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Economic and environmental scheduling of smart homes with microgrid: DER operation and electrical tasks

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ABSTRACT

Microgrids are promising in reducing energy consumption and carbon emissions, compared with the current centralised energy generation systems. Smart homes are becoming popular for their lower energy cost and provision of comfort. Flexible energy-consuming household tasks can be scheduled coordinately among multiple smart homes to reduce economic cost and CO_2. However, the electricity tariff is not always positively correlated with CO_2 intensity. In this work, a mixed integer linear programming (MILP) model is proposed to schedule the energy consumption within smart homes using a microgrid system. The daily power consumption tasks are scheduled by coupling environmental and economic sustainability in a multi-objective optimisation with ε-constraint method. The two conflicting objectives are to minimise the daily energy cost and CO_2 emissions. Distributed energy resources (DER) operation and electricity-consumption household tasks are scheduled based on electricity tariff, CO_2 intensity and electricity task time window. The proposed model is implemented on a smart building of 30 homes under three different price schemes. Electricity tariff and CO_2 intensity profiles of the UK are employed for the case study. The Pareto curves for cost and CO_2 emissions present the trade-off between the two conflicting objectives.

1. Introduction

Due to fossil fuels depletion and global warming, energy cost and pollution reduction are two worldwide popular issues [1]. The UK Climate Change Programming, for example, aims to cut down 80% of carbon emissions by 2050 based on Climate Change Act 2008 [2]. In particular, in UK the energy sector is responsible of the highest amount of greenhouse gases to the atmosphere (i.e. 30%) [3]. At present, electrical supply systems are mainly based on relatively few large plants using conventional fossil fuels and operating in central locations. The power is then distributed to the final user via distribution and transmission networks. Centralised systems show overall energy losses of 65% or more, including losses during electricity generation, transmission and distribution [4]. Microgrid systems are regarded as an alternative to the current centralised energy generation systems, because they can provide economic benefits through avoiding long-distance transmission. Moreover, environmental benefits can be obtained by utilising distributed energy resources (DER) in combination with microgrids, allowing generation of lower amount of pollutants [5]. Besides renewable energy resources, combined heat and power (CHP) generators are utilised in microgrids because of their high efficiency resulting from using the waste heat for thermal energy production. The implementation of micro CHP systems in the UK might reduce emissions of CO_2 by up to 2.1 tons per year per household, compared to condensing boilers and electricity drawn from the grid as reported by the Department of Energy and Climate Change (DECC) [6]. Meanwhile, security and reliability can be gained from interconnection and coordinated control.

Within smart grids, the interactive relationship among the grid operators, utilities and smart homes is the key element that allows smart grid technologies to function together. Energy management of buildings could play an important role in reducing both energy cost and air pollution, since 30–40% of the world's primary energy is consumed in buildings [7]. Within this context, smart homes are seen as a promising solution because of the rapid advances in computing and communication capabilities which can promote the concept further [8]. When smart homes are connected to smart grids, detailed pricing schemes enable customers to schedule their home appliance operations in order to save energy, reduce cost or help grid operations [1,9]. Moreover, energy consumption can be reduced by 10–30% by changing the customers' living behaviour through a demand-side management approach aimed at matching generation values with demand, by controlling the operation of

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Nomenclature

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

Parameters

b_t	electricity price at time t (£/kW h_e)
$C_{i\theta}$	power consumption capacity of task i at operation period θ (kW_e)
C^B	boiler capacity (kW_{th})
C^{CHP}	CHP generator capacity (kW_e)
C^E	electrical storage capacity (kW h_e)
C^{TH}	thermal storage capacity (kW h_{th})
D^E	electrical storage discharge limit (kW_e)
D^{TH}	thermal storage discharge limit (kW_{th})
G^E	electrical storage charge limit (kW_e)
G^{TH}	thermal storage charge limit (kW_{th})
H_t	heat demand at time t (kW_{th})
P_{ji}	processing time of home j task i
p	difference between peak and base electricity demand price from grid (£/kW h_e)
q	charge of the maximum of power demand from the grid (£/kW_e)
r	price of natural gas (£/kW h)
T^S_{ji}	earliest starting time of home j task i
T^F_{ji}	latest finishing time of home j task i
α	CHP heat-to-power ratio
δ	time interval duration (h)
μ^E	cost per unit input (maintenance) for electrical storage unit (£/kW h_e)
μ^{TH}	cost per unit input (maintenance) for thermal storage unit (£/kW h_{th})
η^B	boiler efficiency
η^{CHP}	CHP generator electrical efficiency
η^E	electrical storage charge/discharge efficiency
η^{TH}	thermal storage charge/discharge efficiency
ξ^B	CO_2 intensity of boiler thermal output (kg CO_2/kW h_{th})
ξ^{CHP}	CO_2 intensity of CHP electrical output (kg CO_2/kW h_e)
ξ^G_t	CO_2 intensity of grid electricity at time t (kg CO_2/kW h_e)
κ	agreed electricity peak demand threshold from grid (kWe)

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)
I^{max}	maximum power demand from the grid (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^{ITH}	initial state of thermal storage (kW h_{th})
S^E_t	electricity in storage at time t (kW h_e)
S^{TH}_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)
γ_t	extra electricity load from grid over the agreed threshold κ at time t (kW_e)
ϕ_1	daily electricity cost of a home (£)
ϕ_2	daily CO_2 emissions (kg CO_2)

Binary variables

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

appliances from the customer side [10]. Various dynamic pricing schemes for residential customers, such as real time pricing (RTP), time-of-use (TOU), critical peak pricing (CPP) and critical peak rebate (CPR), are being designed to reduce the electricity demand at peak periods through the consumers' response by changing their behaviour [11]. DECC reviewed 30 trials of demand side response (DSR) in the domestic sector under TOU, CPP and CPR in seven countries, including the USA, the UK, Canada, Australia, Ireland, France and Norway, it concluded that the consumers do shift electricity demand in response to economic incentives.

Energy management in smart homes has been investigated in quite a few recent journal publications. Equipment operations are scheduled based on a given energy profile to obtain minimum operation costs in [12–15]. Logenthiran et al. present a multi-agent system for energy resource scheduling of power system with DERs, and there are three stages for the algorithm behind the system [12]. It targets scheduling each microgrid individually to satisfy its total demand. A dynamic model is proposed for the energy management of a household through a Model Predictive Control (MPC) by Dagdougui et al. [13], which integrates different renewable energy sources and a storage device to fulfil the energy demands of a building. A mixed integer linear programming (MILP) model is developed in [14] for scheduling in microgrids connected to the national grid by incorporating various realistic features. The profit is maximised by maintaining diversity in the production of electricity and scheduling the electricity production, storage and purchase from and sale of electricity to the national grid. Mohamed and Koivo [15] propose a Genetic Algorithm (GA) approach to determine the optimal operating strategy and cost minimisation scheme for a microgrid for residential application.

