International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

| March 2021 | Issue 46 | Volume 13 | Number 1 | Pages 91-102 |
|---|---|---|---|---|

# IMPACT OF WIND TURBINE FOR MANAGEMENT OF RESIDENTIAL ENERGY HUBS USING IGDT CONSIDERING UNCERTAINTY

**H. Shayeghi A.M. Moghaddam**

*Energy Management Research Center, University of Mohaghegh Ardabili, Ardabil, Iran*
*hshayeghi@gmail.com, ammoghaddam1389@gmail.com*

**Abstract-** This paper investigates role of wind turbines installed in the residential sector to reduce the smart building operating cost considering various uncertainties. Three different capacities are considered for turbines to compare its performance in reducing operating costs. The studied smart building includes boiler, battery storage system, CHP, thermal storage system and smart appliances. In this study, instead of modeling various uncertainties such as market price and wind speed, a novel hybrid method of Information Gap Decision Theory (IGDT) and stochastic approach has been introduced to optimal management of smart buildings. This model is a mixed-integer linear programming that provides reliable results in a reasonable amount of time and is solved using General Algebraic Modeling System (GAMS). In the recommended model, the market price uncertainty is expressed by IGDT, while the wind speed uncertainty is applied considering 50 scenarios.

**Keywords:** Wind Turbine, Residential Energy Hub, IGDT, Energy Management, GAMS.

## 1. INTRODUCTION

With the advancement of technology, along with the increasing population, the need for the use of various energies, led by electrical energy, is felt more and more. The use of fossil fuels to meet this volume of demand without proper energy management reduces and even the depletion of these resources [1]. Therefore, today's human beings are trying to use renewable resources to help meet this huge and growing demand. In addition to the use of renewable resources for production, the discussion of the management of these energy resources can also be interesting because there is a very great potential to save of energy in the building through efficient operation [2].

In addition to using renewable energy resources to supply demand, optimizing fossil fuel consumption as well as energy management is more pronounced in terms of environmental and climate change and greenhouse gas emissions [3]. Achieving all these goals requires a comprehensive strategy not only in the field of electrical energy systems but in all energy systems. Thus, energy hub as a new robust method for optimal utilization of multiple energy infrastructures; electricity and gas has been introduced [4]. The input of the energy hub can include numerous energy carriers such as gas, electricity, and direct heat. Combining multiple carriers in the energy hub input's and output's increases the flexibility and reliability of energy services. It also allows the decision-maker to choose more options to supply different loads [4].

According to statistics released by the US department of energy [5], in developed and industrialized countries, about 40% of total energy is consumed in buildings, which the share of electricity is 68%. Interestingly, according to recent research, about 20 to 30 percent of energy consumption in buildings can be saved through optimal consumption and energy management without the need to change the configuration of the power supply system. In this regard, moving towards energy management has attracted the attention of many energy supporters, managers, and designers around the world. As shown in Figure 1, the studied smart building apartment contains CHP generator, boiler, battery and thermal storage devices, wind turbine, and smart scheduled devices.

One of the vital aspects for smart home optimal energy management is applying mechanisms to balance the electricity and heat demands including uncertainty for operation cost minimizing [6]. Information Gap Decision Theory (IGDT) is a power tool to obtain smart home optimal energy management considering market price [7]. In Ref. [8] a multi-objective algorithm was reported to minimize operation cost and peak demand of the smart home for thermal/electrical appliances optimal planning as well as distributed generation sources. A new control strategy and system structure have been presented in [9] to schedule electrical appliances operation.

Using the time-of-use program a novel method has been suggested for minimizing electricity cost in a smart home [10]. A price-based home energy management program was reported in [11] to optimal scheduling of different appliances. An optimal day-ahead planning of CHPs was reported in [12] with applying thermal and electrical storage systems for increasing the benefit. An energy planning problem in a smart home has been developed in Ref. [13] for minimizing operation cost to manage different appliances and energy resources.

Using the IGDT for modeling price uncertainty was reported in Ref. [14] for solving bidding strategy problem. Also, the IGDT method to model load uncertainty has been applied for micro grid operation cost minimizing in Ref. [15].

Based on our experience, the hybrid stochastic-IGDT approach has not been represented in the literature for effective residential power hub energy management system (EMS) in the presence of wind turbine. This paper presents a novel hybrid stochastic-IGDT based approach to solve the risk-based scheduling problem for smart buildings optimal management. The studied smart home includes smart appliances, boiler, CHP, Battery Storage System (BSS), Thermal Storage System (TSS). It should be remembered that market price uncertainty is calculated using IGDT approach while set of scenarios take into account the uncertainty of wind speed [16]. The proposed home energy management model is a mixed-integer linear programming problem that provides reliable results in a reasonable amount of time and is solved using the General Algebraic Modeling System (GAMS) software.

The contribution of this study are introduced as follows:

- A residential hub energy management system optimizing using wind turbine considering
- The residential energy hub operation cost minimizing to plan and prioritize smart appliances performance considering different uncertainties
- Guarantee global optimal planning problem for smart home energy system using mixed-integer non-linear and linear programming

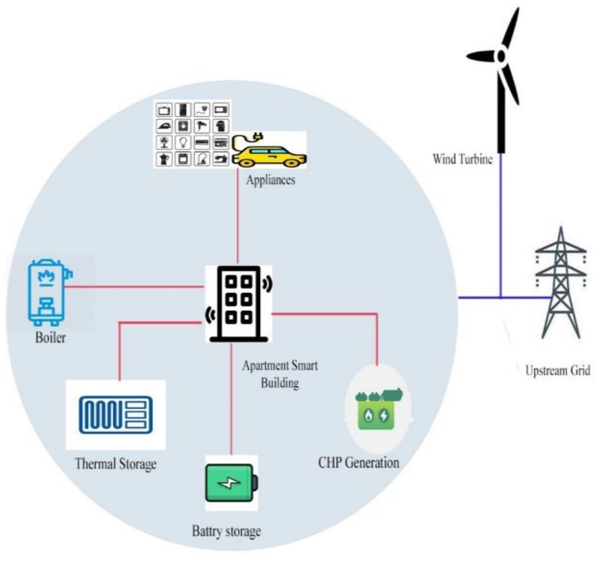


Figure 1. Positive & negative aspect of uncertainty model by IGDT

The remaining part of the paper is arranged according to the following: System model is preparing in Section 2. Hybrid stochastic-IGDT approach is introduced in Section 3 to get risk-based smart home scheduling. The apartment smart building formulation is provided in Section 4. Obtained analytical results are shown in Section 5. Finally, conclusions are delivered in Section 6.

## 2. SYSTEM MODEL

The IGDT is a way to prioritize options and decisions. Information gap means the difference between what is known and what should be known. Unlike other uncertainty modeling methods, IGDT does not require large amounts of data to model uncertainty. The IGDT uses the available data on the uncertainty parameter to inform the user of the negative and positive results for a reasonable decision that may be safe or dangerous. The positive & negative aspect of uncertainty model by IGDT is shown in Figure 2.


