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Robustness Energy Management Module Design for Smart Homes concerning Operation Uncertainty of PVs and WTs Resources

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Abstract

Technology development and increase in residential energy consumption cause moving toward automation and smart home (SH) to be inevitable. Recently, PVs and WTs resources attachment and CHP and Battery energy storage to SH equipment come to some challenges such as output power uncertainty to the energy management system (EMS). Usually, SH has a connection to the city distribution system and can buy or sell energy from or to the utility at the appropriate time. Therefore, this paper presents the new robustness of SH EMS considering real-time energy pricing at the retail power market, which is solved using genetic algorithm technique. The objective function is the summation of CHP emission cost and energy consumption cost for non-interruptible, interruptible and thermostatic loads. Finally, simulation results and numerical studies are applied on test SH, and conceptual results are discussed.

Keywords: Smart Home Energy Management, Robustness Module in smart home, Real-Time Pricing in smart home, Photovoltaic, Wind Turbine, Combined Heat and Power in smart home, Energy management system Battery Energy Storage.
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1. Introduction

Technology development creates a new expectation about household living conditions. Due to a decrease in homes' power consumption cost, automation was found as the only approach to solve this problem. Smart home (SH), an emerging technology at the lowest level, can refer to all services such as messaging and control actions being performed or displayed without homeowner presence in the home environment, homes with these technologies called SH. Remote control of household appliances is also part of an SH. SH control tools can be possibly used to turn on or off home appliances or change devices operation settings based on predefined times. These tools can be used to change devices' operations are changed based on other variation consequences in the home environment. The SH is executed in a programmable and centralized way and uncentralized with separate sensors and controllers. This system uses advanced electronic controllers for controlling lighting, heating, cooling, and entertainment tools. These systems can be used from a particular wiring or wireless network for communication or act as multiple separate systems (such as light sensors that control the light). One of the important aspects of SH is the potential for minimum energy consumption. About this fact, controlling systems consume energy at the SHs. Therefore, it will cause to benefit if cost-saving with them be more than energy consumption. Energy consumption in SHs can be optimized with a change in equipment operation time, limiting on/off time, etc. SH's general idea is that all-electric and electronic controllers connect and with equipment through a common interface. Under new conditions, the use of renewable energy resources became prevalent with ending fossil fuel. In SH, due to updated information and technology and the main structural goal, renewable energy resources management adds to SH tasks until it acts as a more independent system for cost emission minimization. About discussion importance till now, many studies have been conducted .In [1], scheduling micro-grid resources besides battery energy storage has been done by operating and environmental emission costs minimization and solving it using the normal boundary junction solution method. Scheduling microgrid resources is discussed in [2] with hybrid-electric vehicles (EV) using the Monte-Carlo simulation method. The powerful SOS algorithm is applied to solve the proposed planning model. The authors in [4] proposed controlling a residential energy storage system in the power market with or without local DGs by dynamically pricing energy consumption mechanisms. The simulation results show that the local DG cost can be decreased when ESS is installed in an SH.A new energy management system (EMS) has been suggested in [5] process under increasing electricity demand and the need for a smart grid to optimize energy consumption and generation profiles in residential areas. This study's objective functions consist of energy consumption cost and environmental pollution minimization, load profile and social welfare improvement. Reference [5] presents a decentralized framework for aggregators seeking to maximize their profits by minimizing consumer costs, including residential and EVs load demand. The real-time pricing (RTP) model and EV performance management have been used to motivate monetization consumers by reducing some residential loads during peak time. Authors in [6] provided a stochastic framework for a day-ahead market to maximize Disco profits while exposure less risk about the variable rate of electricity prices and variable electricity rates strategy has been analyzed to cover the demand different times such as TOU and RTP. Scheduling of SH in [7] has been done for transferable loads with time has been performed using PSO algorithm. The objective function was total load and consumption cost minimization to improve overall energy efficiency. It is an EMS for monitoring, controlling, and optimizing electricity production and electricity consumption in SHs. The relationship between retailers and their customers was studied in [8]. The retailer considers a day ahead hourly price for electricity with real-time costumers to maximize individual consumption surplus. In [9], network frequency fluctuations are stabilized by low-cost regulators. About the variable nature of renewable energy resources, a market power mechanism with dynamic pricing proposes for real-time pricing tariff and frequency regulation, in addition to allowing market players, including renewable resources and flexible consumers, so that they can frequently negotiate about electricity prices in the wholesale market. EMS was developed in [10] to schedule residential load management to optimize home appliances, which aims to minimize costs to accommodate load demand and electricity prices. The results show that by implementing the proposed model, the cost of energy payment in SHs will be reduced to 53%, and also, we can get to 35% reduction in total load demand. In [11], with the advancement in information technology and smart grids' development devising new approaches to manage energy consumption using the optimal MIP method optimally. The objective function has been defined to reduce the cost of payment and dependence on the national grid. In this study game theory model is designed to optimize consumption. Solving some of the problems, such as the lack of an effective automation system and consumer awareness of time-varying prices, a new technique for optimally and automatically automating energy consumption scheduling is suggested in [12] for residential homes. The main objective is to minimize energy costs by maintaining social and electrical well-being in the SH. Here, the SH study has independent PV with the uncertain generation, enabling the purchase/sale of electricity from the upstream grid. A home load response program has been used in [13] to control and manage household loads such as EVs and minimized customer cost. In [14], a genetic algorithm-based EMS scheduling has been proposed with the goal of power consumption scheduling and energy cost minimization for residential loads, assuming that consumers are aware of the energy price and the hourly demand for the next day. According to the electricity market's energy price, a new method of scheduling for the heating and cooling equipment has been introduced in [15]. The prediction of the ambient temperature and social welfare level is presented for minimizing the consumer energy payment. Introducing simulation algorithms to reduce the home peak load is considered with programmable load transfer between home automation technologies and human behavior in [16]. In [17] linear programming model has been used to optimize system peak load reduction through control periods in home and industrial load control programs. The effect of consumption side management on the reduction level of feeder peak load demand is investigated in [18] by changing the time of use for high power home appliances and capacitors connected to them. In [19] - [20], the consumer load is classified into two types. The first is the load change can be scheduled at different times of the day, such as a washing machine and dishwasher. The second type, non-interruptible loads (NIL) are operated during specific times such as lighting and cooking stoves. Depending on the type of load, technical planning requires as much load change as enabling the consumer to manage their electricity bills and generation companies to get to balance in the consumption level. In [21], a fuzzy control model is proposed to distribute system voltage profile optimization to improve the DC micro-grids' operating condition. Dispatching load economic has been provided in [22] for minimizing DC micro-grid cost via drop control under the real-time pricing conditions of the electricity market, although a model did not consider branch congestion. An online energy/power optimal control method for the use of energy storage in microgrid has been proposed in [23], which is connected to national grids considering future forecasts of power consumption and Renewable energy generation is provided, but they did not take into account safe charging range and lifetime for using of battery equipment. In [24], centralized power management systems are designed to separate microgrids from the city grid by applying unit commitment and optimal power flow to avoid the mixed-integer nonlinear formulation. [25] considers a comprehensive overview of past and recent research on home EMS concerning various load response programs, smart technology, and load scheduling controllers. A home EMS for optimal scheduling of energy resources, including a PV installed on the roofs of houses to minimize costs in three stages, including forecasting, day-ahead scheduling, and actual operation according to home load profiles was developed in [26]. Using Polar Bear Algorithm in [27] to study new EMS in SH with CHP. The main goals of this search are increasing social welfare, reducing cost and air pollution. The authors in [28] established EMS for smart building using the Gray Wolf and Shark algorithm. In this study, although the consumer's cost decreased by 20%, sustainability increased by 18%. As noted above, the presence of energy storage resources beside DGs in SH planning brings challenges that need to be addressed. This paper focuses on renewable energy resources such as photovoltaic (PV) and wind turbine (WT) that have a better response to SHs. These resources' presence in SHs highlights the necessity of energy storage using due to cover available uncertainty at their output power. Since this resource generation is variable, there may be no wind and solar power radiation, and battery energy storage is not only a daily requirement. Also, a shortage in electrical energy should be provided by other ways such as dispatchable sources such as CHP and connection to the upstream network. To optimize SH consumption, the power market retail model is possible based on RTP pricing for purchasing energy from the global network. Therefore, in this research, we consider for maintained factors as given data for our robustness SH EMS to minimize the emission and energy consumption costs for interruptible loads (IL) such as electric vehicle (EV), pool pumps and NIL such as dishwashers and wash machine and thermostatically loads (TCL) such as electric water heaters. The rest of the paper is organized as follows. In the second part, modeling robustness SH EMS is developed, including objective function and technical constraints. In the third section, we propose a robust SHEMS problem against possible scenarios due to wind speed and solar radiation changes. Section 4 describes how to encode the SHEM problem into the genetic algorithm. In section 5, simulation study and sensitivity analysis are applied to validate the performance of the proposed model on a test SH and finally, the results are presented in Section 6.