Energy management involving energy tasks scheduling has also been studied besides the energy resources scheduling mentioned above. In [16], daily deferrable and non-deferrable tasks are scheduled for a typical house with a PV generation and a battery storage within the operation of an electrical demand-side management to improve the energy behaviour with regard to a standard user behaviour. Tascikaraoglu et al. [9] proposed a demand side management strategy based on forecasting residential renewable sources. In-home energy management, appliances control and power flow are investigated. In the work of Kriett and Salani [17], the operating cost of both electrical and thermal supply and demand is minimised in a residential microgrid with a generic MILP model. An MPC scheme is proposed to iteratively produce a control sequence. Caprino et al. [18] presented an approach to schedule the household appliances to limit the peak load of power usage. The appliance loads are classified into time-triggered and event-triggered loads and the physical model of these loads are considered in the model, such as a refrigerator and a washing machine. A demand response management application with RTP is proposed to determine the optimal operation of the residential appliances of a single house in the next 5-min time interval while considering future electricity price uncertainties [19]. The operations of the appliances are classified into flexible/non-flexible and interruptible/non-interruptible tasks. It compares the stochastic optimisation and robust optimisation approaches for the scheduling of the tasks. Baraka et al. [20] design and implement a remotely controlled and energy efficient smart home and they present a heuristic scheduling algorithm for the resource-constraint-scheduling problem using Android tablet as user interface. The tasks to be scheduled are assigned with priority numbers and they are scheduled based on the overall cost limit and power usage limit in any time slot. Rastegar et al. [21] present an optimal and automatic residential load commitment framework, which minimises household payment by determining on/off status of flexible appliances and operation of battery storage and plug-in hybrid electric vehicles. The TOU electricity tariff at three levels is considered in this work. Another appliance scheduling work for a single house is proposed by Adika and Wang [22], where the electrical appliances are clustered based on their time of use probabilities. The aggregate loads of the appliances with similar schedules are tracked for different time periods which have certain power limits. Derin and Ferrante [23] develop a model that considers domestic energy consumption tasks scheduling, where the operation time of electric vehicle batteries, a dishwasher and a washing machine is scheduled. For only those three tasks in a time span of 7 h, the exhaustive search takes 35 min which is relative slow. The computation time has been reduced to be within seconds in our previous work [24,25], in which we consider a group of smart homes with a common microgrid and 12 domestic tasks of each home are available to be scheduled. DER operation and electricity-consumption household appliances are scheduled based on RTP and domestic electrical task time window. Total operation cost of the smart homes is minimised in [24], while fair cost distribution among smart homes is proposed in [25].

However, only economic aspects are considered in all of the works mentioned above. Within the environmental context, demand side management of a domestic dishwasher is investigated by Finn et al. [26] according to renewable energy generation and pricing signals. Three optimisation objectives are examined: cost minimisation, demand on wind generation maximisation and associated carbon emissions minimisation. However, these are optimised separately. In [27], good cycles and battery electric vehicles are scheduled and the impact of introducing flexibility on the demand side is investigated. A household behaviour simulation model is developed to investigate the joint influence of price and CO_2 signals in a demand response programme using a weighted sum approach [28]. Plant operation, system reliability, emissions and costs are addressed individually. Environmental and economic reasons are both considered in the work of Cheong et al. [29], where optimal household appliances scheduling is proposed for one home.

The literature review reported above demonstrates that whereas a wealth of academic studies have been undertaken on smart homes and microgrid systems, the majority deal with one problem at a time, which is either the optimisation of the CO_2 emissions or the optimisation of the costs. Flexible energy-consuming household tasks and DERs operation can be scheduled co-ordinately among multiple homes which share a common microgrid, in order to achieve the desired reduction of both economic costs and CO_2 impact. However, the electricity tariff is not always positively correlated with CO_2 intensity and they may conflict with each other. In this work, an MILP model is proposed to schedule DER operations and the energy consumption of smart homes within a common microgrid. It extends the work presented in [24], where smart homes electric tasks scheduling is provided by only minimising the total energy cost while CO_2 emissions are not considered. The daily power consumption tasks are scheduled in this work by coupling environmental and economic sustainability in a multi-objective optimisation with the ε-constraint method. The two conflict objectives are to minimise the daily energy cost and CO_2 emissions. DER operation and electricity-consumption household tasks are scheduled based on electricity pricing, CO_2 intensity and the electricity task time window. Moreover, the effects on the optimal solution of different price schemes for purchasing the electricity from the grid are evaluated. The proposed model is implemented on a smart building of 30 homes under three different price schemes. Electricity tariff and CO_2 intensity profiles of the UK are employed for the case study. The Pareto curves for cost and CO_2 emissions present the trade-off between the two conflicting objectives for the three price schemes. The results indicate the possibility of cost savings and emissions' reduction through the daily power consumption tasks scheduling and better management of DER operations.

The remainder of this paper is organised as follows: in Section 2, the problem is described briefly with relevant assumptions, constraints and objective functions. In Section 3, the mathematical programming model is provided. In Section 4, the proposed model is applied to a case study with electricity tariff and CO_2 emission intensity profiles of the UK. The computational results are presented and discussed in Section 5. Finally, concluding remarks are given in Section 6.

2. Problem description

In this paper, multiple smart homes in a smart building are considered, where a microgrid system is available as local energy provider as shown in Fig. 1. All the DERs of the microgrid are shared among all smart homes; they include a CHP generator, a boiler, a thermal and/or an electrical storage. The microgrid is connected to the conventional grid so that the full electricity demand can be fulfilled by the conventional grid when the electricity produced by the DERs is insufficient. The electricity generated by the microgrid cannot be sold back to the grid. Each smart home follows its own energy demand curve, depending on the household types, available electrical appliances and living habits. The total electricity demand of the smart building depends on the daily flexible and inflexible domestic appliance tasks in the 30 smart homes. Typical flexible tasks include dishwasher, washing machine and spin dryer while fridge and light are considered as inflexible tasks. The total electricity demand of the smart building depends on the operation time of the domestic appliances, flexible and inflexible tasks. The total heat demand of the whole building is assumed to be provided. Similar to [24,25], the equipment capacities are all assumed; no capital costs are included, only operation and maintenance costs are considered. It is assumed that electricity RTP and CO_2 intensity are forecasted one day in advance; peak demand charge for the electricity used from the grid is also given. A multi-objective MILP approach is developed in this study to minimise the total economic cost and CO_2 emissions. The trade-off between the economic and environmental objectives is then analysed with a set of Pareto-optimal solutions. Moreover, three price schemes are investigated, i.e. RTP, CPP with peak demand charge price scheme, and CPP with demand charge price scheme:

1. RTP, real-time price is applied.
2. CPP with peak demand charge price scheme is adapted from Ontario Energy, Canada [30], in which an agreed power demand threshold (kW) is defined. If the power demand at any time period is over the threshold, an extra tariff is charged over the amount of electricity (kW h), besides the real-time price.
3. CPP with demand charge price scheme is adopted from Nation Grid, US [31], where the bill includes both charges for consumption and demand. The consumption charge is charged based on the total energy consumption in kW h while the demand charge is charged to the highest average power demand in kW measured in a given time interval during the billing period.

