of an Electrical Demand-Side management system is presented by [34], where deferrable and no-deferrable tasks commanded by the user are scheduled for 1 day of a house with PV generation. Kriett and Salani [35] propose a generic mixed integer linear programming model to minimise the operating cost of both electrical and thermal supply and demand in a residential microgrid. A real-time price-based demand response management application is presented by [36] for residential appliances in a single house to determine the optimal operation in the next 5-min time interval by considering future electricity price uncertainties, stochastic optimisation and robust optimisation approaches have been applied. An optimal and automatic residential load commitment framework is proposed by [37] to minimise household payment, which determines on/off status of appliances, charging/discharging of battery storage and plug-in hybrid electric vehicles. Derin and Ferrante [38] develop a model that considers both operation scheduling and electricity consumption tasks order scheduling. But their results indicate relatively high computation time, over 35 min, to schedule only three electricity consumption tasks.

In this work, to extend the scope of single smart home energy management, a smart building composed of multiple smart homes is considered. An MILP model is proposed to minimise the total 1-day-ahead expense of a smart building's energy consumption, including operation and energy costs. A microgrid is available to provide electricity and heat for the smart building, and the smart homes share the common DERs from the microgrid. Both the operations of the DERs and the domestic appliances with their specific energy consumption profiles are scheduled. The scheduling is based on real-time electricity prices at each time interval, renewable energy output forecast, subject to the constraints at the earliest starting time and latest ending time for each appliance provided by the consumers. Scheduling of operations within a microgrid based on real-time electricity price and distributed and diverse energy sources is suggested with the objective of minimising cost. Peak demand charge scheme is also applied to reduce the peak electricity demand from grid. When the demand is below an agreed threshold, the real-time pricing is used; while the demand is over the threshold, then an extra fee is charged to the over-threshold amount. Production of electricity and heat is scheduled on the electricity production from generators, boilers, electricity purchase from and sale to the grid, storage of heat and battery usage. Heat demand is static and assumed to be available from prediction while electricity demand is managed by the scheduling of electrical appliance tasks.

The remainder of this paper is organised as follows. In Section 2, the problem is described briefly with relevant assumptions, constraints and objective. In Section 3, the mathematical model is provided. Then in Section 4, the proposed model is applied to two illustrative examples. The computational results are presented and discussed in Section 5. Finally, conclusions are given in Section 6.

2. Problem description

In this paper, a smart building with a number of smart homes is considered. Example of such smart building is given in Fig. 1. It is assumed to have its own microgrid to provide energy locally, which includes some DERs, such as CHP generator, boiler, wind generator, thermal storage and electrical storage. All homes in the building share common microgrid DERs. It also has a grid connection to obtain electricity during power demand peak hours or sell electricity to the grid when there is surplus electricity generation. Each home has a number of domestic appliances, such as dishwasher, washing machine and oven. The building is assumed to have an energy management system, local controllers for each DER and communication system to distribute the energy consumption scheme. Since the model presented in this work only provides the optimal scheduling for 1 day, equipment capacity selection is not considered here, and all the equipment capacities are given. The real-time electricity price profile from the grid is known and varies within a day. Peak demand charge for the over consumed electricity from the grid is given. It is also assumed that weather forecast can provide 24 h wind speed data. Heat demand of the whole building is given while the electricity demand depends on the operation of domestic appliances.

The overall problem can be stated as follows:

Given are (a) a time horizon split into a number of equal intervals, (b) heat demand of the whole building, (c) equipment capacities, (d) efficiencies of technologies, (e) maintenance cost of all equipment, (f) heat-to-power ratio of CHP generator, (g) charge and discharge limit rates for thermal/electrical storage, (h) gas price, real-time electricity prices from grid and peak demand charge price to the over-threshold amount, (i) peak demand threshold from grid, (j) wind speed, (k) earliest starting and latest finishing times, (l) task capacity profiles, (m) task duration.

Determine (a) energy production plan, (b) task starting time, (c) thermal/electrical storage plan, (d) electricity bought from grid, (e) electricity sold to grid.

So as to (a) minimise daily total cost.

3. Mathematical model

The smart homes power consumption scheduling problem is formulated as an MILP model. The daily power consumption tasks

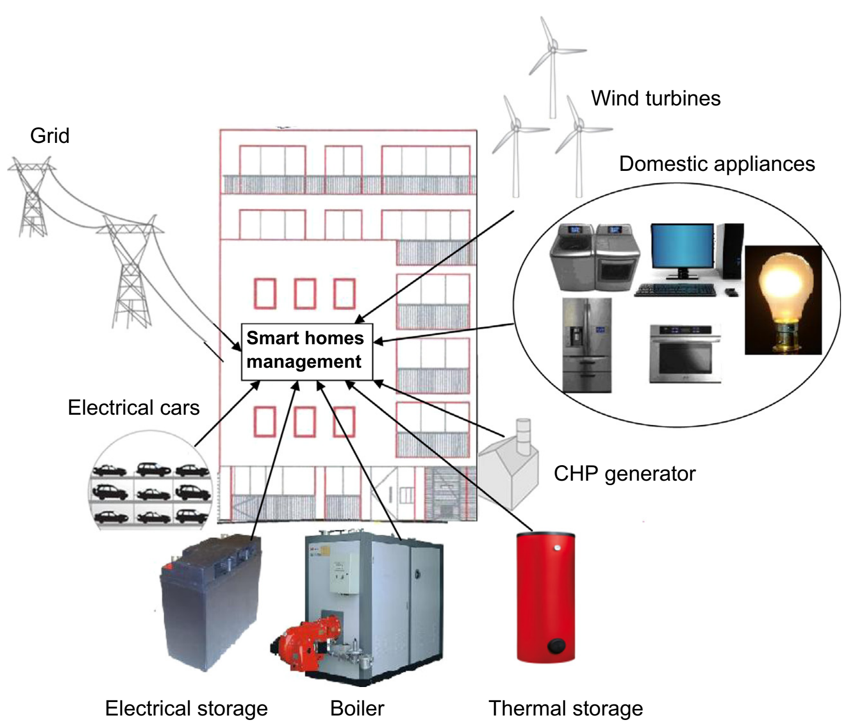

Fig. 1. Example of smart building.

are scheduled based on their given operation time windows, which is defined as the time period between the earliest starting time and latest finishing time of each task. The objective is to minimise the daily total cost and reduce the power consumption peak from grid. The time domain is modelled in a discrete form with intervals of equal length. The key model decision variables include equipment operation, resources utilised and task starting time. These are determined by minimising the daily total cost of all homes subject to equipment capacity constraints, energy demand constraints, electrical/thermal storage constraints and task operation time window.

A list of the notation used in the MILP model is given below, the superscript is used to indicate equipment and the subscript is used for indices:

Indices

i task
j home in the smart building
t time interval
θ task operation period

Parameters

A wind generator blade area (m^2)
b_t electricity buying price from grid at time t (£/kW h_e)
C_i constant power consumption capacity of task i (kW_e)
$C_{i\theta}$ power consumption capacity of task i at operation period θ (kW_e)
C^{CHP} CHP generator capacity (kW_e)
C^W wind generator capacity (kW_e)
C^B boiler capacity (kW_{th})
C^E electrical storage capacity (kW h_e)
C^T thermal storage capacity (kW h_{th})
D^E electrical storage discharge limit (kW_e)
D^T thermal storage discharge limit (kW_{th})
G^E electrical storage charge limit (kW_e)
G^T thermal storage charge limit (kW_{th})
H_t heat demand at time t (kW_{th})
m^E cost per unit input (maintenance) for electrical storage unit (£/kW h_e)
m^T cost per unit input (maintenance) for thermal storage unit (£/kW h_{th})
m^W wind generator maintenance cost (£/kW h_e)
n price of natural gas (£/kW h)
p difference between peak and base electricity demand price from grid (£/kW h_e)
P_{ji} processing time of task i of home j
q electricity selling price to grid (£/kW h_e)
T^F_{ji} latest finishing time of task i of home j
T^S_{ji} earliest starting time of task i of home j
v_t wind speed at time t (m/s)
V^{nom} nominal wind speed (m/s)
$V^{cut\text{-}in}$ cut-in wind speed (m/s)
$V^{cut\text{-}out}$ cut-out wind speed (m/s)
w_t output from wind generator at time t (kW_e)
α CHP heat-to-power ratio
δ time interval duration (h)
ρ air density (kg/m^3)
η^B boiler efficiency
η^{CHP} CHP generator electrical efficiency
η^E electrical storage charge/discharge efficiency
η^T thermal storage charge/discharge efficiency
η^W wind generator power coefficient
κ agreed electricity peak demand threshold from grid (kW_e)

