Multi-Objective Economic and Emission Scheduling of Smart Apartment Building

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In recent years, simultaneous optimization of two conflicted objective functions become an important topic in power system. In this paper, a multi-objective mixed-integer linear programming (MILP) based model is provided for economic-environmental scheduling of a smart apartment building. The first objective function is the operation cost of the building's minimization. The minimization of the CO_2 emission is considered as the second objective function. The proposed multi-objective problem is solved using the weighted sum approach and the ε-constraint method. Then, min-max fuzzy satisfying approach is carried out to select the ideal win-win strategy from the obtained efficient results. The proposed MILP-based sample model is solved using General Algebraic Modeling System (GAMS) under CPLEX solver. Also, two scenarios, weighted sum approach and ε-constraint method scenarios, are used to analyse the efficiency of the proposed sample model. By comparing the obtained results, it can be concluded that with considering the ε-constraint approach, total operation cost of the building is reduced 24.78% by optimizing the model from economical perspectives. On the other hand, solving the proposed model from environmental perspectives led to a decline of 6.96% in CO_2 emission. Also, the weighted sum approach shows a reduction of 25.11% and 10.73% as a result from economic and environmental points of view, respectively.

Keywords: *Multi-objective optimization model, Smart apartment building, CO_2 emission, ε-constraint/weighted sum approach, fuzzy satisfying technique*

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Nomenclature

Sets	
i	Index of smart appliances
j	Index of smart homes
θ	Index of smart appliances' process time
t	Index of time
Parameter	
δ	Time interval duration (h)
λ^{Gas}	Gas tariff (£/kWh)
η^{CHP}, η^{Boiler}, $\eta^{Battery}$, $\eta^{Thermal}$	The combined heat and power (CHP), boiler, battery storage system, and thermal storage system efficiencies (%)
$BCC^{Battery}$	Operation cost of the battery storage system (£/kWh)
$TCC^{Thermal}$	Operation cost of the thermal storage system (£/kWh)
λ_t, λ^{Sell}	Cost of buying/selling power from/to the upstream grid (£/kWh)
ξ^{CHP}	The CO_2 intensity of the CHP electrical output ($kgCO_2/kWh$)
ξ^{Boiler}	The CO_2 intensity of the boiler thermal output ($kgCO_2/kWh$)
ξ_t^{UG}	The CO_2 intensity of the upstream grid ($kgCO_2/kWh$)
$P_{i,\theta}^{App}$	Energy usage of the i^{th} smart appliance at operation period θ (kW)
$Q_{j,t}^{Demand}$	Heat demand of each smart home (kW)
γ^{CHP}	Heat-to-power ratio of the CHP
L^{CHP}, L^{Boiler}, $L^{Battery}$, $L^{Thermal}$	The CHP, boiler, battery storage system, and thermal storage system capacities (kW)
$LC^{Battery}$, $LD^{Battery}$	Charge and discharge limits of the battery storage system (kW)
$LC^{Thermal}$,	Charge and discharge limits of the thermal

$LD^{Thermal}$	storage system (kW)
$BVS^{Battery}$	Initial state of the battery storage system (kWh)
$TVS^{Thermal}$	Initial state of the thermal storage system (kWh)
$M^{Battery}$, $M^{Thermal}$, M^{grid}	Maximum capacities of the battery storage system, thermal storage system, and purchased power from the upstream grid (kW)
$T_{j,i}^{Finish}$, $T_{j,i}^{Start}$	The earliest starting time and latest finishing time of the i^{th} smart appliance in the i^{th} smart home (hours)
P_i	The processing time of the i^{th} smart appliance in the i^{th} smart home (hours)
Variable	
$P_{j,t}^{CHP}$	Electricity output power of the CHP (kW)
$Q_{j,t}^{Boiler}$	Heat output power of the boiler (kW)
$TC_{j,t}^{Thermal}$, $TD_{j,t}^{Thermal}$	The charge and discharge rates of the thermal storage system (kW)
$P_{j,t}^{Import}$, $P_{j,t}^{Export}$	Imported/exported power from/to the upstream grid (kW)
$BC_{j,t}^{Battery}$, $BD_{j,t}^{Battery}$	Charge and discharge rates of the battery storage system (kW)
$BS_{j,t}^{Battery}$	Amount of stored energy in the battery storage system (kWh)
$TS_{j,t}^{Thermal}$	Amount of stored energy in the thermal storage system (kWh)
$BTS_t^{Battery}$	Total amount of stored energy in the battery storage system (kWh)
$TTS_t^{Thermal}$	Total amount of stored energy in the thermal storage system (kWh)
$\omega_{j,i,t}^{App}$	Binary variable; equal to 1 if the i^{th} appliance of the i^{th} smart home be active at time t; otherwise 0
$X_{j,t}^{Grid}$	Binary variable; equal to 1 if electricity is bought from the upstream grid by the i^{th} smart home at time t; equal to 0 if electricity is sold to the upstream grid by the i^{th} smart home at time *t*
$X_{j,t}^{Battery}$	Binary variable; equal to 1 if battery storage system is charged at time t; equal to 0 if battery storage system is discharged at time *t*

1. Introduction

We urgently need to move towards a pollution free planet, to tackle climate change and to drive sustainable development. We can only do that with decisive actions in residential sector [1]. Homes that use energy supplied from fossil fuels are responsible for significant emissions of the CO_2 gases [1]. For instance, in the European Union, buildings consume 40% of overall energy and emit 36% of total CO_2 gases. In the United Kingdom emissions from households' fossil fuel and electricity use are projected to rise by 11% by 2035 compared with 2015 levels. Therefore improving the efficiency of services and appliances that use energy from fossil fuels in residential sector alongside taking the appropriate strategies will lead to CO_2 emission reduction [1]. Other benefits include making energy more affordable, supply more secure and homes more comfortable [2].

