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Weekly Energy Management of a Smart Home based on the Internet of Things

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Abstract: Energy management and related issues are perhaps the most important challenges facing electricity distribution companies in the modern era. Optimizing energy consumption in smart homes has attracted the attention of advanced countries in recent years due to their ability to reduce carbon dioxide gas produced from fossil fuels. For this purpose, in this study, planning the energy management of a smart home based on the Internet of Things to investigate its effect on reducing the weekly cost of energy consumption of a smart home in normal mode and reducing the amount of energy not supplied when the smart home is disconnected from the network, with it is suggested to consider the behavior of household consumers for energy planning during a week. In this study, in addition to considering the role of controllable and uncontrollable household loads in improving the technical and economic goals of the smart home, from distributed energy resources such as energy storage system (ESS), plug in hybrid electric vehicle (PHEV), photovoltaic system (PV) and wind turbine (WT) have been used in smart home energy management. In this research, the linearization of non-linear mathematical equations has been used to reduce the calculation time and reduce the complexity of the calculations. In this study, the smart home is examined in normal mode and in the mode of disconnection from the main network. The results show that the presence of energy resources in smart homes and the optimal energy management of household loads can have an effective effect on reducing the cost of energy consumption and the energy not supplied.

Keywords: *smart home, Internet of Things, home energy resources, reducing the cost of energy consumption, reducing the energy not supplied.*

1- Introduction

A smart home can do all the internal issues of the house in an automated way. A fully intelligent home is not limited to controlling lighting systems or curtains and controlling ventilation. Smart homes should be a constant companion in all dimensions from irrigation to household appliances. The components of the smart home must communicate with each other in an integrated and logical system using modern communication technologies.

A smart home with the IoT can automatically meet the smallest needs of a family. The presented materials show that researchers have done the study of smart homes from different aspects, and in the next section, some of the recent researches that are in line with the subject of the paper have been presented and analyzed.

In recent years, extensive researches have been done in the development algorithm for the optimal use of home energy management systems. In [17], a household appliance-scheduling framework based on mixed integer linear programming is proposed, in which electric energy is only purchased from the grid and the electricity tariff for the next 24 hours is known. In [18], the device performance scheduling method is introduced, in which costs are saved by shifting the consumption time of household loads.

In [19], a smart residential microgrid consisting of 30 homes is considered. A mixed integer linear programming model has been used to minimize the day a-head costs including operating and energy costs. The current research considers solar energy in addition to other resources available at smart home, and instead of considering the definite production of renewable energy sources such as WT and PV, it involves the uncertainty of these resources in planning. Considering a greater number of smart home appliances and their timing is also one of the innovations of this article.

There is a general agreement that user involvement is necessary to achieve better energy management and good organization [20]. Based on this, different methods have been planned for the implementation of demand-oriented home energy management solutions.

The authors in [21] settled and investigated a smart home planning structure using simulation software, and developed an end-user home appliances interface to envision and accomplish home energy consumption through the HEMs. In this paper, user-controlled hourly energy consumption is modeled. The results show the avoidance of energy waste through energy management,

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monitoring and controlling daily energy consumption of smart home.

The authors in [22] introduce intelligent agent-based HEMS, which combine electricity tariff information, smart metering and IoT-based smart home loads to design a smart system in which users, microgrid operators and energy suppliers can benefit from energy management mechanisms.

Providing real-time energy management to smart homes is an important method in achieving energy usage efficiency. Various studies such as [23] have studied real time meter reading which shows bidirectional power exchanges between energy suppliers and consumers via HEMS.

The authors in [24] presented a hybrid renewable energy system that combines a photovoltaic system and a diesel system with battery energy storage. In this study, to determine the variable performance of the hybrid system and to maintain the charge and discharge status of the energy storage battery according to weather conditions, an intelligent home energy management control based on fuzzy logic control is considered. The results obtained in this study show the feasibility and reliability of the proposed system. A self-controlled hybrid renewable energy as a backup source for smart home is introduced and analyzed.

According to the studies presented above, many researches have been done in the field of energy management of smart homes. In recent studies, home energy management has been analyzed from various aspects, but smart home energy management has not been considered in the presence of various energy resources that can participate in home energy management. In addition, reducing the amount of ENS in the presence of a disturbance has not been studied. In addition, reducing the cost of electric energy consumption of the smart home, taking into account the uncertainty of the renewable energy resources available inside the smart home, has not been considered. All past studies on household electrical energy management have used non-linear mathematical equations, which increase the calculation time. In the next section, smart home energy management strategy will be discussed.

2- Problem statement

Planning the optimal use of smart and programmable home equipment is one of the most important activities that smart homes have faced. In addition, the impact of this planning to distribution network exploitation plan is one of the most important activities that distribution operators have face [25]. In this section of the paper, the strategy of energy management in a smart home that is based on the IoT is analyzed and investigated. In the following, the proposed strategy is introduced.

2.1 Proposed strategy for smart home energy management

The home energy management system (HEMS) is actually the main solution for the management of distributed energy at the weak voltage level on the side of home customers. The IoT based HEMS consists of a smart meter (SM), a home controller (HC) and distributed operators installed on home equipment. In fact, HC processes and solves the load-sharing problem from the end user's point of view. In addition to smart home equipment, the proposed method considers ESS as well as PHEV in the load planning process [26-27].

In order to encourage smart home consumers to participate in consumption management programs, electricity distribution companies offer incentives to consumers in the form of tariff reduction, and consumers respond to this request through the HEMS. In IoT, based energy management in smart home and two-way communication between the HEMS and the distribution company requires telecommunication infrastructures at each smart home such as home area network (HAN) and local area network (LAN). The automatic control of smart home loads from the point of view of reducing consumers' costs by the HEMS convinces consumers to participate in demand side management. In the process of smart home energy management, part of the energy consumption by smart home loads may be transferred to other time intervals. Of course, in this process, a multi-price electricity tariff has a great impact on this management. In fact, consumers respond to this change in the price of electricity throughout the week [28].

Today, with the expansion of scattered production resources, the presence of responsive loads and the influence of ESSs on the demand side, smart home load management in order to reduce costs, increasing the reliability of home energy management. Therefore, the home energy management system will have a great role in the optimal planning of the distribution networks [29].

Electricity Generating Companies (GENCOs) and aggregators of small consumers or Distribution Companies (DISCOs) make their offers based on their forecasted load and production to the day ahead market. Therefore, DISCOs offer retail tariffs based on wholesale market prices to final and retail consumers. In the smart home, the smart meter receives the price information through the LAN, and then the home control system associated with each of the smart meters is responsible for controlling smart home loads and setting the operation and shutdown intervals of smart home loads and other available equipment.

In addition, the home control system announces the issue of load utilization by considering time-varying tariffs. It should be noted that, in IoT based home energy management the control signals are distributed from the home control system to the responding loads through the HAN [30-31].

In this study HEMS plays a key role in the implementation of responsive load programs on the side of smart home loads. In a smart home, all electrical loads are fed from electrical resources. Therefore, the presence of such energy resources on the side of smart home loads has doubled the need to manage the consumption side.

In the figure below, energy management in a smart home based on the IoT and in the presence of various energy sources is shown as a proposed strategy.

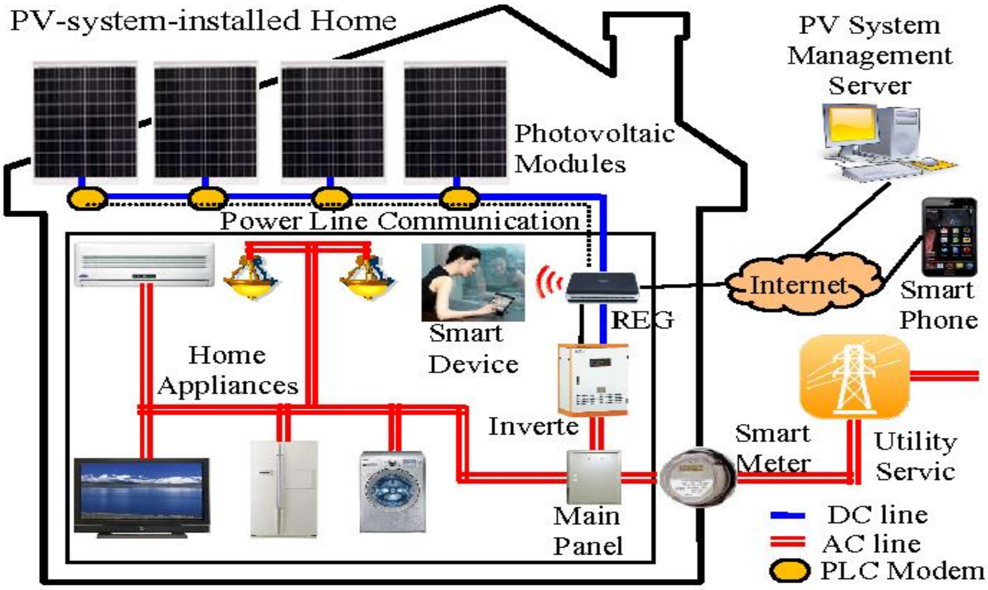

Fig 2.1 Proposed strategy based on IoT.

2.2 Research innovation

In this study, a smart home based on IoT is used to see the results of energy management modeling. This smart home has a variety of responsive and non-responsive loads, ESS, PHEV, and renewable energy resources such as PV and WT. In this study, the uncertainty of renewable energy resources will be modeled with the corresponding PDF.

Therefore, reduce the amount of ENS by energy management in a smart home in the presence of different types of home distributed energy resources is one of the novelties of this research. In addition, another novelty of this research is to reduce the cost of energy consumption during the one-week planning of the smart home by considering the uncertainty of renewable energies. In this study, linear mathematical equations are modeled instead of non-linear mathematical equations to reduce the simulation time.

This study is to observe the effects of energy management during a week for a smart home, that this smart home can reduce the ENS in the event of an error in the microgrid and the disconnection of the smart home from the main grid, and the HEMS can provide a model to reduce the cost of energy consumption of a smart home. Therefore, according to the description provided in this study, statistical methods will be used to model the uncertainty of renewable energy resources.