Figure 2. Positive & negative aspect of uncertainty model by IGDT

Sometimes, the level of uncertainty of an uncertain parameter is so severe that the system may not be able to withstand possible instabilities. This is a feature of IGDT to ensure that the system does not enter to the danger zone. Sometimes when uncertainty occurs, operators have to come up with solutions to manage the uncertainty situation. IGDT is an effective tool for evaluating and comparing strategies adopted in terms of uncertainty, and the decision maker can calculate each strategy efficacy, prioritize it, and calculate its probable objective function. The IGDT consists mainly of three parts that is shown in Figure 3: i) the system model, ii) the operational needs, and iii) the uncertainty model.

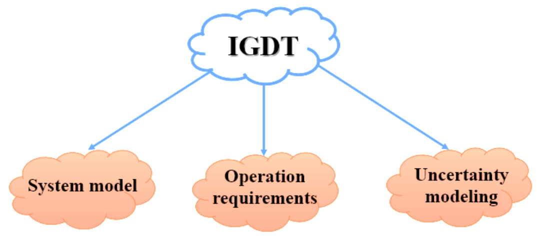


Figure 3. Different parts of IGDT

### 2.1. System Model

Using the IGDT, a system model is described by $Y(Q, L)$ where $Q$ and $L$ are the decision variable and uncertainty parameter. In this work, the market price is assumed that has uncertainty. Also, determining the power produced by each device and the valuet of electricity purchased/ sold to / from the upstream network is considered as the decision variable ($P$). Therefore, the smart home operating cost is expressed as a system model [17].

### 2.2. Operation Requirement

Operating requirement expresses the predicted values of the problem or system, which can be demand, market price and other parameters. Operational necessities are assessed based on IGDT opportunity and robustness functions. IGDT consists of two main functions, resistance and opportunity functions.

Each function is used to evaluate the positive and negative issues of uncertainty and then due to the results, proper decisions are made by the system operator. The resistance function expresses the resistance of the system against increasing the uncertain parameter. The opportunity function represents the benefit of reducing the uncertain parameter.

In simple word, resistance functions find how much more money should be paid to prevent further harmful consequences. Conversely, the opportunity functions determine how the system can profit from the possible decreasing of the uncertain parameter that is as a positive uncertainty effect. Similarly, a possible market prices decreasing could have economic profits for the system.

Operation requirements have been used to describe the expected performance of a smart home in different situations. Different functions like opportunity and robustness evaluate these expectations, which are described as follows:

$$\hat{\alpha}(c_r) = \max_{\alpha}\{\alpha : \max(Obj(P,\lambda)) \le c_r \tag{1}$$

$$\hat{\beta}(c_w) = \min_{\alpha}\{\alpha : \min(Obj(P,\lambda)) \le c_w \tag{2}$$

where, $\alpha$ is the robustness function of the IGDT approach. According to the definition of the robustness function, the critical cost of the objective function must be determined by the operator due to the defined critical value. It should be noted that for the large amount of α, the decision of the operating system of the smart home is tight to uncertainty. The opportunity function in this work is modeled by $\beta$. Unlike the robustness function, where large values were considered, here small values are considered. In other words, a small amount of β means a situation in which it will be possible to reduce operating costs, even at low market prices.

### 2.3. Uncertainty Modeling

The uncertainty model contains previous information about the uncertain parameter. The desired uncertainty is usually expressed based on the predicted value of that parameter and the uncertainty parameter. It should be noted that the use of initiative in selecting and proposing uncertainty models can be very effective. In this regard, different models such as Envelope-bound model, Energy-bound model, model based on the mean value of variance and hybrid model with probabilities is considered. As mentioned earlier, the market price is considered as the uncertainty parameter at this work. The uncertainty model used in this work is the fractional info-gap model, which is a specific model of the Envelope-bound model defined as follows [17]:

$$U(\alpha,\overline{\lambda_t}) = \{\lambda_t : \left|\frac{\lambda_t - \overline{\lambda_t}}{\overline{\lambda_t}}\right| \le \alpha\}; \alpha \ge 0 \ \forall t \tag{3}$$

In this model, uncertain parameter changes are constrained by a definite curve, where the $\overline{\lambda_t}$ specifies the shape of the curve and the $\alpha$ uncertainty parameter indicates the uncertainty size.

### 2.4. Stochastic Formulation

The Stochastic method used in this paper is the Monte Carlo method. The Monte Carlo method is based on repeated sampling to achieve computational results. This method is used to model the uncertainty of wind speed. Also, to reduce the scenario, the K-means method has been used, which has reduced the number of scenarios to 5 scenarios, and XLSTAT software has used to apply this clustering method. Her, the smart building optimal energy consumption scheduling is expressed. The cost function is reducing the smart building operating cost in some scenarios under different wind speeds as:

$$\min(OBJ) = \delta \times \left\{ \begin{array}{c} (\sum_{(j=1)}^{J}\sum_{(t=1)}^{T} \frac{\lambda^{Gas} \times P_{j,t}^{CHP}}{\eta^{CHP}}) + (\sum_{(j=1)}^{J}\sum_{(t=1)}^{T} \frac{\lambda^{Gas} \times Q_{j,t}^{Boiler}}{\eta^{Boiler}}) \\ +(\sum_{(j=1)}^{J}\sum_{(t=1)}^{T} BCC^{Battery} \times BDis_{j,t}^{Battery}) \\ +(\sum_{(j=1)}^{J}\sum_{(t=1)}^{T} TCC^{Thermal} \times TDis_{j,t}^{Thermal}) + (\sum_{(j=1)}^{J}\sum_{(t=1)}^{T} \lambda^{Wind} \times P_{j,t}^{WC}) \\ +\sum_{(j=1)}^{J}\sum_{(t=1)}^{T} \lambda_t^{Market\,Price} \times P_{j,t}^{Import}) - (\sum_{(j=1)}^{J}\sum_{(t=1)}^{T} \lambda_t^{Sell} \times P_{j,t}^{Export}) \\ +(\sum_{(j=1)}^{J}\sum_{(t=1)}^{T} \lambda_t^{Wind} \times P_{j,t}^{Wind}) \end{array} \right\} \forall s \tag{4}$$

The goal function is modeled to minimize the cost of operating a smart apartment. $\lambda^{Gas}$, $\lambda^{MarketPrice}$ and $\lambda^{Wind}$ are gas, electric and wind energy prices in (£/kWh), $\lambda^{Sell}$ is price of power sold to the upstream network in terms of (£/kWh), $\eta^{CHP}$ and $\eta^{Boiler}$ are CHP and boiler efficiency, $BCC^{Battery}$ and $TCC^{Thermal}$ are cost of maintenance of electrical and thermal storage devices in terms of (£/kWh).

## 3. HYBRID IGDT-STOCHASTIC METHOD

This section describes the IGDT approach for solving the optimal scheduling problem despite the risk and uncertainty of market price and wind speed.

### 3.1. Uncertainty Modeling

The information gap decision theory provides the operator with this feature to assess risks and opportunities. This method emphasizes how to make the right decisions with very little information [18, 19]. In uncertainty modeling using IGDT, information can be classified based on uncertain parameters. IGDT is another way to evaluate different strategies if there is uncertainty in the parameters that affect decision making. IGDT assumes a few assumptions about the structure of the uncertainty model. Uncertainties in a decision may lead to one of two things: catastrophic failure or windfall success. These two issues can be considered and examined through the function of robustness and opportunity, which will be explained below [18]. Decisions structure of proposed hybrid stochastic/IGDT optimization approach is shown in Figure 4.