1.1. Literature review

Part of the reviewed papers about the multi-objective problems in power system have been presented as follows: A multi-objective optimization model of hybrid system in the presence of demand response program has been presented in [3]. A master-slave parallel ε-variable multi-objective approach has been utilized in [4] to minimize the non-smooth/convex operation costs of the hybrid power system and the gas emission at the same time. To maximize the occupants' benefits and improve the energy efficiency, a multi-objective model considering retrofitting plan has been provided in [5]. To maximize the annual profit and minimize the annual capital cost of integrated solid oxide fuel cell and gasifier plant, a multi-objective model has been provided in [6]. A nonlinear multi-objective model has been provided in [7] to determine the optimal electricity generation, acquisition quantity, and blending ratio at the same time. Multi-objective scheduling of microgrid has been minimized from cost and emission viewpoints in [8]. A review on multi-objective economic emission dispatch of CHP units is provided in [9]. In [10], the weighted sum method has been utilized to optimize the cost-emission optimization model of the hub system considering demand response program. A renewable-based hub energy system has been studied under economic and environmental constraints under compressed air energy storage system and demand response program in [11]. A particle swarm optimization-based model of CGAM problem has been provided in [12] to maximize the exergetic efficiency and minimize the total cost rate at the same time. A new multi-objective algorithm has been provided in [13] to coordinate the charge and discharge mode of the electric vehicles batteries and control the node voltage at the same time. Stochastic multi-objective model has been provided in [14] for optimal sizing of energy storage system in a microgrid under demand response and reliability constraints.

Literature reviews about the optimal energy management of the smart homes have been investigated as follows: To seek the best size of the residential solar system, a multi-objective model has been provided in [15]. To maximize the comfort level and minimize the bill cost, a multi-objective model of smart home has been provided in [16]. Robust scheduling of the smart home under market price uncertainty has been handled in [17]. The stochastic approach has been utilized in [18] for the optimal scheduling of the smart home under heat demand uncertainty. Risk-based scheduling of smart home considering market price uncertainty has been provided in [19]. Robust optimization method has been utilized in [20] for robust scheduling of smart home under solar irradiation uncertainty. Information gap decision theory method has been utilized in [21] for robust scheduling of smart home under market price uncertainty. Optimal scheduling of multi-smart apartment building considering exchange power capability has been provided in [22]. The authors have proposed an energy management model for a smart home including renewable energy sources such as photovoltaic cells in [23]. Also, optimal scheduling of the smart home in the presence of solar thermal storage system has been provided in [24].

Reviewed papers related to the multi-objective optimal scheduling of the smart homes considering both economic-environmental factors have been summarized as follows: To minimize the bill cost and CO_2 emission, a linear model of the smart home has been provided in [25]. A hub model of the smart home considering economic-environmental factors utilizing weighting method has been provided in [26]. A ε-constraint method has been utilized in [27] for optimum scheduling of the smart home under economic-environmental factors.

It is noteworthy that general deterministic and non-deterministic-based models of smart homes have been investigated and presented in details in Table 1.

Table 1. Reviewed papers in the field of smart homes

Ref.	Wind turbine	Photovoltaic panel	CHP	Boiler	Energy storage system & Electric vehicle that plays the storage role	Thermal storage system and water storage	Solar thermal storage and Stirling engine	Dishwasher, washing machine, Spin dryer, Microwave and etc.	Discomfort Index	Value of lost load	Demand charge index	Peak demand charge index	Imported power from upstream grid	Exported power to the upstream grid	Minimizing the total operation cost	Maximizing the comfort level	Minimizing CO_2 emission	Wind speed (Uncertainty)	Ambient temperature and hot water (Uncertainty)	Solar irradiation (Uncertainty)	Market price (Uncertainty)	Cold demand (Uncertainty)	Heat demand (Uncertainty)	Electricity demand (Uncertainty)	Stochastic optimization	Robust optimization approach	Information gap decision theory	Neural Network
[16]	✗	✗	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✗)	✓(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
[17]	✗	✗	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✗(✗)	✗(✗)	✓(✓)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✓	✗
[18]	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✓)	✗(✗)	✓(✓)	✗(✗)	✓(✓)	✓(✗)	✓	✗	✗	✗
[19]	✗	✗	✓	✓	✓	✗	✓	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✗)	✓(✗)	✓(✓)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✓	✗
[20]	✗	✓	✗	✗	✗	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✗)	✓(✓)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✓	✗	✗
[21]	✗	✗	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✗)	✓(✗)	✓(✓)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✓	✗
[22]	✗	✗	✓	✗	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✗(✗)	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
[24]	✗	✗	✓	✓	✓	✗	✓	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✗)	✓(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
[25]	✗	✗	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✓	✗(✗)	✗(✗)	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
[26]	✗	✓	✓	✗	✓	✓	✗	✓	✗	✗	✗	✗	✓	✗	✓	✓	✓	✗(✗)	✓(✗)	✓(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
[27]	✗	✗	✓	✓	✓	✓	✗	✓	✗	✗	✓	✓	✓	✗	✓	✓	✓	✗(✗)	✗(✗)	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
[28]	✗	✓	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✓	✗(✗)	✓(✗)	✓(✗)	✓(✗)	✓(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
[29]	✗	✓	✗	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✓	✗(✗)	✗(✗)	✓(✓)	✓(✗)	✗(✗)	✗(✗)	✓(✗)	✓	✗	✗	✗
[30]	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓	✗	✓	✓	✗	✗(✗)	✗(✗)	✗(✗)	✓(✗)	✗(✗)	✗(✗)	✓(✗)	✗	✗	✗	✗
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[32]	✗	✗	✗	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✗(✗)	✗(✗)	✓(✗)	✗(✗)	✗(✗)	✓(✗)	✗	✗	✗	✗
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[35]	✓	✓	✗	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✓(✓)	✗(✗)	✓(✓)	✓(✗)	✗(✗)	✗(✗)	✓(✗)	✗	✗	✗	✓
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[37]	✓	✓	✓	✓	✓	✓	✗	✓	✓	✗	✗	✗	✓	✓	✓	✓	✗	✓(✗)	✓(✗)	✓(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
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[45]	✓	✓	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✓(✗)	✓(✗)	✓(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
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[48]	✗	✓	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✓)	✓(✓)	✓(✓)	✗(✗)	✓(✓)	✓(✓)	✓	✗	✗	✗
[49]	✓	✗	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
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[52]	✗	✗	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✗(✗)	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
[53]	✗	✓	✗	✗	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✗	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗
This paper	✗	✗	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✓	✗(✗)	✗(✗)	✗(✗)	✓(✗)	✗(✗)	✓(✗)	✓(✗)	✗	✗	✗	✗

1.2. Differences of weighted sum and ε-constraint approaches

Generally advantages of the ε-constrained method over the weighted sum approach can be listed as follows [54]:

- In the ε-constraint approach, by varying the ε value, different efficient solutions can be produced while in the weighted sum approach, running the model at different weights may result in the same efficient extreme solutions, so more rich representation of the efficient sets of solutions can be obtained with use of ε-constraint approach.
- In the weighted sum approach, the scaling of the objective functions into a common scale has strong influence on the obtained results while in the ε-constrained method, the scaling is not necessary.
- In ε-constrained method, the number of the generated efficient solutions can be controlled by properly adjusting the number of grid points (ε) which is not easy with the weighted sum approach.