In this paper, after studying the topic of energy management in smart homes, which is obtained from the collection of information from another papers, we will start modeling mathematical equations. In mathematical modeling, we will try to use linear mathematical equations to reduce the calculations. In this study, MATLAB and GAMS software are used to view the results. MATLAB software is used to model the production power of PVs and WT, and GAMS software is used to optimize objective functions, smart home loads operation and other energy resources. In this study HEMS plays a key role in the implementation of responsive load programs on the side of smart home loads. In a smart home, all electrical loads are fed from electrical resources. Therefore, the presence of such energy resources on the side of smart home loads has doubled the need to manage the consumption side. In the next section, the modeling of the proposed strategy with mathematical equations related to the smart home, household electrical loads and energy resources available in the smart home is presented.

3- Proposed method

3.1 Explanations

In the previous parts, it was discussed in related to the concept of energy management on the demand side and how to manage energy in smart homes. Also, the new strategy presented in this paper was examined. In this section, suitable mathematical formulas for modeling are presented in related to the modeling of the new strategy presented. Therefore, the objective functions, DERs modeling and all the limitations related to this study are described below.

3.2 Modeling the proposed strategy

The planning of household electrical appliances is usually done with different criteria that must be considered simultaneously in the scheduling process. This section of the paper is a comprehensive framework for energy planning in a smart home during a week with the aim of reducing the cost of energy consumed by the smart home during a week for normal conditions (Normal State) and also reducing the amount of Energy Not Supplied (ENS) in the case of disconnection of the smart home from the grid (Disrupted State).

In this study, the most appropriate time schedule for using household appliances is stated and DERs in smart homes are exploited with the aim of creating a balance between optimization criteria. Therefore, the modeling of this paper is in two state, which are described below.

3.2.1 Normal State

In the normal state of energy management, a smart home is considered consisting of non-responsive loads, responsive loads and DERs. The HEM system for energy management during a week must first receive the price of the electricity tariff for each interval with the aim of minimizing the daily energy cost of the smart home. In the following equation, the first objective function, i.e., the weekly energy consumption cost of the smart home (WHEC), is expressed.

$$OF_1 = WHEC = \sum_{d=1}^{7} \left(\sum_{t \in T} \left(SHTE_{t,d} \times \rho_t \right) \right) \tag{3.1}$$

In this equation, t and T respectively represent the index and time intervals and d represents the days of the week. ρ_t and $SHTE_{t,d}$ shows the electricity tariff and smart home total energy consumption in interval t and day d, respectively.

The total energy consumption of the smart home in each time interval t for each day d, which are modeled based on the energy consumption of household appliances, ESS, PHEV and electric energy production by solar cells and wind turbine, is shown in the following equation.

$$\begin{aligned} SHTE_{t,d} = {} & \overbrace{SHFE_{t,d}}^{1} + \overbrace{\sum_{j \in J} \left(E_j^{RL} \times I_{j,t,d} \right)}^{2} + \overbrace{\left(\frac{1}{\eta^{ESS,ch}} \times \left(E_{t,d}^{ESS,ch} \times I_{t,d}^{ESS,ch} \right) \right)}^{3} \\ & + \overbrace{\left(\frac{1}{\eta^{PHEV,ch}} \times \left(E_{t,d}^{PHEV,ch} \times I_{t,d}^{PHEV,ch} \right) \right)}^{4} - \overbrace{\left(\eta^{ESS,dis} \times \left(E_{t,d}^{ESS,dis} \times I_{t,d}^{ESS,dis} \right) \right)}^{5} \\ & - \overbrace{\left(\eta^{PHEV,dis} \times \left(E_{t,d}^{PHEV,dis} \times I_{t,d}^{PHEV,dis} \right) \right)}^{6} - \overbrace{\left(E_{t,d}^{Renewable} \right)}^{7} \qquad \forall t,d \end{aligned} \tag{3.2}$$

In the first part of the above equation, the total energy consumption of fixed loads in each time interval t for each day d is shown. In the second part of household responsive loads, it is shown that j and J are related to the index of household responsive loads and E_j^{RL} shows the energy consumption of responsive loads. $I_{j,t,d}$ is a binary variable that is for the j-th load in the t-th interval and for the d-th day. If it is 1, it indicates that the j-th load is on. The state vector related to load j is shown in the following relation.

$$I_{j,d} = \left[I_{j,d,1}, I_{j,d,2}, \cdots I_{j,d,\mathrm{T}} \right] \qquad \forall j,d \tag{3.3}$$

In the third and fourth parts, $E_{t,d}^{ESS,ch}$ and $E_{t,d}^{PHEV,ch}$, the amount of energy charged in ESS and PHEV in the time interval t and day d. $\eta^{ESS,ch}$ and $\eta^{PHEV,ch}$ shows the AC to DC conversion factor for ESS and PHEV. $I_{t,d}^{ESS,ch}$ and $I_{t,d}^{PHEV,ch}$ showed the binary indices for ESS and PHEV charging mode in time period t and day d, where 1 means charging mode for ESS and PHEV. It should be noted that the third and fourth part is a non-linear modeling, which will cause calculation problems in the actual implementation and increase the model calculation time. Therefore, to linearize this equation, $ESS\_\mathrm{charge}_{t,d}$ symbol is introduced.

$$ESS\_\mathrm{charge}_{t,d} = E_{t,d}^{ESS,ch} \times I_{t,d}^{ESS,ch} \qquad \forall t,d \tag{3.4}$$

$$-MAX_{ESS}^{ch} \times I_{t,d}^{ESS,ch} \le ESS\_\mathrm{charge}_{t,d} \le MAX_{ESS}^{ch} \times I_{t,d}^{ESS,ch} \qquad \forall t,d \tag{3.5}$$

$$-MAX_{ESS}^{ch} \times \left(1 - I_{t,d}^{ESS,ch}\right) \le \left(ESS\_\mathrm{charge}_{t,d} - E_{t,d}^{ESS,ch}\right) \qquad \forall t,d \tag{3.6}$$

$$\left(ESS\_\mathrm{charge}_{t,d} - E_{t,d}^{ESS,ch}\right) \le MAX_{ESS}^{ch} \times \left(1 - I_{t,d}^{ESS,ch}\right) \qquad \forall t,d \tag{3.7}$$

In this equation, MAX_{ESS}^{ch} is a very big positive value. With the same method, the fourth part, which is a non-linear equation similar to the third part, can be linearly modeled.

In the fifth and sixth parts, $E_{t,d}^{ESS,dis}$ and $E_{t,d}^{PHEV,dis}$ show the amount of energy discharged by ESS and PHEV in the time interval t and day d. $I_{t,d}^{ESS,dis}$ and $I_{t,d}^{PHEV,dis}$ are binary indices of discharge for ESS and PHEV, where 1 means the discharge state in time interval t and day d. $\eta^{ESS,dis}$ and $\eta^{PHEV,dis}$ are AC to DC conversion coefficients for ESS and PHEV. These parts have a non-linear state, which can be modeled into a linear state with the same method introduced in the third part. In this way, all the non-linear equations in this modeling will become linear. In the seventh part, $E_{t,d}^{Renewable}$ shows the expected amount of energy produced by renewable energy sources such as PV and WT in the time period t and day d that are produced by these energy sources. Now, in the following, the modeling of each of the cases mentioned in the above equations will be discussed.

3.2.1.1 Modeling of Household Responsive Loads

In the case of household responsive loads, the intervals allowed to use these responsive loads are modeled as follows.

$$\sum_{t=b_{j,d}}^{g_{j,d}} I_{j,t,d} = U_j \qquad \forall j,d \tag{3.8}$$

In this equation, $b_{j,d}$ and $g_{j,d}$ show the start and end time of using the household responsive loads j for each day d. The required operating time for the j-th responsive load is according to the above modeling, the binary index related to each household responsive load is different according to the electrical energy consumption habits on different days of a week and is equal to zero for each day that is specified outside the interval. To model the use of any electrical device that starts working without interruption, the considered time must be modeled continuously.

$$y_{\mathrm{j},t,d} - z_{\mathrm{j},t,d} = I_{\mathrm{j},t,d} - I_{\mathrm{j},t-1,d} \qquad \forall j,t,d \tag{3.9}$$

$$\sum_{t \in T} y_{\mathrm{j},t,d} = 1 \qquad \forall j,d \tag{3.10}$$

$$y_{\mathrm{j},t,d} + z_{\mathrm{j},t,d} \le 1 \qquad \forall j,t,d \tag{3.11}$$

In these equations, $y_{\mathrm{j},t,d}$ and $z_{\mathrm{j},t,d}$ show the binary indices of the start and shutdown of the responsive load j for each day of the week. $y_{\mathrm{j},t,d} = 1$ means turning on the responsive load j at time t and $z_{\mathrm{j},t,d} = 1$ means turning off the responsive load j in time interval t and day d.

