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Minimizing Total Cost of Home Energy Consumption under Uncertainties

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CONTENTS

Abstract—Along with the development of renewable energy sources, energy storage units are introduced to increase the stability and reliability of electricity production. The storage units can improve the efficiency of energy consumption for consumers as well. By smartly controlling home appliances, renewable energy sources and energy storage units, consumers can satisfy their energy demand with a minimum cost. However, the declined maximum capacity of energy storage units and the unstable power of electricity grid, due to randomly unexpected failures, can cause challenges for consumers' energy plans. In this article, we develop a novel joint chance-constraint mixed-integer linear programming model to support consumers in finding the optimal energy plans for a minimum cost of energy consumption under the simultaneous impact of unexpected failures on energy storage units and electricity grid. A case study for a set of households in Nottingham, United Kingdom, is used to demonstrate the efficiency of the proposed model. Some interesting insights are achieved for home energy management under uncertainties.

1. INTRODUCTION

Nowadays, the use of RESs (e.g., photovoltaic panels and wind turbines) has been widely developed to replace the existing systems of polluting electricity generation. This can help improve environmental quality as well as increase electricity supply. However, the power generated by the RESs is intermittent due to the continuous change of climate (e.g., sun and wind). To increase the stability and reliability of energy conversion in the electricity grid, energy storage units are proposed to store the electricity power when the RESs are copious, and to use smartly this power in the case of energy shortage [1]. The energy storage units are utilized not only for the stability and reliability of the entire electricity grid, but also for improving the efficiency of energy consumption in the home energy management system. Therefore, under the scenarios that the production of electricity grid and/or the capacity of energy storage units are decreased due to some unexpected failures, home energy management system can pose critical issues. Under impact of randomly unexpected failures, the

Keywords: electricity grid, energy storage, joint chance-constraint, mixed-integer linear programming unexpected failure
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NOMENCLATURE

CHP	Combined Heat and Power
CO2	Carbon Dioxide
DES	Distributed Energy System
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
UPS	Uninterruptible Power Supply
UK	United Kingdom
RES	Renewable Energy Source

power of electricity grid is decreased and thus cannot supply enough energy for households' demand. Such the failures can reduce the maximum capacity of energy storage units (e.g., health of battery). Then, households' energy consumption will be affected. The households need to adjust their energy plan (e.g., using home appliances within off-peak hours) and/or cut unnecessary home appliances to minimize total energy consumption cost. In the recent BBC news [2], nearly one million people across England and Wales were affected by the blackout, after the "incredibly rare event" of two power stations disconnecting. It is essential to develop a decision-making support tool for home energy management under the uncertainties.

In this article, we focus on the literature of home energy management system with uncertainties. Among the considered uncertainties, uncertain electricity prices have received much attention by researchers. For example, [3] proposed an optimization model to maximize the utility of the consumer, subject to a minimum daily energy-consumption level, maximum and minimum hourly load levels, and ramping limits on such load levels. In the model, robust optimization techniques are applied to account for the prescribed uncertainty level of electricity prices. [4] addressed an appliance commitment problem under the impact of uncertainties from electricity price and hot water usage. A novel linear-sequential-optimization-enhanced, multi-loop algorithm is developed to schedule thermostatically controlled household loads with a minimum payment or maximum comfort. [5] built a mixed-integer linear programming model for optimally scheduling electricity consumption, generation and storage in a dynamic pricing environment. Robust optimization algorithms are developed to minimize the impact of stochastic input on the objective function. [6] adopted the scenario-based Monte Carlo simulation to deal with uncertainties of real-time electricity prices in the residential appliance scheduling problem. Next, [7] studied the real-time residential appliance scheduling problem in which the conditional value-at-risk is used to balance the expected costs and risks caused by uncertainties of electricity prices.

Besides the studies of uncertain electricity prices, researchers have recently started considering the single-/multi-objective optimization problem in home energy management system with other uncertainties. For example, [8] developed a stochastic scheduling technique for optimally coordinating the electrical appliances with the uncertainties in household appliance operation time and intermittent renewable generation. [9] improved the model in [10], a linear programming routine for reducing the net-peak load with the aid of a grid-connected photovoltaic and a battery system, to investigate the uncertainties of forecasting in both solar radiation and load demand of the building. For a comprehensive review of forecasting errors and uncertainties in home energy management system, readers can refer to [11]. [12] developed a stochastic multi-objective optimization model within model predictive control framework for determining the optimal operational schedules of home appliances (e.g., heating, ventilation and air conditioning systems) in the presence of RESs. Monte Carlo simulation is used to represent uncertainties in electricity price, outdoor temperature, RES generation, water usage and non-controllable loads. [13] built a model-based periodic event-triggered mechanism to handle the uncertainties in the building operation for determining the optimal scheduling of building operation with a minimum energy cost. [14] built a chance-constrained model predictive control algorithm for demand response in a home energy management system. [15] proposed a day-ahead optimal operation strategy, utilizing distributed energy resources based on the framework of interconnected multi-energy system, to investigate the negative impacts of intermittent RESs. [16] constructed a model based on a mixed-integer linear programming framework to investigate the cooperative evaluation of an energy management system operation in a building. The model evaluates the impact of photovoltaic uncertainty on energy management system operation, based on real smart-metering data, and compares with a deterministic photovoltaic production approach. [17] proposed a multi-objective mixed-integer linear programming model for scheduling smart appliances and electrical energy storage, under the uncertainty of user behaviors, such that both the electricity bill and CO2 emissions are reduced. To reduce the conservative level of the robust solution, the authors introduce a parameter that allows to achieve a trade-o between the price of robustness and the protection against uncertainty. Recently, [18] proposed a hybrid robust-stochastic optimization model to study the smart home energy management with uncertainties of energy prices and photovoltaic generation.

A detailed review of uncertainty characteristic approaches for the optimal design of DES can be found in [19]. The authors aim to determine and categorize the most important uncertain parameters in typical DES design models, and review approaches used in the literature to represent their uncertainty. From the literature review, it can be seen that there is no study considering simultaneously the uncertainties of electricity production in the grid and energy storage units in home energy management. The most relevant studies have addressed the degradation of energy storage units under impact of uncertain environments. For example, [20] investigated the practical implementation of exchanging electricity between a distributed smart grid and a smart house under impact of battery degradation involving the battery status (i.e., state of charge, charging speed and temperature clear). [21] considered the operations of customer-side energy storage system to minimize the electricity bill subject to a peak load limitation constraint and uncertain environments. [22] developed a linear programming model, combined with a model predictive control framework, for optimally dispatching the battery of a building under variabilities/uncertainties of the input variables. [23] addressed the joint scheduling problem of large-scale smart appliances and batteries to minimize electricity payment, user's dissatisfaction and battery loss under kinds of constraints. In [24], the authors studied the effects of modeling assumptions, such as the treatment of uncertainties in the input data and battery degradation effects. They performed a comprehensive comparison of seven different energy management strategies (e.g., two optimization-based approaches, two machine learning approaches and three rule-based heuristic approaches) for the small-scale photovoltaic-battery systems.

Robust optimization method has been widely used for solving optimization problems under uncertainties. A joint chance constrained programming, one of robust optimization approaches, is usually developed to deal with the type of uncertainty such as unexpected failures and the joint probability of a multivariate random event. There are several applications of this approach in various areas. For example, [25] built MINLP models for linepack planning problem under supply shortfall or compressor failure in gas transmission network. In the case of unexpected, random gas supply loss, the model was used to evaluate the impact of supply shortfall and search the optimal linepack plan to mitigate the loss. In the case of unexpected, random compressor failure, the model was used to investigate its impact on the linepack planning management. In this article, our model is totally different from the MINLP models of [25]. Our model is formulated to find the optimal scheduling plan such that the total cost of home energy consumption under uncertainties is minimized. The set of decision variables and constraints are also different from those in [25]. We cannot use the models of [25] to solve the energy consumption minimization problem under uncertainties, nor vice versa. In addition, we simultaneously investigate impact of both randomly unexpected failures of energy storages and unstable capacity of electricity grid on the optimal scheduling plan of energy consumption. A similarity between these two works is that the same linearized technique was used to transform a MINLP into a MILP model for solving by commercial solvers. Table 1 summarizes the comparison result of our article and three papers [12, 26] and [25] that have some similar properties. The result shows that [26] did not solve the energy consumption minimization problem under uncertainties, [12] investigated impact of different uncertainties (e.g., electricity price, outdoor temperature, RES generation, water usage and non-controllable loads) on this problem and did not use robust optimization to handle the uncertainties, and [25] solved a linepack planning problem in gas transmission network (not for home energy management).

In summary, the major contributions in our article consist of

- Simultaneously investigating impact of uncertainties (e.g., unexpected failures of electricity grid and energy storage) on the scheduling plan for the cost minimization problem of energy consumption.
- Building a MINLP model for solving the uncertain cost minimization problem.
- Developing the robust optimization method (i.e., joint chance-constraint programming) to handle the uncertainties, and applying the linearized technique of [25] to transform the MINLP into the MILP model that can be solved by commercial solvers.
- Applying the model for solving the case study with various scenarios that is constructed by a network of households in Nottingham, UK.
- Finding interesting insights for the home energy management under uncertainties.