1.3. Contributions

In this paper, a multi-objective optimization model is proposed for cost-emission performance of the smart apartment building. The proposed model is solved using ε-constraint approach and weighted sum method in two different scenarios. Then, to choose the best efficient possible solution among the obtained efficient solutions, fuzzy satisfying approach is utilized. Generally, obtained results denote the possibility of emission reduction and bill savings through better management and scheduling of energy sources and smart appliances. Based on the provided explanation, the novelty of this paper can be listed as follow:

- Utilization of ε-constraint method and weighted sum approach to solve the multi-objective model and employing min-max fuzzy satisfying approach to choose the ideal win-win strategy.

1.4. Structure of proposed paper

Rest of the proposed paper is arranged as follows: Section 2 provides a basic mathematical formulation of the smart apartment building model. Utilized approaches, ε-constraint method and weighted sum approach, to handle the multi-objective model are described in this section, too. Input data and obtained results are presented in section 3. Finally, the paper is concluded in the last section.

2. Problem formulation

In this section, basic formulation of the smart apartment building model is studied through various sub-sections.

2.1. Basic formulation of the smart apartment building

The overall architecture of the proposed MILP-based model of the smart apartment building which contains 10 smart homes is demonstrated in Fig. 1. As shown in the mentioned figure, the smart meter measures and processes the records then transmits them to the upstream grid. On the other hand, the home energy management system controls and schedules smart appliances alongside the controllable distributed energy resources such as CHP and etc. In order to obtain an optimal scheduling strategy, home energy management system needs a variety of input data such as thermal demands, the characteristics of appliances and so on.

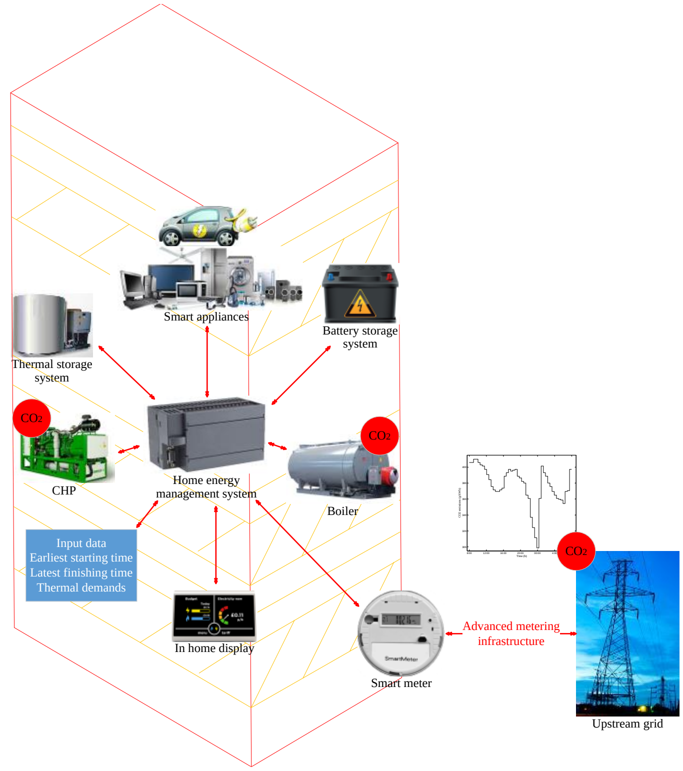

Fig. 1. Overall architecture of the smart apartment building model

2.1.1. Minimizing the total operation cost of the smart apartment building

The first objective function is minimization of the total operation cost of the smart apartment building which contains the operation cost of the CHP, boiler, battery storage system, thermal storage system and the cost/profit of buying/selling power from/to the upstream grid.

$$Min \ \phi_1 = \delta \times \left\{ \begin{array}{l} \left(\sum_{j=1}^{J} \sum_{t=1}^{T} \frac{\lambda^{Gas} \times P_{j,t}^{CHP}}{\eta^{CHP}} \right) \\ + \left(\sum_{j=1}^{J} \sum_{t=1}^{T} \frac{\lambda^{Gas} \times Q_{j,t}^{Boiler}}{\eta^{Boiler}} \right) \\ + \left(\sum_{j=1}^{J} \sum_{t=1}^{T} BCC^{Battery} \times D_{j,t}^{Battery} \right) \\ + \left(\sum_{j=1}^{J} \sum_{t=1}^{T} TCC^{Thermal} \times D_{j,t}^{Thermal} \right) \\ + \left(\sum_{j=1}^{J} \sum_{t=1}^{T} \lambda_t \times P_{j,t}^{Import} \right) \\ - \left(\sum_{j=1}^{J} \sum_{t=1}^{T} \lambda^{Sell} \times P_{j,t}^{Export} \right) \end{array} \right\} \quad (1)$$

2.1.2. Cost versus CO_2 emissions of the smart apartment building

The second objective function is minimization of the total CO_2 emission which includes the emission of the CO_2 by the CHP, boiler and the upstream grid.

$$Min\ \ \phi_2 = \delta \times \left\{ \begin{array}{l} \left(\sum_{j=1}^{J} \sum_{t=1}^{T} \xi^{CHP} \times P_{j,t}^{CHP} \right) \\ + \left(\sum_{j=1}^{J} \sum_{t=1}^{T} \xi^{Boiler} \times Q_{j,t}^{Boiler} \right) \\ + \left(\sum_{j=1}^{J} \sum_{t=1}^{T} \xi_t^{UG} \times P_{j,t}^{Import} \right) \end{array} \right\} \quad (2)$$

2.1.3. Energy balance constraints

The produced electrical and thermal energy must be equal to their demands at each period of time.

$$\begin{array}{l} \sum_{i=1}^{I} \sum_{\theta=1}^{P_i-1} P_{i,\theta}^{App} \times \omega_{j,i,t-\theta}^{App} = P_{j,t}^{CHP} + BD_{j,t}^{Battery} \\ + P_{j,t}^{Import} - BC_{j,t}^{Battery} - P_{j,t}^{Export} \end{array} \quad (3)$$

$$Q_{j,t}^{Demand} = \gamma^{CHP} \times P_{j,t}^{CHP} + Q_{j,t}^{Boiler} + TD_{j,t}^{Thermal} - TC_{j,t}^{Thermal} \quad (4)$$

2.1.4. CHP generator and Boiler constraints

The capacity limitations of the CHP and the boiler can be expressed as follows [55, 56]:

$$\sum_{j=1}^{J} P_{j,t}^{CHP} \le L^{CHP} \quad (5)$$

$$\sum_{j=1}^{J} Q_{j,t}^{Boiler} \le L^{Boiler} \quad (6)$$

2.1.5. Battery storage system constraints

Proposed battery storage system plays a role of central battery storage system. So, each smart home within the smart apartment building can discharge the battery storage system as much as it has charged it by itself at the previous periods. The specialized constraints of the battery storage system are expressed using (7)-(15).