4.2.1.2 ESS Modeling

In the equations presented for ESS, it should be considered for each day of the week that ESS could not be in charge and discharge state in the same interval. Therefore:

$$I_{t,d}^{ESS,ch} + I_{t,d}^{ESS,dis} \leq 1 \qquad \forall t,d \tag{3.12}$$

The state of charge (SOC) related to ESS in order to maintain the daily balance of charge and discharge of ESS is considered as the following equation.

$$\begin{aligned} &SOC_{t,d}^{ESS} = Eb_{0,d} + \sum_{m=1}^{t}\left(ESS\_\text{charge}_{m,d} - ESS\_\text{discharge}_{m,d}\right) \quad \forall t,d \\ &ESS\_\text{charge}_{m,d} = E_{m,d}^{ESS,ch} \times I_{m,d}^{ESS,ch} \\ &ESS\_\text{discharge}_{m,d} = E_{m,d}^{ESS,dis} \times I_{m,d}^{ESS,dis} \end{aligned} \tag{3.13}$$

$SOC_{t,d}^{ESS}$ is the amount of energy available in ESS at the end of time interval t for day d, and in this modeling, m is also the time interval index. $Eb_{0,d}$ is the initial value of the ESS energy level at the beginning of the planning period for each day of the week. It should be noted that the initial value of the ESS energy level for each day is equal to the amount of energy available in the ESS at the end of the previous day (d-1). Therefore, the following equation should be considered in modeling.

$$Eb_{0,d} = SOC_{48,d-1}^{ESS} \qquad \forall d \tag{3.14}$$

In this equation, $SOC_{48,d-1}^{ESS}$ is equal to the amount of energy available in ESS at the end of the previous day, i.e. the state of charge in the 48th interval from day d-1. According to the presented equations related to the ESS state of charge, it is clear that this equation is non-linear, which can be linearized like the previous equations. The discharge rate related to ESS as well as the capacity of ESS are modeled in the following equations.

$$ESS\_\text{discharge}_{t,d} \leq SOC_{t-1.d}^{ESS} \qquad \forall t,d \tag{3.15}$$

$$0 \leq SOC_{t,d}^{ESS} \leq E_{ESS}^{\max} \qquad \forall t,d \tag{3.16}$$

The minimum and maximum amount of charging and discharging of ESS in each interval that is allowed is modeled as the following equation

$$E_{t}^{min,ch} \leq E_{t,d}^{ESS,ch} \leq E_{t}^{max,ch} \qquad \forall t,d \tag{3.17}$$

$$E_{t,d}^{min,dis} \leq E_{t,d}^{ESS,dis} \leq E_{t,d}^{max,dis} \qquad \forall t,d \tag{3.18}$$

3.2.1.3 PHEV Modeling

The above equations can be used to model PHEV as well as ESS. It should be noted that the battery in the PHEV, like the ESS, could not be charged and discharged in the same interval. Therefore, the following equation is considered for this modeling.

$$I_{t,d}^{PHEV,ch} + I_{t,d}^{PHEV,dis} \leq 1 \qquad \forall t,d \tag{3.19}$$

The SOC of the PHEV battery in each interval t and for each day of the week is modeled as follows.

$$\begin{aligned} &SOC_{t,d}^{PHEV} = Ep_{0,d} + \sum_{m=1}^{t}\left(\text{PHEV\_charge}_{m,d} - \text{PHEV\_discharge}_{m,d}\right) \quad \forall t,d \\ &\text{PHEV\_charge}_{m,d} = E_{t,m}^{PHEV,ch} \times I_{t,m}^{PHEV,ch} \\ &\text{PHEV\_discharge}_{m,d} = E_{t,m}^{PHEV,dis} \times I_{t,m}^{PHEV,dis} \end{aligned} \tag{3.19}$$

In this equation, $SOC_{t,d}^{PHEV}$ shows the amount of PHEV energy for each day and at the end of the interval t. $Ep_{0,d}$ shows the initial level of PHEV energy at the beginning of the scheduled interval for day d. It should be noted that the initial value of the PHEV energy level for each day is equal to the amount of energy available in the PHEV at the end of the previous day (d-1). Therefore, the following equation should be considered in modeling.

$$EP_{0,d} = SOC_{48,d-1}^{PHEV} \qquad \forall d \tag{3.20}$$

In this equation, $SOC_{48,d-1}^{PHEV}$ is equal to the amount of energy available in the PHEV at the end of the previous day, i.e. the charge level in the 48th interval from day d-1.

Like ESS, PHEV modeling is also a non-linear equation. For PHEV linearization, the modeling presented in the relevant equations is used. The battery used in the electric vehicle must be charged enough every day in the interval t-1 to be able to discharge to the required amount in the interval t. Therefore, the following equations are considered in modeling.

$$\text{PHEV\_discharge}_{t,d} \le SOC_{t-1,d}^{PHEV} \qquad \forall d, t \le gp_d \tag{3.21}$$

$$\text{PHEV\_discharge}_{t,d} \le \left(SOC_{t-1,d}^{PHEV} - E_{O-H,d}^{PHEV} \right) \qquad \forall d, t \ge cp_d \tag{3.22}$$

In these equations, the PHEV will be outside the house between the time intervals of gp_d and cp_d for each day d, which is different for each day. $E_{O-H,d}^{PHEV}$ shows the amount of energy consumed by the PHEV outside the house on day d, which is different for each day. It should be noted that the battery capacity of the PHEV before leaving the house and for the intervals after the PHEV enters the house is as follows.

$$0 \le SOC_{t,d}^{PHEV} \le E_{PHEV,d}^{max} \qquad \forall d, t \le gp_d \tag{3.23}$$

$$\left(SOC_{t,d}^{PHEV} - E_{O-H,d}^{PHEV} \right) \le E_{PHEV}^{max} \qquad \forall d, t \ge cp, d \tag{3.24}$$

In these equations, $E_{PHEV,d}^{\max}$ is the maximum amount of energy available to the PHEV battery on day d. The amount of energy required by the PHEV battery outside the home must be available in the PHEV battery before leaving the home. This hyperparameter is modeled in the following equation.

$$E_{O-H,d}^{PHEV} \le SOC_{gp-1,d}^{PHEV} \tag{3.25}$$

The minimum and maximum acceptable charge and discharge of PHEV for each day in each interval is calculated as follows.

$$E_t^{min,\text{pp}} \le E_{t,d}^{PHEV,ch} \le E_t^{max,\text{pp}} \qquad \forall t, d \tag{3.26}$$

$$E_t^{min,\text{pn}} \le E_{t,d}^{PHEV,dis} \le E_t^{max,\text{pn}} \qquad \forall t, d \tag{3.27}$$

3.2.1.4 Modeling of PV and WT systems

Considering that the production power of PV and WT systems are uncertain and is in the form of probabilities, the scenario tree method is used to update the expected production power and energy of these renewable DERs. In modeling this part of solar radiation and power generation by WT for each interval, Beta and Rayleigh probability distribution functions (PDF) are used, respectively, based on previous information. Beta function for solar radiation and Rayleigh function for wind speed in each interval t for each day of the week are modeled as follows.

$$f\left(\zeta_{t,d}\right)=\begin{cases}\dfrac{\Gamma\left(\alpha_{t,d}+\beta_{t,d}\right)}{\Gamma\left(\alpha_{t,d}\right)+\Gamma\left(\beta_{t,d}\right)}\left(\zeta_{t,d}^{\left(\alpha_{t,d}-1\right)}\times(1-\zeta_{t,d})^{\left(\beta_{t,d}-1\right)}\right) & \begin{pmatrix}0\le\zeta_{t,d}\le 1,\\ \alpha_{t,d},\beta_{t,d}\ge 0\end{pmatrix} \quad \forall t,d \\ 0 & \left(otherwise\right)\end{cases} \tag{3.28}$$

$$f(V_{t,d})=\frac{(2\times V_{t,d})}{C_{t,d}^{\ 2}}\exp(-(\frac{V_{t,d}}{C_{t,d}})^{2}) \quad \forall t,d \tag{3.29}$$

In relation to solar radiation, $f\left(\zeta_{t,d}\right)$ is beta PDF, which is the density function of a random variable of solar radiation (kw/m2) in the interval t and for each day of the week. In this modeling, $\alpha_{t,d}$ and $\beta_{t,d}$ are parameters of $f\left(\zeta_{t,d}\right)$, which are modeled as below to determine the mean value of $\mu_{t,d}$ and the standard deviation of $\sigma_{t,d}$ for solar radiation.

$$\beta_{t,d}=\left(1-\mu_{t,d}\right)\times\left(\frac{\mu_{t,d}\left(1+\mu_{t,d}\right)}{\sigma_{t,d}^{2}}-1\right) \quad \forall t,d \tag{3.30}$$

$$\alpha_{t,d}=\frac{\mu_{t,d}\times\beta_{t,d}}{1-\mu_{t,d}} \quad \forall t,d \tag{3.31}$$

In addition, in relation to wind speed, Rayleigh's PDF is a special type of Weibull's PDF, whose shape factor is equal to 2. Therefore, the PDF related to wind speed is expressed in the following equation. In this regard, $V_{t,d}$ is the predicted wind speed for interval t on day d. $C_{t,d}$ is the scale coefficient of the Rayleigh PDF in the time interval t and day d. Knowing the mean wind speed ($V_{t,d}^{mean}$) for each interval, $C_{t,d}$ can be calculated as follows.

$$V_{t,d}^{mean}=\int_{0}^{\infty}(V_{t,d}\times f(V_{t,d})\times dV_{t,d})= \int_{0}^{\infty}\frac{(2\times V_{t,d}^{2})}{C_{t,d}^{2}}\exp(-(\frac{V_{t,d}}{C_{t,d}})^{2})\times dV_{t,d}=\frac{\sqrt{\pi}}{2}\times C_{t,d} \quad \forall t,d \tag{3.32}$$

$$C_{t,d}=1.128\times V_{t,d}^{mean} \quad \forall t,d \tag{3.33}$$

Considering that in this study, the scenario tree method will be used to obtain the expected value of PV and WT production power, in the continuation of this modeling for each day of the week of each of the interval t, p states that are discrete is considered. The probability of occurrence of each of the discrete states p is modeled according to the following equation for PV and WT, respectively.

$$\lambda_{P,t,d}^{PV}=\int_{\zeta_{n-1}}^{\zeta_{n}} f_{B}\left(\zeta_{P,d}\right)\times d\zeta_{P,d} \quad \forall t,\mathrm{p},d \tag{3.34}$$

$$\lambda_{p,t,d}^{WT}=\int_{\varphi_{n-1}}^{\varphi_{n}} f(V_{t,d})\times dv_{t,d} \quad \forall t,p,d \tag{3.35}$$

In the modeling of the equation related to PV and WT, ζ_{n-1} and ζ_{n} are the limits of solar radiation, and φ_{n-1} and φ_{n} are the limits of wind for each discrete p-th state. The output power PV and WT for each discrete state p is obtained as follows. It should be noted that this output power is related to each discrete state of an interval and for each day of the week.

$$P^{PV}_{p,t,d} = \eta^{PV} \times S^{pv} \times \zeta_{p,t,d} \qquad \forall t, p, d \tag{3.36}$$

$$P^{WT}_{p,t,d} = \begin{cases} 0 & v^{mean}_{p,t,d} \le v^{c}_{in} & \forall t,d \\ \dfrac{v^{mean}_{p,t,d} - v^{c}_{in}}{v_{rated} - v^{c}_{in}} \times P^{w}_{r} & v^{c}_{in} \le v^{mean}_{p,t,d} \le v_{rated} & \forall t,d \\ P^{w}_{r} & v_{rated} \le v^{mean}_{p,t,d} \le v^{c}_{out} & \forall t,d \\ 0 & v^{c}_{out} \le v^{mean}_{p,t,d} & \forall t,d \end{cases} \tag{3.37}$$

In relation to PV production power, η^{PV} is the efficiency factor for PV and S^{pv} indicates the total area of the solar panel. In this equation, $\zeta_{p,t,d}$ corresponds to the mean value of ζ of the discrete interval p and as a representative of each discrete state for each time interval.