Variables

f_t thermal storage discharge rate at time t (kW_{th})
g_t thermal storage charge rate at time t (kW_{th})
I_t electricity imported from the grid at time t (kW_e)
R_t electricity exported to the grid at time t (kW_e)
S^{IE} initial state of electrical storage (kW h_e)
S^{IT} initial state of thermal storage (kW h_{th})
S^E_t electricity in storage at time t (kW h_e)
S^T_t heat in storage at time t (kW h_{th})
u_t electricity output from CHP generator at time t (kW_e)
x_t heat output from boiler at time t (kW_{th})
y_t electrical storage discharge rate at time t (kW_e)
z_t electrical storage charge rate at time t (kW_e)
ϕ daily total cost of the smart building (£)
γ_t extra electricity load from grid over the agreed threshold κ at time t (kW_e)

Binary variables

E_{jit} 1 if task i of home j starts at time t, 0 otherwise

Next, the constraints involved in the proposed mathematical model are described:

3.1. Capacity constraint

The output from each equipment should not exceed its designed capacity,

CHP generator:

$$u_t \leqslant C^{CHP} \quad \forall t \tag{1}$$

Boiler:

$$x_t \leqslant C^B \quad \forall t \tag{2}$$

Electrical storage:

$$S^E_t \leqslant C^E \quad \forall t \tag{3}$$

Thermal storage:

$$S^T_t \leqslant C^T \quad \forall t \tag{4}$$

3.2. Energy storage constraints

Electricity stored in the electrical storage at time t is equal to the amount stored at $t-1$ plus the electricity charged minus the electricity discharged. Electricity would be lost during the charging and discharging process, for example during any period when amount of electricity δz_t is sent to the electrical storage, only $\delta\eta^E z_t$ will be charged, and the rest being lost, where η^E is turn-around efficiency of electrical storage. Meanwhile, during the discharging process, in order to send δy_t of electricity to the user, $\delta y_t/\eta^E$ of electricity is needed.

$$S^E_t = S^E_{t-1} + \delta\eta^E z_t - \delta y_t/\eta^E \quad \forall t \tag{5}$$

The electrical storage has an initial storage state at the beginning of each sample day. At the end of each day, the electrical storage must return to its initial value, so as to avoid net accumulation. The initial storage state value is optimised through the model to decide the best initial state for 1 day utilisation. Otherwise, the initial state can be obtained from the previous day and at the end of the day, the electrical storage must return to be over certain lower limit to protect the equipment.

$$S^E_0 = S^E_T = S^{IE} \tag{6}$$

The rates of discharge or charge of electricity cannot exceed the electrical storage discharge and charge limits defined by the battery manufacturer, in order to prevent excessive discharge/charge rates that would damage the battery or reduce its capacity:

$$y_t \leqslant D^E \quad \forall t \tag{7}$$

$$z_t \leqslant C^E \quad \forall t \tag{8}$$

Heat stored in the thermal storage at time t is equal to the amount stored at $t-1$ plus the heat charged minus the heat discharged. The heat loss during the heat storage process is represented in the same way as shown for the electrical storage.

$$S_t^T = S_{t_{t-1}}^T + \delta\eta^T g_t - \delta f_t/\eta^T \quad \forall t \tag{9}$$

Stored heat must return to the initial state at the end of the day so that no heat is accumulated over 1 day. The initial storage state value is also optimised through the model.

$$S_0^T = S_T^T = S^{IT} \tag{10}$$

The rates of discharge and charge of heat cannot exceed the thermal storage discharge and charge limits based on the type of storage medium, mass and latent heat of the material:

$$f_t \leqslant D^T \quad \forall t \tag{11}$$

$$g_t \leqslant G^T \quad \forall t \tag{12}$$

3.3. Wind generator ouput

The electricity output from the wind generators is calculated from the wind power generation equation, based on the wind generator blade area, wind speed and wind generator efficiency. The power output is constrained by both cut-in speed and cut-out speed in the model. The cut-in speed is the minimum wind speed at which the wind turbine will generate its designated rated power. While the cut-out speed is wind speed at which the wind generator would be shut down for the safety reasons in order to protect the wind turbine from damage [39].

$$w_t = \begin{cases} 0.5\rho A\eta^W \min(v_t, V^{nom})^3 & \forall t: \; V^{cut-in} \leqslant v_t \leqslant V^{cut-out} \\ 0 & \forall t: \; v_t \leqslant V^{cut-in} \text{ and } v_t \geqslant V^{cut-out} \end{cases} \tag{13}$$

3.4. Energy balances

In each time interval, the total electricity consumption is the sum of the power consumption capacities from all tasks of all homes. The electricity consumed during each time period is supplied by the wind generator, CHP generator, electricity received from the electrical storage and grid, minus electricity sent to the electrical storage and grid. If the power consumption capacity of task i is constant, then the electricity balance can be represented as Eq. (14). But the power consumption capacity of some tasks varies over the operation time intervals, e.g. washing machine has different capacity profiles over washing and spinning processes. Eq. (14a) is more appropriate for such case, in which the electricity consumption is summed over the task operation periods θ.

$$\sum_j \sum_i C_i E_{jit} = w_t + u_t + y_t + I_t - z_t - R_t \quad \forall t \tag{14}$$

$$\sum_j \sum_i \sum_{\theta=0}^{P_{ji}-1} C_{i\theta} E_{ji,t-\theta} = w_t + u_t + y_t + I_t - z_t - R_t \quad \forall t \tag{14a}$$

The heat consumed during each time period is equal to heat supplied by the CHP generator, boiler, heat received from the thermal storage, minus heat sent to the thermal storage.

$$H_t = \alpha u_t + x_t + f_t - g_t \quad \forall t \tag{15}$$

3.5. Starting time and finishing time

The operation time of each task must be within the given time window. The starting time of each task cannot be earlier than the given earliest starting time, and must finish before the latest finishing time. For each task from each home, it has to be started once.

$$\sum_{T_{ji}^S \leqslant t \leqslant T_{ji}^F - P_{ji}} E_{jit} = 1 \quad \forall j, i \tag{16}$$

3.6. Peak demand charge

There is also a desire to reduce the electricity peak demand from the grid to avoid the need for high capacity in the macrogrid–microgrid connection (and to avoid charges levied by the System Operator for consumption at times of macrogrid peak). One way to achieve this is to increase the grid tariff rate for the high electricity load periods, and thus motivating consumers to redistribute or reduce their electricity consumption [40]. In order to reflect this, in our approach, an extra constraint, Eq. (17), is introduced in the model. For each time interval, when electricity load from grid is below the agreed threshold κ, the normal electricity price is applied. But when electricity load from grid is over the agreed threshold κ, the additional amount, γ_t over threshold value, is charged with an extra rate.

$$\gamma_t \geqslant I_t - \kappa \quad \forall t \tag{17}$$

3.7. Objective function

The objective function is to minimise the total daily cost, which includes: the operation and maintenance cost of the CHP generator, wind generator, boiler, electrical storage and thermal storage; the cost of electricity purchased from the grid; the revenue from electricity sold to the grid. Since the equipment capacities are fixed, their capital costs are independent of the schedule and are therefore not considered. If only the real-time pricing is applied, the total cost is calculated as in

$$\begin{aligned} \phi = & \sum_t \delta n u_t/\alpha \quad \text{CHP operation cost} \\ & + \sum_t \delta m^W w_t \quad \text{wind turbine maintenance cost} \\ & + \sum_t \delta n x_t/\eta^B \quad \text{boiler operation cost} \\ & + \sum_t \delta m^E y_t \quad \text{electrical storage maintenance cost} \\ & + \sum_t \delta m^T f_t \quad \text{thermal storage maintenance cost} \\ & + \sum_t \delta b_t I_t \quad \text{electricity buying cost from grid} \\ & - \sum_t \delta q R_t \quad \text{revenue from electricity selling to grid} \end{aligned} \tag{18a}$$

When peak demand charge scheme is applied, the total daily cost is calculated as in Eq. (18b). Below the threshold, the electricity price follows the real-time electricity price but when the demand is over the threshold extra cost is assigned to the additional electricity amount.

$$\begin{aligned}\phi = &\sum_t \delta n u_t/\alpha \quad \text{CHP operation cost}\\ &+\sum_t \delta m^W w_t \quad \text{wind turbine maintenance cost}\\ &+\sum_t \delta n x_t/\eta^B \quad \text{boiler operation cost}\\ &+\sum_t \delta m^E y_t \quad \text{electrical storage maintenance cost}\\ &+\sum_t \delta m^T f_t \quad \text{thermal storage maintenance cost}\\ &+\sum_t \delta b_t I_t \quad \text{electricity buying cost from grid}\\ &+\sum_t \delta p \gamma_t \quad \text{peak demand extra charge from grid}\\ &-\sum_t \delta q R_t \quad \text{revenue from electricity selling to grid}\end{aligned} \tag{18b}$$

4. Illustrative examples

In this section, the proposed MILP model for energy consumption scheduling is applied to two numerical examples: (i) a smart building of 30 homes with same living habits and (ii) a smart building of 90 homes with different living habits.