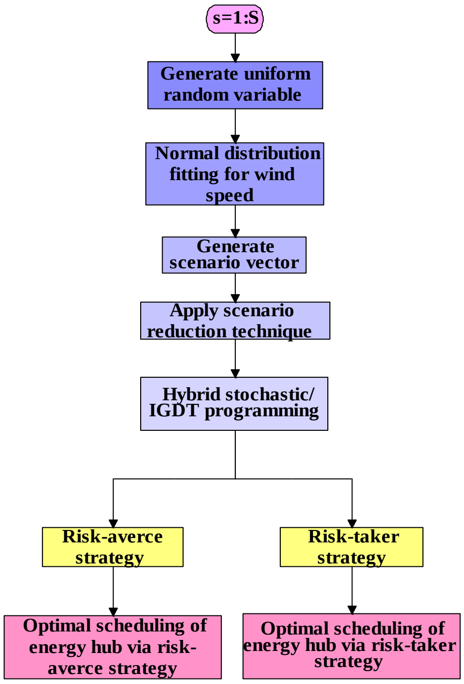


Figure 4. The proposed hybrid stochastic/IGDT optimization approach structure

### 3.1.1. Robustness Function

The robustness function describes the pernicious aspect of uncertainty and addresses the degree of resistance and security of the decision against serious uncertain changes. For a better explanation, assume $a$ is the uncertainty modeling parameter. In this case, the robustness function is given by [18]:

$$\hat{\alpha}(c_r) = \max_{\alpha}\{\alpha : \text{maximum operation cost which is not higher than a specific cost target}\} \quad (5)$$

### 3.1.2. Opportunity Function

The opportunity function expresses the propitious side of uncertainty and examines the possibility of having a profit. It addresses the resistance degree of the decision to the profitable changes of the uncertain parameter. Therefore, it can be described as [18]:

$$\hat{\beta}(c_w) = \min_{\alpha}\{\alpha : \text{ minimum operation cost which is less than a given cost target}\} \quad (6)$$

Figure 4 shows the decisions structure of the suggested hybrid stochastic-IGDT optimization method for optimal scheduling of the energy hub.

## 4. HUB MODELING

For possible interactions between several energy carriers, different technology of converters, storage devices, renewable energy sources, and upstream energy networks are studied in the form of energy hub structure. These technologies require a mathematical model defined in the energy coupling matrix to interact. Therefore, in this section, the mathematical and analytical models of energy hub components are defined, which include converters, energy storage system, and renewable resources [20].

### 4.1. Converters

Converter applies to equipment that change the type of energy provider. Converters are considered to be CHP and boiler in this work. The configuration of each converter and their system constraints are given as:

*a) Boiler*

The boiler's output power must be limited as follows by its built capacity [18]:

$$\sum_{j=1}^{J} Q_{(j.t)}^{CHP} \le L^{Boiler} \quad \forall s \quad (7)$$

where, in the smart apartment, $j$ is the smart house index, $t$ is time step and $L^{Boiler}$ is power of boiler (kWh).

*b) CHP Generator*

The power generated by CHP is limited to its capacity, for this purpose we have [18]:

$$\sum_{j=1}^{J} P_{(j.t)}^{CHP} \le L^{CHP} \forall s \quad (8)$$

where, $LCHP$ is CHP's capacity.

### 4.2. Storage Units

Storage resources are usually used to store the extra energy produced in the system and return it when needed and demand is increased. Here, two types of electrical and thermal storage have been used. Next, charging and discharging way of them is described.

*a) Electrical Storage System (ESS)*

The electric storage used in the smart home consists of several sub-batteries that at each home ($j$) can discharge or charged separately. Battery charge status and electrical storage limitations are stated by Eqs. (9) and (10).

$$BS_{(j.t)}^{Battary} = BS_{(j.t-1)}^{Battary} + (BCh_{(j.t)}^{Battary} \times \eta^{Battery} \times \delta) - \left(\frac{BDis_{(j.t)}^{Battary} \times \delta}{\eta^{Battery}}\right) \forall s \quad (9)$$

$$\sum_{j=1}^{J} BS_{(j.t)}^{Battery} \le L^{Battery} \quad \forall s \quad (10)$$

where, $B_{(j,t)}$, $BCh_{(j,t)}$ and $BDis_{(j,t)}$ are the BSS charging state, charging/discharge cycle connected to the $j$-th smart home at the time $t$ (hour). $\eta^B$ and $L^{Battery}$ are the ESS efficiency (%) and capacity (kWh), δ is simulation time period (hour). The ESS charging/discharging cycle can not occur concurrently at any smart device. Thus, we have:

$$BCh_{(j.t)} \le C^{Battery} \times X_{(j.t)}^{Battery} \quad (11)$$

$$BDis_{(j.t)} \le C^{Battery} \times (1 - X_{(j.t)}^{Battery}) \quad (12)$$

When the ESS is charging at time $t$, the $X^{Battery}{}_{(j,t)}$, is 1, and when it is discharging, the $X^{Battery}{}_{(j,t)}$ is 0. $C^{Battery}$ is the highest capacity of ESS (kW). The ESS's discharge level at each time $t$ is equivalent to or less than the ESS's charge level at the time $t$-1. Therefore, we have:

$$\frac{(BDis_{(j.t)}^{Battry} \times \delta)}{\eta^{Battery}} \le BS_{(j,t-1)}^{Battery} \quad \forall s \quad (13)$$

Total stored energy in the battery at each time is calculated using the total charged batteries at each house in the smart building.

$$BTS^{Battery} = \sum_{j=1}^{J} BS_j^{Battery} \angle t, s \tag{14}$$

where, $BTS$ is the cumulative charge status of the simple electrical storage device (kWh) at the time $t$ (hour). To stop net collection at the end, an electrical storage device (ESD) average charging condition should be close to the primary value. For this reason, the average charge value of a ESD is set to be equal to a variable parameter at the start and end of the study day [21] i.e.:

$$BTS_{(t=1)}^{Battery} = BTS_{(t=T)}^{Battery} = BVS^{Battery} \tag{15}$$

The initial charging level of the battery is denoted by $BVS$ in kWh. The ESD charge/discharge rate should not be greater than a certain number. Therefore, we have:

$$\sum_{j=1}^{J} BDis_{(j.t)}^{Battary} \le LD^{Battery} \ \forall s \tag{16}$$

$$\sum_{j=1}^{J} BCh_{(j.t)}^{Battary} \le LC^{Battery} \ \forall s \tag{17}$$

Therefore, $LC^{Battery}$ and $LD^{Battery}$ are the limits of battery charging and discharging capacity (kW).