2. Modelling of SH Load Scheduling

Electricity is provided for SHs through resources such as PV and WT, heat and power generation and batteries locally and power network can be provided. Home appliances such as smart appliances, sensors and etc. are connected together until form a network for the residential area. The EMS uses this network to collect performance data from all devices, sending control signals and also control them. The load scheduling algorithm is implemented into the home EMS to optimize the consumption of household loads based on available device information, user settings and pricing mechanism. In fact, the main objective is to minimize electricity payments by providing flexibility in the consumption of household loads in accordance to local sources generation and the electricity price of the upstream network while maintaining a certain level of comfort and convenience for the user [29]. But, problem is that loads have different flexibility depending on the dynamics and design characteristics, PV and WT outputs are variable and random, and the energy storage devices with limited capacity cannot fully cover the output uncertainty in these resources. In addition, electricity prices in upstream network is variable during a day which adds to the complexities of SH management. Therefore, due to high uncertainties in SH resource, it is necessary to use the robustness method rather than the conventional deterministic methods.

A) Objective function

Here, Objective function of home load for a day ahead is sum of total payment for energy consumption and environmental emission. The amount of consumption for controllable home appliance must be optimized as decision variable. It should be noted that the energy purchase and sale price can be different in each time interval, which can be modeled according to the charging and discharging status of the battery energy storage in different time periods according to relationship (2).

$$Min.(OF_{Load}^{Scheduling})$$

$$OF_{Load}^{Scheduling} = \sum_{i=1}^{N} \rho_i^{RTP} . \left(\sum_{\delta \in A} \begin{matrix} X_{\delta,i}^{load}) - (P_{pv,i}^{source} + P_{wind,i}^{source} + \\ P_{chp,i}^{source} + P_{Battery,i}^{source(discharge)}) \end{matrix} \right) + \sum_{i=1}^{N} \varepsilon C_i^{chp} \quad (1)$$

$$\rho i = \begin{cases} \rho_{buy,i} \rightarrow \sum_{\delta \in A} \begin{matrix} X_{\delta,i}^{load} \geq (P_{pv,i}^{source} + P_{wind,i}^{source} + \\ P_{chp,i}^{source} + P_{Battery,i}^{source(discharge)}) \end{matrix} \\ \rho_{sell,i} \rightarrow \sum_{\delta \in A} \begin{matrix} X_{\delta,i}^{load} < (P_{pv,i}^{source} + P_{wind,i}^{source} + \\ P_{chp,i}^{source} + P_{Battery,i}^{source(discharge)}) \end{matrix} \\ \rho_{buy,i} \rightarrow \sum_{\delta \in A} \begin{matrix} X_{\delta,i}^{load} \geq (P_{pv,i}^{source} + P_{wind,i}^{source} + \\ P_{chp,i}^{source} - P_{Battery,i}^{source(charge)}) \end{matrix} \\ \rho_{sell,i} \rightarrow \sum_{\delta \in A} \begin{matrix} X_{\delta,i}^{load} < (P_{pv,i}^{source} + P_{wind,i}^{source} + \\ P_{chp,i}^{source} - P_{Battery,i}^{source(charge)}) \end{matrix} \end{cases} \quad (2)$$

B) Technical constraints

Planning constraints on home loads are linked with the operating limitations of a various appliances and the level of user demand for convenience and comfort in the home. Household loads are divided into two categories: controllable and uncontrollable. Due to the operating limitations of the controllable equipment, they are divided into three classes of NIL, IL and TCL. IL are also not independently available at any time and their performance depends on their hardware design specifications. For uncontrolled equipment, they consistently participate in the objective function and do not appear in operational constraints.