4.1. Example 1: Smart building of 30 homes with same living habits

Example 1 considers a smart building system with 30 homes with the following distributed energy resources, and their capacities are obtained according to the total energy demand while the technical parameters and costs are obtained from [12]:

- one CHP generator with a capacity of 20 kW_e and electrical efficiency of 35%. Heat to power ratio is assumed to be equal to 1.3, and natural gas cost is 2.7 p/kW h;
- one wind farm with a capacity of 10 kW_e and a maintenance cost of 0.5 p/kW h_e;
- one boiler with capacity of 120 kW_{th} and natural gas cost is 2.7 p/kW h;
- one electrical storage unit with a capacity of 10 kWh_e, charge/discharge efficiency of 95%, discharge limit and charge limit are both 10 kW_e, and the maintenance cost is 0.5 p/kW h_e;
- one thermal storage unit with a capacity of 20 kWh_{th}; charge/discharge efficiency of 98%, discharge limit and charge limit are both 20 kW_{th}, and the maintenance cost is 0.1 p/kW h_{th};
- a grid connection (allowing import and export of electricity when operating parallel to grid); the real-time electricity price at different times is collected from Balancing Mechanism Reporting System [41] as shown in Fig. 2. When electricity demand from grid is over 30 kW_e, an extra cost of 5 p/kW h_e is charged to the additional electricity. Electricity may also be sold to the grid with 1 p/kW h_e;

Each time interval considered is half an hour. So in total, there are 48 time intervals for a single day. The total heat demand profile is generated for a building with floor area of 2500 m^2 on a sample winter day using CHP Sizer Version 2 Software [42]. For the electricity demand, each home has 12 basic tasks that consume electricity as shown in Table 1. These tasks are available to be scheduled according to the given earliest starting time, latest finishing time, their respective duration and power requirements [43]. All tasks, except the dishwasher and washing machine, have constant power consumption rates given in the table. The electrical profiles for dish washer and washing machine are shown in Fig. 3.

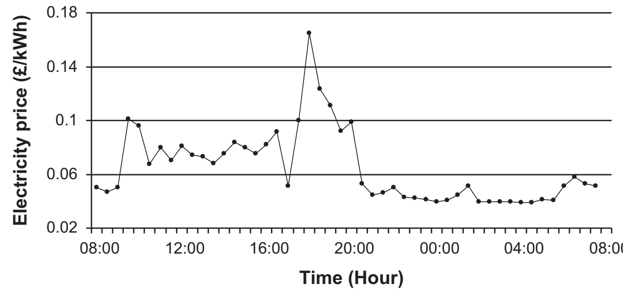

Fig. 2. Electricity tariff (March 3rd, 2011) [41].

Also it is assumed that all homes have the same living habits and every task has to be performed once a day.

There are 10 identical wind generators in the wind farm, with a power coefficient of 45% [39]. The blade diameter is 1.6 m and the wind speed is generated from a Weibull distribution using MATLAB with a mean velocity of 7 m/s. The cut-in and cut-out wind speeds are assumed to be 5 m/s and 25 m/s, respectively, and the nominal wind speed is taken as 12 m/s. The wind generators do not produce any power when the wind speed is under the cut-in speed or above the cut-out speed. When the wind speed is above the nominal wind speed, the power output is at the maximum output, which is equal to the output produced at the nominal wind speed. Between cut-in and cut-out nominal wind speed, the wind generator power output varies according to Eq. (13).

4.2. Example 2: Smart building of 90 homes with different living habits

Example 2 considers a smart building with 90 homes and it has the same distributed energy resources as those in Example 1, but with tripled equipment capacities, and heat demand and peak demand threshold from grid are also tripled. There are still 12 electrical tasks for each home, and task processing duration, time window length and power consumption rate are the same as those in Example 1. The main difference is that the 90 homes have different living habits. The earliest starting time for each task of each home is generated randomly based on the modified hourly operation probability distribution as given in [44]. Only the operation hours with a probability higher than 5% are selected and then the hourly operation possibility is redistributed accordingly. The modified earliest starting time hourly probability distribution for the 12 electrical consumption tasks is presented in Fig. 4, where *y* axis represents the probability percentage. Some tasks have the same hourly probability distribution, so only one distribution plot is presented for each type of tasks.

5. Computation results

Two pricing schemes have been applied for both examples above, which are real-time price scheme and peak demand price schemes. For the real-time price scheme, the objective is to minimise the total daily cost under real-time electricity prices as shown in Eq. (18a), subject to Eqs. (1)–(13) and (14a)–(16). While for the peak demand price scheme, the objective is to minimise the total daily cost together with the extra cost charged for over consumed electricity from the grid as described by Eq. (18b), subject to Eqs. (1)–(13) and (14a)–(17).

For each pricing scheme, four scenarios are deployed, which are (a) macrogrid earliest starting time, (b) macrogrid optimised scheduling, (c) microgrid earliest starting time and (d) microgrid optimised scheduling. Abbreviations are used to indicate the

Table 1
Electricity consumption for tasks in Example 1 [43].

Task	Power (kW)	Earliest starting time (h)	Latest finishing time (h)	Time window length (h)	Duration (h)
Dishwasher	–	9	17	8	2
Washing machine	–	9	12	3	1.5
Spin dryer	2.5	13	18	5	1
Cooker hob	3	8	9	1	0.5
Cooker oven	5	18	19	1	0.5
Microwave	1.7	8	9	1	0.5
Interior lighting	0.84	18	24	6	6
Laptop	0.1	18	24	6	2
Desktop	0.3	18	24	6	3
Vacuum cleaner	1.2	9	17	8	0.5
Fridge	0.3	0	24	–	24
Electrical car	3.5	18	8	14	3

combinations of pricing scheme and scenario, e.g. RMO[2] is short for real-time price scheme macrogrid optimised scheduling scenario while PmE represents peak demand price scheme microgrid earliest starting time scenario.

In the macrogrid scenarios (a, b), electricity is solely bought from grid and heat is produced only by boiler. There is no other DER to provide electricity or heat to the building. For the microgrid scenarios (c, d), DERs are available to provide local electricity and heat. The earliest starting scenario (a scheduling heuristic) means all the domestic electricity appliances are turned on at their given earliest starting time, which is similar to common living habits. For example, the washing machine would be turned on as soon as people want to do some washing, most likely when leaving home for work in the morning. When task operation within time window is allowed in the optimised scheduling scenario, the domestic tasks operation order as well as the equipment operation time could be scheduled in order to minimise the total cost (Eqs. (18a) or (18b)). Tasks, such as interior lighting and fridge, have fixed electricity consumption time period and have no other alternatives. Tasks with flexible operation time can be scattered as much as possible to avoid electricity consumption peak and utilise electricity generated from local generators as much as possible. Also, when electricity is cheaper from grid, it will be imported from the grid instead of being generated from generators which could also be stored in the battery for later use.

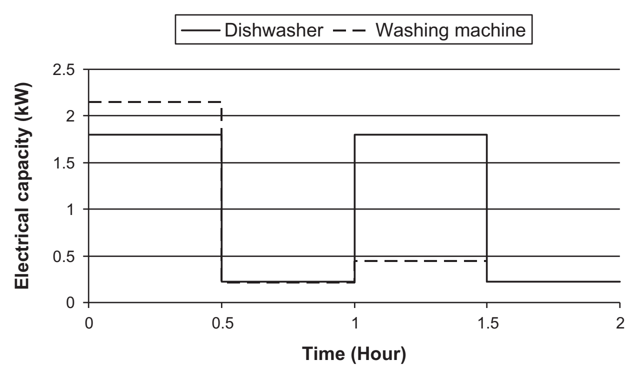

Fig. 3. Electricity utilisation profiles of dishwasher and washing machine.