The remaining parts of this article are organized as follows. The domestic energy cost minimization problem under uncertainties is described in Section 2. The joint chance-constraint MILP model for solving the problem is presented in Sections 3. The numerical experiments, carried out on the case study in Nottingham, UK, are shown in Section 4. Finally, the conclusions and future work are provided in Section 5.

2. HOME ENERGY CONSUMPTION UNDER UNCERTAINTIES

Development of RESs and energy storage units has improved the efficiency of energy consumption for customers. Any negative impact on the capability of RESs and the capacity of

Paper	Model	Uncertainty	Application
[26]	Linear programming,		Home energy management
	MILP		
	MINLP		
	Quadratic programming		
[12]	MILP	Electricity price	Home energy management
	MINLP	Outdoor temperature	
	Monte Carlo simulation	RES	
		Water usage	
		Non-controllable loads	
[25]	MILP	Gas supply shortfall	Gas transmission network
	MINLP	Compressor failure	
	Robust optimization		
Our article	MILP	Electricity grid	Home energy management
	MINLP	Energy storage units	
	Robust optimization		

TABLE 1. A comparison of our article and other papers.

energy storage units may significantly affect the efficiency of home energy management system. A model of domestic energy streams in a smart house is shown in Figure 1. It consists of (i) electricity supplies: the electricity grid, photovoltaic, micro CHP and UPS; (ii) electricity demands (i.e., home appliances): television, fridge, light, radiator, shower, etc.; and (iii) energy storage: battery. In the electricity supplies, the UPS is used as an essential fail-safe device. If power goes down, it provides brief ride-through time during the automatic switch-over to auxiliary power. All the domestic energy devices can be controlled by a controller, that allows consumers to be able to turn on/off them.

Figure 2 illustrates the relationship of domestic energy streams in terms of mathematical notations, where y_t^{GRD} and z_t^{GRD} are the amount of electricity bought from and sold to the grid at a specific time t, respectively; s_t^{PHO} is the amount of electricity generated by photovoltaic at time t; ρy_t^{CHP} is the amount of electricity transmitted from the amount of bought gas y_t^{CHP} by micro CHP (with ρ represents the transmission coefficient) at time t; u_t^{BAT} and v_t^{BAT} are the charging and discharging rate of the battery at time t; and d_{jt} denotes the amount of electricity consumed by home appliance j at time t. This figure also represents the balance equation of domestic energy streams in a smart house.

In this study, we consider the cost minimization problem of energy consumption on a network of households under uncertainties (see Figure 3). The problem aims to minimize total energy cost (including buying gas for micro CHP, and buying/selling electricity from/to the grid) subject to the predefined constraints. Constraints may include the equations of energy balance, the profiles of energy consumption for home appliances, the maximum capability of electricity grid, computing the amount of electricity in energy storage units, the maximum capacity of energy storage units (the health of battery is taken into consideration), and the maximum charging and discharging rates (battery consistency, charging method, and temperature influence the charge and discharge rates in the current state of battery). The equations of energy balance do not include heat stream to heat store. Contribution of heat stream to energy balance is integrated in the transmission coefficient of CHP from gas to electricity. In addition, this problem studies the impact of unexpected failures on the electricity supply capability of the grid and the capacity of energy storage units, which affects significantly the energy consumption plan of consumers.

3. A JOINT CHANCE-CONSTRAINT MILP MODEL

In this section, we present a MINLP model to address the domestic energy cost minimization problem under uncertainties. Next, a joint chance-constraint programming technique is developed to solve this problem efficiently. A summary of mathematical notations is presented in Table 2. In the table, the unit measures are not described since they depend on the division of time slot, e.g., 15 minutes, 30 minutes or 60 minutes for a time slot, in the study. The relevant parameters and variables would be updated based on the division of time slot.

3.1 A MINLP model

Based on the offline optimization models in [28] and [29], we develop a MINLP model for the home energy cost minimization problem under uncertainties. As compared with the original models, it can be seen that our model has adapted the objective function 1 and the set of constraints 2–3, 5, 7–11 to formulate the cost minimization problem of energy consumption on a network of households under uncertainties. In addition, to deal with uncertainties that were not

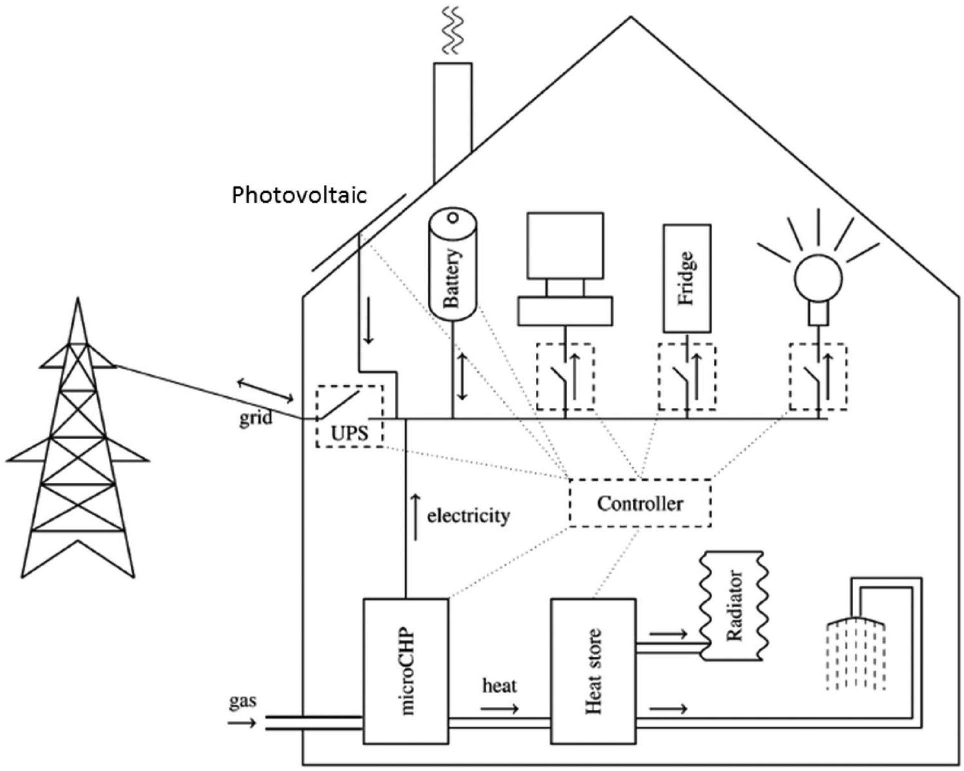


FIGURE 1. A model of home energy streams [27]: (i) Electricity supplies: the electricity grid, photovoltaic, micro CHP and UPS; (ii) Electricity demands (i.e., home appliances): television, fridge, light, radiator, shower, etc.; and (iii) Energy storage: battery.

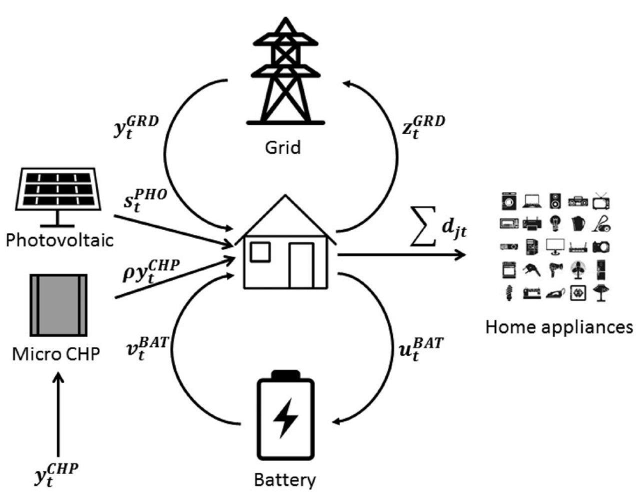


FIGURE 2. A representation of variables.

considered in [28] and [29], we add new constraints 4 and 6 in this model. Then, these new constraints are linearized into linear constraints by the joint chance-constraint programming method that was developed by [25]. In the proposed model, we extend the joint-chance constraint programming method for solving the home energy cost minimization problem under uncertainties. This model's objective function, constraints and uncertainties will be discussed in next subsections.