C) NIL Home appliance operation modelling

NIL are allowed to start after the time tb and before time te to complete their task. The power consumption of NIL is assumed to be constant and their operation duration is equivalent to L_{NL} time interval. According to the assumptions, status of the power consumption of NIL are modeled following the equation (3) to (5) into the planning time horizon. Which P_{NL}^{Load} is the rated power of non-interrupted equipment and $X_{NL,i}^{load}$ is the rated power of non-interrupted equipment in ith time interval. Therefore, the number of time intervals tb until te must be less than L_{NL}. On the other hand, the constraints of the NIL must also be satisfied, which is incorporated in modeling in accordance to relation (5) [30].

$$X_{NL,i}^{load} = 0 \rightarrow \forall i < t_b, i > t_e \quad (3)$$

$$\sum_{i=t_b}^{t_e} X_{NL,i}^{load} = L_{NL}.P_{NL}^{Load} \rightarrow t_1 \leq i \leq t_{24} \quad (4)$$

$$\sum_{i=j}^{j+L_{NL}-1} X_{NL,i}^{load} \geq (X_{NL,j}^{load} - X_{NL,j-1}^{load}).L_{NL} \rightarrow t_b < j \leq t_e - L_{NL} + 1 \quad (5)$$

D) IL appliances operation modelling

Interruptible home appliances include electric vehicle, pool pump and etc. Similar to NIL, these types of loads must also work between tb and te time interval. All the energy required to perform the equivalent task should be equal to E_{IL}. In addition, it is assumed that the power of IL can be varied from zero to the maximum value that these limitations are incorporated into the proposed modeling according to equations (6) and (7) [31].

$$X_{IL,i}^{load} = 0 \rightarrow \forall i < t_b, i > t_e \quad (6)$$

$$\sum_{i=t_b}^{t_e} X_{IL,i}^{load}.\Delta t = E_{IL} \rightarrow X_{IL,i}^{load} \leq P_{IL}^{MAX}, t_1 \leq i \leq t_{24} \quad (7)$$

E) Thermostat-controlled devices Operation Modelling

Thermostat-controlled devices are also one type of IL. Water heaters, air conditioners and refrigerators are three types of thermostats loads that Water heater is considered in this article. It is assumed that the water heater is capable of continuously changing its electric power proportionally from zero to maximum. Heat energy must satisfy the demand of the consumers in each time zone. Index $X_{TCL,i}^{Load}$ and C_n are status of hot water consumption and heat consumption at time interval ith respectively accordance to relation (9). That d_i is demand for hot water drawn in time interval ith and C_{water} is specific heat of water, θ_{req} and $\theta_{e,i}$ are desire water temperature and ambient temperature at time interval ith. The heat storage during time interval ith should not exceed the maximum water storage which can be modeled according to relation (10). That M is the volume of water in the complete storage, indexes θ_{up} and θ_0 are upper limit of the temperature and the initial temperature of the reservoir, respectively. Index α is the constant coefficient for the unit conversion between joules and kWh. Here, heat loss is considered equal to zero [32].

$$\sum_{n=1}^{i} X_{TCL,i}^{Load} \geq \sum_{n=1}^{i} C_n \rightarrow t_1 \leq i \leq t_{24} \quad (8)$$

$$C_i = \alpha.d_i.C_{water}.(\theta_{req} - \theta_{e,i}) \rightarrow t_1 \leq i \leq t_{24} \quad (9)$$

$$\sum_{n=1}^{i} X_{TCL,i}^{Load} \geq \alpha.M.C_{water}.(\theta_{up} - \theta_0) + \sum_{n=1}^{i} C_n \rightarrow t_1 \leq i \leq t_{24} \quad (10)$$

F) WT operation Modelling

The performance of a WT is mechanically complex because the wind speed and direction are widely variable. Webial distribution is usually used to model and generate wind data at the installation site. The output of the WT is a function of its velocity, direction and kinetic energy and its mechanical properties that are modeled by Equation (11). WT maximum and cut off output power are $P_{WT\max}$ and P_{furl} in accordance to v_{rated} and v_{cutout}, respectively and index v_w is wind speed at tower height. Here, the power curve against wind speed is modeled by Equations (11). The index m is considered to be 3. The measured values at any altitude can be converted rapidly to the height of the installation by the power rule according to the relation (12). Where α is the constant of power rule. This value is less than 0.1 for flat areas, greater than 0.25 for dense forest areas. Usually 0.14 is a good reference for roughly flat areas such as tall buildings. Finally, the electrical power generated by the turbine can be calculated using Equation (13). Index A_W is WT surface in term of m2. Index η_g is efficiency of WT and its associated equipment. Here, required number of WTs to supply a portion of home appliances is determined using relation (14), a safety factor index that is usually 1.2 and the power output of the WT is in term of watts [33].

$$P_{WT} = \begin{cases} 0 & ; v_W \le v_{cutin}, v_W \ge v_{cutout} \\ P_{WT\max} \times \left(\dfrac{v_W - v_{cutin}}{v_{rated} - v_{cutin}} \right)^m & ; v_{cutin} \le v_W \le v_{rated} \\ P_{WT\max} + \dfrac{P_{furl} - P_{WT\max}}{v_{cutout} - v_{rated}} \times (v_W - v_{rated}) & v_{rated} \le v_W \le v_{cutout} \quad ; \end{cases} \tag{11}$$

$$Vw = v_w^{measure} \times \left(\frac{h_{hub}}{h_{measure}}\right)^a \tag{12}$$

$$P_{wind\_out} = P_{WT} \times A_W \times \eta_g \tag{13}$$

$$N_{turbine} = \frac{P_L \times SF}{P_{wind-out}} \tag{14}$$

G) PV Panel Operation Modelling

The output power generated by the PV module is determined by the relation (15). PV arrays are usually equipped with a maximum power point tracking system and this controller is responsible for maintaining at the MPP, ie the maximum output power S_{PP} for the PV system. The PV module must provide part of the estimated load demand as E_L. The number of modules required for solar energy generation can be estimated by Relation (15) [27].

$$P_{PV} = H_t(AV) \times A_{PV} \times \eta_{pv} \tag{15}$$

$$A_{PV} = \frac{E_L}{H_t(AV) \times A_{FC} \times \eta_{pv} \times \eta_{inv} \times A_{Tcf}} \tag{16}$$

$$N_{PV} = \frac{P_{PV}}{S_{PP}} \tag{17}$$

H) Combined Heat and Power Operation Modelling

Small gas turbines which are called microturbines, commonly used to provide electrical and thermal energy simultaneously in some buildings. The fuel cost of microturbine is calculated as a second-order function of active power generation for residential consumption in accordance relation (18). Here, the cost of microturbine greenhouse gas emissions is modeled according to relation (20), which β_i defines the positive coefficient and εC_i^{chp} the cost of environmental pollution [34].