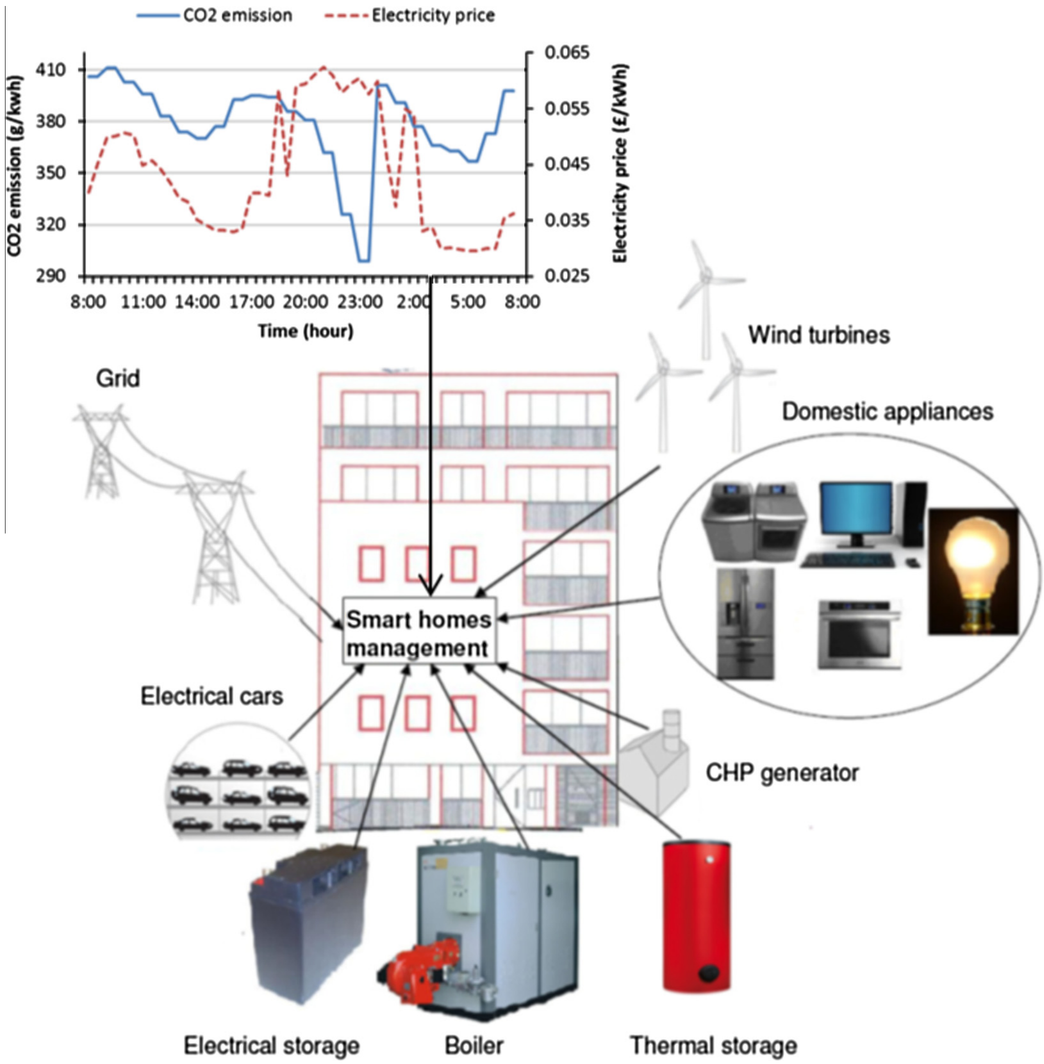

Fig. 1. Example of a smart building.

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 for the over-threshold amount, (i) peak demand threshold from grid, (j) demand charge based on the maximum power demand from the grid, (k) CO_2 emission intensity, (l) earliest starting and latest finishing times, (m) task capacity profiles, and (m) task duration.
Determine (a) energy production plan, (b) task starting time, (c) thermal/electrical storage plan, and (d) electricity bought from grid.
So as to (a) find the optimum energy consumption scheduling and DER operation with minimum economic cost and environmental impact and to (b) fulfil the energy demand (both heat and electricity) of the smart homes using a microgrid.

3. Mathematical formulation

The energy consumption management problem is formed as an MILP model which addresses the economic and environmental sustainability in a multi-objective optimisation model. The daily power consumption tasks are scheduled based on their given operation time window (between earliest starting time and latest ending time) and daily electricity price and CO_2 emissions intensity profiles. The objective is to minimise the daily power cost and CO_2 emissions and shave the power consumption peak. The economic cost and CO_2 emissions are minimised subject to relevant constraints, including equipment capacity constraints, energy demand constraints and electrical/thermal storage constraints.

The constraints imposed on the optimisation are:

3.1. Capacity constraints

The output from each equipment should be limited within its designed capacity.

CHP generator:

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

Boiler:

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

Electrical storage:

$$S_t^E \leqslant C^{E} \qquad \forall t \tag{3}$$

Thermal storage:

$$S_t^{TH} \leqslant C^{TH} \qquad \forall t \tag{4}$$

3.2. Energy storage constraints

Electricity stored at time t is equal to the amount stored at $t-1$ plus the electricity charged minus the electricity discharged. Electricity loss during the charging and discharging process is counted by η^E (turn around efficiency of electrical storage); for example, if during any period δ, only $\eta^E \delta z_t$ will be charged while the rest is lost. On the other hand, during the discharging process, in order to supply δy_t to the customer, $\delta y_t/\eta^E$ of electricity is required.

$$S_t^E = S_{t-1}^E + \eta^E \delta z_t - \delta y_t/\eta^E \qquad \forall t \tag{5}$$

It is assumed that no daily electricity accumulation is allowed. At the end of each day (the last time interval T), the electrical storage must return to its initial storage state.

$$S_0^E = S_T^E = S^{IE} \tag{6}$$

The rates of discharge or charge of the electricity are assumed to be within the electrical storage discharge and charge limits, according to its own designed capacity:

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

$$z_t \leqslant G^E \qquad \forall t \tag{8}$$

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. Stored heat must return to the initial state at the end of each day, no heat is accumulated over one day.