5.1. Example 1: real-time price and peak demand price schemes

The planning horizon for both examples is from 8 am in a day to 8 am on the next morning. The optimal electricity balance and total daily cost resulting from Example 1 under the real-time price scheme is shown in Fig. 5. Under the RMO scenario, the tasks are scheduled based on the real-time electricity pricing. Tasks are preferred to be performed when electricity price is low, e.g. during night time. The total cost is reduced from £154 in the RME scenario to £137 in the RMO scenario. The electricity demand from the grid is scattered while the peak demand from the grid is decreased from 301 kW in RME scenario to 186 kW in the RMO scenario. Under the real-time price scheme for the RmE and RmO scenarios, the electrical storage is used to store electricity when there is an excess; it is mainly for utilising the wind generator output more efficiently. There is no excess electricity sold to the utility grid in Example 1. The total cost is reduced to £123 in the RmO scenario. With the earliest starting time scenarios, the peak hours are mainly during the evening when occupants are back from work. In the RmO scenario, the peak demand from the grid is decreased from 270 kW in the RmE scenario to 153 kW in the RmO scenario, and the electricity demand is flatter in RmO than RmE. During the day, about 30% of the total electricity and 18% of total heat are produced from the CHP in the RmE scenario and 45% of electricity and 27% of heat are produced from the CHP in the RmO scenario.

The optimal electricity balance and total 1 day cost resulting from Example 1 under peak demand price scheme is shown in Fig. 6. When extra cost is charged for the over consumed electricity from grid, the peak demand is reduced through optimisation.

Under the PMO scenario, the tasks are scattered according to real-time prices and peak demand extra charge. The total cost for PME scenario is £186 while it decreases to £157 when optimised scheduling is applied in the PMO scenario. The peak demand from grid is reduced to 184 kW. There are still peaks in the early morning and evening which cannot be avoided, mainly because of the inflexible time window requirement for specific tasks. It happens even in the PmO scenario although the demand pattern is smoother. Under microgrid scenarios, the total cost is £165 in the PmE scenario, which is further reduced to £127 in the PmO scenario. The peak demand from the grid is reduced from 270 kW in the PmE scenario to 121 kW in the PmO scenario. The demand pattern in the PmO scenario is smoother than that in the PmE scenario.

The comparison between the real-time price scheme and peak demand price scheme of Example 1 is presented in Table 2. It is clearly shown that by applying the optimised scheduling scenarios, the total cost is always lower than that of the earliest starting time scenarios. When peak demand extra cost is considered, although the total cost under each scenario is higher than that of the real-time price scheme, the total peak demand over the whole day is quite different. It can be seen from Figs. 5b and 6b, the electricity demand over the day is flatter in Fig. 6b. The total peak demand over the threshold has been reduced from 586 kW h in RMO

[2] Format '*xyz*' is used for abbreviation, where '*x*' represents real-time price scheme (R) or peak demand price scheme (P); '*y*' represents macrogrid (M) or microgrid (m) and '*z*' represents earliest starting time (E) or optimised scheduling (O).

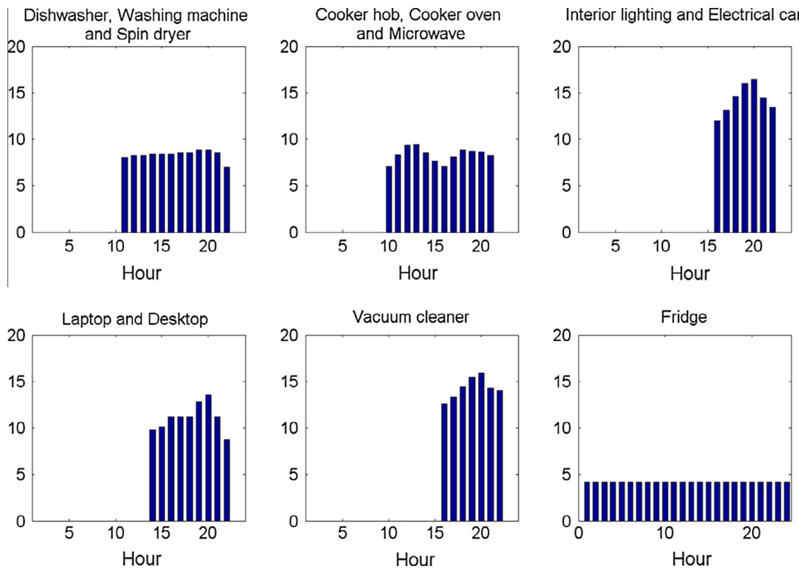

Fig. 4. Earliest starting time hourly probability distribution for electrical consumption tasks [44].

scenario to 350 kW h in PMO scenario, satisfying the aim of the peak demand schemes to reduce the peak demand from the grid. It indicates that even without microgrid, the task starting time scheduling can help in peak demand reduction and cost savings. When microgrid is applied, more savings can be achieved and peak demand from grid can be reduced further by obtaining electricity from local DERs. By utilising microgrid and the peak demand price scheme, the total cost is the lowest while highest peak demand from the grid is reduced to 121 kW in PmO scenario (which is 153 kW in the RmO scenario). The total peak demand over the threshold of 30 kW in PmO scenario is 67 kW h, which represents about 6% of the total electricity demand (1056 kW h).

The heat balances for microgrid scenarios are shown in Fig. 7. Since all the heat in the macrogrid scenarios is provided by the boiler and heat demand profile is the same under all scenarios, heat balances for macrogrid scenarios are not presented. Under the microgrid earliest starting time scenarios, the heat output from CHP varies, while under the microgrid optimal scheduling scenarios, the heat output from CHP is constant and CHP operates at its full capacity.

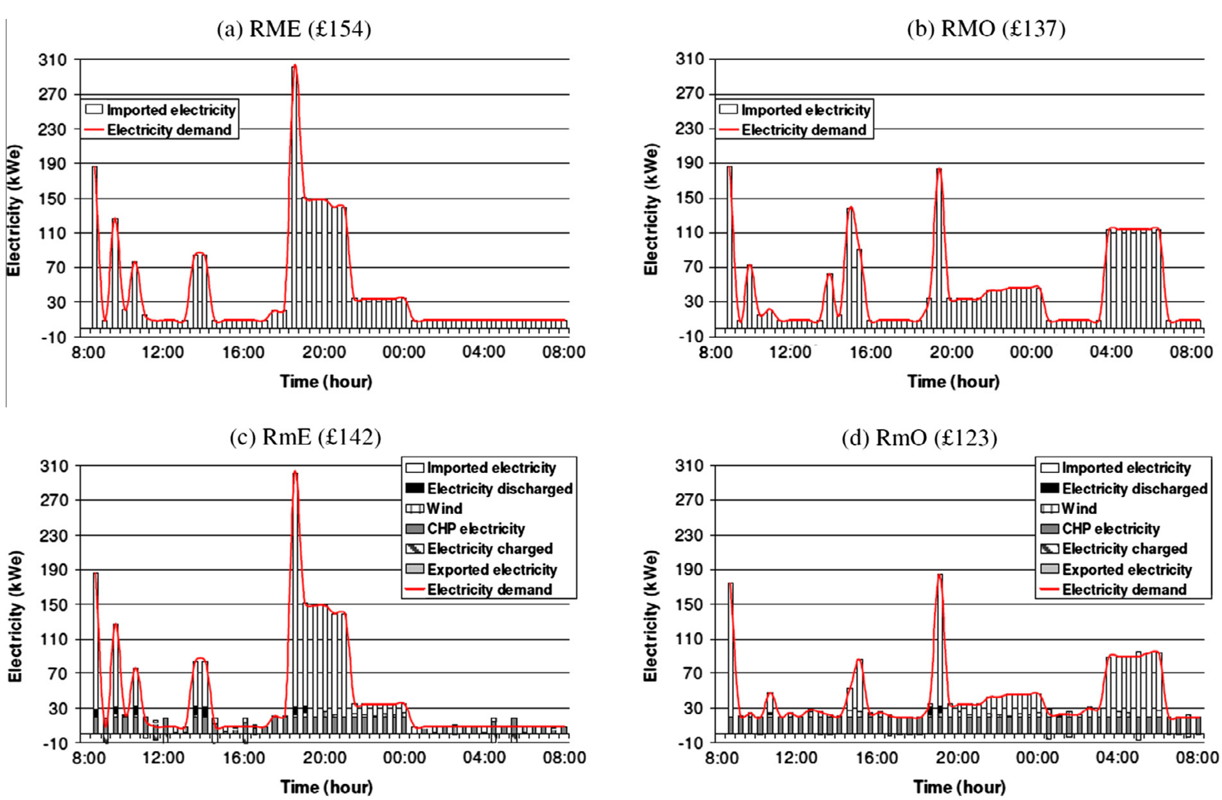

Fig. 5. 30 homes: electricity balance and total cost under real-time price scheme.