*b) Thermal Storage System (TSS)*

A TSS, similar to the role of the ESS, is applied as the thermal energy storage main source in this smart building, and its size is equal to the size of a sub-thermal storage device in each smart house [18]. Equations (18) and (19) express the SOC of a thermal storage device and its limits.

$$TS_{(j,t)}^{Thermal} = TS_{(j,t-1)}^{Thermal} + (TC_{(j.t)}^{Thermal} \times \eta^{Thermal} \times \delta) - -(\frac{TDis_{(j,t)}^{Thermal} \times \delta}{\eta^{Thermal}}) \ \forall s \tag{18}$$

$$\sum_{j=1}^{J} TS_{(j,t)}^{Thermal} \le L^{Thermal} \ \forall s \tag{19}$$

where, $T(j,t)$ is the TSS charge state, $T_C(j,t)/T_{Dis}(j,t)$ are the value of TSS charge/discharge in each residential unit at time $t$, respectively, $\eta_{Tl}$ and $L_{Thermal}$ are TSS efficiency (%) and capacity (kWh), and $\delta$ is simulation time period (hour). The TSS's discharge level at each time $t$ is equivalent to or less than the TSS's charge level at the time $t$-1. Thus, we have [22].

$$\frac{(TDis_{(j,t)}^{Thermal} \times \delta)}{\eta^{Thermal}} \le TS_{(j,t-1)}^{Battery} \ \forall s \tag{20}$$

Total stored energy in the battery at each time is calculated using the total charged batteries at each house in the smart building. It's also formed that no thermal mass is allowed. So, the charge level of the thermal storage device (TSD) will be equivalent to its primary state at the end of the sample day. Thus, at the start and end of the sample day the charging status of the TSD is configured to be equivalent to a variable parameter. Thus, we have:

$$TS_{(j,t)}^{Thermal} = TS_{(j,t-1)}^{Thermal} + (TC_{(j.t)}^{Thermal} \times \eta^{Thermal} \times \delta) - -(\frac{TDis_{(j,t)}^{Thermal} \times \delta}{\eta^{Thermal}}) \ \forall s \tag{21}$$

$$\sum_{j=1}^{J} TS_{(j,t)}^{Thermal} \le L^{Thermal} \tag{22}$$

where, $TTS$ is the cumulative charge status of the simple battery storage device (kWh) at the time $t$ (hour), and the initial charging level of battery is denoted by $TVS^{Thermal}$ in kWh. TSD charging/discharging level is limited by its built charging/discharge capacity as:

$$\sum_{j=1}^{J} TDis_{(j,t)}^{Thermal} \le LD^{Thermal} \ \forall s \tag{23}$$

$$\sum_{j=1}^{J} BCh_{(j.t)}^{Battary} \le LC^{Battery} \ \forall s \tag{24}$$

Therefore, $LC^{Thermal}$ and $LD^{Thermal}$ are thermal capacity (kW) charging and discharging limits. Finally, it is not permitted to charge and discharge the TSD at once.

$$\sum_{j=1}^{J} TDis_{(j,t)}^{Thermal} \le LD^{Thermal} \ \forall s \tag{25}$$

$$\sum_{j=1}^{J} BCh_{(j.t)}^{Battary} \le LC^{Battery} \ \forall s \tag{26}$$

When the TSS is charging at time $t$, the $X^{Thermal}(j,t)$ is 1, and when it is discharging, it is 0. The $C^{Thermal}$ is the highest capacity of TSD (kW).

### 4.3. Wind Turbine

The production of wind turbines depends on the wind speed and can be expressed as

$$P_{wind} = \begin{cases} 0 & \text{if } \ v \le V_{ci} \\ P_{wind}^{rate} \times (\frac{v - V_{ci}}{V_R - V_{ci}}) & \text{if } \ V_{ci} \le v \le V_R \\ P_{wind}^{rate} & \text{if } \ V_R \le v \le V_{co} \\ 0 & \text{if } \ V_{co} \le v \end{cases} \quad \forall s \tag{27}$$

where, $P_{wind}$, $V_{ci}$, $V_R$ and $V_{co}$ are the rated wind turbine output power, the cut in, the nominal and the cut out speeds, respectively [21, 23].

### 4.4. Electrical Load

$$\sum_{i=1}^{I} \sum_{\theta=1}^{P_i-1} P_{i,\theta}^{App} \times \omega_{j,i,t-\theta}^{App} = P_{j,t}^{CHP} + BDis_{j,t}^{Battery} - BCh_{j,t}^{Battery} + +P_{j,t}^{Import} - P_{j,t}^{Export} \ \forall s \tag{28}$$

The interface is the operating time of each smart device, $P^{App}(i,\theta)$ is the safe power consumption of the smart device.

### 4.5. Thermal Load

The $y^{CHP}$ is the ratio of electrical to thermal power conversion in CHP and $E_{(j,t)}^{Demand}$ is heat demand and we have [24]

$$E_{(j,t)}^{Demand} = \gamma^{CHP} \times P_{(j,t)}^{CHP} + Q_{(j,t)}^{Boiler} + +TDis_{(j,t)}^{Thermal} - TCh_{(j,t)}^{Thermal} \tag{29}$$

### 4.6. Determine Start and Finish Time of Smart Devices

$$\sum_{t=T_{(j.t)}^{Start}}^{T_{j,t}^{Finish}} \omega_{(j,i,t)}^{App} \tag{30}$$

Intelligent device interface, $T_{Start,j,t}$ and $T_{Finish,j,t}$ are the nearest and farthest time of switching on and off device related to $j$th residential unit in terms of hour. The $P_i$ is the running time of the $i$th device (hour) and $\omega^{APP}{}_{(j,i,t)}$ is a binary vector that is 1 if the $i$th device linked to the $j$th smart home is active; otherwise it is 0.

## 5. CASE STUDY

The optimal smart home planning method is applied to an apartment that has 10 houses and 12 smart devices in each house. Figure 1 shows conceptual model of this smart apartment. The power consumption of these 12 devices, as well as their starting and finishing time, are stated in Tables 1 and 2. The simulation time interval is 30 minutes.

The price of the power sold to the upper network is 4 p/kWh and also the price of gas is 2.7 p/kWh. Heat demand and market price are shown respectively in Figures 5 and 6. Table 3 displays technical data of CHP, boiler, BSS, TSS, wind turbine and converter. Table 4 shows the power consumption and length of appliances operation time. As mentioned previously, 5 scenarios are considered to be the most probabilistic scenarios that obtain from K-means method, for modeling wind speed uncertainty as Figure 7.

## 6. SIMULATION RESULTS

The results assess in 5 scenarios which are described in Table 6. Initially, without considering wind turbine and uncertainty in the market price, and then with the existence of wind turbine with different capacity, it has been studied to compare the impact of wind turbines on reducing operating costs. According to the results in table 5, the operating cost has reached the lowest value despite the wind turbine with a capacity of 6 kW (0.6 kW per residential unit). Therefore, this capacity has been used to provide results. In the next step, by applying uncertainty in the market price, using the IGDT method, the performance of the smart apartment is examined. Without considering wind turbine, the objective function is 17.818 £ With the addition of wind turbines in a certain state, this amount is decreased according to the capacity of the turbine, which can be seen in Table 5. This study, which was conducted by three well-known IGDT modes, including Risk Nature, Risk taker, and Risk Averse, the results which were compiled with the uncertainty parameters in Table 7. Finally, despite all the uncertainties in the market price and wind speed, the smart home performance has been studied and the results is depicted in Figures 9 to 13.