The stored energy in the battery storage system at each period is expressed using (7). Also, stored energy at each period could not exceed the specific level. In this regard, (8) is provided. To limit the discharge rate of the battery storage system by the amount of stored energy, (9) is provided.

$$\begin{array}{l} BS_{j,t}^{Battery} = BS_{j,t-1}^{Battery} \\ + (BC_{j,t}^{Battery} \times \eta^{Battery} \times \delta) - \left(\dfrac{BD_{j,t}^{Battery} \times \delta}{\eta^{Battery}} \right) \end{array} \quad (7)$$

$$\sum_{j=1}^{J} BS_{j,t}^{Battery} \le L^{Battery} \quad (8)$$

$$\frac{BD_{j,t}^{Battery} \times \delta}{\eta^{Battery}} \le BS_{j,t-1}^{Battery} \quad (9)$$

To avoid the simultaneous charge and discharge of the battery storage system, (10) and (11) are provided.

$$BC_{j,t}^{Battery} \le M^{Battery} \times X_{j,t}^{Battery} \quad (10)$$

$$BD_{j,t}^{Battery} \le M^{Battery} \times (1 - X_{j,t}^{Battery}) \quad (11)$$

In order to avoid the net accumulation at the end of the sample day, stored energy in the battery storage system at the end of the sample day should be equal to its initial amount. In this regard, (12) and (13) are provided.

$$BTS_t^{Battery} = \sum_{j=1}^{J} BS_{j,t}^{Battery} \quad (12)$$

$$BTS_{t=0}^{Battery} = BTS_{t=24}^{Battery} = BVS^{Battery} \quad (13)$$

To limit the charge and discharge rate of battery storage system by its designed capacity, (14) and (15) are presented.

$$\sum_{j=1}^{J} BD_{j,t}^{Battery} \le LD^{Battery} \quad (14)$$

$$\sum_{j=1}^{J} BC_{j,t}^{Battery} \le LC^{Battery} \quad (15)$$

It should be mentioned that the technical constraints of the thermal storage system are formulated similarly.

2.1.6. Starting/finishing time of smart appliances

A set of most common controllable smart appliances such as washing machine, dish washer, microwave, fridge, etc., have been considered in this model. Each smart appliance within each smart home is scheduled to be operated within the specific time interval $T_{j,t}^{Start}$, $T_{j,t}^{Finish}$ which is set and determined by the residents of each smart home based on their priorities and preferences. The mathematical formulation of the mentioned statements are expressed as follows:

$$\sum_{t=T_{j,i}^{Start}}^{T_{j,i}^{Finish}-P_i} \omega_{j,i,t}^{App} = 1 \quad (16)$$

2.1.7. Upstream grid constraints

To avoid the simultaneous exchange power between the smart apartment building and the upstream grid, (17) and (18) are provided.

$$P_{j,t}^{Import} \le M^{grid} \times X_{j,t}^{Grid} \quad (17)$$

$$P_{j,t}^{Export} \le M^{Grid} \times (1 - X_{j,t}^{Grid}) \quad (18)$$

2.2. Utilized approaches to solve the multi-objective model

In single-objective mathematical programming problems, there is only one optimal solution that obtained through optimizing the model. In contrast, in multi-objective mathematical programming problems, there are more than just one objective function. In other words, there is a set of optimal solutions that are introduced as Pareto-optimal instead of one optimal solution. Generally, in multi-objective mathematical programming problems, different objective functions are required to be optimized simultaneously with considering sets of inequality and equality constraints. In this regard, several approaches such as weighted sum approach, ε-constraint approach, evolutionary algorithm, etc. have been utilized to handle the multi-objective problems. Each mentioned techniques has specific procedures for solving multi-objective problems. In this paper, the proposed multi-objective smart apartment building model has been solved utilizing weighted sum approach and ε-constraint method which are explained with more details as follows:

2.2.1. Weighted sum method

In weighted sum approach, Pareto-optimal solutions are obtained by changing weighting factors within the specific intervals [10].

$$\min \phi = w_1\phi_1 + w_2\phi_2$$
$$s.t.$$
$$\begin{cases} w_1 + w_2 = 1 \\ Other\ \ technical\ \ constraints \end{cases} \quad (19)$$

It should be noted that the provided multi-objective model involves two conflicted objective functions which are different in dimensions. To compare the obtained results with each other, the fuzzy satisfying approach is presented to change each objective function results into per unit values. This approach is explained with more details in subsection 2.2.3.

2.2.2. Ɛ-constraint method

The mathematical formulation of the ε-constraint method can be written as follows [3]:

$$\min\ \phi_1(x) \quad (20)$$
$$s.t.$$
$$\begin{cases} \phi_2(x) \le \varepsilon \\ Other\ \ technical\ \ constraints \end{cases}$$

As shown by (20), the second objective function is considered as constraint and bounded by ε which can be varied between the specific intervals ($\phi_2^{\min}, \phi_2^{\max}$). So, in this method, Pareto-optimal solutions are obtained through optimizing the first objective function by varying the ε value from $\phi_2^{\min}$ to $\phi_2^{\max}$.

Finally, the fuzzy satisfying approach is utilized to compare the obtained results.

2.2.3. Fuzzy satisfying approach

With the aim of comparing and selecting the ideal result among the obtained efficient results, the obtained results through weighted sum approach and ε-constraint method should change into per unit value. In this regard, min-max fuzzy satisfying approach is employed.

The linear membership function for the n[th] solution of the i[th] objective function can be written as follows [3]:

$$\phi_i^n = \begin{cases} 1 & \phi_i^n \le \phi_i^{\min} \\ \dfrac{\phi_i^n - \phi_i^{\max}}{\phi_i^{\min} - \phi_i^{\max}} & \phi_i^{\min} \le \phi_i^n \le \phi_i^{\max} \\ 0 & \phi_i^n \ge \phi_i^{\max} \end{cases} \quad (21)$$

Where $\phi_i^{\min}$ and $\phi_i^{\max}$ are considered as upper and lower bounds of the i^{th} objective function. ϕ_i^n indicates the ideal degree of the n[th] solution of the i^{th} objective function.