3.1.1. The objective function. This cost minimization problem aims to seek the optimal energy plans for a minimum cost of energy consumption under the simultaneous impact of unexpected failures on energy storage units and electricity grid. In the proposed model, the objective function is thus the minimization of total cost of energy consumption for all houses $i \in I$ during time horizon T, i.e., a subtraction between cost of bought gas and electricity amount $c_t^{CHP} y_{it}^{CHP} + c_t^{GRD} y_{it}^{GRD}$ and revenue of sold electricity amount $p_t^{GRD} z_{it}^{GRD}$ (see the objective function (1)). The optimal energy plan based on the decision variables such as the amount of gas bought (y_{it}^{CHP}), the amount of electricity bought (y_{it}^{GRD}) and the amount of electricity sold (z_{it}^{GRD}) has to be determined to minimize the total cost.

$$\min \sum_{i \in I} \sum_{t \in T} \left(c_t^{CHP} y_{it}^{CHP} + c_t^{GRD} y_{it}^{GRD} - p_t^{GRD} z_{it}^{GRD} \right) \qquad (1)$$

3.1.2. Set of constraints. Finding the optimal energy plans has been subjected to a set of constraints including the equations of energy balance, the profiles of energy consumption for home appliances, the maximum capability of

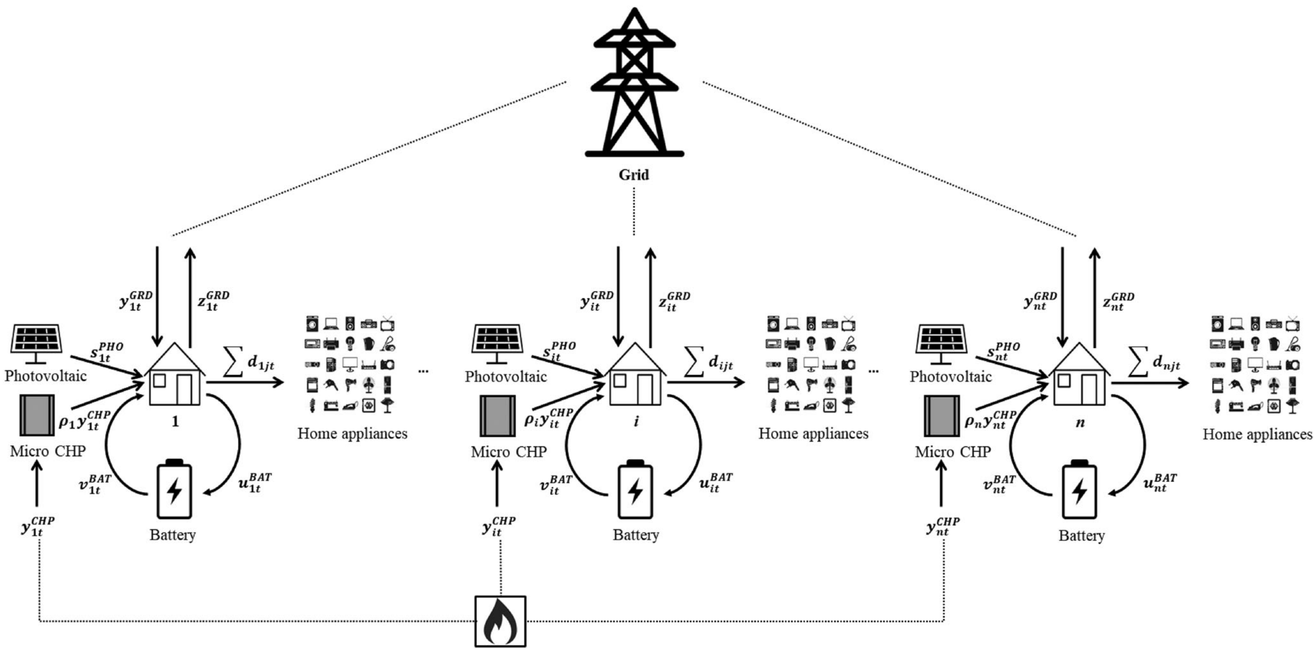


FIGURE 3. A network of home energy consumption.

electricity grid, computing the amount of electricity in energy storage units, the maximum capacity of energy storage units, and the maximum charging and discharging rates. In the MINLP model, constraints (2) represent the balance equations of acquired energy (on the left hand side) and consumed energy (on the right hand side) in each house $i \in I$ and at each time slot $t \in T$. Constraints (3) ensure that activities $j \in J$ in house $i \in I$ are scheduled between the required interval of the earliest starting time ET_{ij} and the latest starting time LT_{ij}. The constraints aim to capture types of different household, e.g., day-time operation and nighttime operation. Constraints (4) ensure that total amount of bought electricity for all households are not allowed to exceed the maximum capacity of electricity generation in the grid. Constraints (5) are used to update the current amount of electricity in energy storage units, computed by energy storage units in previous state along with charge and discharge rates in current state. Constraints (6)-(9) represent the minimum and maximum values of energy storage units, charge rate, discharge rate and micro CHP. Since only a charge or discharge state is allowed to do at a specific time, we added the binary decision variables w_{it}^{BAT} into the right-hand side of constraints (7)-(8) to ensure this. Constraints (10) and (11) are binary decision variables and non-negative values for bought and sold electricity.

$$\text{s.t. : } \rho_i y_{it}^{CHP} + y_{it}^{GRD} + s_{it}^{PHO} + v_{it}^{BAT} = z_{it}^{GRD} + \sum_{j \in J} d_{ijt} x_{ijt} + u_{it}^{BAT} \, \forall i \in I, t \in T, \tag{2}$$

$$\sum_{t=ET_{ij}}^{LT_{ij}} x_{ijt} = 1 \, \forall i \in I, j \in J, \tag{3}$$

$$\sum_{i \in I} y_{it}^{GRD} \le \theta_t^{\max}(\zeta) \, \forall t \in T, \tag{4}$$

$$e_{it}^{BAT} = e_{i,(t-1)}^{BAT} + u_{it}^{BAT} - v_{it}^{BAT} \, \forall i \in I, t \in T, \tag{5}$$

$$0 \le e_{it} \le \gamma_{it}^{\max}(\xi) \, \forall i \in I, t \in T, \tag{6}$$

$$0 \le u_{it}^{BAT} \le CR_i^{\max} w_{it}^{BAT} \, \forall i \in I, t \in T, \tag{7}$$

$$0 \le v_{it}^{BAT} \le DR_i^{\max}(1 - w_{it}^{BAT}) \, \forall i \in I, t \in T, \tag{8}$$

$$0 \le \rho_i y_{it}^{CHP} \le \kappa_{it}^{\max} \, \forall i \in I, t \in T, \tag{9}$$

$$x_{ijt}, w_{it} \in \{0, 1\} \, \forall i \in I, j \in J, t \in T, \tag{10}$$

$$y_{it}^{GRD}, z_{it}^{GRD} \ge 0 \, \forall i \in I, t \in T. \tag{11}$$

3.1.3. Uncertainties. This work has investigated the home energy cost minimization problem under the simultaneous impact of unexpected failures on energy storage units and electricity grid. In this model, the impact of unstable electricity generation (due to a shortage of electricity grid) and the declined maximum capacity of energy storage units (due to an unexpected random failure) on the cost minimization problem are thus formulated in the right hand side of Constraints (4) and (6), respectively, where $\theta_t^{\max}(\zeta)$ represents the uncertain capacity of electricity generation in the grid at time t, and $\gamma_i^{\max}(\xi)$ represents the uncertain capacity of energy storage units in house i. Because these constraints possess the nonlinear properties, we need to

Notation	Description
Sets and indexes:	
T	Set of discrete times (indexed by t)
I	Set of households (indexed by i)
J	Set of home appliances (indexed by j)
h	Number of discrete times
n	Number of households
m	Number of home appliances
Parameters:	
c_t^{CHP}	Unit cost of gas bought at time t
c_t^{GRD}	Unit cost of electricity bought at time t
p_t^{GRD}	Unit price of electricity sold at time t
s_{it}^{PHO}	Amount of electricity generated by photovoltaic in house i at time t
d_{ijt}	Electricity consumption of home appliance j in house i at time t
ET_{ij}	Earliest starting time of home appliance j in house i
LT_{ij}	Latest starting time of home appliance j in house i
ρ_i	Transmission coefficient of CHP in house i
$\kappa_{it}^{\max}$	Maximum capacity of CHP in house i at time t
$CR_i^{\max}$	Maximum charge rate of energy storage unit (i.e., battery) in house i
$DR_i^{\max}$	Maximum discharge rate of energy storage unit (i.e., battery) in house i
$\gamma_{it}^{\max}$	Maximum capacity of energy storage unit (i.e., battery) in house i at time t
$\theta_t^{\max}$	Maximum capacity of electricity generation at time t
α	Confidence level for the capacity of electricity generation in the grid
β	Confidence level for the capacity of energy storage units
Decision variables:	
x_{ijt}	Binary variable for operating home appliance j in house i at time t
y_{it}^{CHP}	Amount of gas bought by house i at time t
y_{it}^{GRD}	Amount of electricity bought by house i at time t
z_{it}^{GRD}	Amount of electricity sold by house i at time t
u_{it}^{BAT}	Charge rate of energy storage unit (i.e., battery) in house i at time t
v_{it}^{BAT}	Discharge rate of energy storage unit (i.e., battery) in house i at time t
w_{it}^{BAT}	Binary variable for charge and discharge of battery in house i at time t
e_{it}^{BAT}	Amount of electricity in energy storage unit (i.e., battery) in house i at time t

TABLE 2. The list of notations.

develop a solution method to handle them. A joint chance-constraint programming method will be developed to linearize the nonlinear terms in the constraints in next subsection.