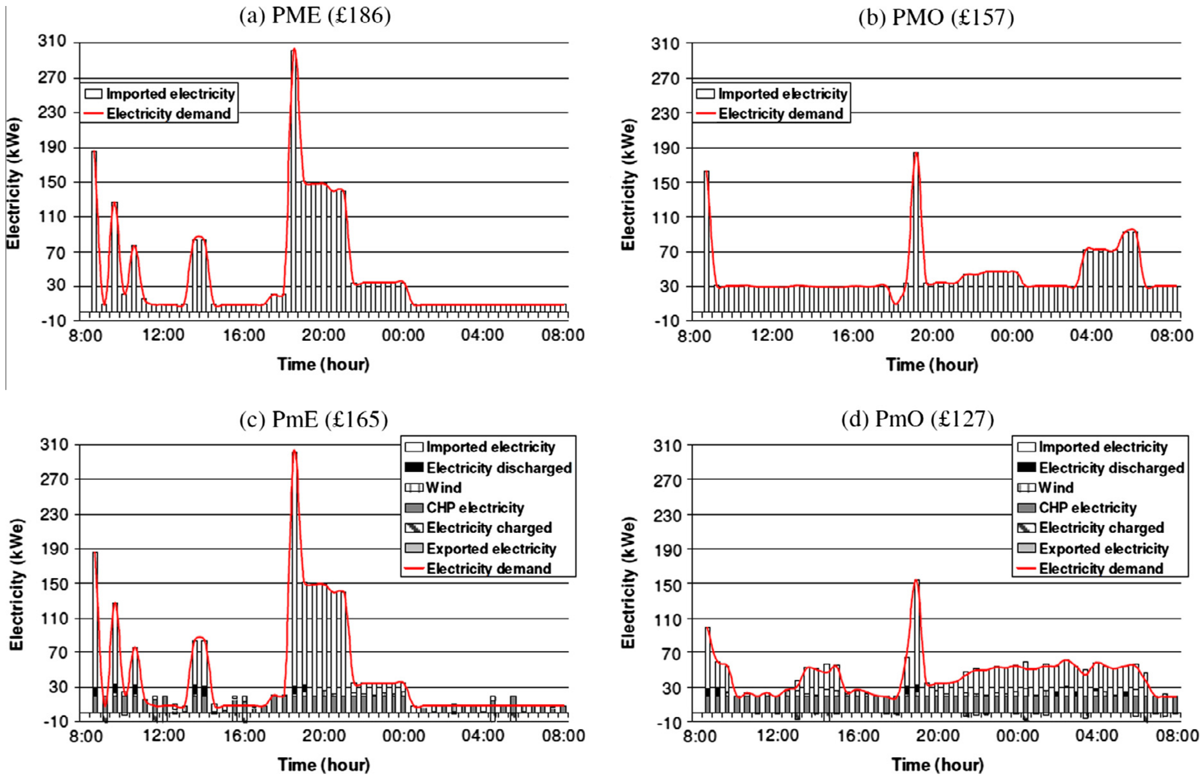

Fig. 6. 30 homes: electricity balance and total cost under peak demand price scheme.

Table 2
Results of Example 1 under two pricing scheme.

	Total cost (£)	Peak demand from grid (kW)	Total peak demand (kW h)	CHP production (kW h)	Peak demand over total demand (%)
RME	154	301	640	0	61
RMO	137	186	586	0	55
RmE	142	270	475	322	45
RmO	123	153	252	480	24
PME	186	301	640	0	61
PMO	157	184	350	0	33
PmE	165	270	473	322	45
PmO	127	121	67	480	6

5.2. Example 2: real-time price and peak demand price schemes

The optimal electricity balance and total daily day cost resulting from Example 2 under real-time price scheme are shown in Fig. 8. Under the RMO scenario, all tasks are scheduled based on the real-time electricity price to obtain minimum daily energy cost. The total cost is reduced to £409 in the RMO scenario, which is 12% cost savings. As shown in Fig. 8b, task starting times are shifted to midnight when electricity price is low. The electricity demand from the grid is scattered and the peak demand is decreased from 424 kW in the RME scenario to 363 kW in the RMO scenario. Under the RmE and RmO scenarios, equipment operation time from each technique is scheduled accordingly to minimise the total operation cost. When time window is allowed, tasks with flexible operation time are scattered as much as possible as in Example 1. The power consumption peak periods are shifted to the early morning when the electricity buying price is cheaper. The total cost is £354 in the RmO scenario. The electrical storage is used to store electricity. There is no excess electricity sold to the utility grid in Example 2. This is mainly due to the small CHP capacity and cannot provide extra electricity. Also, the electricity selling price to the grid is relative low. The boiler capacity can fulfill the peak heat demand, but when the heat demand is over the boiler capacity and the electricity demand is low, it is possible to sell electricity to grid from the microgrid. In that case, CHP generator has to provide more electricity than needed to cover the increased heat demand. The excess electricity can be stored in battery for later use or sold to the grid. However, when electrical storage is full, export to the grid is the only option although the selling price is low. In the RmE and RmO scenarios, the total costs are £409 and £354, respectively. The electricity peak demand from the grid is decreased from 358 kW in the RmE scenario to 283 kW in the RmO scenario. During the day, about 37% of the total electricity and 22% of total heat are produced from the CHP in the RmE scenario and 44% of electricity and 26% of total heat are produced from the CHP in the RmO scenario. The total electricity demand of the smart building is 3169 kW h.

The optimal electricity balance and total daily cost resulting from Example 2 under peak demand price scheme are shown in Fig. 9. When the extra cost is charged for the over consumed electricity from the grid, the peak demand is reduced through task scheduling. The total costs are £546 and £474 for the PME scenario and PMO scenario. Under the PMO scenario, the peak demand from grid is reduced to 340 kW compared to the PME scenario. The

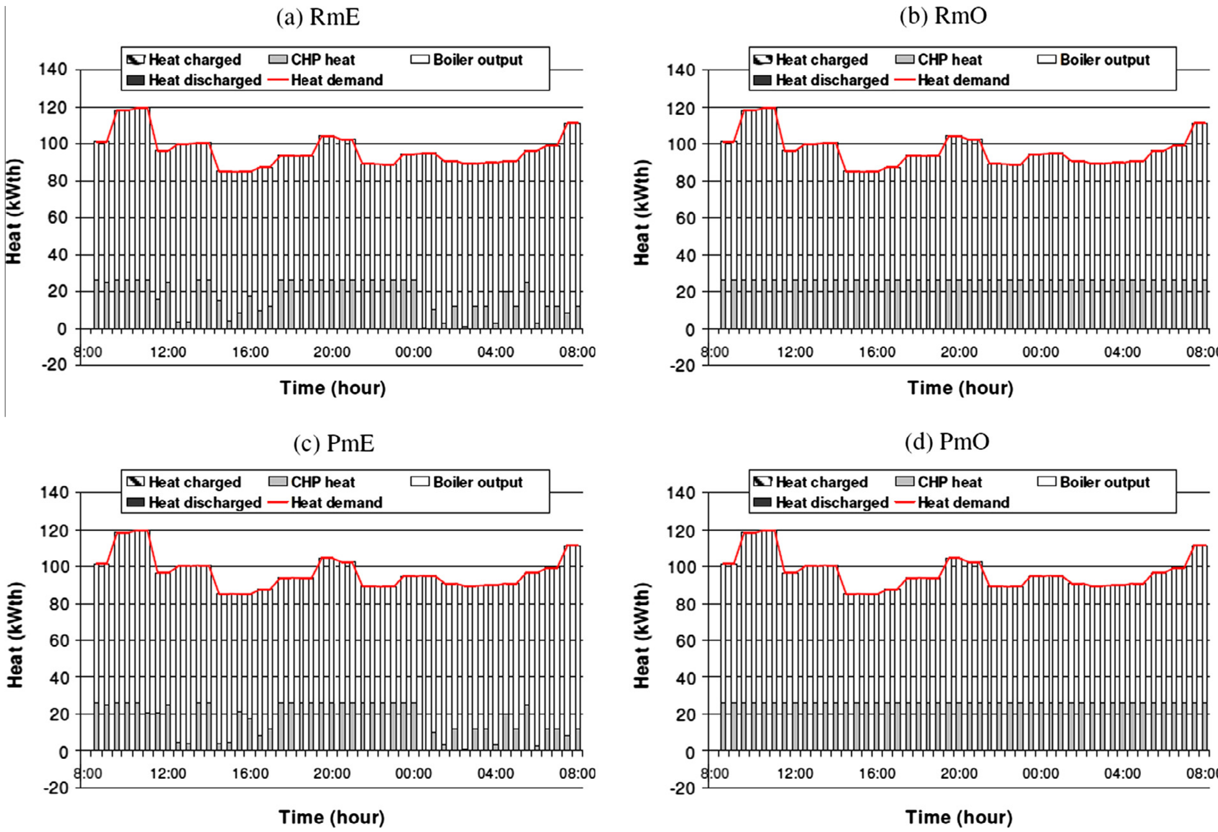

Fig. 7. 30 homes: heat balance for microgrid scenarios.