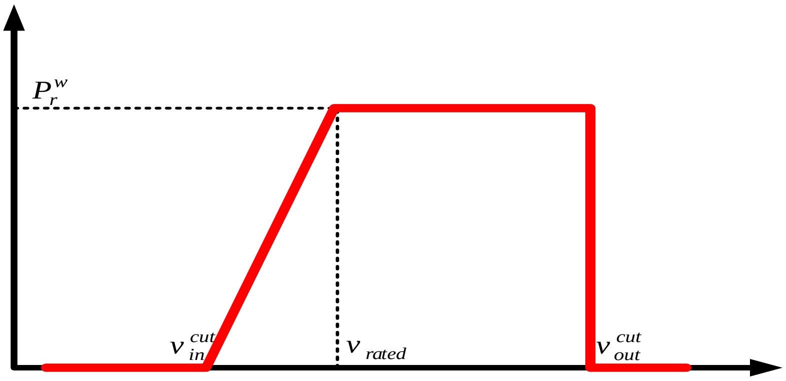

Fig 3.1 WT production power.

Also, in relation to the production power of WT, P^{w}_{r} is the nominal power of WT and $P^{WT}_{p,t,d}$ is the value of the production power of WT at hour t. v^{c}_{out}, v^{c}_{in} and v_{rated} respectively indicate the maximum acceptable wind speed, the minimum acceptable wind speed and the nominal speed for a specific WT. $v^{mean}_{p,t,d}$ is the mean wind speed and represents every discrete state for every hour of the day. The expected output power (kw/interval) as well as the expected total energy (kwh/interval) obtained from PV and WT renewable DERs for an interval t and for each day of the week are modeled as follows.

$$\lambda^{Renewable}_{t,p,d} = \lambda^{PV}_{P,t,d} \times \lambda^{WT}_{p,t,d} \qquad \forall t, p, d \tag{3.38}$$

$$\sum_{p=1}^{Np} \lambda^{Renewable}_{t,p,d} = 1 \qquad \forall t, d$$

As in the above equation, the sum of the probabilities of production power PV and WT for each time interval t should be equal to one. The following figure shows the scenario tree for the probability intervals of PV and WT production power for each time interval.

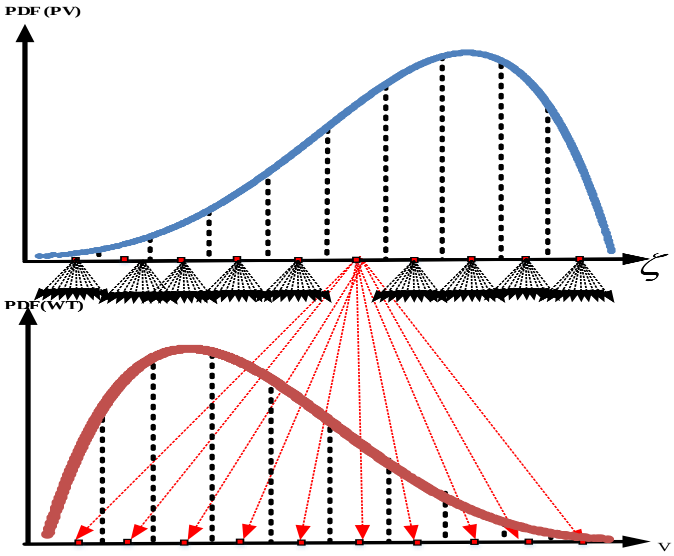

Fig 3.2 Scenario tree for PV and WT production power.

It should be noted that this figure is valid for intervals of time when there is sunlight, and for hours when there is no sunlight, only the production power wt should be considered in the calculations. Therefore, the production capacity of energy sources for all hours of the day and night with the presence of sunlight ($t \in pv_t$) and without the presence of sunlight ($t \notin pv_t$) as well as the production energy of these renewable sources have been modeled.

$$\begin{cases} p_{t,d}^{Renewable} = \sum_{p \in P} \left(\lambda_{p,t,d}^{PV} \times P_{p,t,d}^{PV} \times \lambda_{p,t,d}^{WT} \times P_{p,t,d}^{WT} \right) & \forall d, t \in pv_t \\ p_{t,d}^{Renewable} = \sum_{p \in P} \left(\lambda_{p,t,d}^{WT} \times P_{p,t,d}^{WT} \right) & \forall d, t \notin pv_t \end{cases} \tag{3.39}$$

$$E_{t,d}^{Renewable} = p_{t,d}^{Renewable} \times DELTA_t \qquad \forall t, d$$

In this modeling, it is important to mention that the amount of energy that flows from the main distribution network to the desired smart home must have a limit on energy injection. The lack of such a limit in energy consumption causes many technical obstacles, including the creation of peak load and load density in different intervals. The following modeling is considered for this case.

$$0 \le SHTE_{t,d} \le TE_t^{\max} \qquad \forall t, d \tag{3.40}$$

In this modeling, $TE_t^{\max}$ is the maximum amount of energy each programmable house can receive from the main grid in each interval t.

3.2.2 Disrupted state

In this state, the objective function is to reduce the amount of ENS of a smart home in weekly planning. Modeling in this state is considered with the assumption that if the smart home is interrupted for a period of half an hour for any reason, the ability of the smart home to supply the home loads with energy management and with the presence of DER. The main goal in this study is whether the smart home can reduce the ENS. Therefore, in the following objective function, the amount of ENS of the smart home is modeled in the state where it is cut off from the upstream.

$$OF_2 = WENS = \left| \sum_{d=1}^{7} \left[\sum_{t=1}^{48} ENS_{t,d} \right] \right| = \left| \sum_{d=1}^{7} \left[\sum_{t=1}^{48} \left[E_{t,d}^{DER} - TE_{t,d} \right] \right] \right| \tag{3.41}$$
$$s.t \quad \left\{ \left[E_{t,d}^{DER} - TE_{t,d} \right] > 0 \quad \Rightarrow \quad ENS_{t,d} = 0 \quad \forall t,d \right.$$

In this equation, $WENS$ represents ENS for a smart home during a week, while its energy is supplied by the DERs in the home during a critical time that is cut off from the upstream for half an hour. $E_{t,d}^{DER}$ is equal to the total energy of ESS, PHEV, WT and PV in the smart home, which is shown in the following equation.

$$E_{t,d}^{DER} = \left(\eta^{ESS,dis} \times \left(E_{t,d}^{ESS,dis} \times I_{t,d}^{ESS,dis} \right) \right) - \left(\eta^{PHEV,dis} \times \left(E_{t,d}^{PHEV,dis} \times I_{t,d}^{PHEV,dis} \right) \right) - \left(E_{t,d}^{Renewable} \right) \quad \forall t,d \tag{3.42}$$

Also, in the following, $TE_{t,d}$ which represents the total energy consumption of the equipment in the smart home, has been modeled for each interval.

$$TE_{t,d} = SHFE_{t,d} + \sum_{j \in J} \left(E_j^{RL} \times I_{j,t,d} \right) \quad \forall t,d \tag{3.43}$$

In this state, the purpose of the study is not to calculate energy. Therefore, in intervals when the total energy production of DERs in the smart home is more than the total energy consumption of the home equipment, the total energy consumption is provided and the amount of ENS in that interval will be equal to zero. Therefore, this condition should also be considered in modeling.

The amount of energy injection by the DERs available in the smart home depends on their SOC. As mentioned in the previous equations, the minimum and maximum charge and discharge of ESS and PHEV resources are included in the modeling. Therefore, the amount of ESS and PHEV energy that can discharge in each interval can be modeled by comparing the SOC available for that source at that load level by the following equations for each day of the week.

$$\begin{cases} SOC_{t,d}^{ESS} < E_{t,d}^{\min,dis} & \Rightarrow \quad E_{t,d}^{ESS} = 0 & \forall t,d \\ SOC_{t,d}^{ESS} \geq E_{t,d}^{\max,dis} & \Rightarrow \quad E_{t,d}^{ESS} = E_{t,d}^{\max,dis} & \forall t,d \\ E_{t,d}^{\min,dis} \leq SOC_{t,d}^{ESS} < E_{t,d}^{\max,dis} & \Rightarrow \quad E_{t,d}^{ESS} = SOC_{t,d}^{ESS} & \forall t,d \end{cases} \tag{3.44}$$

$$\begin{cases} SOC_{t,d}^{PHEV} < E_{t,d}^{\min,\mathrm{pn}} & \Rightarrow \quad E_{t,d}^{PHEV} = 0 & \forall t,d \\ SOC_{t,d}^{PHEV} \geq E_{t,d}^{\max,\mathrm{pn}} & \Rightarrow \quad E_{t,d}^{PHEV} = E_{t,d}^{\max,\mathrm{pn}} & \forall t,d \\ E_{t,d}^{\min,\mathrm{pn}} \leq SOC_{t,d}^{PHEV} < E_{t,d}^{\max,\mathrm{pn}} & \Rightarrow \quad E_{t,d}^{PHEV} = SOC_{t,d}^{PHEV} & \forall t,d \end{cases} \tag{3.45}$$

The percentage of supplied load of the smart home for each interval by the DERs can be modeled by the following equation.

$$SL_{t,d} = \frac{E_{t,d}^{DER}}{TE_{t,d}} \quad \forall t,d \qquad s.t \begin{cases} SL_{t,d} < 1 & \Rightarrow \%SL_{t,d} = SL_{t,d} \times 100 \quad \forall t,d \\ SL_{t,d} \geq 1 & \Rightarrow \%SL_{t,d} = 100 \quad \forall t,d \end{cases} \tag{3.46}$$

According to this modeling, in the intervals where the total energy production of DERs in smart home is more than the total energy consumption of the home equipment, the value of SL in that interval will be greater than one.