3.2. A Joint chance-constraint programming model

A robust optimization approach, based on the joint chance-constraint programming [25], is developed to deal with the nonlinear properties in the MINLP model. For the constraints (4), let $Y_t = \sum_{i\in I} y_{it}^{GRD}\,\forall t \in T$. Given that a confidence level $\alpha \in [0,1]$ for the capacity of electricity generation in the grid, the minimum probability of occurring the event that $Y_t \leq \theta_t^{\max}(\zeta)\,\forall t \in T$ is formulated by a joint chance constraint programming

$$P\{Y_t \leq \theta_t^{\max}(\zeta), \forall t \in T\} \geq \alpha.$$

It is corresponding to

$$\inf_{P\in\mathbf{P}} P\{Y_t \leq \theta_t^{\max}(\zeta), \forall t \in T\} \geq \alpha,$$

where $\mathbf{P}$ is the set of all probability distributions for random variable $\theta_t^{\max}(\zeta)$ with known mean and variance (μ_t, σ_t^2).

Bonferroni's inequality leads to

$$\sup_{P\in\mathbf{P}} P\{\cup_{t\in T} Y_t > \theta_t^{\max}(\zeta)\} \leq 1-\alpha.$$

In addition, we have

$$P\{\cup_{t\in T} Y_t > \theta_t^{\max}(\zeta)\} \leq \sum_{t\in T} P\{Y_t > \theta_t^{\max}(\zeta)\}\,\forall P \in \mathbf{P}.$$

Set

$$\sum_{t\in T} P\{Y_t > \theta_t^{\max}(\zeta)\} \leq 1-\alpha,$$

and let $1-\alpha = \epsilon$, we obtain

$$\sum_{t\in T} P\{Y_t > \theta_t^{\max}(\zeta)\} \le \epsilon.$$

Next, let $\epsilon = \sum_{t\in T} \epsilon_t$, we get

$$\begin{aligned} &P\{Y_t > \theta_t^{\max}(\zeta)\} \le \epsilon_t \, \forall t \in T \\ &\iff P\{Y_t - \theta_t^{\max}(\zeta) > 0\} \le \epsilon_t \, \forall t \in T \\ &\iff P\{Y_t \le \theta_t^{\max}(\zeta)\} \ge 1-\epsilon_t \, \forall t \in T \\ &\iff \inf_{P\in\mathbf{P}} P\{Y_t \le \theta_t^{\max}(\zeta)\} \ge 1-\epsilon_t \, \forall t \in T \end{aligned}$$

where $\sum_{t\in T} \epsilon_t \le 1-\alpha$.

Set $\epsilon_t = \frac{1-\alpha}{h}$, the joint chance constraint programming can be derived into

$$Y_t \le \mu_t + \sigma_t \sqrt{\frac{h}{1-\alpha} - 1} \, \forall t \in T.$$

Then, constraints (4) can be written by

$$\sum_{i\in I} y_{it}^{GRD} \le \mu_t + \sigma_t \sqrt{\frac{h}{1-\alpha} - 1} \, \forall t \in T. \quad (12)$$

Similarly, constraints (6) can be derived into

$$e_{it} \le \mu_i + \sigma_i \sqrt{\frac{h+n}{1-\beta} - 1} \, \forall i \in I, t \in T, \quad (13)$$

where (μ_i, σ_i^2) are the known mean and variance for random variable $\gamma_i^{\max}(\zeta)$, and $\beta \in [0, 1]$ is a confidence level for the capacity of energy storage units.

Since constraints (12) and (13) are linear constraints, we can use any MILP solver for the domestic energy cost minimization problem under the impact of unexpected failures of electricity generation and energy storage units. The linearized model for the home energy cost minimization problem under uncertainties can be presented as follows:

[MILP]:

$$\begin{aligned} &\min \sum_{i\in I} \sum_{t\in T} \left(c_t^{CHP} y_{it}^{CHP} + c_t^{GRD} y_{it}^{GRD} - p_t^{GRD} z_{it}^{GRD} \right) \\ &\text{s.t.}: \rho_i y_{it}^{CHP} + y_{it}^{GRD} + s_{it}^{PHO} + v_{it}^{BAT} = \\ &z_{it}^{GRD} + \sum_{j\in J} d_{ijt} x_{ijt} + u_{it}^{BAT} \, \forall i \in I, t \in T, \\ &\sum_{t=ET_{ij}}^{LT_{ij}} x_{ijt} = 1 \, \forall i \in I, j \in J, \\ &\sum_{i\in I} y_{it}^{GRD} \le \mu_t + \sigma_t \sqrt{\frac{h}{1-\alpha} - 1} \, \forall t \in T, \\ &e_{it}^{BAT} = e_{i,(t-1)}^{BAT} + u_{it}^{BAT} - v_{it}^{BAT} \, \forall i \in I, t \in T, \\ &e_{it} \le \mu_i + \sigma_i \sqrt{\frac{h+n}{1-\beta} - 1} \, \forall i \in I, t \in T, \\ &0 \le u_{it}^{BAT} \le CR_i^{\max} w_{it}^{BAT} \, \forall i \in I, t \in T, \\ &0 \le v_{it}^{BAT} \le DR_i^{\max} (1 - w_{it}^{BAT}) \, \forall i \in I, t \in T, \\ &0 \le \rho_i y_{it}^{CHP} \le \kappa_{it}^{\max} \, \forall i \in I, t \in T, \\ &x_{ijt}, w_{it} \in \{0, 1\} \, \forall i \in I, j \in J, t \in T, \\ &y_{it}^{GRD}, z_{it}^{GRD} \ge 0 \, \forall i \in I, t \in T. \end{aligned}$$

We can use the simplex method in any MILP solver (e.g., CPLEX or GUROBI) to solve the linearized model. A flowchart for the proposed solution approach is shown in Figure 4. The condition for termination is to reach the predefined value of the absolute gap tolerance between the current solution and the optimality.

4. NUMERICAL EXPERIMENTS

In this section, we investigate an efficacy of solving the domestic energy cost minimization problem under the simultaneous impact of unexpected failures of electricity grid and energy storage units by the proposed model. We evaluate the efficacy on a case study in Nottingham, UK. The model is implemented in Visual Studio C++ and solved by the IBM ILOG CPLEX version 12.7 callable library. The experiments are run on the Microsoft Windows 7 Enterprise PC with an Intel Core i3-6100 Processor 2.30 GHz and 8 GB of RAM. The condition for termination in CPLEX is to reach the default value of the absolute gap tolerance (1e-6).

4.1. A case study

According to the report of the UK energy consumption [30], the domestic sector accounts for the second largest share of the final energy consumption at 28% (Figure 5). The fast growth of the UK population [31] has increased challenges in the domestic energy management. Therefore, it is essential to utilize efficiently home appliances, renewable energy resources and energy storage units.

We construct a case study based on the households' domestic energy consumption (e.g., $n = 100$) in Nottingham, UK. All the households are identical and use the same set of home appliances (e.g., $m = 15$). The description and electricity consumption of each home appliance are provided in Table 3. We investigate the domestic energy consumption of households within 24-hour (i.e., time slot = 1 hour and $h = 24$). In addition, each household is equipped a solar photovoltaic generation (e.g., 4 kWh), a battery storage (e.g., capacity 19.2 kW, and maximum charge/discharge rates 3.6 kWh or 0.2 C - a slow charger that can take between 6 and 12 hours for a full charge), and a micro CHP (e.g., capacity 7.5 kWh, and energy conversion rate 20%). The solar insolation data within a summer and winter day are shown in Figure 6.