$$FC_i^{chp} = \alpha_{\text{m-i}} + B_{\text{m-i}} \times (P_i^{chp}) + \gamma_{\text{m-i}} \times (P_i^{chp})^2 \tag{18}$$

$$Q_i^{chp}(t) = 2 \times P_i^{chp} \tag{19}$$

$$\varepsilon C_i^{chp}(t) = \beta_i \times P_i^{chp} \tag{20}$$

I) Battery Energy Storage Modelling

Energy storage systems are commonly used to cover the uncertainty of solar and wind power generation in SHs. Since, η_{batt} is the battery efficiency at charge and discharge state and SOC^{batt} is storage status of the battery, therefore, power delivery or absorption and safety operating condition are calculated as relation (21).

$$\begin{aligned} &SOC_{\min}{}^{batt} \le SOC^{batt}(t) \le SOC_{\max}{}^{batt} \\ &P_{Batt}^{s}(t) = \eta_{\text{batt}} \times (SOC^{batt}(t) - SOC^{batt}(t-1)) \end{aligned} \tag{21}$$

3. Renewable Resources Uncertainty Modelling and Robustness Approach in SH Load Scheduling

A) WT and PV Panels Uncertainty Modelling

Since, renewable resources such as WT and PV panels are variable in nature and there is not accurate method to predict available generation, it must be seen uncertainties of resources for load scheduling of SHs. Here, probabilistic tree scenario based method is used to uncertainty modelling. Due to efficient scenarios extraction from density distribution function corresponding to the generation of WT (δ_{Wind}) and PV (δ_{pv}) sources equation block (22) has been used.

$$
\begin{aligned}
&S_w = \{(P_{Wind}{}^1, \rho_w{}^1), (P_{Wind}{}^2, \rho_w{}^2), ...(P_{Wind}{}^{Sn}, \rho_w{}^{Sn})\} \\
&\rho_w{}^1 + \rho_w{}^2 + ... + \rho_w{}^{Sn} = 1 \\
&S_{PV} = \{(P_{PV}{}^1, \rho_{PV}{}^1), (P_{PV}{}^2, \rho_{PV}{}^2), ...(P_{PV}{}^{Sm}, \rho_{PV}{}^{Sm})\} \\
&\rho_{PV}{}^1 + \rho_{PV}{}^2 + ... + \rho_{PV}{}^{Sm} = 1 \\
&S = S_w \times S_{PV} \\
&\sum_{s \in S} \rho_w \times \rho_{PV} = 1
\end{aligned}
\tag{22}
$$

B) Robustness approach

One of the most common solutions to optimization problems against occurrence of various possible scenarios is to minimize the mathematical expectation of the desired objective function. Usually, objective function in such problems is defined on economic basis which is actually known as the stochastic model. In this paper, new approach is proposed to schedule SH load consumption under different sun radiation and wind-speed scenarios according to relation (23) .

$$
\begin{aligned}
&u_E(OF_i) = \sum_{s=1}^{N_s} \Pr_i^s .OF_i^s \\
&s.t. \rightarrow X_i = \{X_{NL,i}^{load}, X_{IL,i}^{load}, X_{TCL,i}^{load}, P_i^{pv}, P_i^{wind}, P_i^{chp}, P_i^{batt}\} \\
&OF_i^s = f(X_i, Scenarios) \rightarrow OF_i = \{OF_i^1, OF_i^2 ... OF_i^{Ns}\}
\end{aligned}
\tag{23}
$$

If, there are no guarantees for occurrence a particular scheduling state, the process will run at a certain level over all space parameters with uncertainty, in addition, it is often necessary to pay attention to the technical and economic surplus estimates. Here, a unique type of economic evaluation is considered with regard to the worst case scenario with the highest cost according to the relationship (24). Eventually, final solution to SH consumption scheduling has been robusted based on the cost of the worst-case scenario according to the relation (25).

$$
u_{WC}(OF_i) = Max\{OF_i^s \,|\, s = 1,2,.., N_s\} \tag{24}
$$

$$
\underset{X = Loads, pv, wind, chp, batt}{Min} .(u_E(OF_i), u_{WC}(OF_i)) \tag{25}
$$

4. Coding Procedure of Robustness SH Load Scheduling Problem in Genetic Algorithm

Intelligent Genetic Algorithm is one of the searching and optimization methods for mathematical problem based on the principles and mechanisms of natural genetics and choosing the survival of the fittest. The algorithm starts by production of the initial population equivalent to the chromosomes, and then the population fitness score is calculated, among the chromosomes, some are selected based on their priority order and then merge using genetic operators such as cross-over and mutation, which, from the algorithmic point of view can be evaluated as tools for modifying current responses. To solve the scheduling problem of SH loads, the GA deals with the coded form of the problem parameters or variables of the problem as described below. To execute the problem solution by genetic algorithm, first the parameter values include IL, NIL and TCL information, WT speed-power prediction and solar radiation with specified mean and standard deviation, technical and economic characteristics of combined heat and power unit and energy storage devices of SH are interred into the proposed model. Then, price of selling electricity to the grid and the price of buying electricity from grid based on the RTP as well as the total number of scenarios corresponding to uncertainties related to the solar radiation for the PV sources and the wind speed have been calculated and enter into modeling for WT resources. At the continuous, the initial population of genetic algorithm chromosomes consisting of six house loads including 2 NIL, 1 washing machine and 1 dishwashers, and 1 IL including electric vehicle and 1 TCL including 1 water heater, CHP production, and battery charge and discharge level are defined for next 12-hour according to table (1). At the first step, the chromosomes are randomly generated in accordance above table, and the fitness of each chromosome as a parent or a solution to the SH scheduling optimization problem using the relation (1) as an objective function is evaluated.