The normalized form of the provided conflicted objective functions can be written as follows:

$$\phi_{1,pu} = \frac{\phi_1 - \phi_1^{\max}}{\phi_1^{\min} - \phi_1^{\max}} \quad (22)$$

$$\phi_{2,pu} = \frac{\phi_2 - \phi_2^{\max}}{\phi_2^{\min} - \phi_2^{\max}} \quad (23)$$

The membership function of the n[th] solution can be expressed as follows:

$$\phi^n = \min(\phi_1^n, ..., \phi_N^{N_P}) \quad (24)$$

The ideal-chosen solution provides a win-win situation between the conflicted objective functions. Mathematical formulations of the mentioned statement is expressed as follows:

$$\phi^{\max} = \max(\phi^1, ..., \phi^{Np}) \quad (25)$$

Finally, it should be noted that the general flowchart of the utilized approaches, ε-constraint, weighted sum and min-max fuzzy satisfying approaches, are demonstrated in Fig. 2.

3. Numerical simulation

The proposed MILP-based model of the smart apartment building contains CHP, boiler, battery storage system, thermal storage system and smart appliances with the capability of exchanging power with upstream grid. The scheduling period in this paper is 24 hour with the time span of 30 minutes which started from 08:00 AM of the sample day and finish at 08:00 AM of the next sample day. It is noteworthy that, the proposed MILP-based model were conducted using GAMS [57] and CPLEX [58] software packages on an Intel(R) Core(TM) i7-6500U 2.50 GHz CPU laptop with 8 GB of RAM.

3.1. Input data

Technical information of the CHP, boiler, battery storage system, thermal storage system, heat demand of each smart home, market price, cost of selling power to the upstream grid, and gas price are adopted from [17]. The technical data of the smart appliances are taken from [17], too. Finally, the CO_2 emissions of the CHP, boiler and the upstream grid profile during the study period are provided in Table 2 and Fig. 3, respectively [27].

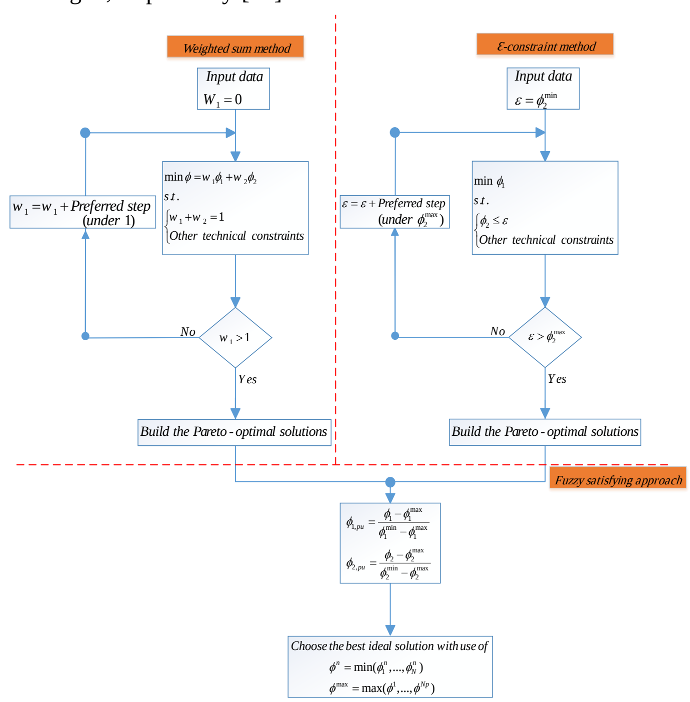

Fig. 2. Flowchart of the Ɛ-constraint, weighted sum, and fuzzy satisfying approaches

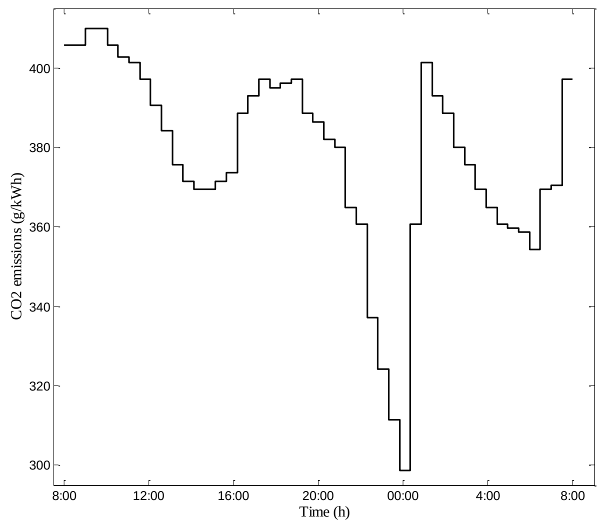

Fig. 3. The CO_2 emission of the upstream grid profile

Table 2. The CO_2 emission of the CHP and the boiler

	Unit	Natural	Unit	Natural
ξ^{CHP}	kg CO_2/kWh	0.0396	0.5049	0.5445
ξ^{Boiler}	kg CO_2/kWh	0.0186	0.2923	0.3109

3.2. Simulation results

The multi-objective model of the smart apartment building has been studied in two scenarios. In the first scenario, operation of the smart apartment building has been investigated through weighted sum approach. Then, the same multi-objective problem has been solved with considering the ε-constraint approach in the second scenario. Obtained results of two scenarios are provided in Fig. 4. It should be noted that point B indicates the win-win strategy which was chosen by min-max fuzzy satisfying method. Also, due to linear nature of the proposed model, the obtained results are close and similar to each other in two scenarios. It should be mentioned that in this figure, point A indicates the lowest value of the CO_2 emission (highest value of the total operation cost) and point C indicates the highest value of CO_2 emission (lowest value of the total operation cost). For better analyzing, total operation cost of the smart apartment building in two scenarios, in three different points which have been described previously are presented in details in Table 3.