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

$$S_0^{TH} = S_T^{TH} = S^{ITH} \tag{10}$$

The rates of discharge and charge of heat cannot exceed the thermal storage discharge and charge limits based on the designed capacity:

$$f_t \leqslant D^{TH} \qquad \forall t \tag{11}$$

$$g_t \leqslant G^{TH} \qquad \forall t \tag{12}$$

3.3. Energy balances

The electricity demand is fulfilled by the electricity generated by the CHP generator, the electricity received from the electrical storage and the grid minus the electricity sent to the electrical storage.

$$\sum_j \sum_i \sum_{\theta=0}^{P_{ji}-1} C_{i\theta} E_{ji,t-\theta} = u_t + y_t - z_t + I_t \qquad \forall t \tag{13}$$

The heat demand is fulfilled by the heat generated from the CHP generator, the boiler, the heat received from the thermal storage minus heat sent to the thermal storage.

$$H_t = \alpha u_t + x_t + f_t - g_t \qquad \forall t \tag{14}$$

3.4. Starting time and finishing time

The operation of each task must start after the given earliest starting time and finish before the latest ending time. The binary variable E_{jit} indicates "task i from home j that is done at time t". Hence, each task from each home, done between the earliest starting time and the latest finishing time minus the task processing time, has to be started within this predetermined time window.

$$\sum_t E_{jit} = 1 \qquad \forall j, i, \qquad T_{ji}^S \leqslant t \leqslant T_{ji}^F - P_{ji} \tag{15}$$

3.5. Peak demand charge

In order to avoid the need for high capacity in the macrogrid–microgrid connection, the electricity peak demand from the grid is reduced. This avoids charges to be levied by the system operator for using electricity from the macrogrid during peak times. This implemented into the model via extra constraints, see Eq. (16). For each time interval, if the electricity load from the grid, I_t, is below the agreed threshold κ, normal electricity prices apply. But if I_t exceeds κ, the amount over the threshold γ_t is counted and is charged at an extra rate in Eq. (18b). Since the objective function Eq. (18b) is to be minimised, the γ_t value needs to be minimised too, which means it should be equal to $I_t - \kappa$ if $I_t - \kappa$ is positive or equal to 0 if $I_t - \kappa$ is negative.

$$\gamma_t \geqslant I_t - \kappa \qquad \forall t \tag{16}$$

3.6. Demand charge

The maximum of power demand from the grid per day is defined as follows:

$$I^{\max} \geqslant I_t \qquad \forall t \tag{17}$$

3.7. Objectives

The first objective is to minimise the total daily electricity cost. Under the RTP price scheme this includes: the operation and maintenance cost of the CHP generator, the electrical storage and the thermal storage; and the cost of electricity purchased from the grid. As mentioned earlier, capital costs are not considered.

$$\phi_1 = \sum_t \left[\delta\left(r u_t/\eta^{CHP} + b_t I_t + r x_t/\eta^B + \mu^E y_t + \mu^{TH} f_t\right)\right] \tag{18a}$$

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 while extra cost is applied when the demand is over the agreed threshold.

$$\phi_1 = \sum_t \left[\delta\left(r u_t/\eta^{CHP} + b_t I_t + r x_t/\eta^B + \mu^E y_t + \mu^{TH} f_t + p\gamma_t\right)\right] \tag{18b}$$

When the demand charge is applied for the total daily cost, the penalty based on the maximum power demand from the grid is included in the objective function.

$$\phi_1 = \sum_t \left[\delta\left(r u_t/\eta^{CHP} + b_t I_t + r x_t/\eta^B + \mu^E y_t + \mu^{TH} f_t\right)\right] + q I^{\max} \tag{18c}$$

The other objective is to minimise the total CO_2 emissions, which includes: the CO_2 emissions from the use of CHP generator and boiler, and from the conventional electricity grid.

$$\phi_2 = \sum_t \left[\delta\left(\xi^{CHP} u_t + \xi_t^G I_t + \xi^B x_t\right)\right] \tag{19}$$

The above two objective functions are considered in a multi-objective formulation as:

$$\operatorname*{Min}_{x \in Q} \{\phi_1(x),\ \phi_2(x)\} \tag{20}$$

where x is the vector of decision variables and Q is the space of feasible solutions defined by the following constraints.

3.8. The ε-constraint method with two objectives

The ε-constraint method pre-defines a virtual grid in the objective space and solves different single-objective problems constrained to each grid cell. All Pareto-optimal solutions can be found only if this grid is fine enough such that at most one Pareto-optimal solution is constrained in each cell. Applying the ε-constraint to the proposed multi-objective problem $\mathrm{Min}_{x \in Q}\{\phi_1(x),\ \phi_2(x)\}$ it keeps ϕ_1 as the objective function, while ϕ_2 is considered as a constraint. A single-objective function is obtained as:

$$\min_{x \in Q} \phi_1(x) \tag{21}$$

$$\text{s.t. } \phi_2(x) \leqslant \varepsilon_2$$

By minimising ϕ_1 and ϕ_2 individually, the maximum and minimum values of ϕ_2 are obtained, which are used to define values of ε_2. For each point $M + 1$: $\varepsilon_2 = \phi_2^{\max} - \frac{\phi_2^{\max} - \phi_2^{\min}}{M}\lambda$, where M is the number of self-defined intervals between the maximum and minimum values of ϕ_2 and $\lambda = 0, \ldots, M$.

4. Case study

The case study analysed in this paper considers a smart building of 30 homes having the same living habits. The distributed energy resources and their capacities are assumed to be provided, while the technical parameters and the costs are taken from [32] and summarised in Table 1, the operation costs of the CHP and boiler are based on natural gas:

- one CHP generator with heat to power ratio of 1.2;
- one boiler;
- one electrical storage unit, the charge and discharge efficiencies are assumed to be the same at 95%, and the discharge limit and charge limit are both 10 kW_e;
- one thermal storage unit, the charge and discharge efficiencies are assumed to be the same at 98%, and the discharge limit and charge limit are both 20 kW_{th};
- a grid connection (allowing import of electricity when operating parallel to the conventional grid).
- Under the peak demand charge price scheme, when the power supplied from the conventional grid is over the agreed threshold, extra 5p/kW h_e is charged to the electricity consumed extra (kW h).
- Under the demand charge price scheme, the demand charge is calculated based on the maximum power demand from the grid on the day at the rate of 19p/kWh_e.

48 time intervals of half hour each are assumed. The total heat demand profile is provided assuming a building with floor area of 2500 m^2 on a sample summer day using CHP Sizer Version 2 Software [33]. The 12 basic electrical tasks of each home are presented in Table 2. These tasks are available to be scheduled according to their given time window, between the earliest starting time and latest finishing time: their respective processing times and power requirements are based on [34]. All tasks except the dishwasher and the washing machine have constant power consumption rates as shown in Table 2. The electrical profiles for the dish washer and the washing machine are given as in Fig. 2. Finally, it is assumed that all the homes have the same living habits and every task has to be done once in a day.

The electricity tariff and the CO_2 intensity profiles in the UK on August 17th, 2013 are assumed for the case study and the CO_2 intensity is based on gCO_2/kW h electricity. As shown in Fig. 3, the profiles of the electricity tariff and the CO_2 intensity have different peak hours in the UK and the differences between the maximum and minimum values are 53% and 27% respectively. The two profiles have different peaks and it may result from electricity generation of different energy sources over the day or even the importation of the electricity from the international market. This highlights a conflict in selecting the electricity consumption

Table 1
Technical parameters and costs of the DERs in the case study [32].