If there is a lack of solar photovoltaic generation, a power is imported from the grid (e.g., maximum capacity 500 kW) at the prescribed rates to satisfy the households' unmet demand. We consider Economy 7 and 10 tariffs [32] for trading the

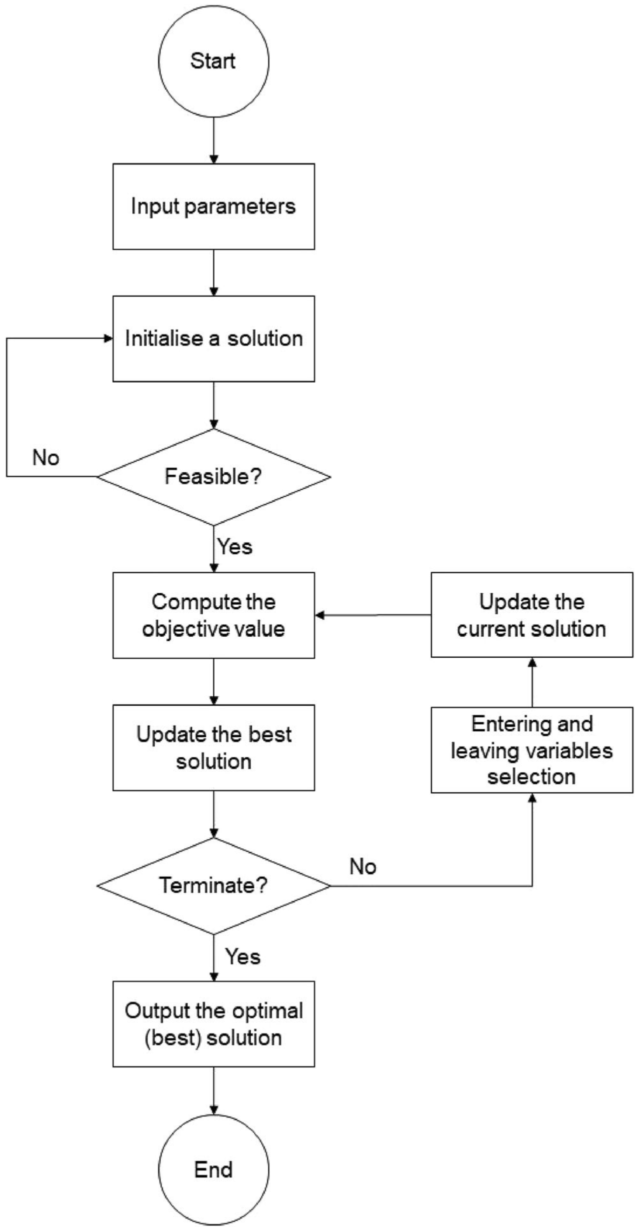


FIGURE 4. A flowchart for the proposal solution approach.

power from/to the grid. In particular, Economy 7 with an off-peak time period of 7 hours (e.g., 23:00–6:00) is levied at 8.00 pence/kWh, and the remaining time is charged at 15.98 pence/kWh (Figure 7a). Economy 10 with an off-peak time period of 10 hours (e.g., 5:00–13:00, 16:00–20:00, and 22:00–24:00) is levied at 8 pence/kWh, and the remaining time is charged at 15.98 pence/kWh (Figure 7b).

In the case study, we consider two types of household: (i) day-time operation and (ii) nighttime operation. All the activities of home appliances can be postponed. Among them, A1 (boiler) and A2 (fridge) have longer postponed interval than the others. For example, A1 (boiler) and A12 (fridge), $ET=0$ and $LT=23$ for both the households. For the remaining home appliances, $ET=0$ and $LT=11$ for the day-time operational households, while $ET=12$ and $LT=23$ for the nighttime operational households.

In addition, for the grid's uncertain capacity $\theta_t^{\max}(\zeta)$ we use mean and variance $(\mu_t;\sigma_t^2)=(200;16)\,\forall t\in\{6-9,16-21\}$ and $(\mu_t;\sigma_t^2)=(400;16)$ for the remaining time slots. For the battery storage's uncertain capacity $\gamma_i^{\max}(\zeta)$, its mean and variance $(\mu_i;\sigma_i^2)=(11;0.09)\,\forall i\in I$. Confidence values $\alpha=0.85$ and $\beta=0.80$ are applied for the grid's capacity and the battery storage's capacity, respectively. These values can be determined based on the historical data of failure events in electricity grid and energy storage or expert ideas. Users (i.e., consumers) can input the values into the model based on their experience. We also investigate the impact of unexpected disruptions, i.e., grid failure (i.e., $\theta_t^{\max}=0$) and storage failure (i.e., $\gamma_i^{\max}=0$) at some specific time slots, on the total cost of domestic energy consumption. Figures 8 and 9 show the scenarios of grid and battery storage failures, respectively. In the figures, Scenario 1 shows uncertain capacity of grid or battery storage without the impact of unexpected disruptions while Scenario 2 shows the capacity with the impact of unexpected disruptions.

In summary, there are 16 scenarios investigated in total. Each scenario is involved with a set of uncertainties in the electricity grid and the battery storage units. Our proposed model is applied to solve the instances to seek the optimal energy plans for households.

4.2. Results and discussions

In this section, we present the results (e.g., total cost and computational time) of our model for solving the case study. Based on the combination of solar insolation data (e.g., summer and winter), economic tariffs (e.g., Economic 7 and 10), and the grid's and battery storage's uncertain scenarios in the case study, sixteen instances are constructed. From Table 4, it can be seen that the average total cost for winter day (£383.23) is about 9 times higher than that for summer day (£42.83). That is because the power generated by photovoltaic in winter (5.2 kW) is lower than that in summer (30 kW), the households need to buy additional energy from the grid to satisfy their demand. In addition, the computational result shows that Economy 10 is more efficient than Economy 7 in both of seasons. In particular, the households may reduce 76.24% and 19.33% of the average total cost for summer and winter by using Economy 10 instead of Economy 7, respectively.

As investigating the uncertainties of grid and battery storage separately, it can be seen that impact of unexpected disruptions on battery storage affects significantly total cost (e.g., increasing 5.50% and 0.84% for summer and winter, respectively). The results show that the unexpected disruptions have greater impact on total cost in summer than that in winter. As for the impact of different scenarios in the grid's uncertain capacity, unexpected disruptions continue to increase average total cost (e.g., increasing 781.38% and 9.77% for summer and winter, respectively). These demonstrate the significant impact of unexpected failures/temporary disruptions in the grid and battery storage on the total cost of domestic energy consumption network.

Among two household types, total energy consumption cost for day-time operational household is lower than that for nighttime operational household. This is true because the negative impact of unexpected failures in the grid and the battery storage usually occurs in the time period after 15:00. The economic tariff's benefit in this period is not enough to offset the impact.

As compared with the energy consumption plan without the grid's and battery storage's unexpected failures, our energy consumption plan can reduce up to 30% total cost of energy consumption for the households. Once again, this shows that our model can solve efficiently the domestic energy cost minimization problem under the impact of unexpected failures in the power grid and battery storage.

For the instances of summer day (Instances 1–8), the average computational time is 1257 seconds. The corresponding value for the instances of winter day (Instances 9–16) is 590 seconds. This shows that the instances of summer day could be more difficult to solve by our model than the instances of winter day. The minimum value of computational time is 19 seconds for instance 7, and the maximum value is 4015 seconds for instance 4. The average computational time for solving all the instances is 924 seconds. This demonstrates the efficiency of our model for solving the large-sized instances, and thus it can be applied for more challenging and practical problems.

4.3. Sensitivity analysis

In this section, we analyze the impact of change of confidence level for the capacity of electricity generation in the grid (α) and that for the capacity of energy storage (β) on total cost of energy consumption. Table 5 shows the results of solving the energy cost minimization problem (i.e., Instance 1 of the case study) with a range of various confidence values α and β. Since the denominators of right-hand side in constraints 12 and 13 are $(1-\alpha)$ and $(1-\beta)$ respectively, $\alpha = 0.99$ and $\beta = 0.99$ are used to compute the corresponding values in the constraints.

From Table 5, it can be seen that total cost is not affected by change of confidence level β. For confidence level α, as increasing its value, total cost will be reduced. This could be because the average capacity of energy storage is much smaller than the average capacity of electricity generation in the grid. Figure 10 illustrates the impact of increasing confidence level α on total cost. Total cost could be approximately decreased by 50% with a high confidence level for the capacity of electricity generation in the grid (or a low probability of randomly unexpected failures). Therefore, the risk management of electricity generation in the grid is very important to reduce total cost for consumers.

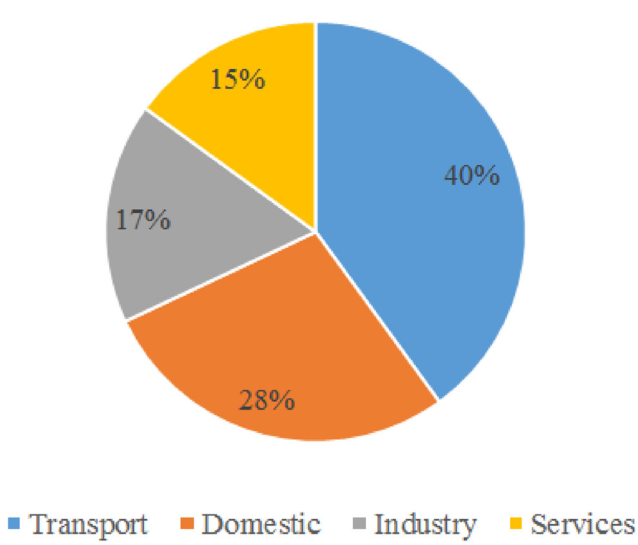


FIGURE 5. UK energy consumption percentage.