Table 1. Smart devices earliest starting time

| | Smart home | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Smart appliances | | | | | | | | | | |
| 1 | Dishwasher | 12 | 11 | – | 13 | – | 18 | 14 | 16 | 11 | – |
| 2 | Washing machine | 16 | 14 | – | 11 | – | 22 | 22 | 20 | 16 | – |
| 3 | Spin dryer | 19 | 17 | – | 14 | – | 1 | 1 | 23 | 19 | – |
| 4 | Cooker hob | 15 | 10 | – | 13 | 10 | 14 | 18 | 11 | 10 | – |
| 5 | Cooker oven | 11 | 15 | – | 20 | 13 | 13 | – | – | 19 | 20 |
| 6 | Microwave | 21 | 13 | – | 20 | 12 | 17 | – | 18 | 20 | 10 |
| 7 | Interior lighting | 18 | – | 20 | 20 | 22 | 19 | – | 17 | 20 | 21 |
| 8 | Laptop | 19 | – | 17 | 17 | 19 | 21 | – | 18 | 19 | 19 |
| 9 | Desktop | 17 | – | 16 | – | 14 | 19 | 20 | 22 | 20 | – |
| 10 | Vacuum cleaner | 18 | – | 19 | – | 20 | 16 | 22 | 21 | 21 | 21 |
| 11 | Fridge | 1 | – | 1 | – | 1 | 1 | 1 | – | 1 | 1 |
| 12 | Electrical car | 21 | – | 20 | – | 19 | 18 | 17 | – | 21 | 19 |

Table 2. Latest finishing time of smart devices

| | Smart home | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Smart appliances | | | | | | | | | | |
| 1 | Dishwasher | 20 | 18 | – | 19 | – | 23 | 18 | 20 | 15 | – |
| 2 | Washing machine | 19 | 16 | – | 14 | – | 1 | 24 | 22 | 18 | – |
| 3 | Spin dryer | 24 | 21 | – | 17 | – | 6 | 3 | 1 | 20 | – |
| 4 | Cooker hob | 16 | 11 | – | 15 | 13 | 17 | 23 | 15 | 15 | – |
| 5 | Cooker oven | 12 | 16 | – | 22 | 16 | 16 | – | – | 24 | 1 |
| 6 | Microwave | 22 | 14 | – | 22 | 15 | 20 | – | 20 | 21 | 11 |
| 7 | Interior lighting | 24 | – | 2 | 2 | 4 | 1 | – | 23 | 2 | 3 |
| 8 | Laptop | 1 | – | 22 | 20 | 24 | 3 | – | 22 | 24 | 24 |
| 9 | Desktop | 23 | – | 20 | – | 19 | 1 | 1 | 1 | 24 | – |
| 10 | Vacuum cleaner | 2 | – | 23 | – | 1 | 22 | 4 | 4 | 4 | 5 |
| 11 | Fridge | 24 | – | 24 | – | 24 | 24 | 24 | – | 24 | 24 |
| 12 | Electrical car | 7 | – | 3 | – | 23 | 2 | 1 | – | 6 | 5 |

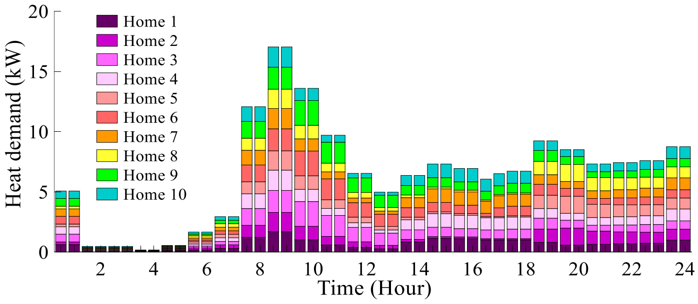


Figure 5. Heat demand [25]

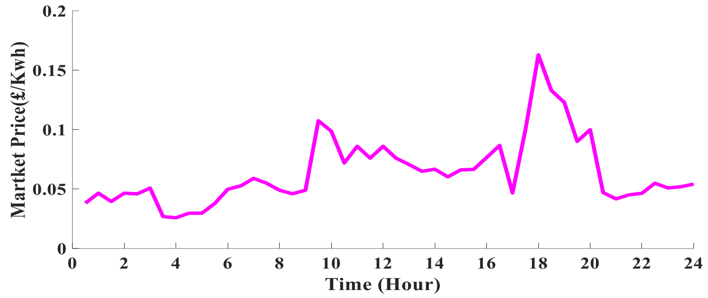


Figure 6. Market Price [25]

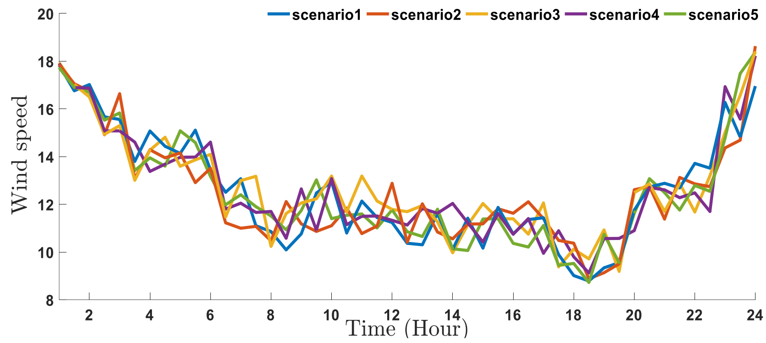


Figure 7. Wind Speed [26]

Table 3. Technical data of CHP, boiler, BSS, TSS, wind turbine and converter

| Parameters | Units | Values | Parameters | Units | Values |
|---|---|---|---|---|---|
| CHP Generator | | | | | |
| $L^{CHP}$ | KWe | 4 | $\eta^{CHP}$ | % | 35 |
| $\gamma^{CHP}$ | | 1.3 | | | |
| Boiler | | | | | |
| $L^{Boiler}$ | KWTh | 24 | $\eta^{Boiler}$ | % | 85 |
| Battery Storage System | | | | | |
| $L^{Battery}$ | KWeh | 4 | LCBattery | KWe | 4 |
| $BC^{Battery}$ | p/KWeh | 0.5 | LDBattery | KWe | 4 |
| $\eta^{Battery}$ | % | 95 | MBattery | KWe | 2 |
| Thermal Storage System | | | | | |
| $L^{Thermal}$ | KWThh | 6 | LCThermal | KWTh | 6 |
| $TC^{Thermal}$ | p/KWthh | 0.1 | LDThermal | KWTh | 6 |
| $\eta^{Thermal}$ | % | 98 | MThermal | KWTh | 3 |
| Wind Turbine | | | | | |
| $\lambda^{Windl}$ | | 0 | | | |

Table 4. Power Consumption and length of operation time of appliances

| Appliances | Power Consumption (KW) | Length of Operation Time (hour) |
|---|---|---|
| Washing Machine | Figure 8 | 2 |
| Dish Washer | Figure 8 | 2 |
| Tumble Dryer | Figure 8 | 1.5 |
| Cooker Hob | 3 | 0.5 |
| Cooker Oven | 5 | 0.5 |
| Microwave | 1.7 | 0.5 |
| Interior Lighting | 0.84 | 6 |
| Laptop | 0.1 | 2 |
| Desktop | 0.3 | 3 |
| Vacuum Cleaner | 1.2 | 0.5 |
| Fridge | 0.3 | 24 |
| Electrical Car | 3.5 | 3 |