Because the purpose is calculating the supplied load of the smart home. Therefore, in those intervals, the value of SL is considered equal to 100%. In this part of the paper, different considered states were introduced and the modeling related to each state was explained. In this study, the main objective functions were introduced for smart home, and each of these functions was modeled with all the necessary assumptions.

In the next section, the necessary input data for simulating the energy management of a smart home during a week, as well as information about DERs and household equipment are given in this section. Also, the simulation of the results of the modeling done for each of these states is presented.

4- Results and Analysis

4.2 Initialization

According to the mathematical equations presented in the last section and the modeling done for the objective functions and DERs, the results of this modeling are examined and compared with the corresponding figures and tables. The results of this study are analyzed in two different cases. First, energy management inside the smart home in normal state is considered to optimize the objective functions. Then, the results of the study are examined in the case of disruption and disconnection of the smart home from the main network.

4.2 Imput data

The input data necessary to view the results of this study is stated in this section. This study is planned for weekly energy management of a smart home. The usage time of non-responsive appliances in each interval and for each day of a week is shown in the figure below.

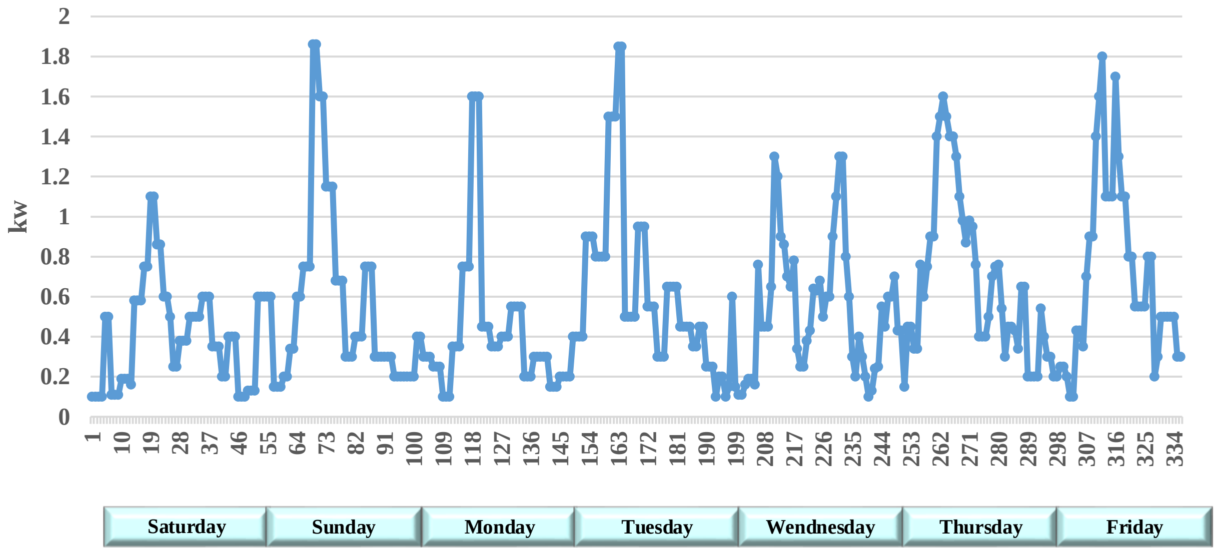

Fig 4.1 Weekly non-responsive smart home load.

As shown in this figure, the consumption pattern of non-responsive loads in a smart home is different on different days of a week. It should be noted that the model of non-responsive loads cannot be changed and energy management cannot change this model.

Also, each hour consists of two half-hour intervals, which makes a total of 48 intervals in a day and 336 intervals in a week. In the tables below, the information about ESS used in the smart home is stated.

Table 4.1 ESS information.

Data	Value
$Eb_{0,1}$	1.062 kwh
ESS Battery Capacity	4.25 kwh
$E_t^{max,dis}$	0.530 kwh/interval
$E_t^{min,dis}$	$0.25\times 0.530 = 0.133$ kwh/interval
$E_t^{max,ch}$	0.530 kwh/interval

$E_t^{min,ch}$	$0.25\times 0.530 = 0.133$ kwh/interval
$\eta^{ESS,ch}$	0.96
$\eta^{ESS,dis}$	0.96

This table shows all the necessary information for ESS modeling for a smart home. The type of ESS and its capacity are shown to be the same for all days with initial charge for the first day.

Also, the minimum charge and discharge rate for each interval is assumed to be 25% of the maximum charge and discharge rate. In the tables below, the information about PHEV used in the smart home is stated.

Table 4.2 PHEV information.

Data	Sat.	Sun.	Mon.	Tues.	Wed.	Thurs.	Fri.
Out of Home Intervals	18-28	14-30	20-28	16-26	15-24	15-35	20-40
$EP_{0,1}$	1.7 kwh						
$E_{O-H,d}^{PHEV}$	4.25 kwh	5.1 kwh	3.4 kwh	5.95 kwh	5.1 kwh	3.4 kwh	5.95 kwh
PHEV Battery Capacity	6.8 kwh						
$E^{\max,pn}$	0.86 kwh/interval						
$E^{\min,pn}$	$0.25\times 0.86 = 0.2126$ kwh/interval						
$E^{\max,pp}$	0.86 kwh/interval						
$E^{\min,pp}$	$0.25\times 0.86 = 0.2126$ kwh/interval						
$\eta^{PHEV,ch}$	0.96						
$\eta^{PHEV,dis}$	096						

In this table, all the necessary information for PHEV modeling for smart home is shown. The minimum charge and discharge rate of PHEV for each interval is assumed to be 25% of the maximum charge and discharge rate.

In this study, the energy management of a smart home is considered. This smart home consists of 7 types of electric responsive loads, and the information of each of these responsive loads is shown in the table below. Washing machine, Dish washer, Cloth dryer, Slow cooker, Microwave oven, and Robot vacuum cleaner are responsive household loads whose energy consumption intervals can be changed by the owners of smart homes and their optimal use time can be obtained for different purposes.

For example, one of these household responsive loads is a washing machine. 3 intervals, i.e. one and a half hours, are considered for the operation of the washing machine. The energy consumption of this responsive load is 1.5 kwh/day, which means 0.5 kwh/interval. The suggested time intervals of this responsive time are shown for each day of the week. The information related to the time intervals suggested by the owner of the smart home, taking into consideration the comfort of the residents of the smart home, for each day of the week, is shown in this table, and the optimal time intervals selected for each respondent, taking into account the suggested intervals [36]. In the optimization of the objective functions, the respondent should be used every time in the suggested interval because these suggested intervals are chosen by the home owners and are considered based on their comfort and convenience. Because the consumption patterns of home owners are different foe each day of a week, therefore their suggested intervals are also different. The smart home energy management system selects intervals to achieve the goal of energy consumption for the smart home.

Table 4.3 Responsive loads information.

Responsive Loads	Consumption		Operation	Sat.	Sun.	Mon.	Tues.	Wed.	Thurs.	Fri.
	(Wh/day)	(Wh/interval)	(h)							
Washing Machine	1.5	0.5	1.5	16-48	20-48	25-44	16-48	14-44	22-42	26-46
Dish Washer	1	0.5	1	38-48	42-48	40-47	36-44	40-48	40-48	30-37
Cloth Dryer	1.4	0.7	1	1-14	1-16	1-20	3-30	4-17	1-20	1-21
Slow Cooker	1.2	0.4	1.5	20-35	18-25	16-20	18-38	22-33	10-30	20-25
Microwave Oven	0.8	0.4	1	32-42	30-48	34-48	26-40	30-48	33-43	31-41
Robot Vacuum Cleaner	0.9	0.3	1.5	1-48	1-48	1-48	1-48	3-40	2-42	6-46
Kitchen Hood	0.5	0.5	0.5	40-48	36-44	38-48	34-46	38-41	33-43	30-44

The electricity tariff price is shown in the figure below for one day. This electricity tariff is the same for all days of the week.

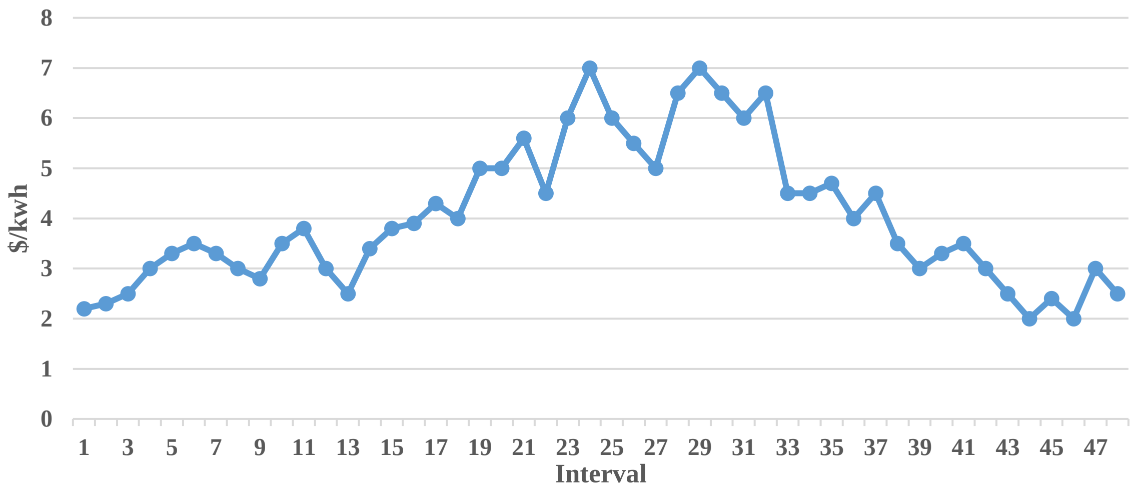

Fig 4.2 Daily electricity price tariff.