Notation	Description	Electricity consumption (kW)	Postponed activity
A1	Boiler	24.00	Yes
A2	Oven	4.40	Yes
A3	Shower	3.50	Yes
A4	Grill/Hob	3.00	Yes
A5	Washing machine	3.00	Yes
A6	Tumble dryer	1.50	Yes
A7	Dishwasher	1.50	Yes
A8	Iron	0.90	Yes
A9	Television	0.80	Yes
A10	Microwave	0.75	Yes
A11	Toaster	0.75	Yes
A12	Fridge	0.70	Yes
A13	Vacuum cleaner	0.60	Yes
A14	Hair dryer	0.25	Yes
A15	Light	0.24	Yes

TABLE 3. A set of home appliances.

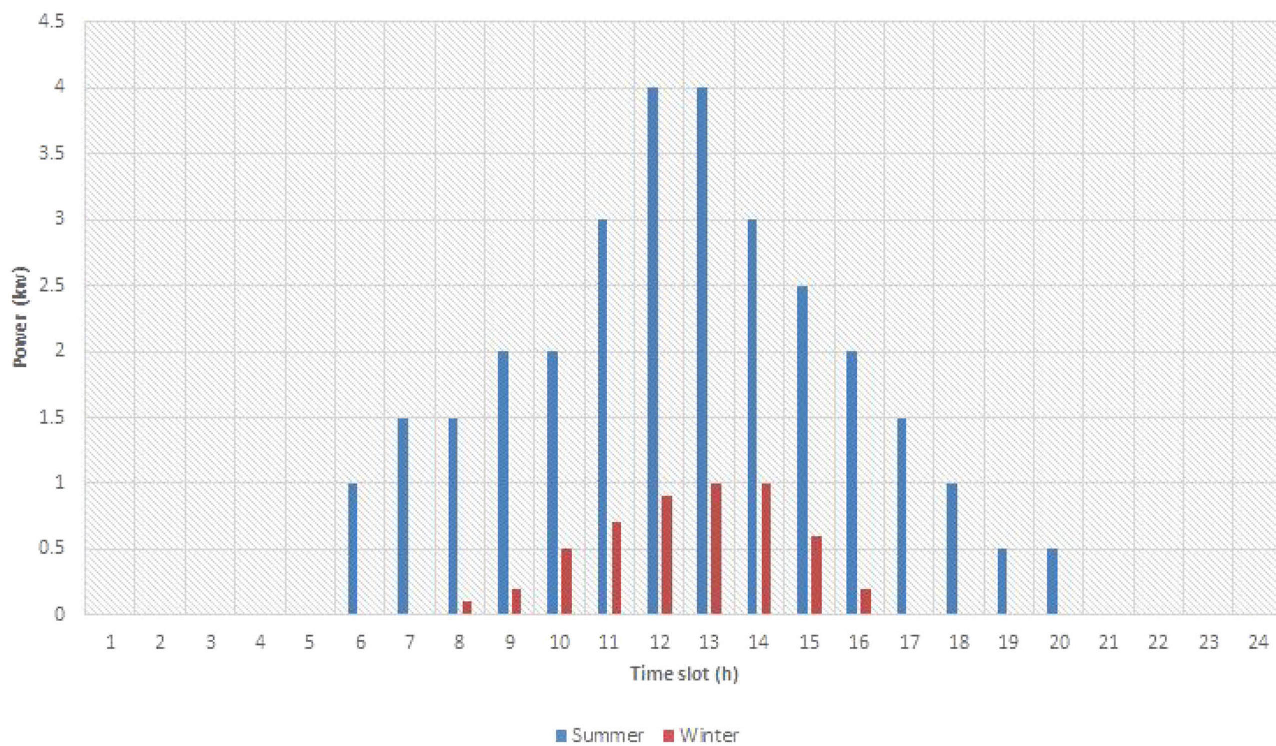


FIGURE 6. Solar insolation data. (a) Economy 7. (b) Economy 10.

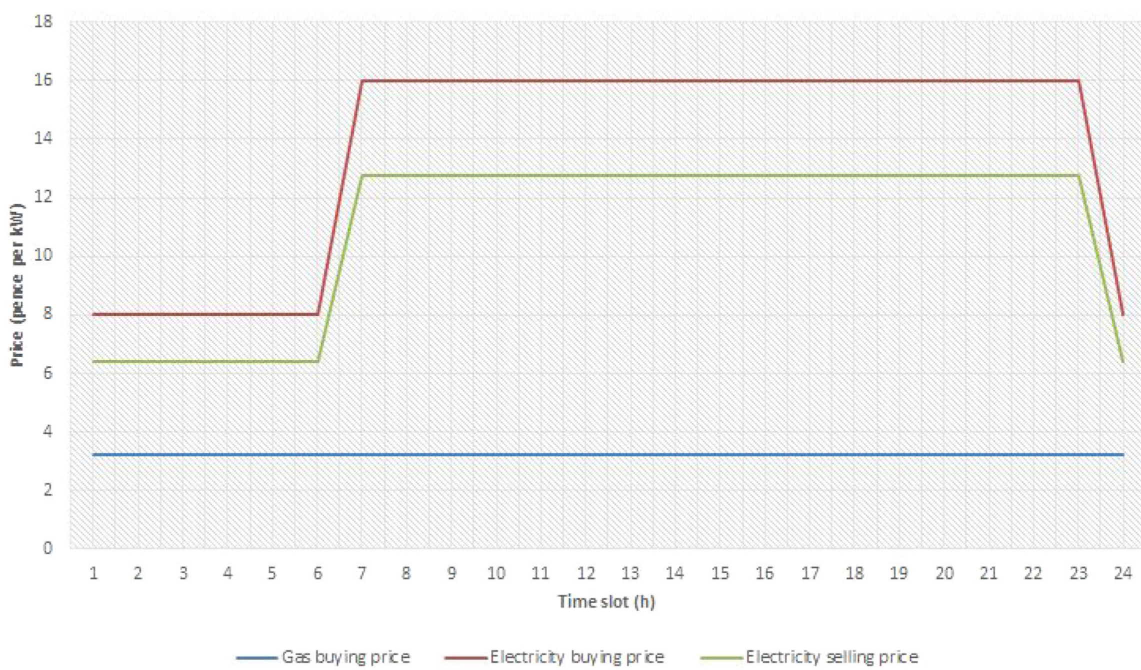
4.4. Comparison Analysis

To prove the efficiency of our proposed model as compared with the existing models, we make a comparison of these models on the case study. We solved the case study by the models of [12] and [26], and compared the results obtained with our model's result. Since their models did not consider the uncertainties (i.e., random unexpected failures on energy storage units and electricity grid), they were not used in their models. In addition, because the model of [12] is a stochastic multi-objective optimization model, to be able to make the comparison we used the minimization of total energy consumption cost as only the objective function in their model. The uncertainties such as electricity price, outdoor temperature, RES generation, water usage and non-controllable loads were also set to be deterministic to run this model for the case study. The energy consumption plans found by these two models were used to compute total costs for the problem under uncertainties.

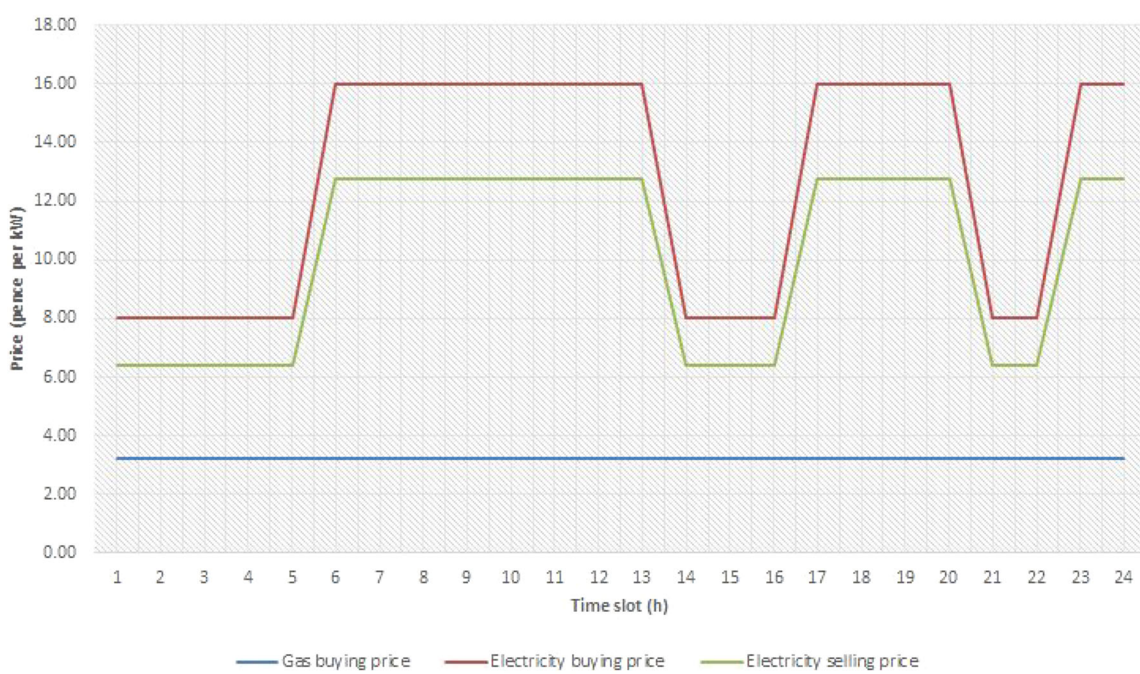
Table 6 shows the numerical results of this comparison. It can be seen that there is no difference of total costs of three models for the instances without disruptions. For other instances with disruptions, total costs of the models of [12] and [26] are increased as compared with our model's total cost. In particular, the average increments of total costs for the models of [12] and [26] are 6.58% and 15.23% respectively on the instances (summer and economy tariff 7), 7.97% and 14.69% on the instances (summer and economy tariff 10), 1.69% and 4.73% on the instances (winter and economy tariff 7), and 1.55% and 3.76% on the instances (winter and economy tariff 10). The overall average increments of total costs are 4.45% and 9.60% for the models of [12] and [26], respectively. There is no much difference in the computational time of all the models. It took about 15 minutes on average to solve the instances. The results show that our model outperforms, in terms of the solution quality, the existing models for solving the energy consumption cost minimization problem with uncertainties.