	Capacity	Efficiency (%)	Operation/maintenance cost
CHP	20 kW_e	40	2.7p/kW h
Boiler	120 kW_{th}	85	2.7p/kW h
Electrical storage	10 kW_e h	95	0.5p/kW h_e
Thermal storage	20 kW_{th} h	98	0.1p/kW h_{th}

Table 2
Electricity consumption task [34].

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

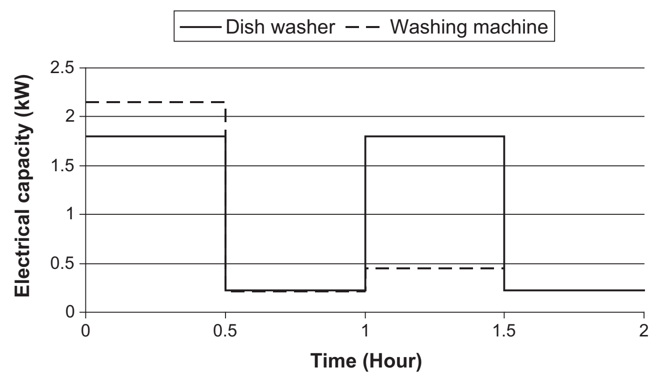

Fig. 2. Electrical capacity profiles of dish washer and washing machine.

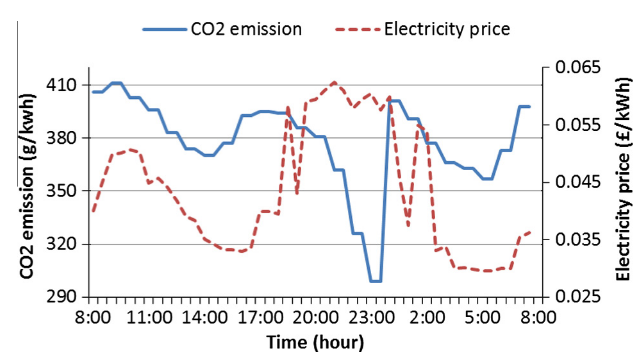

Fig. 3. Electricity tariff and CO_2 intensity of the UK (August 17th, 2013) [36,37].

hours based on environmental and cost view points. The two profiles depend heavily on the electricity generation resources of the specific time period. In the UK, the electricity is mainly produced from natural gas (44%), hard coal (28%) and nuclear energy (18%) [35].

The CO_2 emission rates from the CHP and the boiler operation are given in Table 3, and they are assumed to be constant over the time period. The carbon footprint of the use phase for the system is assessed considering a functional unit of 1 kW h of electrical output and 1 kW h of thermal output, for the CHP and the boiler respectively. A boiler efficiency of 85% is assumed in this study. For the CHP, it is assumed as a fuel cell unit with 10 kW capacity and 40% electrical efficiency. The "natural gas supply" impact is referred to the extraction and distribution of the natural gas up to the system and it is country specific, while the "direct emissions" impact is referred to the specific use of the system. The carbon footprint is calculated by GaBi 6.0 sustainability software [35]. One point to address here is that the carbon footprint for the CHP listed in the table is the total emissions of heat and electricity produced by the CHP based on electricity output. CHP produces heat and power simultaneously with heat to power ratio equal to 1.2. This results in 0.1714 gCO_2/kW h of electricity produced from the CHP. This value is much lower than the values presented in Fig. 3.

5. Computational results

Three different price schemes are applied for the case study: RTP, peak demand charge and demand charge, as described in the problem description (see Section 2). Under each price scheme, the objective is to minimise the total energy cost given in Eq. (21) with their corresponding constraints. Under RTP price scheme, the constraints are Eqs. (1–15), (18a) and (19). Under peak demand charge price scheme, the objective is subject to constraints Eqs. (1–16) and (18b). While under the demand charge price scheme, the constraints include Eqs. (1–15), (17), (18c) and (19).

5.1. Computational environment

The ε-constraint method is applied for the energy consumption management problem with the electricity tariff and the CO_2 intensity profiles for the case study. Both DER operation and electrical tasks operating time are scheduled for one day, from 8 am to 8 am on the next day.

The developed MILP model is implemented using CPLEX 12.4.0.1 in GAMS 23.9 (www.gams.com) [38] on a PC with an Intel(R) Core(TM) i7-4770 CPU, 3.40 GHz CUP and 16.0 GB of RAM. Under RTP price scheme, there are 1132 equations, 17,815 continuous variables and 17,280 discrete variables and for each run it takes about 0.34 s CUP time. When the peak demand price scheme is applied, there are 1,180 equations, 17,863 continuous variables and 17,280 discrete variables and for each run it takes about 0.48 s CUP time. While with the demand charge price scheme, there are 1,179 equations, 17,814 continuous variables and 17,280 discrete variables and for each run it takes about 0.39 s CUP time.

Table 3
Carbon footprint for the CHP and the boiler.

	Natural gas supply	Direct emissions	Total
CHP (kg CO_{2eq}/kW h electrical output)	0.0396	0.5049	0.5445
Boiler (kg CO_{2eq}/kW h thermal output)	0.0186	0.2923	0.3109

5.2. Pareto curves

The three price schemes are applied for the case study and Fig. 4 presents the Pareto curves for cost and CO_2 emissions from a sample summer day. Three points from each curve in Fig. 4 are selected respectively as marked with letters,

1. Point As, where the costs are the minimum;
2. Point Cs, where the kg CO_{2eq} are the minimum;
3. Point Bs, which represents a point with trade-off between the two conflicting objectives, they are the 15th point on the curves;
4. Numbers 1–5 represent curves RTP, κ = 60 kW, 30 kW, 15 kW and Demand charge respectively.

For the peak demand charge price scheme, the scheduling with each threshold value is analysed individually. All the curves follow the same trend, CO_2 emissions decrease while cost increases. Under RTP price scheme, the difference between the maximum and minimum values for cost and CO_2 emissions is 13% and 7% respectively. As shown, the curve represented is made of 21 points (from A1 to C1), the curve shows a steep decrease in CO_2 emissions over the first 15 points (up to B1) with values for the CO_2 dropping from 551 to 526 kg, while the cost difference is less than £0.3. After point B1, the CO_2 emissions drop at a slower rate up to 515 kg (C1). All five curves shown in Fig. 4 reach the same final value for the CO_2 emission (see C1–C5). This is because the results are obtained by minimising the single objective CO_2 emissions. However, when the single objective cost is minimised, the cost values are different (see A1–A5). The three curves under the peak demand price scheme (κ = 60 kW, 30 kW and 15 kW) are very similar and the cost increases when the threshold value decreases, as expected. When the thresholds are applied, the largest CO_2 emissions obtained are about 530 kg for all curves, this is much lower than that from the RTP price scheme. This is because, under the peak demand charge price scheme, the peak demand over the threshold is limited by the three sample threshold values (κ = 60 kW, 30 kW and 15 kW) individually, the model spreads the electricity demand over the day to limit the demand from the grid, rather than using the time periods when electricity is cheap but the CO_2 emissions are high. When demand charge is applied, the resulting curve is similar to the curve obtained for 15 kW except the first few points. Detail energy balances of the three sample points are given in the next sub-section.