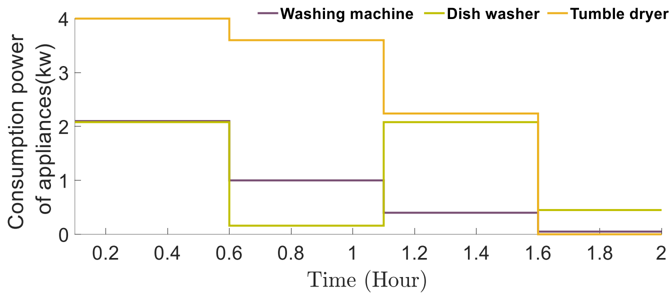


Figure 8. Consumption power of appliances

Table 5. Equipment full energy within 24 hour and values of objective functions

| Units | Scenario 1 | Scenario 2 | | |
|---|---|---|---|---|
| | kW h | kW h | kW h | kW h |
| Cost Function | 17/818 | 14.88 | 12.03 | 9.37 |
| CHP | 187.64 | 188.016 | 188.37 | 188.49 |
| Boiler | 99.40 | 99.016 | 98.72 | 98.59 |
| BSS discharge rate | 32.37 | 52.70 | 60.55 | 69.23 |
| BSS charge rate | 37.97 | 58.40 | 67.10 | 76.71 |
| BSS stored power | 112.96 | 109.20 | 112.93 | 121.87 |
| TSS discharge rate of | 75.741 | 52.63 | 56.64 | 57.63 |
| TSS charge rate | 78.864 | 79.30 | 83.46 | 84.49 |
| TSS stored Ppower | 180.26 | 194.88 | 195.61 | 197.64 |
| Wind turbine | ----- | 95.34 | 190.67 | 286 |
| Imported power from the upstream grid | 448.73 | 497.94 | 436.85 | 390.41 |
| Exported power to the upstream grid | 20.205 | 84.30 | 118.05 | 160.13 |
| Wind Turbine Capacity (kW) | | 0.2 | 0.4 | 0.6 |

Table 6. IGDT approach for smart home

| scenarios | Wind Turbine | Market price Uncertainty | Wind Speed Uncertainty |
|---|---|---|---|
| 1 | × | × | × |
| 2 | ✓ | × | × |
| 3 | ✓ | ✓ | × |
| 4 | ✓ | × | ✓ |
| 5 | ✓ | ✓ | ✓ |

Table 7. IGDT approach for smart home

| Strategy | Capacity of wind turbine (kW) | Objective Function | Uncertainty Parameter(α) |
|---|---|---|---|
| | 0.2 | 14.88 | - |
| Risk Nature | 0.4 | 12.03 | - |
| | 0.6 | 9.37 | - |
| | 0.2 | 14 | 0.188 |
| Risk Taker | 0.4 | 11.5 | 0.403 |
| | 0.6 | 8.67 | 0.657 |
| | 0.2 | 15.5 | 0.25 |
| Risk Averse | 0.4 | 13 | 0.54 |
| | 0.6 | 10.3 | 0.757 |

Table 8. Energy production of different devices in different strategies

| strategy | Turbine Cap. | CHP | Boiler | Import | Export | ESS | TSS |
|---|---|---|---|---|---|---|---|
| | 0.2 | 188 | 98/957 | 499/19 | 75/66 | 112/83 | 184/70 |
| Risk averse | 0.4 | 188/431 | 98/788 | 438/62 | 101/82 | 115/15 | 183/19 |
| | 0.6 | 188/560 | 98/670 | 396/32 | 145/45 | 126/43 | 179/61 |
| | 0.2 | 144/370 | 126/624 | 506/53 | 47/41 | 107/43 | 150/64 |
| Risk-Taker | 0.4 | 131/319 | 145/814 | 426/40 | 65/174 | 95/17 | 145/48 |
| | 0.6 | 113/325 | 145/200 | 345/27 | 106/71 | 86/19 | 137/46 |
| | 0.2 | 188/016 | 99/016 | 494/94 | 84/297 | 111/06 | 193/38 |
| Risk-Neutral | 0.4 | 188/371 | 98/720 | 442/85 | 188/05 | 112/52 | 210/28 |
| | 0.6 | 188/496 | 98/598 | 381/41 | 160/13 | 120/84 | 216/48 |

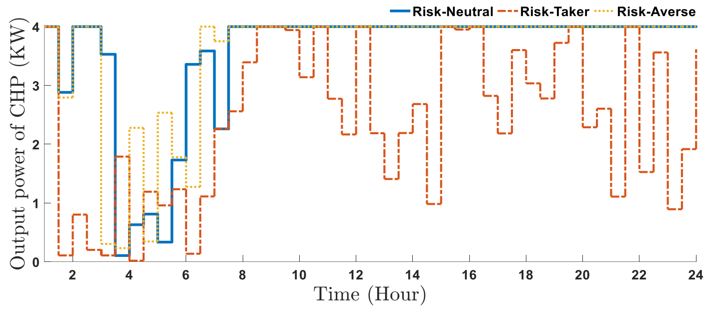


Figure 9. CHP Output power with 0.6 kW capacity of wind turbine

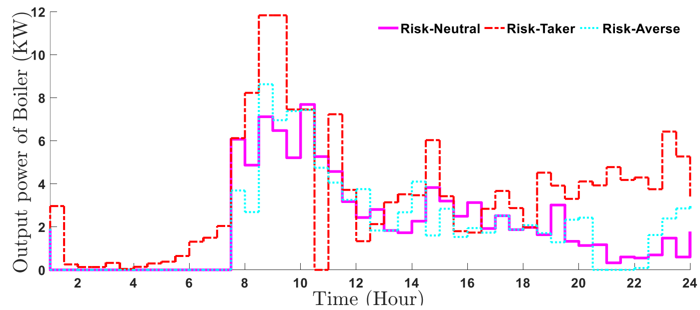


Figure 10. Boiler Output power with 0.6 kW capacity of wind turbine

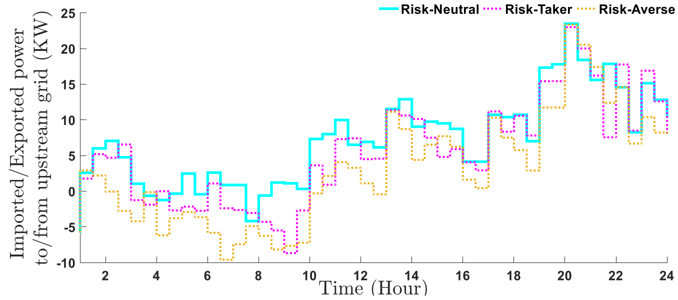


Figure 11. Imported/exported power to/from upstream grid with 0.6 kW capacity of wind turbine