Table.1.
Typical chromosome structure for coding robustness SH load scheduling problem in GA

Loads			***DGs***	***ES***
NIL (t1,..,t12)	IL (t1,..,t12)	TCL (t1,..,t12)	CHP (t1,..,t12)	Battery (t1,..,t12)
CW, DW1	EV	WH	CHP	Battery

It should be noted that the genetic algorithm is an unconstrained solution method, thus violating from any technical constraints for IL, NIL and TCL and operation from the dispatchable source such as CHP and batteries is added to the objective function as penalty. Due to the existence and modeling of uncertainties in WT and PV panel production in the SH, a number of production scenarios equal to $S = S_w \times S_{PV}$ have been formed, violation rang of constraint (3) to (10) for NIL, IL and TCL are $Penalty_{NL}^s$, $Penalty_{IL}^s$ and $Penalty_{TCL}^s$, respectively and violation of the constraint (21) for the battery energy storage in each chromosomes equal to

$Penalty_{battery}^{s}$ is produced by the genetic algorithm must be considered in accordance to relation (26).

$$\underset{X_i=Loads,pv,wind,chp,batt}{OF_i} = OF_i^S + Penalty_{NL}^S + Penalty_{IL}^S + Penalty_{TCL}^S + Penalty_{battery}^S$$
$$s.t. \rightarrow X_i = \begin{Bmatrix} X_{NL,i}^{load}, X_{IL,i}^{load}, X_{TCL,i}^{load}, P_i^{pv}, \\ P_i^{wind}, P_i^{chp}, P_i^{batt} \end{Bmatrix} \quad (26)$$

Genetic based solution flowchart of SH consumption scheduling with regard to the uncertainty of WT production and PV panel are shown in figure (1).

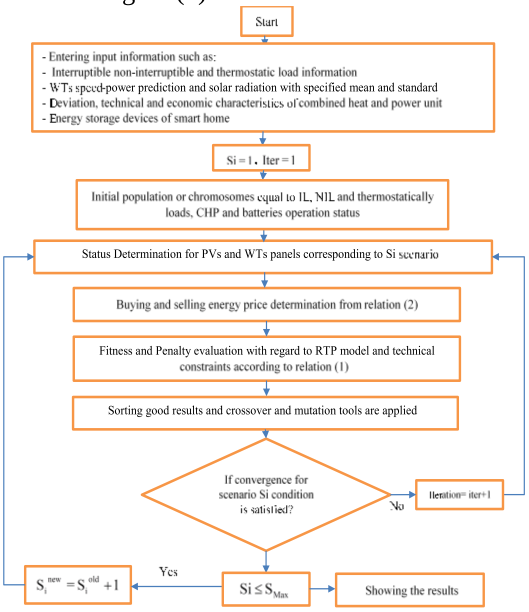


Fig. 1. Genetic based solution flowchart of SH consumption scheduling with regard to the uncertainty of WT production and PV panel

Since, SH load consumption scheduling must be robust against all WT and PV production scenarios, therefore, after calculating the penalties of all possible states, the minimum mathematical expectation value of the objective function from relationship (23) and the worst-case scenario from relationship (24) is computed as relation (25). After sorting the chromosomes with higher fitness, the crossover process is performed between the pairs of chromosomes for child production with P_C probability. At the next step, the mutation operator is applied for the child chromosomes in the problem solving process with probability pm. Then, the chromosome fitness for each of them is evaluated that equal to evaluating new solutions to the above-mentioned problem from the relationship (26). This trend is repeated for the next generation of solutions until converge condition is satisfied.

A) Numerical Studies and Simulation Results

In this section, simulation studies are applied to validate performance of the proposed robust model for 12-hour of a day ahead SH consumption scheduling due to uncertainties in PV and WT generation and CHP and battery energy storage participation in a smart test house. The installed capacity of the PV panel and WT system is 5 kW and 2 kW respectively. Specifications of WT include low cut-off V_{ci} and high cut-off speed V_{co} and normal operating speed V_N which are 5 m/s, 25 m/s and 15 m/s, respectively. The radiation and wind for the next day are shown in figure (2), half of these information has been used.

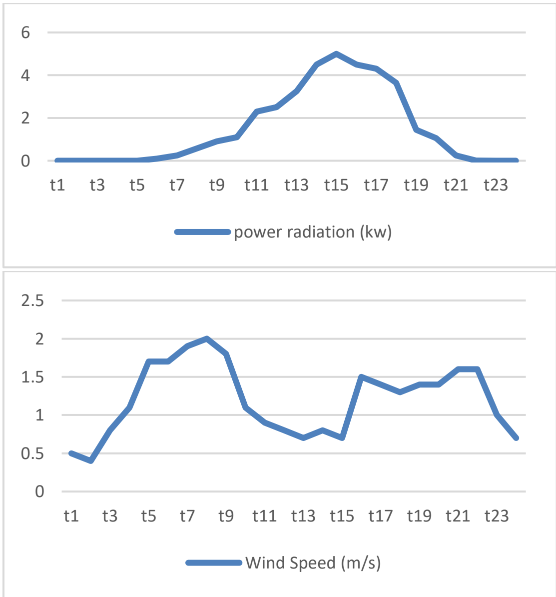


Fig. 2. radiation-power curve of PV and wind-power curve of WTs for the next day

The uncertainty of the radiation curve for the PV panel ith three scenarios and uncertainty of the wind for the WT resource can be modeled by five scenarios according to Table (2).

Since all loads of test SH are controllable therefore optimal determination of their consumption by the proposed algorithm will form the daily load profile. Here, the minimum and maximum energy storage capacity of the battery is 1.5 kWh to 5 kWh, respectively, with charging and discharging efficiency of 0.98 and 0.95, respectively. The initial storage of battery to start the SH operation scheduling test is 2.5 kWh. The SH is equipped with a power and heat generating unit that has a 5 kW installed capacity with coefficients cost α, β and γ are 3, 1.6 and 0.0003, respectively. The constant coefficient for environmental emission is 0.25. The startup and shutdown costs are 50 $ and 20 $, respectively, and it was off for two time interval before the start of CHP scheduling. The parameters of SH appliances and their settings for a certain level of comfort in the SH have been described in tables (3) to (5). The rated power of the water heater is 6.5 kW, the initial, the maximum, and required temperature are 30, 80 and 47° C, respectively. The value of α is 1/3600000 and M is 189.25, C is 431.7 and R is 0.7623. Table 4 shows the hot water demand and ambient temperature. Two types of tariffs have been considered for the purchase price of electricity from the real-time pricing model. Selling prices based on hours owner are determined which has been displayed at the table (5).

5. Case Studies

Robust modeling of SH load scheduling with respect to the assumed parameters and uncertainties of PV and WT generation in addition to the presence of dispatchable resources such as CHP and battery storage in MATLAB coding software has been solved as a mathematical optimization problem. Genetic algorithm is used for simulation studies. Then, sensitivity analysis for the proposed model are studied under the following conditions.