5.3. Energy balances

Fig. 5 shows the electricity balances for the UK for points C1–C5 as labeled in Fig. 4. Since the electricity balances are very similar

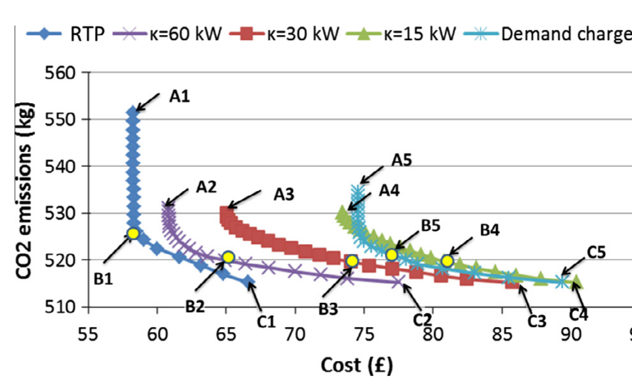

Fig. 4. Pareto curves for cost and carbon footprint for the UK, August 17th, 2013.

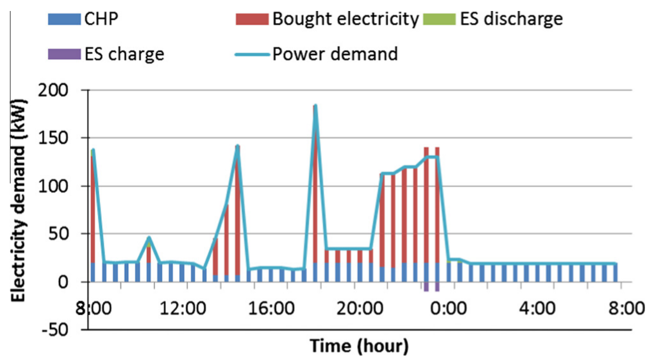

Fig. 5. Electricity balance for point Cs.

for all points C1–C5 under all price schemes, only one figure is presented for a generic Cs. The total kg CO_{2eq} is the single objective, hence the electricity demand is scheduled based on minimising the carbon footprint of the electricity consumption of the smart homes. In this case, the CHP operates at full capacity most of the time because of its low CO_2 intensity and the remaining demand is satisfied by the electricity from the grid. Except for two peaks which appear in the early morning and in the evening where the tasks are inflexible, the electricity from the grid is bought during the time periods when the grid CO_2 intensity is low (see Fig. 3), i.e. 14:00–15:30 and 21:30–0:00. The electrical storage is only charged for two time periods during the day.

Fig. 6 shows the electricity balances for points A1 and B1 presented in Fig. 4. RTP is applied for these two points. For point A1, the electricity demand is scheduled based on the electricity price profile only to minimise the total cost. As expected, the electricity demand peak hours appear in the early morning 4:00–7:00am when the electricity tariff is low as shown in Fig. 3. These peak hours move half hour early in point B1, which represents a trade-off between the two objectives. Compared with point A1, the CHP is providing constant electricity at full capacity not only during the day but also during the night time 0:00–3:30 am. For these two points, the electrical storage works more frequently than Cs, but it still does not play an important role here.

Fig. 7 presents the electricity balances for the indicated points in Fig. 3 under peak demand charge price scheme, for the three different thresholds considered. For points A2–A4, the total electricity demands are scattered over the day, resulting in flatter profiles compared to point A1, except for the time periods with inflexible tasks (lights and fridges). As threshold values are applied, the CHP generates electricity at full capacity during most of the time of the day to avoid the peak demand penalty. While for points B2–B4, the peak demand hours move to the period 20:00–0:00 compared to point B1, which is a period that shows a trade-off between the two objectives, based on both the profiles of electricity price and CO_2 intensity (see Fig. 3). The electricity demands for these points are similar except some small differences during the period 8:00–16:00. Moreover, the maximum power demands from the grid are reduced together with the total electricity demands from the grid. These are shown in Table 4 along with all other results for all sample points.

Electricity balances for points A5 and B5 are presented in Fig. 8 under the demand charge scheme. As shown in the figure, for point A5, the maximum demand power from the grid is 79.7 kW which is relative low compared with the other points shown in Figs. 6 and 7. The electricity form the grid is mainly bought during the time periods with low electricity prices. When emissions are considered in the optimisation model (point B5), the electricity demand profile is reshaped to move the electricity buying periods to the time with a trade-off between the two profiles of electricity prices and CO_2 intensity. Again the maximum power demand from the grid is 79.7 kW. For all the sample points, the electrical storage is charged when electricity from the grid/CHP is low and discharged when the electricity from the grid is high. However, this is not used frequently, only 2–4 time periods in the sample day. This is because heat demand is relatively low in summer, hence the electricity output from CHP is limited by this constraint, as a small amount of electricity would be stored in the electrical storage. The usage of the electricity stored also depends on the electricity price from the grid. The electrical storage is not utilised if the price differences between the time intervals cannot cover the maintenance cost and the cost of the charge/discharge energy loss.

Fig. 9 presents the heat balance for points A1 and B1 under RTP price scheme (when current electricity prices are considered) and points A2 and B2 with 60 kW threshold under peak demand charge price scheme. When the RTP price scheme is applied to a typical UK summer day, the CHP generator does not operate constantly when only cost is minimised. This is mainly because of the low heat demand during summer period, where the electricity produced from the CHP cannot provide more electricity unless the corresponding heat generated can be consumed or stored in the thermal storage. The thermal storage works here to balance the CHP generation over the day but still it cannot store heat more than its designed capacity. Thermal storage is used to balance the heat output from the CHP. During the time interval when there is high electricity demand with low heat demand, the thermal storage is charged and heat is released when the heat demand is high. In this case, the thermal storage stores the heat during the day and discharges it during the night, when the heat demand is high under both price schemes. The thermal storage works for 8 time intervals in the sample day for storing heat. But when CO_2 emissions are considered, CHP operates at full capacity as much as possible to reduce the CO_2 emissions. When peak demand charge price scheme and demand charge price scheme are applied, the heat balances are for point As and Bs are similar since the heat demand is

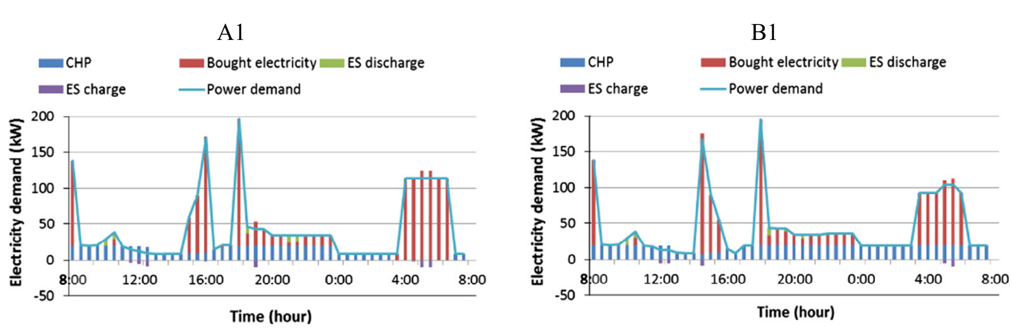

Fig. 6. Electricity balances for points A1 and B1 under RTP price scheme.