5. CONCLUSIONS AND FUTURE WORK

In this article, the energy cost minimization problem under simultaneous impact of unexpected failures (i.e., power grid and battery storage) was investigated. A joint chance-constraint MILP model was proposed to seek the optimal energy consumption plans. The model's efficiency is demonstrated by a case study in Nottingham, UK. The results show that our model can find an efficient economic tariff for minimization of total energy cost under various scenarios. Economy 10 is suggested to use, regardless of seasonal solar power generation, impact of the grid's and battery storage's unexpected failures, and household types. We can save more total energy cost in summer, since total power (kW) generated by photovoltaic in summer is greater than that in winter in the UK. Impact of the grid's unexpected failure on total energy cost is more significant than that of the battery storage's unexpected failures. Total energy cost for day-time operational household is lower than that for nighttime operational



(a) Economy 7



(b) Economy 10

FIGURE 7. Electricity and gas tariffs. (a) Without the impact of unexpected disruptions. (b) With the impact of unexpected disruptions.

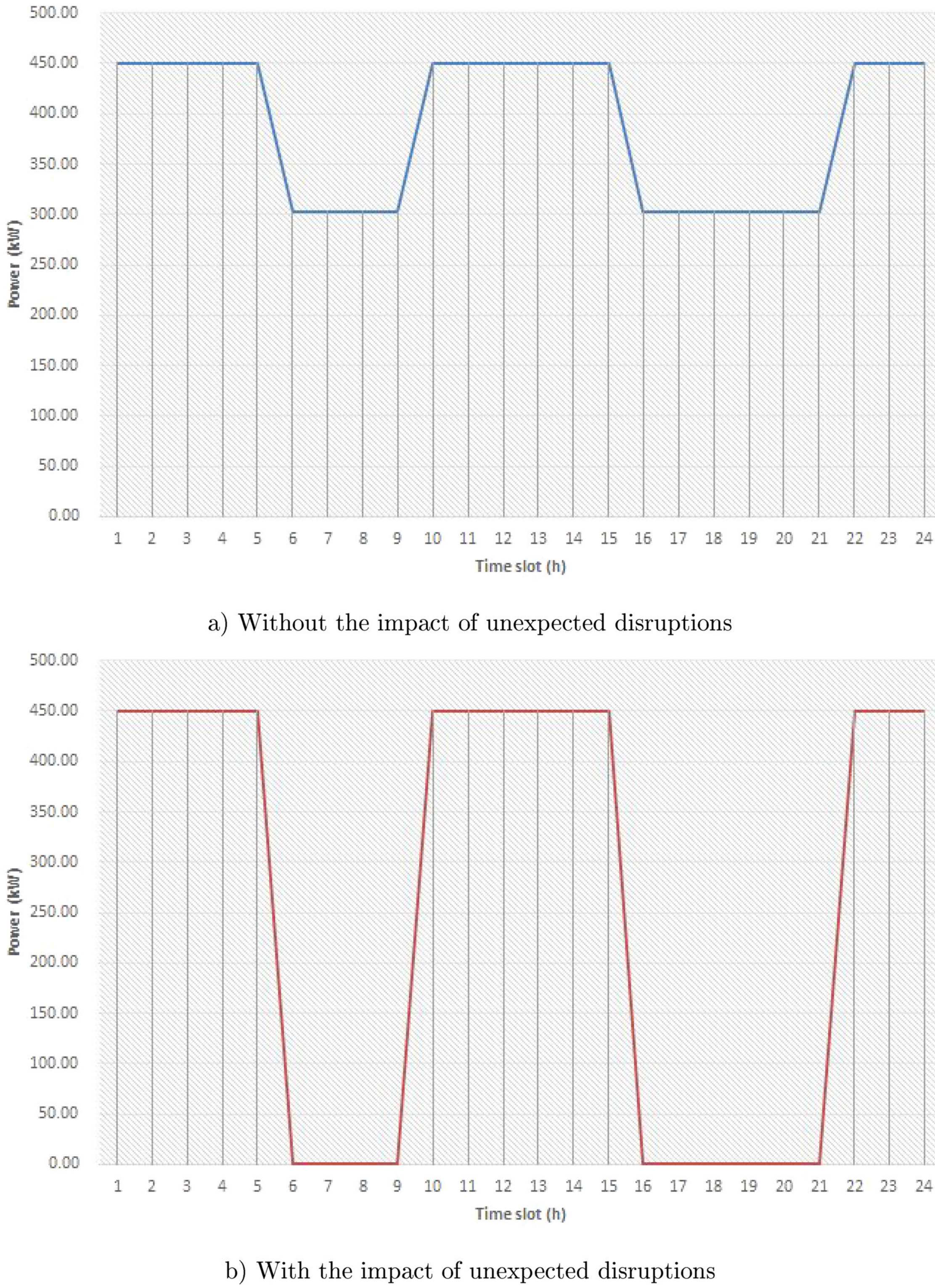
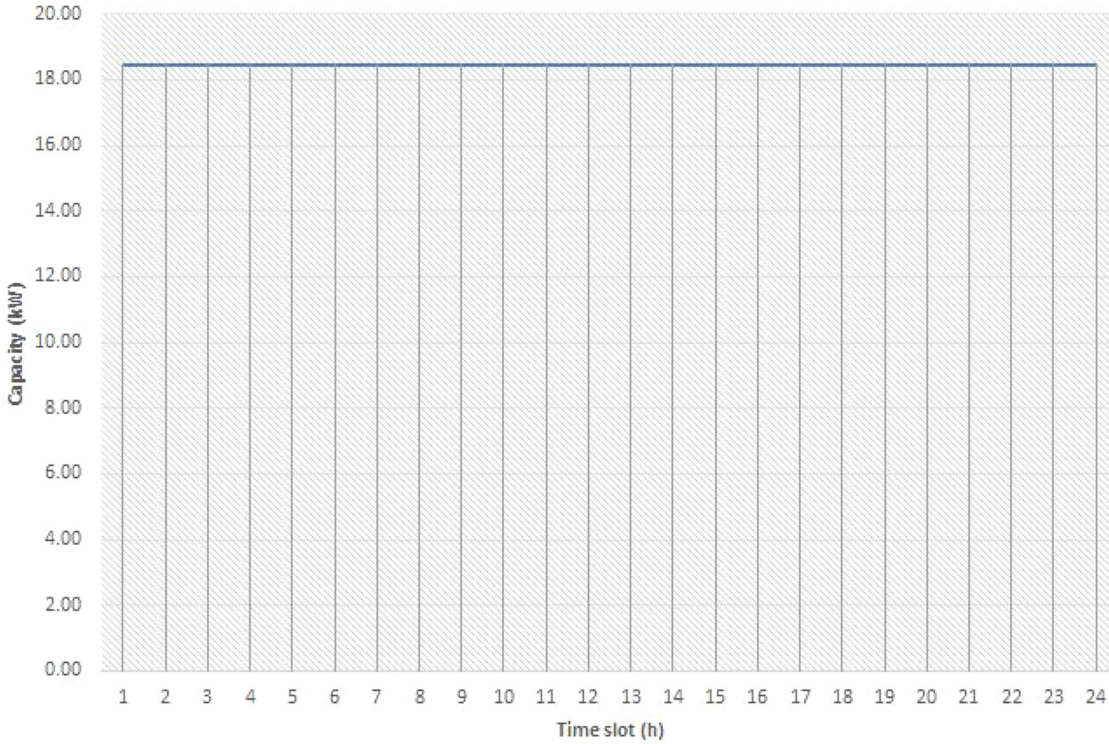
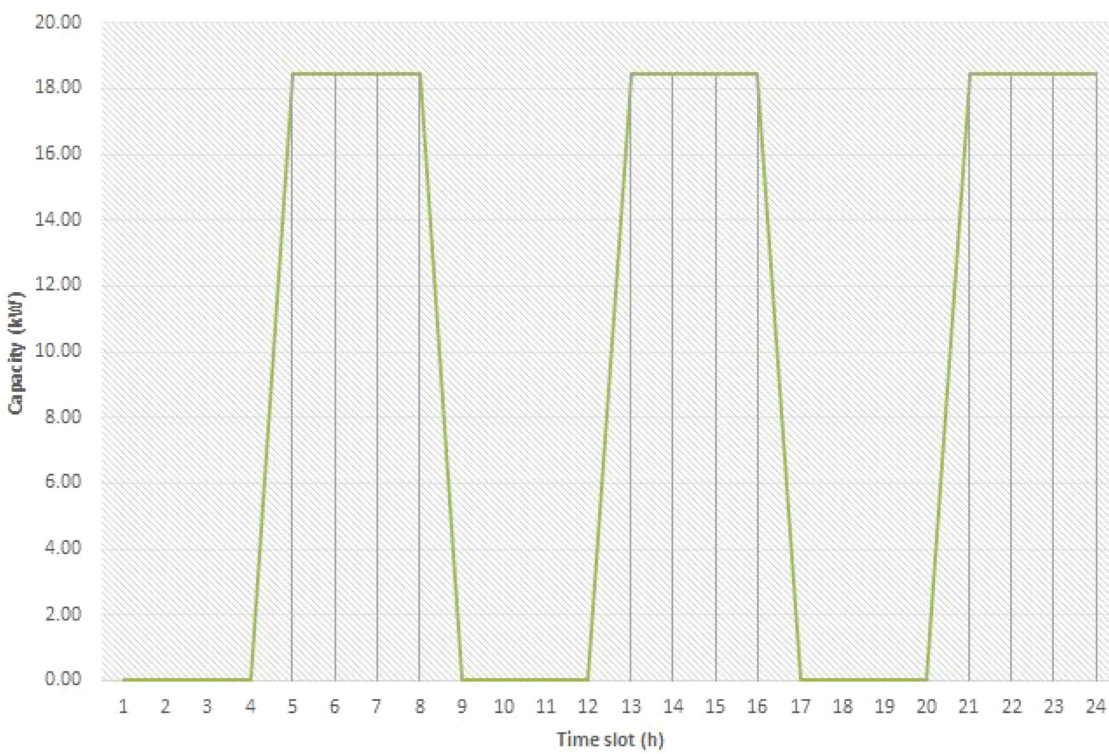