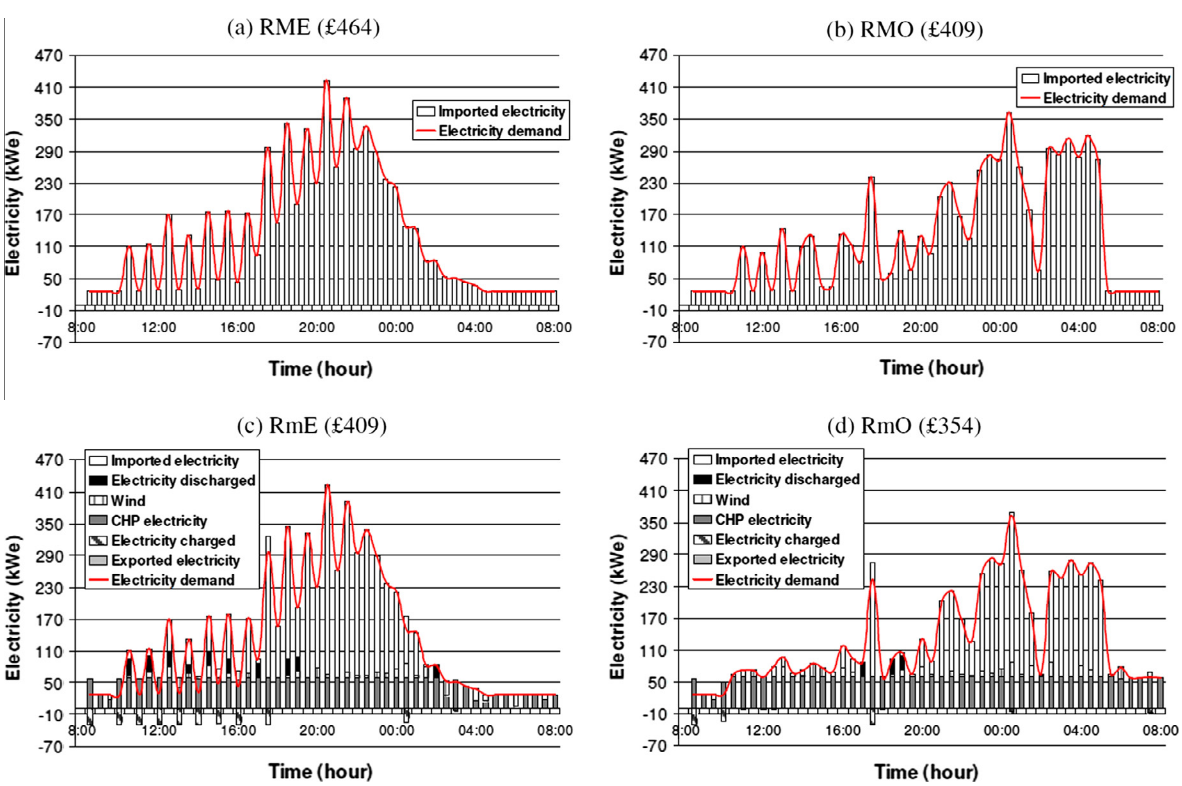

Fig. 8. 90 homes: electricity balance and total cost under real-time price scheme.

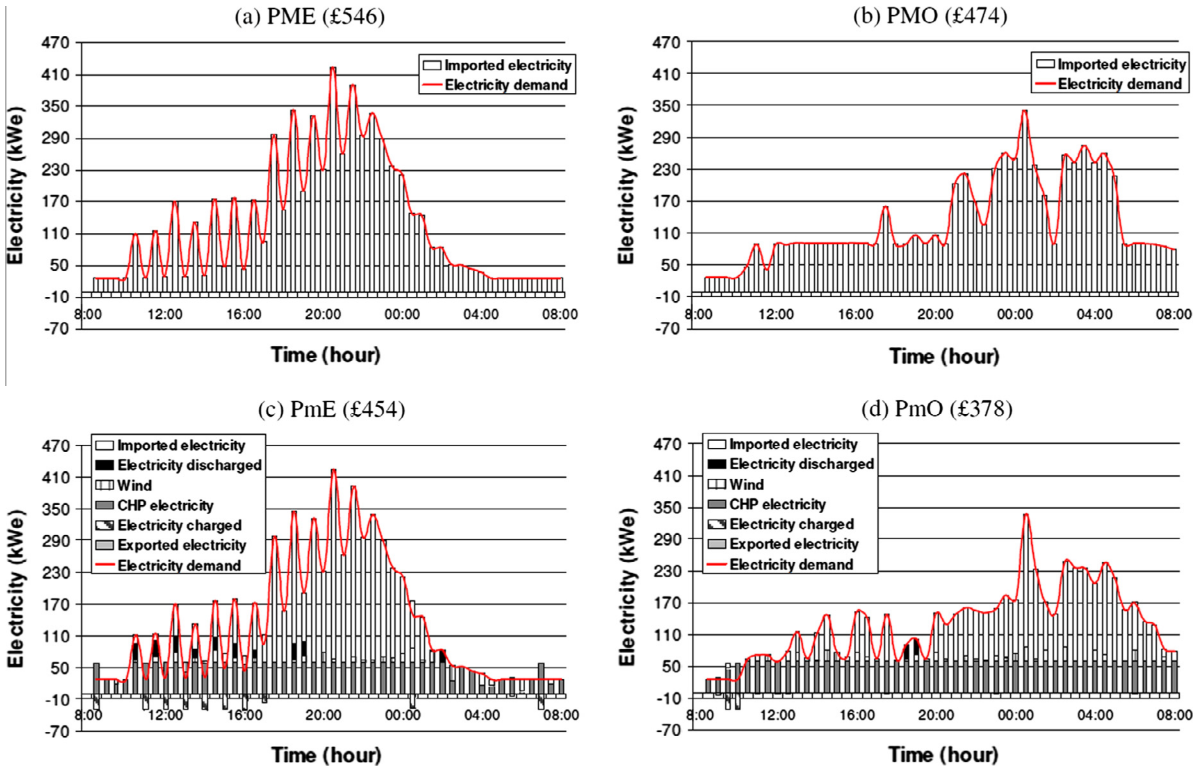

Fig. 9. 90 homes: electricity balance and total cost under peak demand price scheme.

Table 3
Results of Example 2 under two pricing scheme.

	Total cost (£)	Peak demand from grid (kW)	Total peak demand (kW h)	CHP production (kW h)	Peak demand over total demand (%)
RME	464	424	1646	0	52
RMO	409	363	1566	0	49
RmE	409	358	902	1183	28
RmO	354	283	738	1393	23
PME	546	424	1646	0	52
PMO	474	340	1191	0	38
PmE	454	358	880	1183	28
PmO	378	250	360	1401	11

energy consumption peaks are in the mid-night instead of the evening in this scenario. Since there is no DER to provide electricity, the tasks are scattered as much as possible to reduce the peak demand extra charge over the threshold at 90 kW. Under microgrid scenarios, PmE scenario and PmO scenario, the total costs are both lower than that from the macrogrid scenarios, which are £454 and £378, respectively. Also the peak demand from grid is reduced from 358 kW in the PmE scenario to 250 kW in the PmO scenario. The PmO scenario has the flattest electricity demand.