In the discussion of small-scale domestic PV systems, the power of solar cells considered for all days is the same and equal to 1500 W, which is made of 6 solar panels with 250 W. The area of the panels of the smart house is assumed to be equal to 6m2 [32].

In this study, solar radiation is considered between 11 and 38. It should be noted that the solar radiation information in this study is presented hourly, but in this study, 30-minute intervals are considered. According to these explanations, in this study, the information of solar radiation in each interval is assumed to be equal to the information of the same hour.

According to the information about solar radiation and the specifications of solar panels, the production power of the PV system for each day of a week is shown in the figure below.

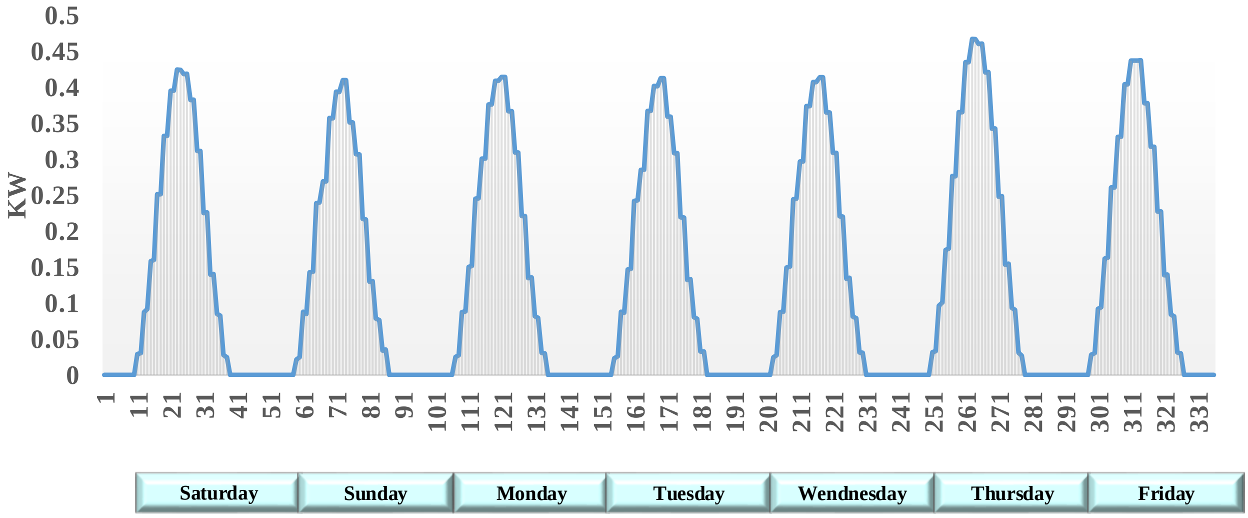

Fig 4.3 PV system production.

As it is clear from the production power of the PV system, the production power increases with the beginning of the sun's rays, and after sunset, the production power reaches zero. In addition, because the sun's radiation is different on different days, the production power is different.

In this study, a WT with a nominal production power of 1 kw, v_{in}^{c} is equal to 3 m/s, V_{rated} is equal to 12 m/s and v_{out}^{c} is equal to 25 m/s. The production power of the WT for each day of the week is shown in the figure below. According to the quantities provided for wind speed, the amount of power produced at each intervals is different.

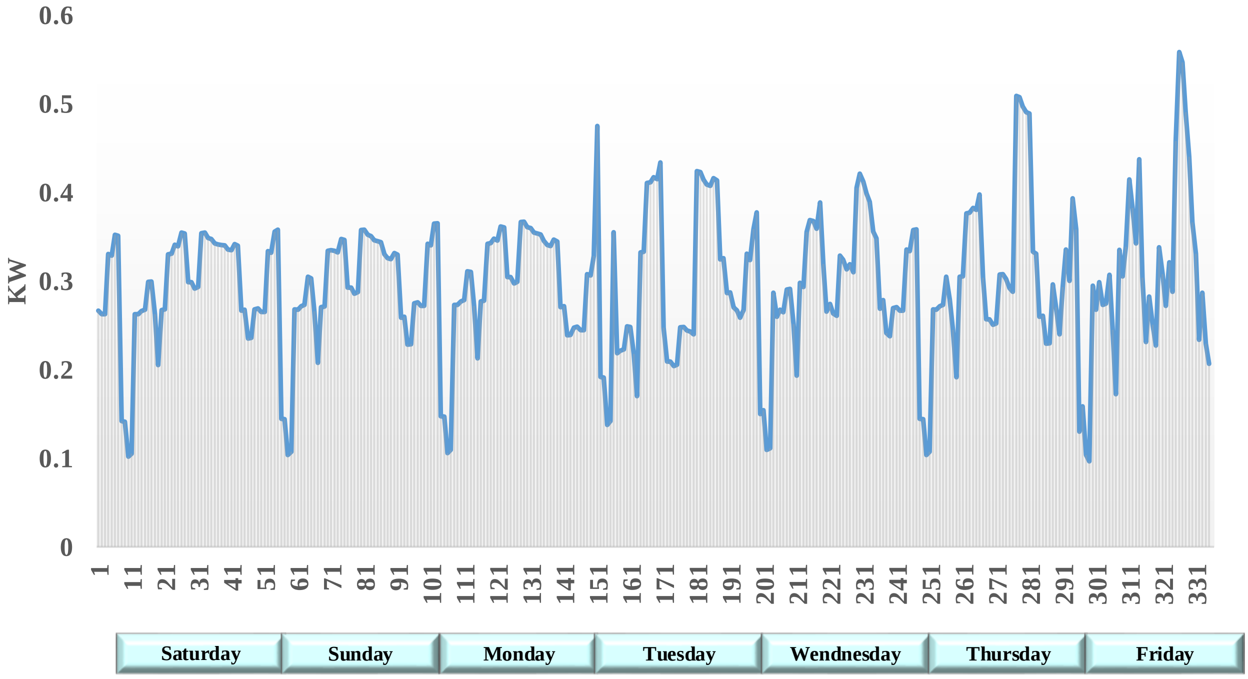

Fig 4.4 WT power production.

According to the provided input data, the results of the modeling will be analyzed in the following.

4.3 Simulation results

After stating the input data of the studied topic, the results of the simulation with the provided assumptions are shown. First, the results of the study for the normal state and no disruption are presented, and then the results are presented for the state of disconnection of the smart home from the main network.

The results of each of these situations are expressed with the corresponding figures and tables, and a general evaluation of energy management in a smart home is expressed for planning a week.

4.3.1 Normal State

In this state, no error is expected for the smart home. In this state, the smart home is able to buy energy from the main network and is planned for a week with the aim of reducing the home energy cost, and the optimal use of DERs is determined for a week.

The following table shows the results of the simulation for the normal state. As shown in this table, the results are compared with each other in the presence of DERs and in the absence of DERs.

According to the results of this table, the positive effect of the presence of DERs in improving the objective function is clear. In addition, in table 5.5, suitable time intervals for using household responsive loads with and without DERs are shown.

Table 4.4 Simulation results in normal state.

OF1=WHEC	Without DERs	982.191 $	+ 69.00 %
	With DERs	304.435 $	
HEC(Saturday)	Without DERs	107.512 $	+ 83.68 %
	With DERs	17.541 $	
HEC(Sunday)	Without DERs	147.184 $	+ 64.63 %
	With DERs	52.048 $	
HEC(Monday)	Without DERs	111.690 $	+ 83.04 %
	With DERs	18.946 $	
HEC(Tuesday)	Without DERs	149.425 $	+ 60.47 %
	With DERs	59.063 $	
HEC(Wendnesday)	Without DERs	128.099 $	+ 73.76 %
	With DERs	33.631 $	
HEC(Thursday)	Without DERs	173.394 $	+ 64.71 %
	With DERs	61.190 $	
HEC(Friday)	Without DERs	164.893 $	+ 62.39 %
	With DERs	62.017	

Table 4.5 Optimum intervals for using household responsive loads.

Day	DER	washing machine	Dish washer	clothes dryer	slow cooker	microwave oven	robot vacuum cleaner	Kitchen hood
Sat.	Wo	44-45-46	44-45	1-2	33-34-35	39-40	44-45-46	44
	W	44-45-46	46-47	1-2	24-25-26	41-42	44-45-46	48
Sun.	Wo	44-45-46	44-45	1-2	18-19-20	44-45	44-45-46	44
	W	46-47-48	45-46	1-2	18-19-20	46-47	44-45-46	44
Mon.	Wo	42-43-44	44-45	1-2	16-17-18	44-45	44-45-46	44
	W	42-43-44	45-46	1-2	17-18-19	46-47	45-46-47	48
Tues.	Wo	44-45-46	43-44	3-4	36-37-38	39-40	44-45-46	44
	W	46-47-48	43-44	3-4	25-26-27	39-40	44-45-46	46
Wed.	Wo	42-43-44	44-45	12-13	25-26-27	44-45	3-4-5	39
	W	42-43-44	44-45	12-13	23-24-25	47-48	16-17-18	39
Thurs.	Wo	40-41-42	44-45	1-2	12-13-14	43-44	2-3-4	43
	W	40-41-42	46-47	1-2	11-12-13	42-43	2-3-4	43
Fri.	Wo	44-45-46	36-37	1-2	20-21-22	39-40	44-45-46	44
	W	44-45-46	36-37	1-2	20-21-22	40-41	4-45-46	44

The optimal ESS charging and discharging intervals for each day are shown in the figure below. As it is clear in this figure, because the energy consumption pattern is different every day for the smart home, the ESS has a different charge and discharge pattern in the time intervals of each day. In addition, the amount of optimal charging and discharging is different based on the needs of the smart home.