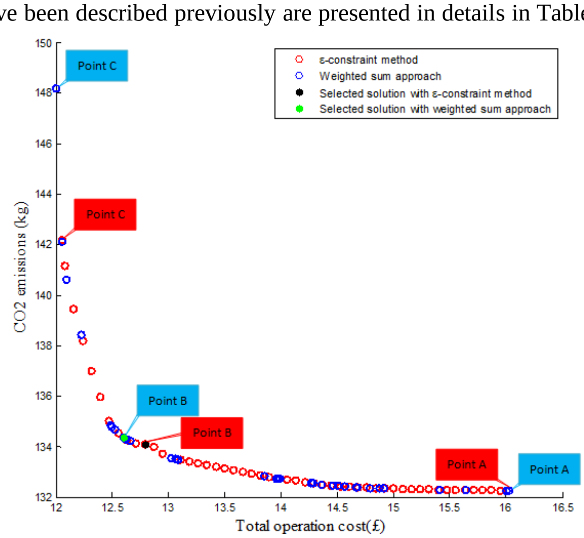

Fig. 4. Pareto set for multi-objective smart building model

For accurate and better explanation, output of different equipment within the smart apartment building in three points (A, B and C) and in two different scenarios have been illustrated by Figs. 5-13 and reported numerically in Table 4.

The output power of the CHP and boiler are provided in Figs. 5 and 6. By analyzing the obtained results, it can be realized that with optimizing the model from CO_2 emission minimization viewpoints, the home energy management system tends to use more CHP than the boiler. For instance, in ε-constraint scenario, output power of the CHP, in point C in comparison to points B and A, is increased 68.71 kWh and 2.74 kWh, respectively. In contrast, output power of the boiler is decreased 88.88 kWh and 3.44 kWh, respectively. So, it can conclude that the simultaneous production of heat and electricity by the CHP causes the superiority of this equipment to the boiler.

The charge and discharge rates and state of charge of the battery storage system are provided in Figs. 7 and 8, respectively. By analyzing the results, it can be understood that the charge and discharge rates of the battery storage system in Point A is higher than other points. For example, in ε-constraint scenario, charge rate of the battery storage system in points B and C is increased 7.68 kWh and 19.02 kWh respectively in comparison to Point A. Also, in Points B and C, discharge rate of the battery storage system is increased 8.83 kWh and 19.06 kWh, respectively. In other words, with minimizing the operation cost, the home energy management system tends to charge and discharge the battery storage system more which makes the emission of the CO_2 to be increased.

Table 3. Detailed operation cost of the smart apartment building

		Weighted sum approach	ε-constraint method
Point A		£	£
	Total cost	16.027	16.027
	The cost of produced power by CHP	5.953	5.953
	The cost of produced heat by the boiler	1.675	1.675
	The cost of discharged power by battery storage system	0.024	0.024
	The cost of discharged heat by thermal storage system	0.022	0.022
	The cost of imported power from the upstream grid	8.351	8.351
	The profit of exported power to the upstream grid	0	0
		Kg	Kg
	Total emission cost	132.266	132.266
	The CO_2 emission of the CHP electrical output	42.022	42.022
	The CO_2 emission of the boiler thermal output	16.399	16.399
	The CO_2 emission of upstream grid	73.845	73.845
Point B		£	£
	Total cost	12.601	12.791
	The cost of produced power by CHP	5.848	5.848
	The cost of produced heat by the boiler	1.731	1.73
	The cost of discharged power by battery storage system	0.058	0.046
	The cost of discharged heat by thermal storage system	0.021	0.021
	The cost of imported power from the upstream grid	4.971	5.175
	The profit of exported power to the upstream grid	0.028	0.028
		Kg	Kg
	Total emission cost	134.367	134.086

	The CO_2 emission of the CHP electrical output	41.280	41.277
	The CO_2 emission of the boiler thermal output	16.940	16.933
	The CO_2 emission of upstream grid	76.147	75.876
Point C		£	£
	Total cost	12.002	12.056
	The cost of produced power by CHP	2.791	3.303
	The cost of produced heat by the boiler	3.360	3.086
	The cost of discharged power by battery storage system	0.128	0.072
	The cost of discharged heat by thermal storage system	0.016	0.016
	The cost of imported power from the upstream grid	6.045	5.609
	The profit of exported power to the upstream grid	0.339	0.032
		Kg	Kg
	Total emission cost	148.161	142.162
	The CO_2 emission of the CHP electrical output	19.7	23.317
	The CO_2 emission of the boiler thermal output	32.891	30.210
	The CO_2 emission of upstream grid	95.570	88.635

The charge and discharge rates and state of charge of the thermal storage system are provided in Figs. 9 and 10, respectively. By analyzing the results, it can be concluded that with minimizing the proposed model from CO_2 emission viewpoints, the home energy management system tends to charge and discharge thermal storage system more and more, which makes the total operation cost to be increased as much as possible. For instance, in ε-constraint scenario, charge rate of the thermal storage system is increased 2.98 kWh and 11.85 kWh respectively in Points B and A in comparison to Point C. Also, discharge rate of this equipment is increased 2.86 kWh and 11.38 kWh in Points B and A, respectively.

Table 4. Total obtained results within the 24 hour

		Weighted sum approach	ε-constraint method
		kWh	kWh
Point A	The electrical output power of the CHP	154.351	154.352
	The thermal output power of the boiler	105.502	105.505
	Charge rate of the battery storage system	8.419	8.422
	Discharge rate of the battery storage system	9.7	9.701
	Stored energy in the battery storage system	62.777	62.707
	Charge rate of the thermal storage system	39.786	39.786
	Discharge rate of the thermal storage system	44.216	44.211
	Stored energy in the thermal storage system	179.524	188.053
	Imported power from the upstream grid	395.828	395.829
	Exported power to the upstream grid	0	0
Point B	The electrical output power of the CHP	151.622	151.613
	The thermal output power of the boiler	108.988	108.941
	Charge rate of the battery storage system	21.23	16.099
	Discharge rate of the battery storage system	23.162	18.533
	Stored energy in the battery storage system	94.716	98.207
	Charge rate of the thermal storage system	38.204	36.81
	Discharge rate of the thermal storage system	42.689	41.349
	Stored energy in the thermal storage system	168.079	170.284
	Imported power from the upstream grid	399.808	399.313
	Exported power to the upstream grid	1.9	1.9
Point C	The electrical output power of the CHP	72.36	85.645
	The thermal output power of the boiler	211.639	194.383
	Charge rate of the battery storage system	52.189	27.441
	Discharge rate of the battery storage system	51.102	28.766
	Stored energy in the battery storage system	89.135	78.78
	Charge rate of the thermal storage system	27.389	27.938
	Discharge rate of the thermal storage system	32.301	32.834
	Stored energy in the thermal storage system	123.497	149.392
	Imported power from the upstream grid	502.788	466.614
	Exported power to the upstream grid	22.6	2.125