The comparison between the real-time and peak demand price schemes of Example 2 is presented in Table 3. Similarly to Example 1, the total cost is always lower for the optimised scheduling scenarios than that of the earliest starting time scenarios. The total cost under each scenario from peak price scheme is higher than that of the real-time price scheme. As expected, the peak demand price schemes reduce the peak demand from the grid. The highest peak demand in the PMO scenario is smaller than that from the RMO scenario, and the total daily peak demand has also been reduced. The electricity demand over the day in Fig. 9b is flatter than that shown in Fig. 8b. The total peak demand over the threshold has been reduced from 1566 kW h in the RMO scenario to 1191 kW h in the PMO scenario. The task starting time optimal scheduling can reduce peak demand and achieve higher cost savings. Microgrid provides local electricity by utilising DERs, which further reduce the peak demand from the grid and obtain more savings. By applying microgrid and the peak demand price scheme in the PmO scenario, the total cost is the lowest and the peak demand from the grid is reduced to 250 kW (from 283 kW in the RmO scenario). Total peak demand from the grid over the threshold 90 kW in the PmO scenario is reduced to 360 kW h, which is 11% of the total electricity demand.

The heat balances for microgrid scenarios are shown in Fig. 10. Under the earliest starting time scenarios, the heat output from CHP varies, while under the optimal scheduling scenarios, the heat output from CHP is constant except from the beginning of the day and CHP almost operates at its full capacity.

5.3. Comparison between Example 1 and Example 2

By comparing with the scenarios where all tasks start at their earliest possible starting time, there are obvious savings through task starting time scheduling in both examples under the two

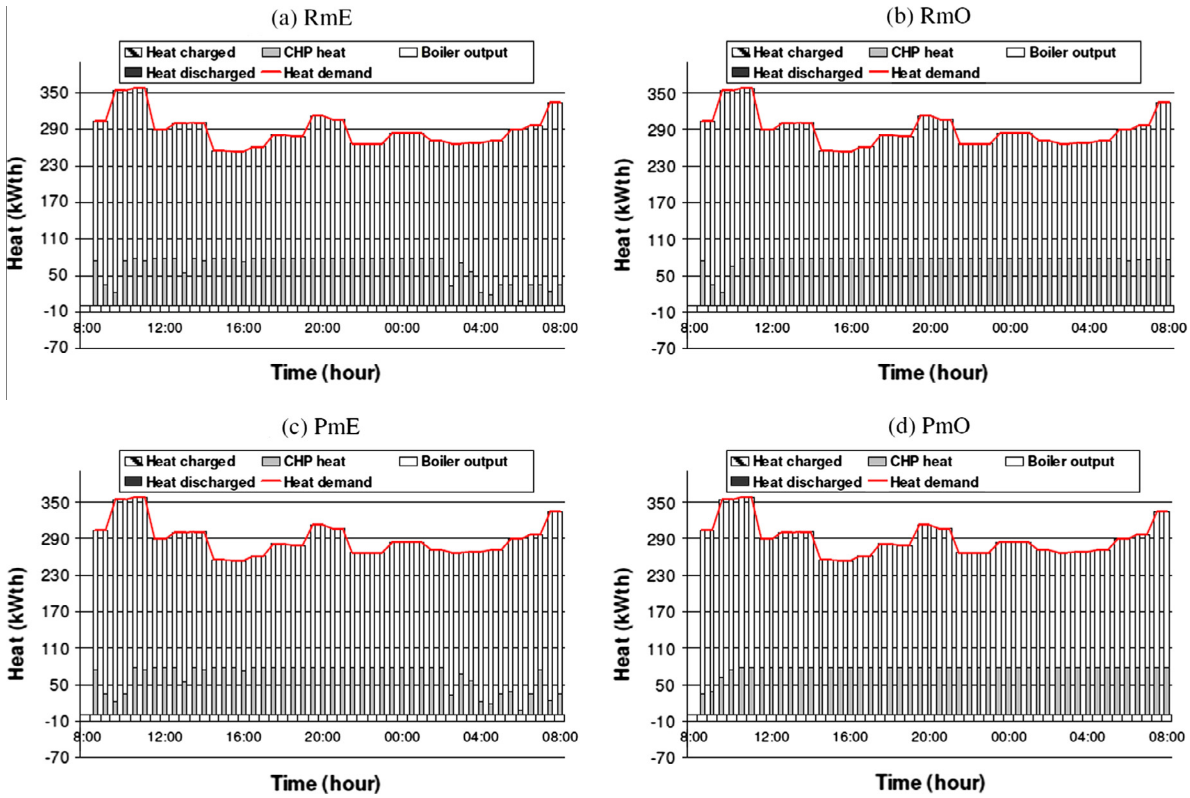

Fig. 10. 90 homes: heat balance for microgrid scenarios.

Table 4
Comparison between earliest starting time and optimised scheduling scenarios.

Example	Scenario	Cost savings (%)	Peak demand savings (%)
1	RM(E–O)	11	9
	Rm(E–O)	13	47
	PM(E–O)	16	45
	Pm(E–O)	23	86
2	RM(E–O)	12	5
	Rm(E–O)	13	18
	PM(E–O)	13	28
	Pm(E–O)	17	59

Table 5
Model statistics.

Example	Scenario	Continuous equations	Continuous variables	Discrete variables	CPU (s)
1	RmO	1178	17,814	17,280	0.2
	PmO	1226	17,862	17,280	0.3
2	RmO	1898	52,374	51,840	0.8
	PmO	1946	52,422	51,840	1.3

pricing schemes. Compared with the earliest starting time scenarios, the cost savings and total peak demand savings from the grid between earliest starting scenario by scheduling task starting time are presented in Table 4 under different scenarios. With the real-time price scheme, both examples have similar cost savings, while under the peak demand scheme, Example 1 demonstrates more cost savings. While Example 2 considers 90 homes with different living habits and with different earliest starting time for flexible tasks. So as expected, its average power peak is lower than that from the same living habits assumed in Example 1, since the tasks are scattered even without scheduling. As shown in Table 4, under all scenarios Example 1 has higher peak demand savings percentage from the grid. In both examples, when microgrid is utilised, the lowest cost saving is 13% while the lowest peak demand saving is 18%. Microgrid application is an important alternative solution for cost and peak demand reductions. There are peak demand savings even only real-time price scheme is applied as shown in Table 4. However, the peak demands are accidentally reduced there resulting from task starting time optimised scheduling based on electricity real-time price. When peak demand price scheme is applied, the total peak demands from grid are minimised from objective function, which are reduced by 86% and 59% in the peak demand price scheme microgrid scenarios for Examples 1 and 2, respectively.

The developed MILP model is implemented using CPLEX 12.4.0.1 in GAMS 23.9 (www.gams.com) on a PC with an Intel Core 2 Duo, 2.99 GHz CPU and 3.25 GB of RAM. The model statistics of the microgrid optimised scheduling scenarios under the two pricing schemes are presented in Table 5 for both examples, where numbers of continuous equations, continuous and discrete variables and CPU time taken are presented. With an optimality gap as 0.1%, even in Example 2, scheduling scenarios RmO and PmO require 0.8 CPU *s* and 1.3 CPU *s*, respectively, for the scheduling. It is evident that the proposed MILP model is able to offer significant cost savings and peak demand savings with very modest computational difficulties for smart buildings with the same living habit or different ones.

6. Concluding remarks

An MILP model has been proposed for energy consumption and operation management in a smart building with multiple smart homes. Two examples of 30 homes with same living habit and 90 with different living habits for a winter day have been studied. Twelve domestic electrical tasks and equipment operations are scheduled based on given time windows, real-time half-hourly grid electricity prices and peak demand extra charge to obtain the minimum cost and energy demand. Significant cost savings and peak demand savings have been achieved in both examples.

The power output from the wind generator varies according to the weather conditions. The proposed MILP scheduling model can use the power generated by wind generators when available, providing further savings for the customers. Under the optimised scheduling scenario, the CHP generator is used more efficiently and provides heat more steadily than under the earliest starting time scenario. When the peak demand price scheme is applied, the highest peak demand from the grid and total peak demand over the threshold can significantly be reduced.

This power demand reduction has the benefit of releasing the burden on the central grid and reducing the expense of upgrading the current grid infrastructure to fulfill increasing energy demand. The power demand reduction also depends on the family living habits: for instance, if they prefer doing the washing during night time when electricity price from the grid is cheaper, there will be more savings. Without changing living habits totally, if the tasks have wider time windows, the cost saving and peak demand shaving could be further improved. On the other hand, when the domestic task scheduling is implemented in real life, it could also affect people's behaviour and wider time windows may be preferred to obtain more cost savings.