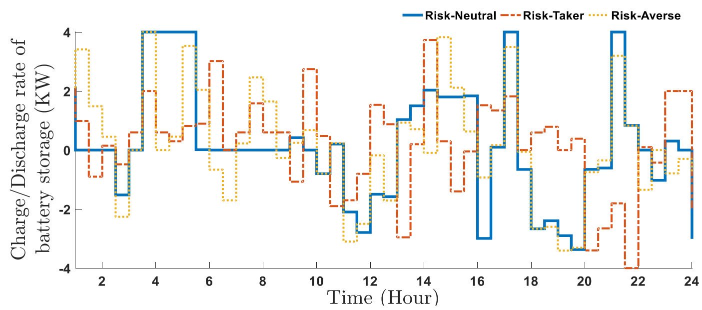


Figure 12. Charge/discharge rate of battery with 0.6 kW capacity of wind turbine

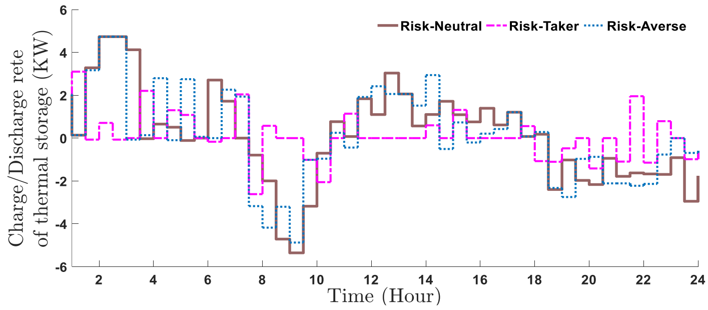


Figure 13. Charge/discharge rate of thermal storage with 0.6 kW capacity of wind turbine

## 7. CONCLUSION

In this work, the performance of wind turbines in three different capacities in the operation of smart homes using the IGDT risk method is evaluated. The smart home has CHP, Smart appliances, Boiler, electric and thermal storage and wind turbine. In this article, wind turbines with three capacities of 0.2, 0.4 and 0.6 kW are considered for each house. Based on the obtained results, with the presence of wind turbine in three defined capacities, the amount of objective function for capacity of 0.2, 16.5%, for capacity of 0.4 about 32.5% and for capacity of 0.6 by 45.4% in the amount of operating costs due to the first scenario (17.818) has decreased (Table 5). Then, by applying the uncertainty in market price by IGDT method and wind speed by stochastic method, the system model presented by Risk base and Risk-averse are applied in the form of robustness and opportunity functions. By studying the results of resistance function of the IGDT, considering the risk averse strategy, the operating cost of the smart home is increased by 5%, while the resistance of the smart building against the increasing of market price is increased to 25%. It is indicated that the smart building is robust to the market price increasing for 0.2 kW of wind turbine capacity. With 0.4 kW of wind turbine capacity, operation cost is increased by 8%, while the resistance of the smart building is increased to 54% against the market price increasing, and at the largest capacity of wind turbine, operating cost of the smart home increased by 10%, while the resistance of the smart building is increased to 75% against the market price increasing.

On the other hand, using the results of the IGDT opportunity function in the form of a risk seeker strategy, the smart home can get 18.8% economic gains from a market price reduction of up to 1 £ to 14 at the first capacity of wind turbine. With the 0.4 kW capacity of wind turbine smart home can get 40.3% economic gains from a market price reduction and 65.7% economic gains at the largest capacity of wind turbine. With the help of these strategies, which are derived from the function of resistance and opportunity, the smart home energy management system can make the right decisions to handle different uncertainty output conditions.

## NOMENCLATURE

### 1. Sets

$t$ Time step

$j$ Smart appliances index

$\theta$ Operation time index of every smart appliance

### 2. Parameters

$\delta$ Simulation time interval (hour)

$\lambda^{Gas}$ $\lambda^{sell}$ Gas price and selling power cost to grid (£/kwh)

$\lambda_t^{MarketPrice}$ $\hat{\lambda}_t^{MarketPrice}$ Real and Forecasted market price (£/kwh)

$\eta^{CHP}, \eta^{Boiler}, \eta^{Battery}$ $\eta^{Thermal}$ CHP, Boiler, BSS & TSS efficiencies (%)

$BCC^{Battery}, TCC^{Thermal}$ Battery/thermal storage system maintenance cost (£/kwh)

$\gamma^{CHP}$ Power to heat conversion ratio in CHP generator

$P_{i,\theta}{}^{App}$ $i$th appliance consumption power (kw)

$P_i$ Operation time of $i$th appliance length (hour)

$LD^{Battery}$, $LC^{Battery}$ Discharge/charge battery storage system limit (kw)

$LD^{Thermal}$, $LC^{Thermal}$ Discharge/charge thermal storage system limit (kw)

$L^{CHP}$, $L^{Boiler}$, $L^{Battery}$, $L^{Thermal}$ CHP, boiler, BSS, TSS capacities (kwh)

$T_{j,i}{}^{Start}$, $T_{j,i}{}^{Finish}$ $i$th appliance earliest starting/ latest finishing time for the $j$th smart home (hour)

### 3. Variable

$P_{j,t}^{CHP}$, $Q_{j,t}^{Boiler}$ CHP/boiler output power for $j$th smart apartment at time t (kw)

$P_{j,t}^{Import}$, $P_{j,t}^{Export}$ Imported/exported power from/to upper grid for jth smart home at time $t$ (kw)

$TC_{j,t}^{Thermal}$, $TD_{j,t}^{Thermal}$ TSS charge/discharge rate for $j$th smart home at time $t$ (kw)

$BC_{j,t}^{Battery}$, $BD_{j,t}^{Battery}$ BSS charge/discharge rate for $j$th smart home at time $t$ (kw)

$BS_{j,t}^{Battery}$, $TS_{j,t}^{Thermal}$ Battery/thermal storage system SOC for jth smart home at time $t$ (kwh)

$BTS_t^{Battery}$, $TTS_t^{Thermal}$ Total SOC of central battery/thermal storage system at time $t$ (kWh)

$BVS^{Battery}$, $TVS^{Battery}$ Battery/thermal storage system initial state (kWh)

### 4. Binary Variable

$X_{j,t}^{Grid}$ is 1 if electricity is bought from upper grid by the $j$th smart home, otherwise 0

$X_{j,t}^{Thermal}$ is 1 if TSS is charged at time $t$; if discharged equal to 0.

$X_{j,t}^{Battery}$ is 1 if BSS is charged at time $t$; if discharged equal to 0.

$\omega_{j,t}^{App}$ is 1 if the $i$th device for $j$th smart home is active; otherwise 0

### 5. Function

$\alpha(c_R)$, $\beta(C_W)$ Robustness and opportunity functions

$C^{Battery}$, $C^{Thermal}$, $C^{Grid}$ Maximum capacity of BSS,TSS and bought power from upper grid (kW)

$C_R$, $C_W$ Critical cost for the robustness and opportunity function (£)

## REFERENCES


[1] D. Setlhaolo, X. Xia, "Combined Residential Demand Side Management Strategies with Coordination and Economic Analysis", Int J Electr Power Energy Syst, No. 79, pp. 150-60, 2016.

[2] M. Liserre, T. Sauter, J.Y. Hung, "Integrating Renewable Energy Sources into the Smart Power Grid Through Industrial Electronics", IEEE Industrial Electronics Magazine, Vol. 4, No. 1, pp. 18-37, 2010.

[3] A. Dolatabadi, B. Mohammadi Ivatloo, M. Abapour, S. Tohidi, "Optimal Stochastic Design of Wind Integrated Energy Hub", IEEE Transactions on Industrial Informatics, 2017.