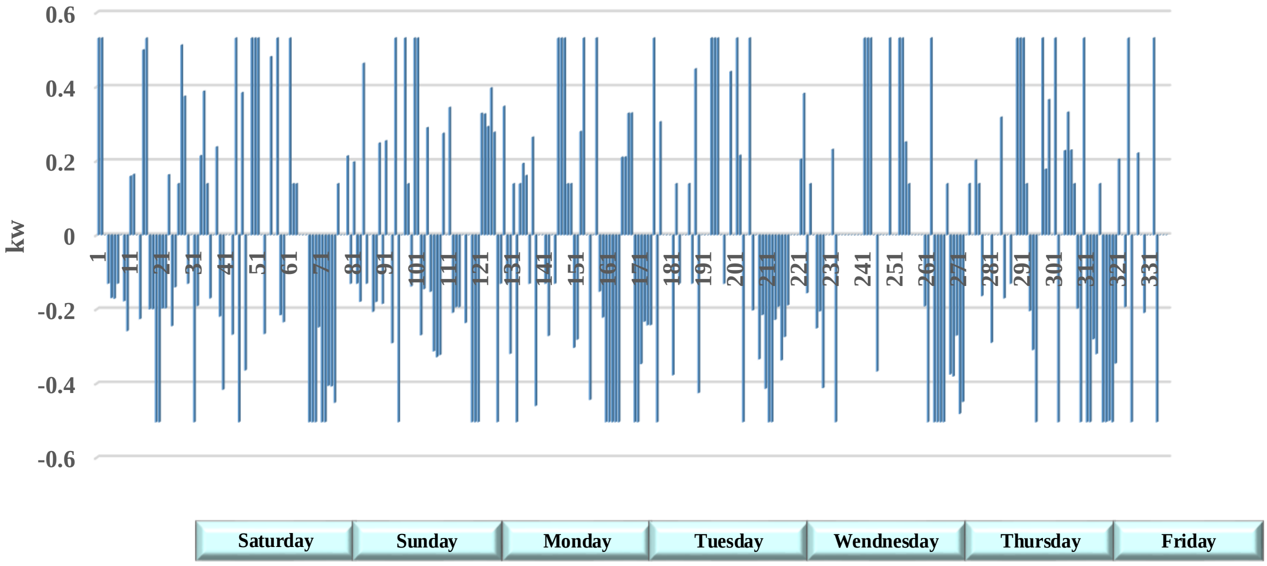

Fig 4.5 Charging and discharging of ESS.

The optimal PHEV charging and discharging intervals for each day are shown in the figure below. As it is clear in this figure, because the electric vehicle usage pattern is different every day for smart home owners, PHEV has a different charging and discharging pattern in the time intervals of each day. According to this figure, there is no charge or discharge during the intervals when the car is outside the home.

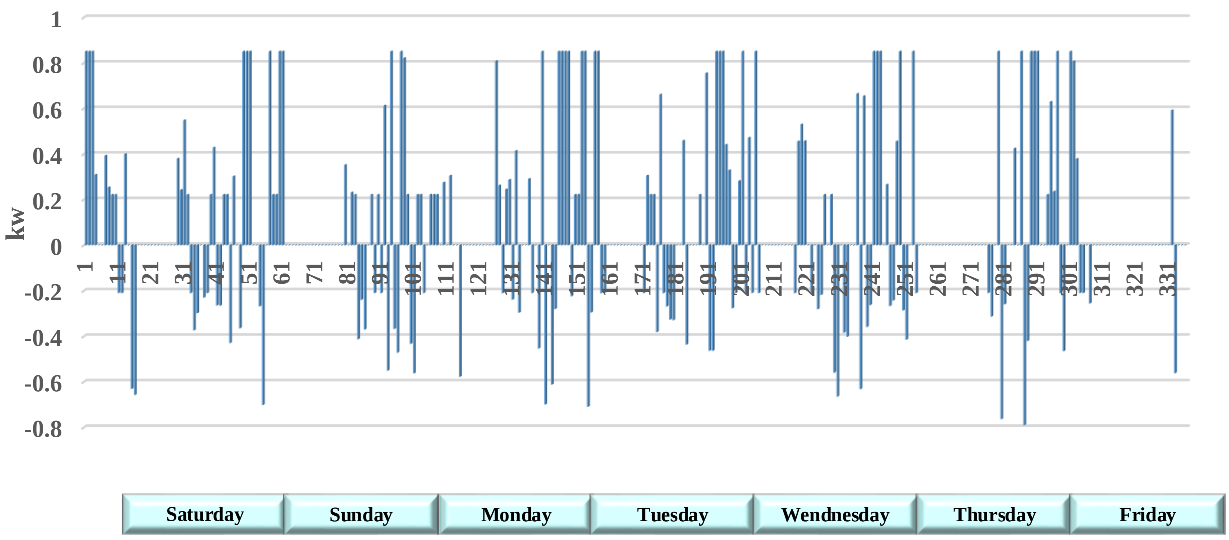

Fig 4.6 Charging and discharging of PHEV.

The comparison of the weekly energy consumption curve of the smart home with and without the presence of DERs is shown in the figure below. The presence of DERs reduces the amount of energy consumed by the smart home in most intervals. As it is clear in this figure, the increase in energy consumption of the smart home in some intervals is due to the charging of ESS and PHEV.

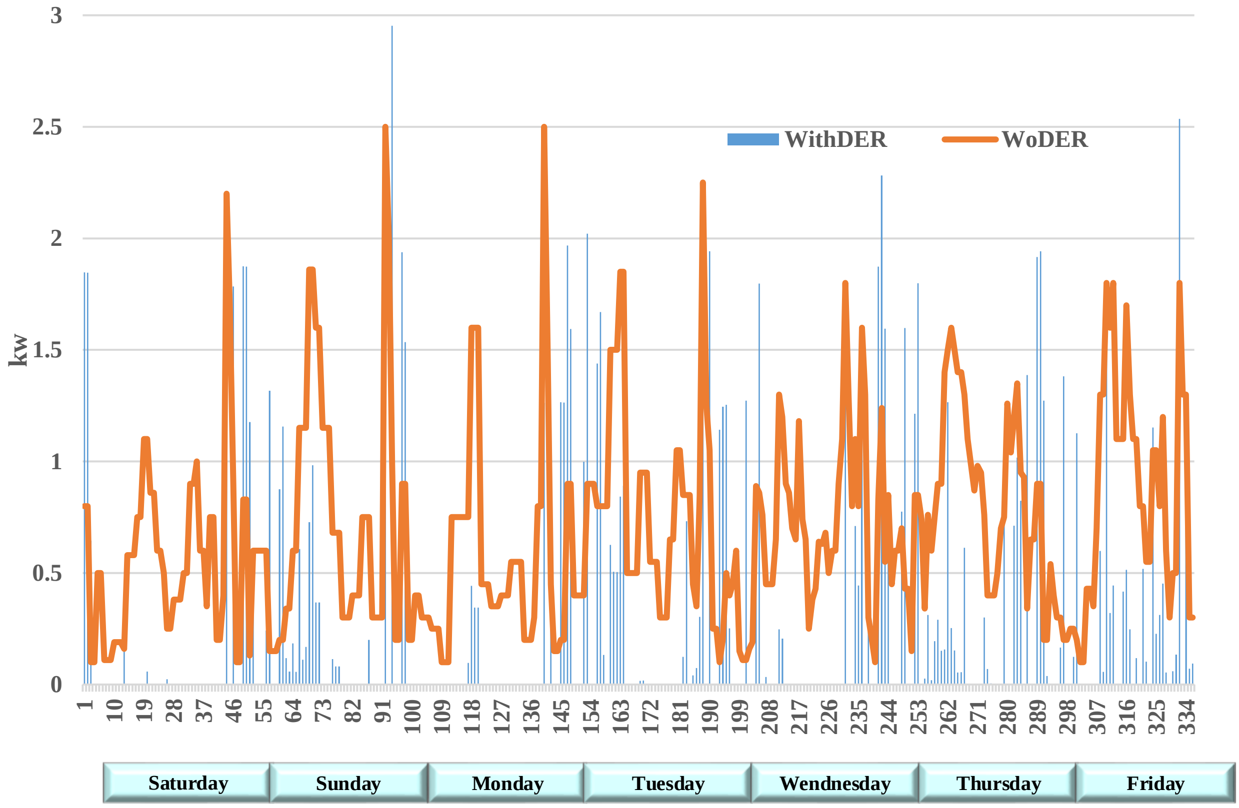

Fig 4.7 Weekly smart home energy consumption.

4.3.2 Disrupted State

In this state, it is assumed that if the smart home is disconnected from the main network for any interval and does not receive energy in that interval, can it provide the amount of energy it needs through DERs or not. Therefore, the amount of ENS has been studied in this case. The table 4.6 shows the effect of the presence of DERs in improving ENS.

As shown in this table, the presence of DERs can supply the amount of energy needed by the electrical appliances of the home if the smart home is disconnected from the network.

Table 4.6 Simulation results in disrupted state.

OF2=WENS	Without DERs	236.49 kwh	+ 85.33 %
	With DERs	34.69 kwh	
ENS(Saturday)	Without DERs	27.01 kwh	+ 91.63 %
	With DERs	2.26 kwh	
ENS(Sunday)	Without DERs	34.83 kwh	+ 83.63 %
	With DERs	5.70 kwh	
ENS(Monday)	Without DERs	27.3 kwh	+ 88.75 %
	With DERs	3.07 kwh	
ENS(Tuesday)	Without DERs	37.95 kwh	+ 83.66 %
	With DERs	6.20 kwh	
ENS(Wendnesday)	Without DERs	31.67 kwh	+ 86.92 %
	With DERs	4.14 kwh	
ENS(Thursday)	Without DERs	40.78 kwh	+ 88.00 %
	With DERs	4.89 kwh	
ENS(Friday)	Without DERs	36.95 kwh	+ 77.25 %
	With DERs	8.43 kwh	

The amount of ENS of the smart home for each interval is shown in the figure below. As it is clear in this figure, the amount of ENS in each time interval is proportional to the amount of energy consumed in that interval.

