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Research Article

Modeling household electricity consumption using agent-based simulation

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Abstract

Electricity is one of the most significant energy sources in the modern world. Over the last century, there has been no significant change in the centrally controlled structure of electrical power grids, especially in developing countries. Global population and economic expansion, together with air pollution, put further strain on the electricity industry. The power electrical grid, as the main structure for power transmission, has to reconsider its concepts. Currently, critical peak load caused by residential customers has attracted utilities to pay more attention to residential demand response (RDR) programs. With the rise in household computing power and the increasing number of smart appliances, more and more residents can participate in demand response (DR) management through the home energy management system (HEMS) to prioritize the start-up of electrical appliances according to the necessity of use and efficiency. This research is an applied case study designed for cold regions with an average household population of three people. It is suggested that, in addition to, time of consumption and household type, the cluster of appliances affects the price of consumption, and the cost paid by users varies depending on the cluster of appliances used by different households at different times. To evaluate the potential for changing prices to better consumption criteria, a multi-agent hierarchical model including utility and different types of households and appliances is presented in this study that takes into consideration two main objectives, including peak smoothing and energy consumption reduction. Based on the specified indicators, the analytical results of two scenarios were analyzed, and it was concluded that variable pricing of appliance consumption can reduce electricity consumption and smooth the peak load curve.

Keywords:
Agent-based modeling and simulation;
Demand response;
Electricity consumption;
Electricity demand profiles

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1. Introduction

In modern economies worldwide, electricity is arguably the most versatile energy source and is closely linked to both social and economic progress. Electrical power has increased faster than any other fuel, which has led to a steady increase in the fuel mix's overall proportions (Lin & Zhu, 2020). This trend is expected to continue in the next years as growing, especially rural, segments of the world's population in emerging countries start moving up the energy ladder and connecting to electrical grids. Fossil fuels provide the vast bulk of the primary power source that humans use to generate electricity (Kumar et al., 2023). Since fossil fuels are becoming less and less available over the present century, they must be replaced since they seriously damage the atmosphere, ecosystems, and human health. The primary source of greenhouse gas (GHG) emissions from human activities, especially CO2, into the earth's atmosphere is the burning of fossil fuels. Therefore, the anticipated production of power is closely linked to greenhouse gas emissions and human-caused climate change (Sharda et al., 2021). Predictions about the evolution of the global energy infrastructure over the next millennium provide the basis of the assessment of the expected environmental harm caused by human activities. Architects, administrators, energy legislators, authorities, and creators around the world are focusing on using energy sources with the least amount of pollution to generate electricity because both environmental degradation and global warming are recognized as major problems. Consequently, the development of carbon-free power-generating techniques should focus on the extent to which energy contributes to global greenhouse gas emissions (Khan et al., 2016). Renewable energy sources (RES) are now used to meet the world's energy demands. Renewable energy sources (RES) include biomass, water power, geothermal energy, wind, solar power, and maritime energy. The green renewable power source is the main, unadulterated, and infinite source of electricity. Around the world, authorities are encouraging people to use sustainable energy sources, preserve energy, and offer rewards to those who do so (H¨o¨ok & Tang, 2012).

To meet these challenges, the scientific community as well as industrial entities, are taking steps to upgrade their grid infrastructure and related technologies to ensure energy production and supply over the next century. While many of the current solutions that must meet demand are based on the traditional idea of increasing supply to meet demand, demand response by managing demand opposes the aforementioned idea and seeks to match the available energy. To effectively manage the demand response, utilities use different signals such as price. One of the pricing methods that can be considered is different pricing for electrical appliance clusters (Simsar et al., 2023). Thus, this study aims to develop an extendable agent-based model of household energy consumption, which can simulate the consumption of appliances to identify the influence of the various pricing for each cluster of appliances. Regarding organization, section 2 reviews the literature and studies on the models of household electricity consumption. Section 3 presents the proposed framework. Section 4 describes the scenario analysis in the research. Section 5 discusses the model validation and results of the experiments. Finally, the paper is concluded in Section 6.