FIGURE 8. The electricity grid's uncertain capacity scenarios. (a) Without the impact of unexpected disruptions. (b) With the impact of unexpected disruptions.



a) Without the impact of unexpected disruptions



b) With the impact of unexpected disruptions

FIGURE 9. The battery storage's uncertain capacity scenarios.

Instance	Season	Tariff	Grid disruption	Battery disruption	Total cost (£)	Time (s)
1	Summer	Economy 7	No	No	59.40	88
2				Yes	61.83	1959
3			Yes	No	73.89	196
4				Yes	81.75	4015
5		Economy 10	No	No	1.84	36
6				Yes	1.96	2605
7			Yes	No	30.83	19
8				Yes	31.15	1141
9	Winter	Economy 7	No	No	410.40	236
10				Yes	414.20	167
11			Yes	No	434.60	98
12				Yes	437.70	501
13		Economy 10	No	No	318.80	43
14				Yes	318.80	119
15			Yes	No	362.70	140
16				Yes	365.80	3418

TABLE 4. Computational results for the case study.

		β										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
α	0.0	71.39	71.39	71.39	71.39	71.39	71.39	71.39	71.39	71.39	71.39	71.39
	0.1	70.98	70.98	70.98	70.98	70.98	70.98	70.98	70.98	70.98	70.98	70.98
	0.2	70.50	70.50	70.50	70.50	70.50	70.50	70.50	70.50	70.50	70.50	70.50
	0.3	69.90	69.90	69.90	69.90	69.90	69.90	69.90	69.90	69.90	69.90	69.90
	0.4	69.17	69.17	69.17	69.17	69.17	69.17	69.17	69.17	69.17	69.17	69.17
	0.5	68.24	68.24	68.24	68.24	68.24	68.24	68.24	68.24	68.24	68.24	68.24
	0.6	66.97	66.97	66.97	66.97	66.97	66.97	66.97	66.97	66.97	66.97	66.97
	0.7	65.12	65.12	65.12	65.12	65.12	65.12	65.12	65.12	65.12	65.12	65.12
	0.8	62.02	62.02	62.02	62.02	62.02	62.02	62.02	62.02	62.02	62.02	62.02
	0.9	55.02	55.02	55.02	55.02	55.02	55.02	55.02	55.02	55.02	55.02	55.02
	0.99	35.78	35.78	35.78	35.78	35.78	35.78	35.78	35.78	35.78	35.78	35.78

TABLE 5. Impact of confidence levels on total cost.

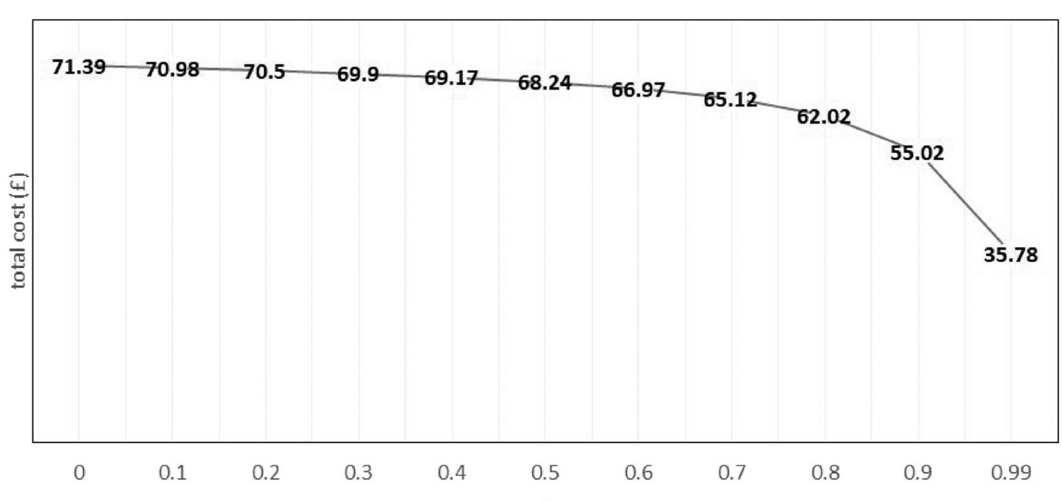


FIGURE 10. Impact of confidence level α on total cost.

Instance	Season	Tariff	Grid disruption	Battery disruption	Total cost (£)		
					Our model	[12]	[26]
1	Summer	Economy 7	No	No	59.40	59.40	59.40
2				Yes	61.83	65.90	70.85
3			Yes	No	73.89	80.58	88.64
4				Yes	81.75	89.22	100.15
Average					69.22	73.78	79.76
Increment (%)						6.58	15.23
5		Economy 10	No	No	1.84	1.84	1.84
6				Yes	1.96	2.54	3.17
7			Yes	No	30.83	32.28	33.94
8				Yes	31.15	34.36	36.49
Average					16.45	17.76	18.86
Increment (%)						7.97	14.69
9	Winter	Economy 7	No	No	410.40	410.40	410.40
10				Yes	414.20	420.30	429.53
11			Yes	No	434.60	444.21	460.95
12				Yes	437.70	450.67	476.31
Average					424.23	431.40	444.30
Increment (%)						1.69	4.73
13		Economy 10	No	No	318.80	318.80	318.80
14				Yes	318.80	324.25	331.58
15			Yes	No	362.70	370.30	382.24
16				Yes	365.80	373.94	384.78
Average					341.53	346.82	354.35
Increment (%)						1.55	3.76
Overall increment (%)						4.45	9.60

TABLE 6. Comparison results of our model and the existing models for the case study.

household. There is a significant impact of change of confidence level for the capacity of electricity generation in the grid (α), no impact of change of confidence level for the capacity of energy storage (β) on total cost of energy consumption. In addition, our solution can reduce total cost for a set of households as compared with the solution without unexpected failures, as well as the solutions obtained by the existing models of [12] and [26]. Furthermore, our model can obtain the optimal solutions for the large-sized instances in a reasonable computational time.

The mathematical model and solution approach are developed in general, and UK is used as a case study to demonstrate the efficiency of the proposed model and solution. They can be applied for other countries with the similar conditions. In the case that other countries have additional specific constraints, the model can be extended to deal with the problem of energy consumption optimization.

In the future, this model may be extended to investigate other probability distributions of random and unexpected failure events on the grid and battery storage. The impact of single-/multi-phase home appliances may be studied and integrated into our model. Furthermore, a stochastic optimization method can be developed to model the problem under the impact of uncertainty of renewable generation. Then, uncertain solar insolation data can be collected to generate the probability distribution of the data that is integrated into the stochastic optimization model to find the optimal energy plans.

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