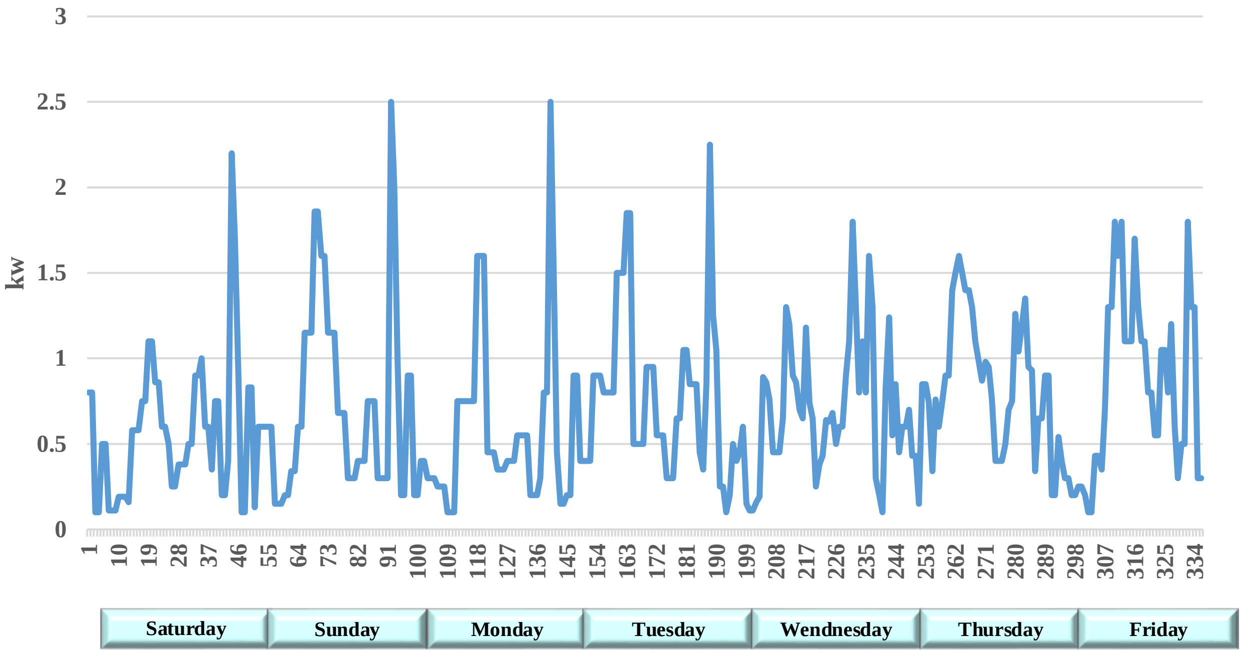

Fig 4.8 ENS without DERs in disrupted state.

In the figure below, the amount of ENS with the presence of DERs is shown. As it is clear in this figure, the amount of ENS in each interval in the presence of DERs is proportional to the amount of energy consumed in smart home in that interval and the amount of optimal operation of DERs.

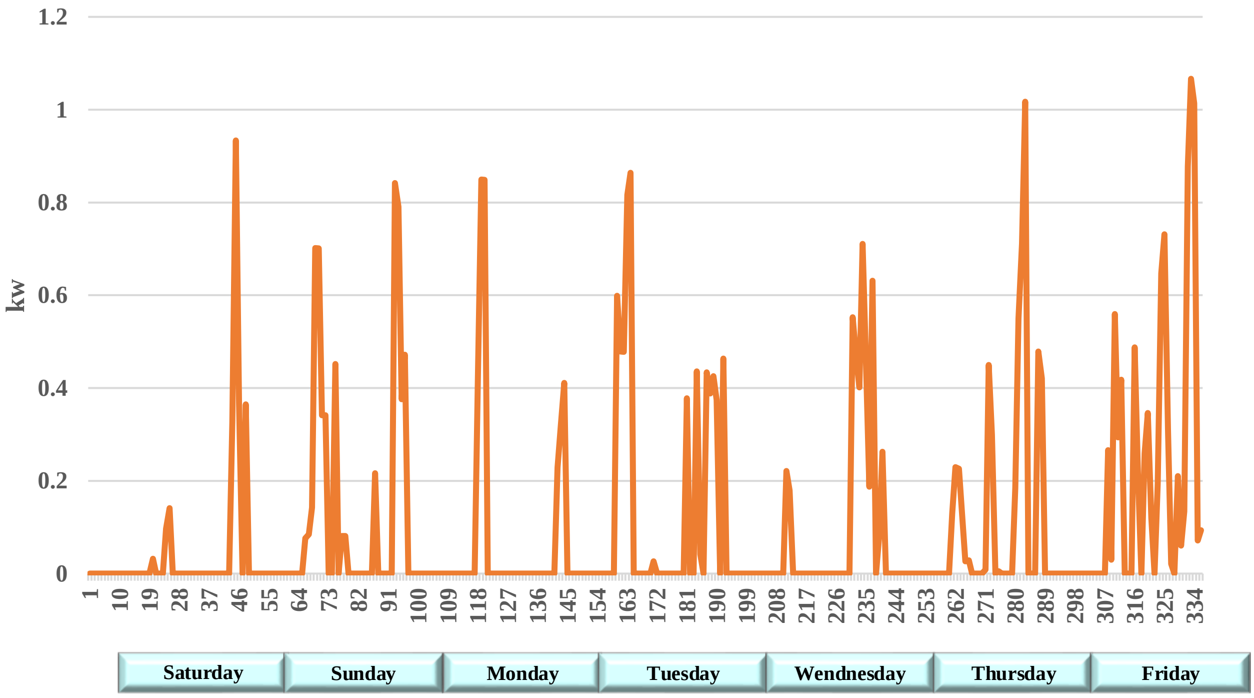

Fig 4.9 ENS with presence of DERs in disrupted state.

In this section of the paper, the results of the introduced modeling were examined in two different states. In the first state, the smart home has the ability to purchase energy from the distribution network, and in this state, the effect of the presence of DERs was shown in the relevant tables and figures.

The results in this state showed that the presence of DERs has a positive effect on reducing the cost of home electric energy consumption during weekly planning. In the second state of this study, the smart home is disconnected from the main network and is in a disruption state. In this state, the effect of the presence of DERs in reducing the amount of ENS was shown in the table and figures.

5- Conclusion

In this study, an optimal energy management model for a smart home is proposed, which aims to achieve the minimum energy cost of the smart home for a week. This study has been investigated in two states, normal state and disrupted state. The optimal modeled solution has been obtained using linearized mathematical formulas in GAMS software.

According to the results obtained in the last seasons for both states, it can be seen that the presence of distributed energy resources can reduce the cost of energy consumption of smart homes in normal state and the amount of ENS in disrupted state.

Based on the obtained numerical results, the energy management of the smart home has improved the energy cost of the smart home by a good percentage in the normal state, and the amount of ENS has improved by a good percentage. In addition, the optimal utilization of energy resources such as ESS, PHEV, PV, WT, and household electrical responsive loads has been optimized in addition to optimal energy management by considering the objective functions, and the optimal utilization of these energy resources has been obtained for each time intervals.

From the obtained results, it can be concluded that due to the development of technology and electrical appliances used in homes, energy management is very important and for the development of smart cities and the creation of the necessary infrastructure to make life smarter and to increase people's comfort, studies and implementation should be carried out.

It should be noted that increasing the reliability of distribution networks is very important, and the management of electric energy in smart homes can be aimed at achieving this goal. Because if energy management is implemented intelligently in all homes of a distribution network, it improves the technical and economic goals and is a step in the direction of intelligent distribution networks.

Smart projects should be increased so that technology can be used optimally. Also, due to the reduction of fossil fuel resources, energy management and the use of renewable energy sources are essential for electric energy management.

According to the results of the paper, various ideas can be proposed to improve the results for future studies. In order to develop the energy management capabilities of homes, taking into account new concepts in planning and optimal operation, new studies can be presented to improve technical and economic goals.

In order to cover new studies in energy planning of smart homes and increase the percentage of participation of the demand side in energy management, new models should be developed in a proper way, which are suggested below.

- Energy interactions between smart homes to improve the technical and economic goals of distribution networks. In this case, the homes can share some energy among themselves and play a significant role in improving resilience in disrupted state.
- The impact of energy management on the demand side at higher levels of energy interactions between distribution companies and wholesale markets or the proposal to sell surplus energy of smart microgrids to the wholesale market is also discussed, rather than the economic efficiency of the company. improved distribution.
- The use of new methods of energy management, including artificial intelligence and the use of machine learning in the field of energy interactions between smart homes, is one of the new issues of energy management on the demand side.
- The use of artificial intelligence during the occurrence of errors in microgrids to improve resilience and other technical components of microgrids is one of the suggestions of this field.
- The use of artificial intelligence to predict the energy production of non-renewable units and predict the demand load on the side of household loads or any type of electric load can be used in the time and accuracy of energy management planning in normal mode and in the occurrence of the event is effective.
- The use of artificial intelligence in determining the electricity tariff at different hours of the day and the use of incentive methods to control energy consumption on the demand side are suitable suggestions in this field.
- Due to the change in the technical and economic approach of the automobile industry at the international and national level, based on the replacement and use of hybrid cars and rechargeable motorcycles, which results in the growth of consumption in the electric energy sector. The results of the analysis and review of this paper can be of interest to the ministry of energy and electric power distribution companies in the resilience studies of transmission and distribution networks.

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