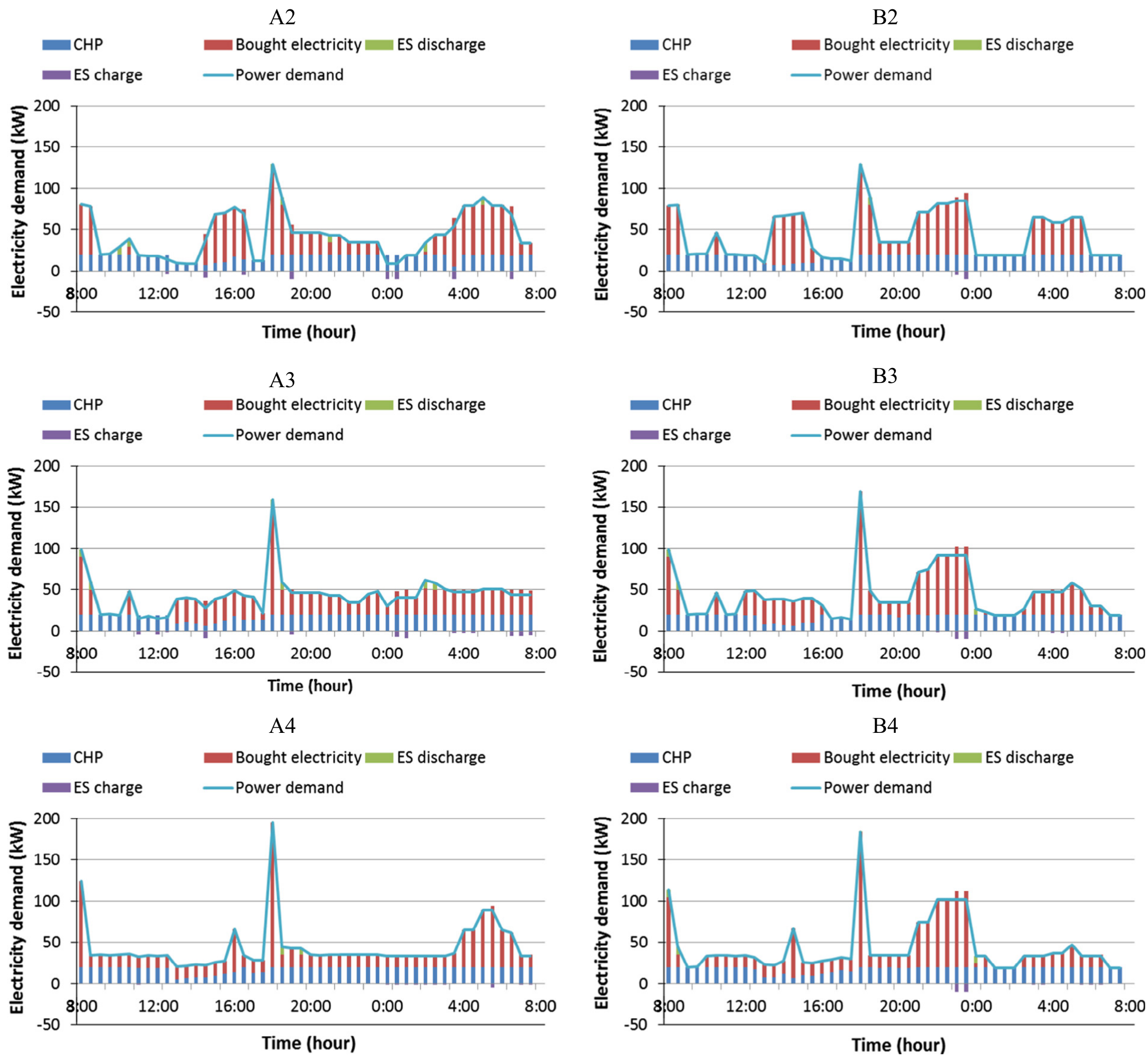

Fig. 7. Electricity balances for points A2–A4 and B2–B4 under peak demand charge price scheme.

given rather than the electricity demand. Only heat balances for points A2 and B2 are presented here.

5.4. Total demands and peak demands over the different price schemes

Table 4 provides the maximum power demands from the grid and the total electricity demands from the grid over the agreed demand thresholds for the selected points in the case study, with data profiles of the UK. As indicted from the results in the table, the peak demand price scheme (under thresholds 60 kW, 30 kW and 15 kW) targets at minimising total demand over the given electricity threshold (kW h). On the other hand, the demand charge price scheme targets at minimising the maximum power demand from the grid (kW). Compared with the results from the RTP price scheme, when the peak demand charge price scheme is applied, the maximum power demand from the grid and the total electricity demand from the grid over the agreed demand threshold can be both reduced for most of the points. High threshold (i.e. 60 kW) is good for all parameters except for cost. The maximum power demand from the grid is reduced as well as the total demand from the grid (including threshold) and so are the emissions. In this case, the stress caused by the smart homes to the grid is then reduced. When different threshold values are applied, the total costs are affected because of the penalty, while the CO_2 emissions are not affected much. Under the peak demand price scheme, the total electricity amount over the threshold increases when the CO_2 emission constraint becomes tighter (points B and C). In this case study, the total electricity demand of all domestic tasks is 1,056 kW h, which means the average electricity power demand is 44 kW over the sample day. If the CHP operates at full capacity all the time, the remaining 24 kW electricity needs to be provided by the grid (averagely during the day). Then if the threshold is below 24 kW, the demand from the grid will be charged by the penalty for sure. But there are some inflexible tasks which cannot be avoided, so penalty is even charged when the threshold is assigned as 60 kW.

When the demand charge price scheme is applied, i.e. the maximum power demand from the grid is minimised rather than the total demand from the grid over the threshold, the maximum power demand is reduced directly to 79.7 kW for point A5, which is even 20% lower than the maximum power obtained in point A2. By applying this price scheme, the maximum CO_2 emissions are similar to those obtained by applying peak demand price scheme with thresholds, which is 534.5 kg. Table 5 provides the total

Table 4
Peak demand from grid and total electricity demand for the three price schemes.