Table.2.
Uncertainty modeling for the PV panel and WT resources

Scenarios	ρ_{PV}^{S}	AF_{PV}^{S}	
Scenario1	0.5	AF(t1:t6) = 1	AF(t7:t12) = 1
Scenario2	0.3	AF(t1:t6) = 0.98	AF(t7:t12) = 0.96
Scenario3	0.2	AF(t1:t6) = 1.03	AF(t7:t12) = 1.05
Scenarios	ρ_{Wind}^{S}	AF_{Wind}^{S}	
Scenario1	0.50	AF(t1:t6) = 1	AF(t7:t12) = 1
Scenario2	0.15	AF(t1:t6) = 0.99	AF(t7:t12) = 0.98
Scenario3	0.15	AF(t1:t6) = 1.01	AF(t7:t12) = 1.02
Scenario4	0.10	AF(t1:t6) = 0.97	AF(t7:t12) = 0.95
Scenario5	0.10	AF(t1:t6) = 1.02	AF(t7:t12) = 1.05

Table.3.
parameters of NIL and ILin SH

Home Appliances (group 1)	NIL			
	P_{NL}^{Load} (KW)	t_b (Hour)	t_e (Hour)	L_{NL} (Hour)
Washing machine	1.2	2	8	4
Dish washer	0.5	5	12	3
Home Appliances (group 2)	IL			
	P_{IL}^{Load}	t_b	t_e	E_{IL}
Electric vehicle	2.5	4	11	3* $P_{N\ EV}$

Table.4.
parameters of TCL in SH

time	t1	t2	t3	t4	t5	t6
$\theta_{e,i}$	21	23	25	28	29	30
time	**t7**	**t8**	**t9**	**t10**	**t11**	**t12**
$\theta_{e,i}$	32	35	37	39	41	44
time	**t13**	**t14**	**t15**	**t16**	**t17**	**t18**
$\theta_{e,i}$	21	23	25	28	29	30
time	**t19**	**t20**	**t21**	**t22**	**t23**	**t24**
$\theta_{e,i}$	32	35	37	39	41	44

time	t1	t2	t3	t4	t5	t6
d_i	60	85	90	105	120	140
time	**t7**	**t8**	**t9**	**t10**	**t11**	**t12**
d_i	32	35	37	39	41	44
time	**t13**	**t14**	**t15**	**t16**	**t17**	**t18**
d_i	60	85	90	105	120	140
time	**t19**	**t20**	**t21**	**t22**	**t23**	**t24**
d_i	165	185	160	150	140	120

Table.5.
selling and purchase electrical energy prices to/from network using RTP model

Time	t1	t2	t3	t4	t5	t6
Sell	.7	.7	.7	.7	.8	.9
RTP1	8	10	12	14	15	17
RTP2	8	12	14	16	18	20
time	**t7**	**t8**	**t9**	**t10**	**t11**	**t12**
Sell	0.13	0.13	0.13	0.13	0.13	0.15
RTP1	18	20	24	22	20	18
RTP2	22	19	14	13	12	11

-Case Study 1: Robust scheduling of NIL in SH in the absence of Battery Storage

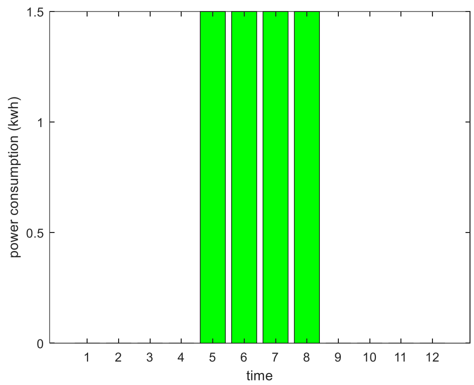
-Case Study 2: Robust scheduling of NIL and IL in SH Loads in the absence of Battery Storage

-Case Study 3: Robust scheduling of NIL, IL and TCL in the Presence of Battery Storage

The population of chromosomes is estimated at 5000. The GA is able to execute a ceiling of 100 iterations for the final solution. The crossover probability for the chromosomes is 0.8 and the probability of mutation is 0.2. The numerical results obtained from solving the case studies are discussed and summarized as bellow.

A) Case Study 1: Robust Scheduling of NIL in SH in the Absence of Battery Storage

Robust scheduling only for NIL of SH including a washing machine and dishwasher in the absence of a battery storage for the half of next day from 1am to 12pm considering assumed parameters and uncertainties in WT and PV panel resources have been implemented and it should be noted that pricing of two RTP tariffs is based on the 2 kW exchange in the model. The simulation results for SH load scheduling are shown as figure 3.



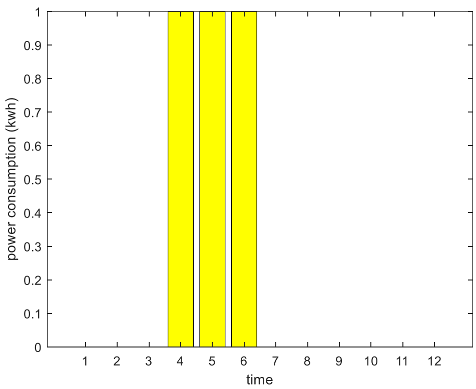


Fig. 3. Robust scheduling of a) washing machine and b) dishwasher for the half of next day (case1)

In our robust scheduling model for the use of washing machines t5, t6, t7 and t8 and for the t4, t5 and t6 washing machines have been proposed. As can be seen from the simulation results, the controllable NIL such as the washing machines and dishwasher can be scheduled in the permitted operation periods from t2 to t8 and from t5 to t11 for doing their tasks during 4 and 3 Sequential time periods, respectively. Operational cost and environmental pollution have been calculated 9.919 $ for scheduling goal. Beside WT and the PV panel resources installed in the SH, there is a combined heat and power unit whose output is determined to sell power to the grid or to contribute to the home load as shown in figure 4.

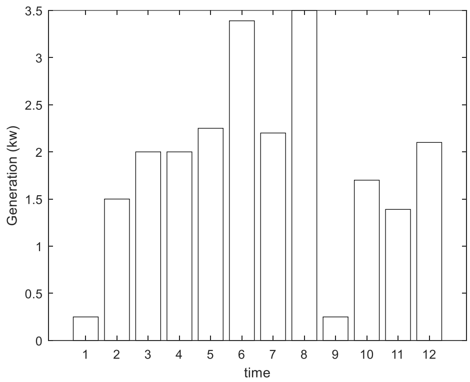


Fig. 4. combined heat and power unit output for the half of next day (case1)

The simulation results verify this fact that scheduling of combined heat and power unit for energy provision in SH is based on radiation level and wind speed for selling electrical energy to the national grid using RTP model. Until to period t5 solar panel will has no output due to the absence of radiation and the WT unit producing less than 1 kW, Therefore, CHP energy generation will be sold to the grid due to lack of consumer scheduling for these periods While, NIL demand at period t4 is equal to 1kW, at periods t5 and t6 is equal to 2.5 kW and at the period t7 and t8 is equal to 1.5 kW. That CHP unit is not capable of supplying home load demand at time period t5 and WT production is used to supply the remaining load because the PV panel has no production while at time period t5 WT production is due to production uncertainty will be more than 1 kW that will be able to sell part of the production to the upstream grid based on RTP model in addition to supplying the SH. For the rest of the scheduling periods, the production of WT, PV panel and CHP will be sold to grid.