[4] M. La Scala, A. Vaccaro, A.F. Zobaa, "A Goal Programming Methodology for Multiobjective Optimization of Distributed Energy Hubs Operation", Applied Thermal Engineering, Vol. 71, No. 2, pp. 658-666, 2014.

[5] M. Fotuhi Firuzabad, M.H. Barmayoon, A. Rajabi Ghahnavieh, M. Moeini Aghtaie, "An Investigation on the Role of Energy Storage Usage in Residential Energy Hubs", 23rd Iranian Conference on Electrical Engineering, Tehran, Iran, pp. 1636-1641, 2015.

[6] A. Maleki, M. Gholipour Khajeh, Ameri, "Optimal Sizing of a Grid Independent Hybrid Renewable", International Journal of Electrical Power & Energy Systems, Vol. 83, pp. 514-524, 2016.

[7] K. Zare, S. Nojavan, B. Mohammadi Ivatloo, "Application of Fuel Cell and Electrolyzer as Hydrogen Energy Storage System in Energy Management of Electricity Energy Retailer in the Presence of the Renewable Energy Sources and Plug-In Electric Vehicles", Energy Convers Manage Vol. 136, pp. 404-417, 2017.

[8] E. Shirazi, S. Jadid, "Optimal Residential Appliance Scheduling under Dynamic Pricing Scheme via HEMDAS", Energy and Buildings No. 93, pp. 40-49, 2015.

[9] M. Shakeri, M. Shayestegan, H. Abunima, S.M. Salim Reza, M. Akhtaruzzaman, A.R.M. Alamoud, et al., "An Intelligent System Architecture in Home Energy Management Systems (HEMS) For Efficient Demand Response in Smart Grid", Energy and Buildings, Vol. 138, pp. 154-164, 2017.

[10] S. Rajalingam, V. Malathi, "HEM Algorithm Based Smart Controller for Home Power Management System", Energy and Building, Vol. 131, pp. 184-192, 2016.

[11] M. Rastegar, M. Fotuhi Firuzabad, H. Zareipour, "Home Energy Management Incorporating Operational Priority of Appliances", Int. J. Electr. Power Energy Syst., Vol. 74, pp. 286-292, 2016.

[12] M. Kia, M. Setayedh Nazar, M.S. Sepasian, A. Heidari, P. Siano, "Optimal Day Ahead Scheduling of Combined Heat and Power Units with Electrical and Thermal Storage Considering Security Constraint of Power System", Energy, Vol. 120, pp. 241-252, 2017.

[13] M. Rahmani Andelibi., "Scheduling Deferrable Appliances and Energy Resources of a Smart Home Applying Multi-Time Scale Stochastic Model Predictive Control", Sustain Cities Soc, Vol. 32, pp. 338-347, 2017.

[14] S. Nojavan, K. Zare, "Risk-Based Optimal Bidding Strategy of Generation Company in Day-Ahead Electricity Market Using Information Gap Decision Theory", Int. J. Electr Power Energy Syst., Vol. 48, pp. 83-92, 2013.

[15] S. Nojavan, M. Majidi, K. Zare, "Performance Improvement of a Battery/PV/Fuel Cell/Grid Hybrid Energy System Considering Load Uncertainty Modeling Using IGDT", Energy Convers Manage, No. 147, pp. 29-39, 2017.

[16] J. M Morales, A. J. Conejo. K. Liu, J. Zhong, "Pricing Electricity in Pools with Wind Producers", IEEE Trans Power Syst, Vol. 27, No. 3, pp. 1366-1376, 2011.

[17] D. Zhang, S. Liu, L. G. Papageorgiou, "Fair Cost Distribution Among Smart Homes with Microgrid", Energy Convers Manage Vol. 80, pp. 498-508, 2014.

[18] A. Najafi Ghalelou, S. Nojavan. K. Zare, "Heating and Power Hub Models for Robust Performance of Smart building Using Information Gap Decision Theory", Electrical Power and Energy Systems, Vol. 98, pp. 23-35, 2018.

[19] M. Rastegar, M. Fotuhi Firuzabad, H. Zareipour, M. Moeini Aghtaieh, "Probabilistic Energy Management Scheme For Renewable-Based Residential Energy Hubs", IEEE Transactions on Smart Grid, Vol. 8, No. 5, pp. 2217-2227, 2017.

[20] M. Geidl, G. Andersson, "A Modeling and Optimization Approach for Multiple Energy Carrier Power Flow", IEEE Russia Power Tech., St. Petersburg, Russia, pp. 1-7, 2005.

[21] P. Giorsetto, K.F. Utsurogi , "Development of a New Procedure for Reliability Modeling of Wind Turbine Generators", IEEE Trans. Power Apparat Syst., Vol. 102, No. 1, 1983.

[22] A. Shahmohammadi, M. Moradi Dalvand, M.S. Ghazizadeh, A. Salemnia, "Energy Hubs' Structural and Operational Linear Optimization with Energy Storage Elements", 2nd International Conference on Electric Power and Energy Conversion Systems (EPECS), Sharjah, United Arab Emirates, pp. 1-6, 2011.

[23] J.F. Restrepo, F.D. Galiana, "Assessing the Yearly Impact of Wind Power through a New Hybrid Deterministic/Stochastic Unit Commitment", IEEE Trans. Power Syst., Vol. 26, No. 1, pp. 401-410, 2011.

[24] B. Khoshnevisan, S. Rafiee, M. Omid, H. Mousazadeh, S. Shamshirband, S.H.A. Hamid, "Developing a Fuzzy Clustering Model for Better Energy Use in Farm Management Systems", Renewable and Sustainable Energy Reviews, Vol. 48, pp. 27-34, 2015.

[25] BMRS T.N.E.T. Arrangements, www.bmreports.com, 2018-06-29.

[26] N. Pardo, J.A. Moya, "Prospective Scenarios on Energy Efficiency and $CO_2$ Emissions in the European Iron & Steel Industry", Energy, Vol. 54, pp. 113-128, 2013.

## BIOGRAPHIES

**Hossein Shayeghi** received Ph.D. degree in Electrical Engineering from Iran University of Science and Technology, Tehran, Iran in 2006. He is currently a Full Professor and the Scientific Director of the Energy Management Research Center, University of Mohaghegh Ardabili, Ardabil, Iran. His research interests are power system control and operation, microgrid and smart grids control and energy management and FACTs device. He has authored and co-authored of 12 book chapters in international publishers and more than 420 papers in international journals and conference proceedings that received in Google Scholar more than 5501 citations with an H-index equal to 38. He has been included in the Thomson Reuters' list of the top one percent of most-cited technical Engineering scientists in 2015-2020, respectively. He is editor-in-chief of Journal of Operation and Automation in Power Engineering and Journal of Energy Management and Technology and also senior member of IEEE.

**Amir Mohammad Moghaddam** was born in Zanjan, Iran, in 1996. He received the B.Sc. degree in Electrical Engineering in 2017, and the M.Sc. degree in Technical Engineering from University of Mohaghegh Ardabili, Ardabil, Iran in 2020. His research interests are renewable energy, smart grids, energy managemant, information gap decision theory (IGDT).