Price scheme	Point	Maximum power demand from the grid (kW)	Total demand from grid over the threshold (kW h)	Total demand from the grid (kW h)	CO_2 emissions (kg)	Total cost (£)
RTP	A1	176.2	–	744.4	551.3	58.3
	B1	174	–	624.4	526	58.5
	C1	164.2		635.7	515.2	66.6
60 kW	A2	99.4	19.7	623.5	531	60.8
	B2	99.4	32.9	623.8	520	64.9
	C2	137.5	206.8	625.6	515.2	77.5
30 kW	A3	129.4	70.5	623.8	530	65.1
	B3	149.2	202.1	623.8	519.6	74
	C3	149.2	377.2	623.5	515.2	85.8
15 kW	A4	175.1	263.5	623.8	530.1	73.4
	B4	164	324.2	623.8	520	80.8
	C4	164.2	474	658	515.2	90.4
Demand charge	A5	79.7	–	623.7	534.5	74.6
	B5	79.7	–	623.8	521	77.1
	C5	119.5			515.2	89.4

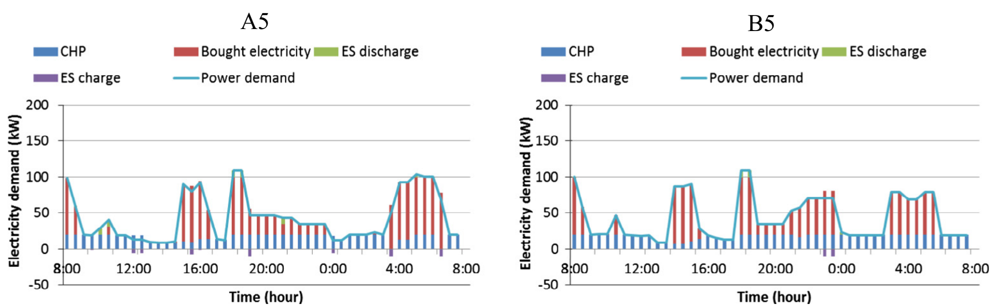

Fig. 8. Electricity balances for points A5 and B5 under demand charge scheme.

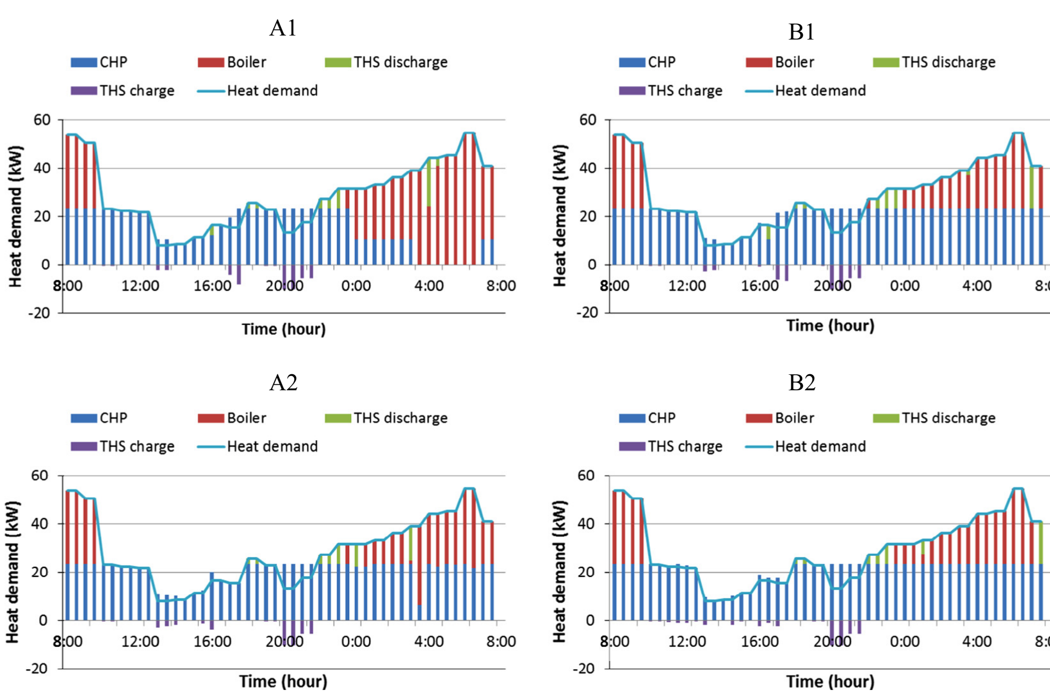

Fig. 9. Heat balance for points A1, A2, B1 and B2.

Table 5
Total demands from the grid over the thresholds for the RTP and demand charge price schemes.

Price scheme	Point	Total demand from grid over 60 kW (kW h)	Total demand from grid over 30 kW (kW h)	Total demand from grid over 15 kW (kW h)
RTP	A1	321.2	482.7	577.8
	B1	207.5	365.6	455.6
	C1	263.3	415.0	498.2
Demand charge	A5	116.8	324.0	464.9
	B5	59.6	288.4	436.7
	C5	233.8	401.2	496.9

demands over the three sample thresholds under the RTP and demand charge price scheme. Compared with the values presented in Table 5, the total demands over the thresholds from the other two price schemes are higher than those from the peak demand charge price scheme individually. Under each threshold, the total demands over the thresholds of points A1, B1, and C1, A5, B5 and C5 do not follow a trend at all, B1 and B5 just happen to have the lowest values for all three points.

6. Concluding remarks

An MILP model has been proposed to schedule the energy consumption of smart homes within a microgrid. Both environmental and economic minimisations are addressed in a multi-objective optimisation with ε-constraint method. The model has been implemented on a case study of 30 smart homes with the same living habits under three price schemes. Twelve domestic electrical tasks are scheduled together with DER operation in the shared microgrid. Electricity tariff and CO_2 emission intensity are assumed to be available for the optimal scheduling of the smart homes. Data profiles for a typical summer day in the UK are applied. Optimal results with trade-off between economic cost and environmental emissions are obtained.

When the economic cost and environmental emissions conflict with each other, the proposed MILP optimisation model determines the Pareto-optimal curve between cost and CO_2 emissions, and it can provide valuable guidelines to decide demand side energy management and DER operation. Also, scheduling of the DER operations and electrical tasks depend heavily on the energy demand patterns, which in turn are affected by seasons, the cost and CO_2 intensity profiles, and the electricity price scheme. The proper scheduling of electrical appliances presented in this work shows that DERs can be utilised more efficiently in a smart building. CHP systems operate constantly under the optimisation model, meaning that installing CHP generators will be a big step towards the reduction of CO_2 emissions in the energy sector. Compared with the RTP price scheme, maximum power demands from the grid and total peak demands over certain thresholds can be reduced by applying penalty price schemes, such as peak demand charge price scheme and price demand price scheme. The results show that the peak demand charge price scheme can reduce demand over the agreed threshold from the grid, which means less stress for the electricity grid. Designing the right threshold is important, and this study shows that it should be based on the average power demand from the grid over the day.

The proposed methodology is general and it provides a framework for scheduling the energy consumption of smart homes by considering both economic and environment aspects. Other home energy consumption tasks can be easily added, such as air conditioners, TVs, DVDs and even swimming pool heating systems. The future work may consider more environmental impact factors besides CO_2 emissions, such as acidification potential (AP) and primary energy (PE). Also renewable energy resources can be added in the model to achieve higher cost and emission reduction, including wind generator, solar panel and heat pumps.

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