B) Case Study 2: Robust Scheduling of NIL and IL into SH in the Absence of Battery Storage

In case 2, robust scheduling of NIL and IL into the SH in the absence of battery storage with regard to production uncertainty of WT and PV panel resources for half of next day will be studied from 1am to 12pm. But, it should be noted that the rest of the technical and economic parameters remain unchanged as compare to case study 1. Numerical studies and simulation results for robust scheduling of SH NIL and IL under the new conditions are in accordance to figure (5).

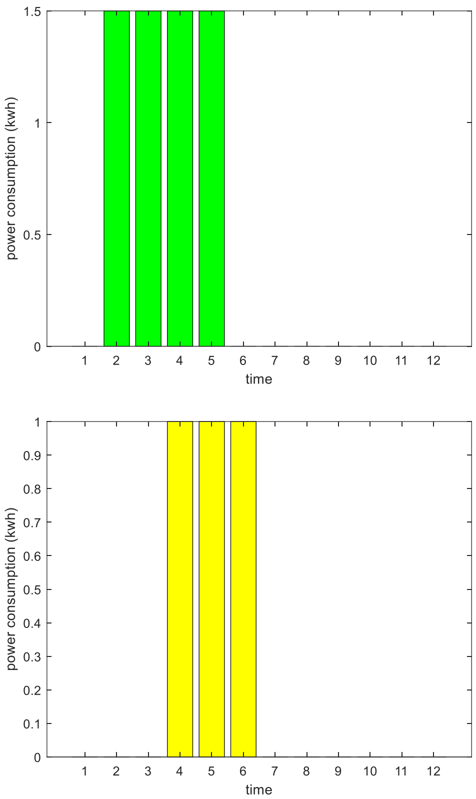


Fig. 5. robust scheduling of a) washing machine and b) dishwasher into the SH under condition case 2

As can be seen from the simulation results under the new conditions, the scheduling of dishwasher operating time did not change compared to the previous study but the washing machine consumption is shifted from t5-t8 to t2-t5 until electric vehicle consumption to optimize over the t4-t11 time period according to figure (6).

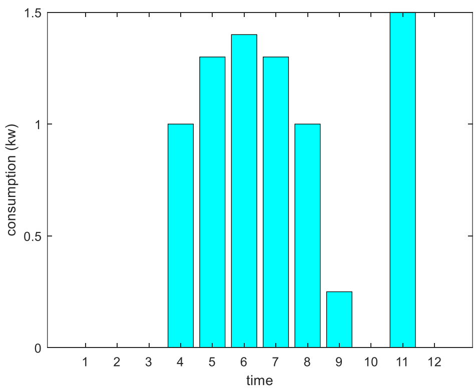


Fig. 6. robust scheduling of EV consumption under condition case 2

As can be seen from figure (6) electric vehicle consumption at t10 is cut off and rescheduled at t11 indeed there is no continuity for robust scheduling of electric vehicle consumption over time periods. Robust scheduling for electric vehicle has been optimally performed within the permissible range of t4-t11 time period which total consumption is triple of rating capacity, in fact, another limitation of electric vehicle operation is satisfied. The CHP production under the new conditions is shown in figure (7).

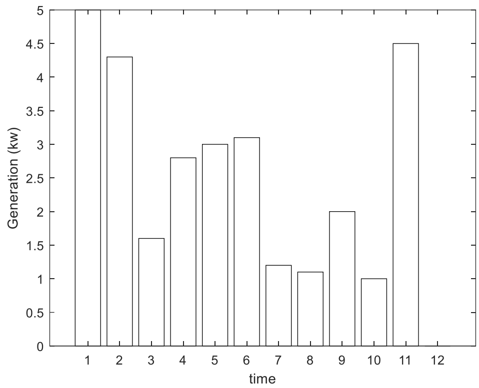


Fig. 7. CHP production under condition case 2

CHP production scheduling in the presence of IL for the SH is carried out so that, from time period t1 to t6 in addition to providing CW and DW loads demand part of production alongside available WT production sells to the upstream grid. As can be seen from the results, from t5 time period indeed after availability of PV panel production alongside WT generation in SH CHP unit production contribution to supply the electric vehicle loads will decrease during the permissible operating time periods t4-t11 due to minimization of cost and environmental pollution specially in time period t9 that limit to the up ceiling of 2kW. At this case study scheduling of SH loads is calculated 10.719$ for the half of next day.

C) Case Study 3: Robust scheduling of NIL, IL and TCL in the Presence of Battery Storage

In case 3, robust scheduling of NIL and TCL in the presence of battery storage for SH considering uncertainty in WT and PV panel generation will run for the half of the next day from 1:00am to 12:00pm. In this case study all technical and economic parameters remain unchanged as compare to case study 1. Numerical studies and simulation results are presented for robust scheduling of SH loads under the new conditions as shown in figure (8).

The simulation results under the new conditions show that the dishwasher and washing machine scheduling time are shifted from t4-t6 to t3-t5 and t5-t8 to t1-t4 compared to the previous study. As can be seen, increase in thermostatically load demand lead to more shifts in NIL load consumption over periods of low load even in the presence of energy storage. Under the new conditions, the scheduling results for the electric vehicle consumption over the time interval t4-t11 can be optimally determined as shown in figure (9). It is generally seen from the simulation results that the demand for thermostatic load consumption is optimally more scheduled at time periods t8 to t12 compared to other periods, which totally should be provided with the demand for NIL and IL through WT, PV and CHP unit as well as battery storage based on operating cost and RTP for global network. The CHP unit power output and performance status of battery storage are shown in figures (11) and (12), respectively.