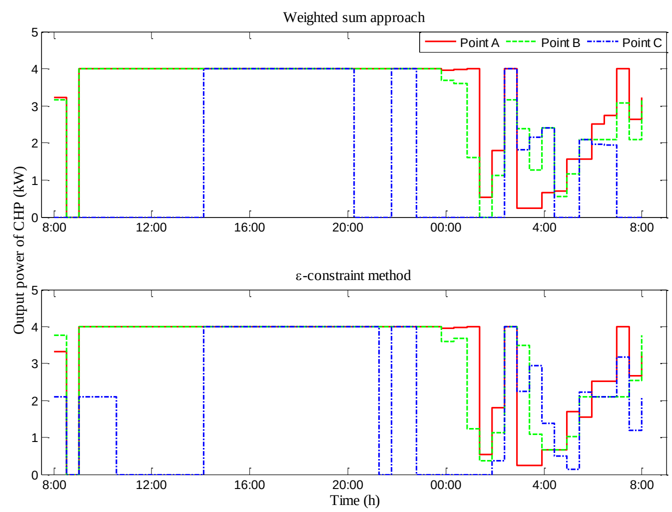

Fig. 5. The output power of CHP

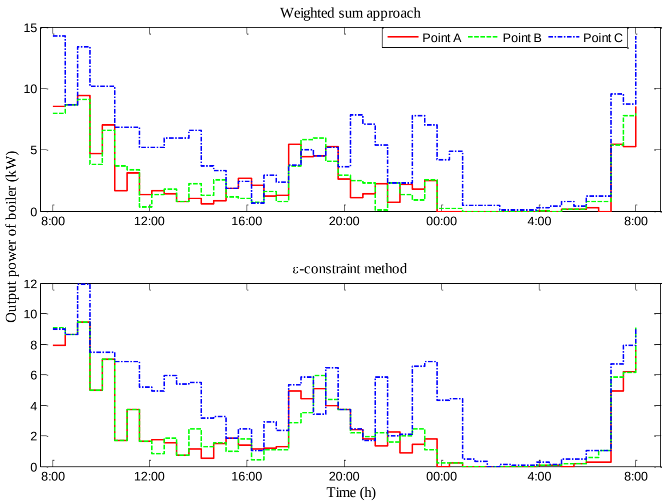

Fig. 6. The output power of the boiler

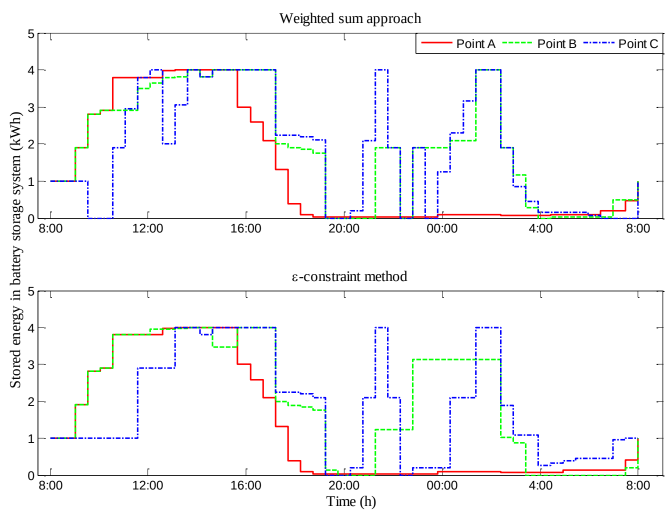

Fig. 7. Amount of stored energy in the battery storage system

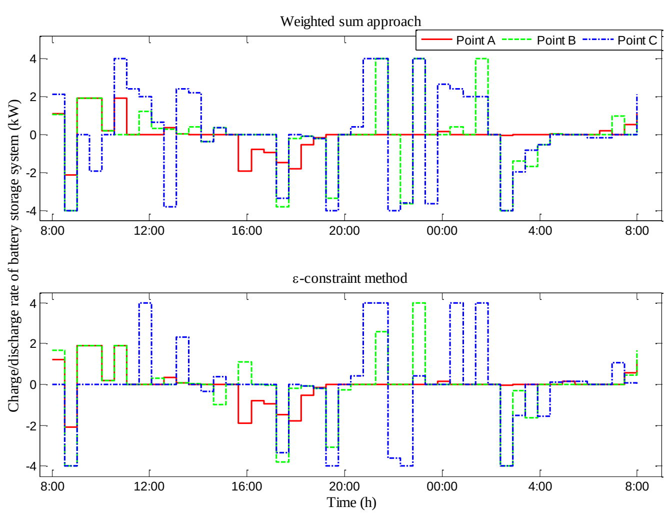

Fig. 8. Charge and discharge rates of the battery storage system

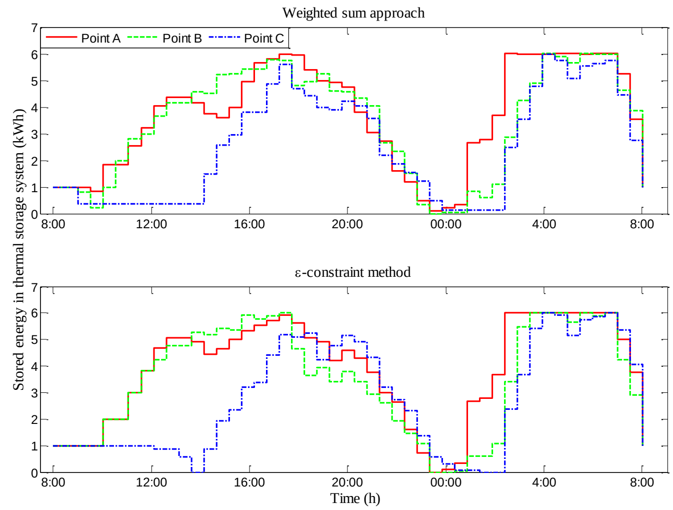

Fig. 9. Amount of stored heat in the thermal storage system

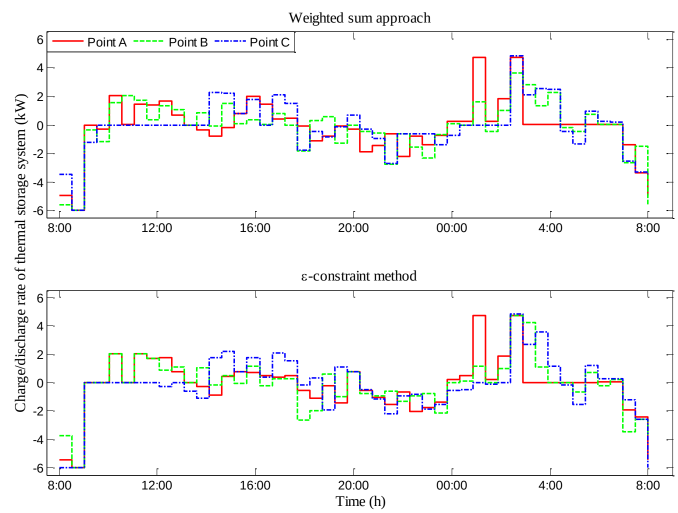

Fig. 10. Charge and discharge rates of the thermal storage system

Imported/exported power from/to the upstream grid is provided in Fig. 11. As shown in this figure, with minimizing the provided model from CO_2 emission viewpoints, the home energy management system tends to exchange negligible amount with upstream grid in comparison to minimize the provided model from the total operation cost viewpoints. For example, in point A, amount of exchanged power with upstream grid is zero. In contrast, in point B, amount of imported/exported power from/to the upstream grid is about 3.48 kWh and 1.9 kWh, respectively. Furthermore, amount of imported/exported power from/to the upstream grid in Point C is increased to 70.78 kWh and 2.125 kWh, respectively.

The best-selected operation time for the first smart home's laptop and the fourth smart home's tumble dryer are selected randomly and represented in Figs. 12 and 13, respectively. For instance, the best operation time of a laptop which belongs to the first smart home, in Point B is set between 21:00-23:00 and 22:30-00:30 in two scenarios, respectively.

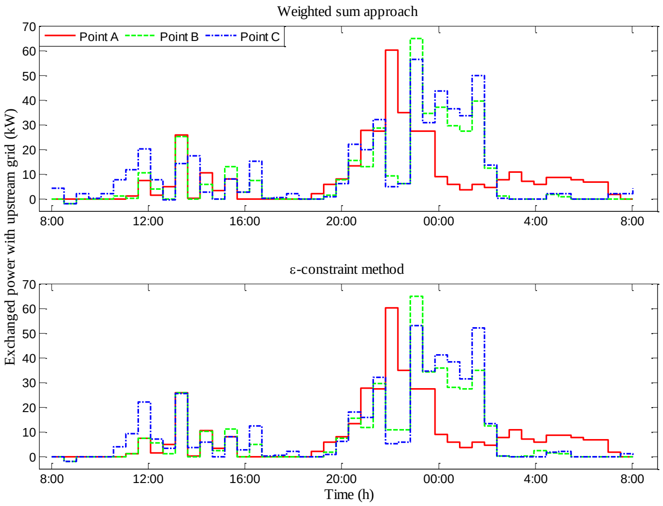

Fig. 11. Exchanged power with upstream grid

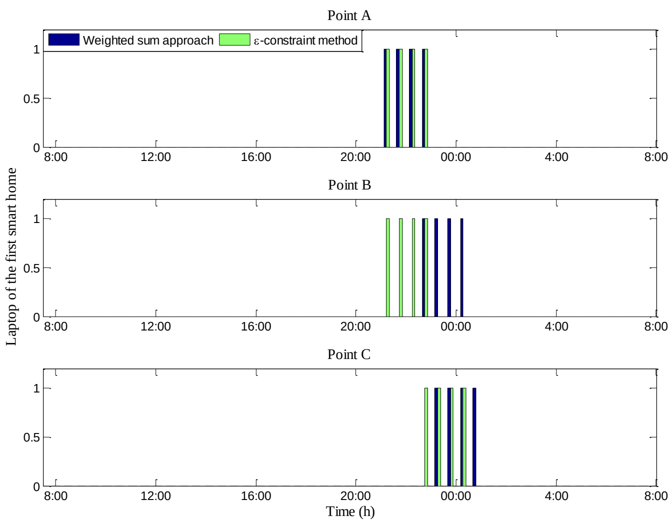

Fig. 12. The operation time of the first smart home's laptop

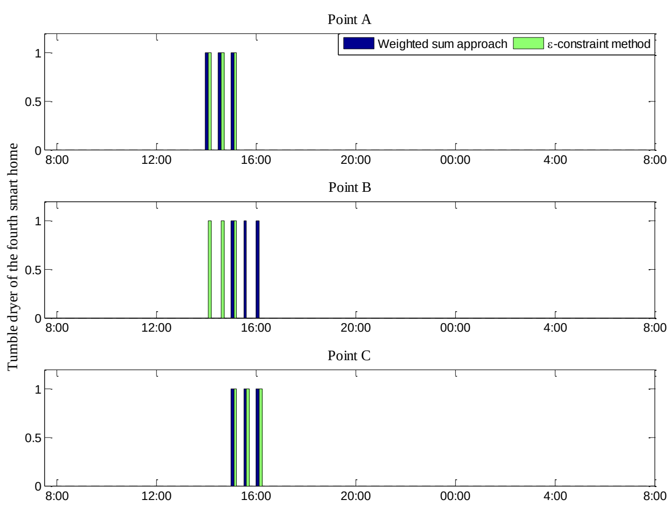