In the area of smart grids, it is considered that there is two-way communication between power supplier and customers. The power will be distributed according to the demand and supply. Traditional methods provide the customers only common flat electricity pricing while the smart grid could provide real-time electricity pricing. This model considers the problem from the point of view of the customers, with a given real-time electricity price profile over time. In the future, it might be possible to include this model as part of a full smart grid model where the electricity price is optimised along with the scheduling of tasks.

Acknowledgements

The authors would like to thank Dr. Nouri J. Samsatli and Dr. Songsong Liu for useful discussions. Di Zhang gratefully acknowledges financial support from the Schlumberger Foundation and Centre for Process System Engineering.

References

[1] Clastres C. Smart grids: another step towards competition, energy security and climate change objectives. Energy Policy 2011;39:5399–408.
[2] Mitra J, Suryanarayanan S. System analytics for smart microgrids. In: IEEE PES general meeting. IEEE; 2010. p. 1–4.
[3] Ustun TS, Ozansoy C, Zayegh A. Recent developments in microgrids and example cases around the world—a review. Renew Sustain Energy Rev 2011;15:4030–41.
[4] Marnay C, Venkataramanan G, Stadler M, Siddiqui AS, Firestone R, Chandran B. Optimal technology selection and operation of commercial-building microgrids. IEEE Trans Power Syst 2008;23:975–82.
[5] Asano H, Bando S, Watanabe H. Methodology to design the capacity of a microgrid. In: 2007 IEEE international conference on system of systems engineering. IEEE; 2007. p. 1–6.
[6] King DE, Morgan MG. Customer-focused assessment of electric power microgrids. J. Energy Eng. 2007;133:150–64.
[7] Obara S. Equipment arrangement planning of a fuel cell energy network optimized for cost minimization. Renew Energy 2007;32:382–406.
[8] Bagherian A, Tafreshi SMM. A developed energy management system for a microgrid in the competitive electricity market. In: 2009 IEEE Bucharest PowerTech. IEEE, Bucharest; 2009. p. 1–6.
[9] Mohamed FA, Koivo HN. System modelling and online optimal management of microgrid using mesh adaptive direct search. Int J Electr Power Energy Syst 2010;32:398–407.
[10] Morais H, Kádár P, Faria P, Vale ZA, Khodr HM. Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. Renew Energy 2010;35:151–6.
[11] Silva M, Morais H, Vale Z. An integrated approach for distributed energy resource short-term scheduling in smart grids considering realistic power system simulation. Energy Convers Manage 2012;64:273–88.
[12] Hawkes AD, Leach MA. Modelling high level system design and unit commitment for a microgrid. Appl Energy 2009;86:1253–65.
[13] Lior N. Sustainable energy development: the present (2009) situation and possible paths to the future. Energy 2010;35:3976–94.
[14] Escrivá-Escrivá G. Basic actions to improve energy efficiency in commercial buildings in operation. Energy Build 2011;43:3106–11.
[15] Yohanis Y, Mondol J, Wright A, Norton B. Real-life energy use in the UK: how occupancy and dwelling characteristics affect domestic electricity use. Energy Build 2008;40:1053–9.
[16] Hu W, Chen Z, Bak-Jensen B. Optimal operation strategy of battery energy storage system to real-time electricity price in Denmark. In: IEEE PES general meeting. IEEE; 2010. p. 1–7.
[17] Pedrasa MAA, Spooner TD, MacGill IF. Coordinated scheduling of residential distributed energy resources to optimize smart home energy services. IEEE Trans Smart Grid 2010;1:134–43.
[18] Wissner M. The smart grid – a saucerful of secrets? Appl Energy 2011;88:2509–18.
[19] Lugo-Cordero HM, Fuentes-Rivera A, Guha RK, Ortiz-Rivera EI. Particle swarm optimization for load balancing in green smart homes. In: 2011 IEEE congress of evolutionary computation. IEEE; 2011. p. 715–20.
[20] Zoka Y, Sugimoto A, Yorina N, Kawahara K, Kubokawa J. An economic evaluation for an autonomous independent network of distributed energy resources. Electr Power Syst Res 2007;77:831–8.
[21] Logenthiran T, Srinivasan D, Khambadkone AM. Multi-agent system for energy resource scheduling of integrated microgrids in a distributed system. Electr Power Syst Res 2011;81:138–48.
[22] Dagdougui H, Minciardi R, Ouammi A, Robba M, Sacile R. Modeling and optimization of a hybrid system for the energy supply of a "Green" building. Energy Convers Manage 2012;64:351–63.
[23] Rojchaya S, Konghirun M. Development of energy management and warning system for resident: an energy saving solution. In: 2009 6th International conference on electrical engineering/electronics, computer, telecommunications and information technology. IEEE; 2009. p. 426–9.
[24] Naraharisetti PK, Karimi IA, Anand A, Lee D-Y. A linear diversity constraint – application to scheduling in microgrids. Energy 2011;36:4235–43.
[25] Chen C-Y, Tsoul Y-P, Liao S-C, Lin C-T. Implementing the design of smart home and achieving energy conservation. In: 2009 7th IEEE international conference on industrial informatics. IEEE; 2009. p. 273–6.
[26] Mohamed FA, Koivo HN. Online management genetic algorithms of microgrid for residential application. Energy Convers Manage 2012;64:562–8.
[27] Mouret S, Grossmann IE, Pestiaux P. Time representations and mathematical models for process scheduling problems. Comput Chem Eng 2011;35:1038–63.
[28] Shaik MA, Floudas CA, Kallrath J, Pitz H-J. Production scheduling of a large-scale industrial continuous plant: short-term and medium-term scheduling. Comput Chem Eng 2009;33:670–86.
[29] Maravelias CT, Sung C. Integration of production planning and scheduling: overview, challenges and opportunities. Comput Chem Eng 2009;33:1919–30.
[30] Sun H-C, Huang Y-C. Optimization of power scheduling for energy management in smart homes. Proc Eng 2012;38:1822–7.
[31] Sou KC, Weimer J, Sandberg H, Johansson KH. Scheduling smart home appliances using mixed integer linear programming. In: IEEE conference on decision and control and European control conference. IEEE; 2011. p. 5144–9.
[32] Nistor S, Wu J, Sooriyabandara M, Ekanayake J. Cost optimization of smart appliances. In: 2011 2nd IEEE PES international conference and exhibition on innovative smart grid technologies. IEEE; 2011. p. 1–5.
[33] Costanzo GT, Kheir J, Zhu G. Peak-load shaving in smart homes via online scheduling. In: 2011 IEEE international symposium on industrial electronics. IEEE; 2011. p. 1347–52.
[34] Castillo-Cagigal M, Gutiérrez A, Monasterio-Huelin F, Caamaño-Martín E, Masa D, Jiménez-Leube J. A semi-distributed electric demand-side management system with PV generation for self-consumption enhancement. Energy Convers Manage 2011;52:2659–66.
[35] Kriett PO, Salani M. Optimal control of a residential microgrid. Energy 2012;42:321–30.
[36] Chen Z, Wu L, Fu Y. Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization. IEEE Trans Smart Grid 2012:1–9.
[37] Rastegar M, Fotuhi-Firuzabad M, Aminifar F. Load commitment in a smart home. Appl Energy 2012;96:45–54.
[38] Derin O, Ferrante A. Scheduling energy consumption with local renewable micro-generation and dynamic electricity prices. In: Proceedings of the first workshop on green and smart embedded system technology: infrastructures, methods and tools, Stockholm, Sweden, Stockholm; 2010. p. 1–6.
[39] Villanueva D, Feijóo A. Wind power distributions: a review of their applications. Renew Sustain Energy Rev 2010;14:1490–5.
[40] Electricity Prices|OEB; 2012. <http://www.ontarioenergyboard.ca/OEB/Consumers/Electricity/Electricity+Prices#rpp> [cited 01.09.12].

[41] Balancing Mechnism Reporting System. The new electricity trading arrangements 2010; 2012. <http://www.bmreports.com/bsp/SystemPricesHistoric.htm> [cited 01.09.12].
[42] Energy A. CHP Sizer Version 2. AEA Technology plc. London, UK: The Carbon Trust; 2004.
[43] Domestic Electrical Energy Usage. Electropaedia 2010; 2012. <http://www.mpoweruk.com/electricity_demand.htm> [cited 01.09.12].
[44] Paatero JV, Lund PD. A model for generating household electricity load profiles. Int J Energy Res 2006;30:273–90.