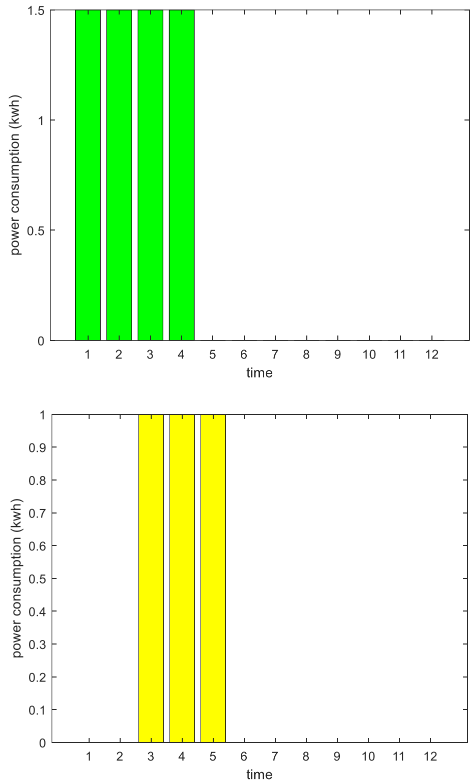


Fig. 8. robust scheduling of a) washing machine and b) dish washer based battery energy storage into the SH under condition case 3

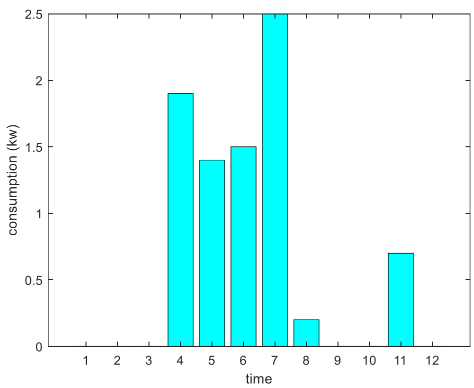


Fig. 9. scheduling results for the IL consumption of electric vehicle in the presence of energy storage under condition case 3

The simulation results are indicated that the range of IL consumption increased for the time period t4-t7 and decreased for the time period t8-t11 as compare to the case 2. Also, we are faced with cut off electric vehicle load for time period t9 in addition to t10. This shift in SH consumption is driven by the demand increasing for thermostatically loads which are added to the total loads demand by availability of PV panel production in addition to WTs. The robust TCL consumption scheduling such as electric water heater for the SH in the presence of a battery storage is illustrated in figure (10).

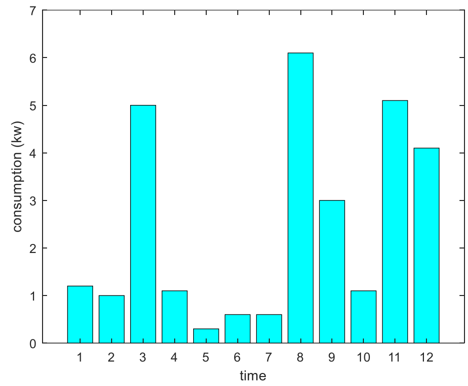


Fig. 10. robust TCL consumption scheduling under condition case 3

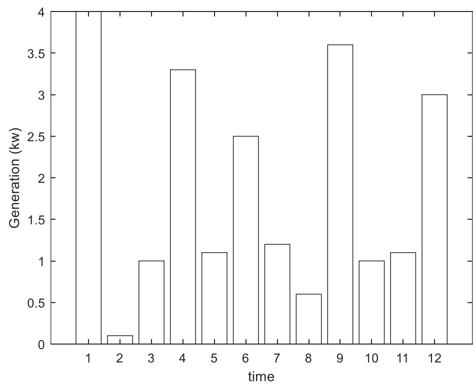


Fig. 11. CHP unit power output for SH load demand provision under condition case 3

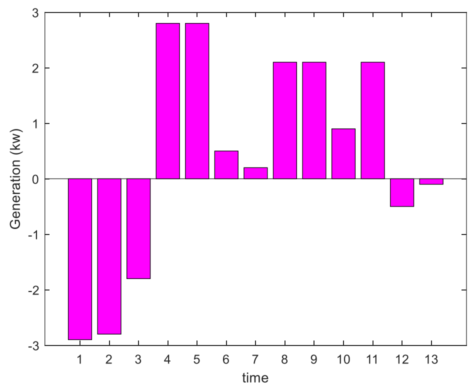


Fig. 12. status of battery storage for SH load demand provision under condition case 3

It should be noted that the battery storage beside CHP unit is used at discharge mode to cover the uncertainty of WT and PV resources production for time periods t1-t5 and it inject totally 12.6kwh energy to system, while from time period t6 to t9 battery will be switched to charge mode due to availability of surplus PV panel output equal to 4.1kWh and again, from the time period t10 to t12 return to discharge mode for energy injection to SH system equal to 2.8kwh. Meanwhile, operating costs and environmental pollution have been calculated as an objective function for the goal of scheduling SH loads equal to 12,229$ for the half of next day.

6. Conclusion

At this paper genetic algorithm based robust scheduling of smart home loads has been proposed with regard to uncertainty of wind turbine and photovoltaic panel power generation beside use of dispatchable resources such as CHP and battery storage in grid connected state. At the first, modeling of NIL, IL and TCL in smart home was performed and then non-dispatchable resources such as wind turbine and photovoltaic panel as well as dispatchable source such as CHP unit have been modeled. Further, modeling of renewables resources uncertainty and the robustness approach into the smart home load scheduling in the presence of a battery storage were illustrated. The robust scheduling problem of smart home loads was coded in the genetic algorithm based on the technical and economic assumptions and flowchart was solved. Assumptions include RTP model in retail electricity market, minimization of CHP emissions and energy consumption for interuptible household loads such as electric vehicle and non-interuptible household loads such as washing machine and dishwasher and thermostatically household loads such as electric water heaters. Simulation for model validation have been studied in three studies, in case study 1 robust scheduling for NIL only, in case study 2 robust scheduling for non-interuptible and interruptible loads and in case study 3 robust scheduling for NIL, IL and TCL in the presence of a battery storage have been evaluated. The simulation results show that increasing load types from only all types of loads in case 2 and mentioned loads in case 3 shifts the use from peak-load to low-load hours and use of battery storage to supply them in shortage of renewable energy in the smart home. Then, dispatchable resources are initially scheduled to meet load demand, if insufficient production is available through renewable resources such as wind turbine and photovoltaic panel and battery storage to supply load therefore, purchasing energy from the network based on real-time pricing is final alternative. But, if at some time periods surplus renewable generation was available in the SH, at robust scheduling the storage units would first be charged, and then, uncertainty over renewable energy sources would lead to the option of selling energy to the utility at their suggested price.

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