Fig. 13. The operation time of the fourth smart home's tumble dryer

4. Conclusion

In this paper, a multi-objective optimization model has been proposed for cost-emission scheduling of the MILP-based model of the smart apartment building which consists of advanced metering infrastructure, home energy management system, smart meter, in-home display equipment, CHP, boiler, battery storage system, thermal storage system, and smart appliances. The aim of the proposed model is minimizing two conflicting objective functions namely total operation cost and CO_2 emission. In the first scenario, the ε-constraint method is utilized to solve the provided model while weighted sum approach is used in the second scenario. After that, fuzzy satisfying method is employed to select the best possible solution among the obtained efficient solutions. By analyzing the obtained results, it can be realized that in ε-constraint approach, total operation cost experienced a fall of 4.03£ under economic point of view. Also, CO_2 emission is increased 6.96% from 148.16 Kg to 132.26 Kg. Furthermore, in weighted sum approach, total operation cost is decreased 25.11% under economic viewpoint, while CO_2 emission is decreased 6.96% under environmental viewpoint. It should be mentioned that the developed MILP-based model of the smart apartment building is implemented using CPLEX solver in GAMS software.

Notably, the cost-emission optimal scheduling of interconnected multi-smart apartment buildings considering power exchange capability among them alongside the overall electrical and thermal energy losses of each building with use of normal boundary intersection, lexicographic programming, and goal programming approaches can be considered as a challenging future work.

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