2. Literature Review

With the pyramidally serious environmental pollution as well as the increasingly tense relationship between energy supply and demand, the contradiction between the use of inefficient and single types of energy and the reserve of resources is gradually deepening (Hua et al., 2025). Residential consumers play an important role in the sustainable transition of the energy system by leveraging their household loads for demand response (DR). Sridhar et al. analyzed the enrollment rates of residential consumers within DR through an agent-based model (ABM). Both economic and noneconomic (social/behavioral) parameters that influence consumer enrollment in DR are considered. An energy management model, a home energy management system (HEMS), is used to identify the potential economic savings of consumers enrolling in DR. Consumers are randomly assigned to different neighborhoods and have different social relationships (e.g., friends, neighbors), which, in turn, influences their decision-making in the ABM (Sridhar et al., 2024). In recent years, researchers have focused on problems including price, consumption of energy (Sadeqi & Roozmand, 2023), and agent-based modeling and simulation (Vanhée & Borit, 2024). Customers and utilities may lessen pricing volatility and peak demand by using demand response. To lower the needs for infrastructure related to energy generating, demand itself can be made more flexible rather than requiring electricity generation to adjust to fluctuations in demand. Demand response is a cost-effective and promising approach that will increase the flexibility of power demand and allow individual consumers to modify their demand plans in order to satisfy their energy supply requirements (Simsar et al., 2023). Additional options include lowering energy and utility costs by installing efficient renewable energy systems, educating consumers about their energy usage, utilizing energy-efficient appliances, replacing traditional devices with smart ones, and leveraging contemporary power communication technologies (Del Mar Sol`a et al., 2023). An intelligent energy management system called a home energy management system lets homeowners monitor how much energy is produced, stored, and used (Shareef et al., 2018). Using communication and sensing techniques used in houses, a personal smart device allows for real-time control and monitoring of many intelligent home device functions (Han et al., 2011). By evaluating the user interface panel and using feedback from sensing devices to regulate the difference error between the input and output signals, the HEMS framework functions as a feedback control system that instructs intelligent appliances (Chen et al., 2021). HEMS offers a number of features, including monitoring the performance of electrical components and transmitting vital data about the energy usage of each household appliance in real time (Son et al., 2010). Managing various home appliances remotely or manually; administration for the generation, conservation, and use of power; If any irregularities are found, an alert will be sounded; Maintain energy and price records in real time to cut down on power usage (Sare et al., 2014). These days, HEMS is crucial because of its computerization capabilities and operational recommendations, which lower power consumption and boost efficiency. HEMS are demand-response devices that adjust and lower demand to improve the energy generation and consumption profile of a consumer's house (Jin et al., 2017).

With the advent of the smart electrical grid, people may now plan their domestic energy usage to save money on energy and lower the power Peak-to-Average Ratio (PAR) (Dragomir & Dragomir, 2023). The ability to schedule home device operations in HEMS allows users to achieve their goals and priorities while minimizing energy use, electricity costs, peak load demand, and user comfort (Yang et al., 2023). Efficient scheduling techniques include the ability to switch between non-schedulable electrical items such as screens, lighting, presses, kitchen appliances, and portable devices, as well as schedulable electrical devices such as electric vehicles, washing machines, dryers, heating systems, and cooling systems at any time (Zhou et al., 2016). Many schedule control strategies have been used to provide the most efficient appliance scheduling. scheduling energy use while taking a number of tactics into account (Yoshihisa et al., 2012). Before scheduling, the energy management control must receive the output power from Demand Response (DR), Distributive Generation (DG), and Real Time Pricing (RTP). RTP makes use of the forecasted data. Each device includes a smart plug to enable completely autonomous control of household appliances, and a scheduling system controller will establish a wireless networking connection with each terminal (Yang et al., 2018). HEMS used to schedule home devices by shifting or reducing loads by taking advantage of the DR program to run appliances at the time of low rates of electricity thereby ensuring the comfort of users (Haider et al., 2016). HEMS schedules high-consumption appliances to consume power from clean energy resources during periods of peak demand or when grid power rates are high, this result in reducing the grid's burden and ensuring its stability (Luo et al., 2018). with the aid of devices that continuously monitor the amount of electricity consumed by various home electronics and assess energy usage patterns at the appliance level. In order to reduce power consumption and associated costs, HEMS provides a range of consumption plans (Bapat et al., 2011). Demand response reduces the need to invest in production during peak hours, improves efficiency and stability, and has several financial and environmental advantages. It is particularly successful at moving consumption away from peak hours. The proper signal must be given to the final consumer in order to be able to create a win-win situation for customers and utilities (Simsar et al., 2023). It has been demonstrated that DEMAND programs provide both the supply and demand sides with a number of operational and financial advantages (Siano, 2014; Zhang et al., 2018). Although most DR providers serve commercial and industrial clients, residential demand response (RDR) has gained increased attention in recent years due to the sharp increase in home power usage, particularly air conditioning. (National Energy Administration of China, 2019; Xie et al., 2018). High home energy consumption has emerged as the primary cause of the majority of peak demand and significant peak-valley variations during heat waves in hot summers (Mhanna et al., 2016). Numerous in-depth studies have been conducted on the modeling of home power consumption profiles. However, the goal of the study has a significant influence on the approach choice. Twelve distinct household load curve models were examined and assessed by Grandjean et al., who divided them into two primary categories: Top-down and bottom-up (Grandjean et al., 2012).

Agent-based modelling is and simulation (ABMS) known as a modelling and simulation technique capable of modelling complex systems composed of interacting autonomous 'agents' (Segovia et al., 2022). Numerous domains, including supply chain management (Rahman et al., 2021), marketing (Rand & Stummer, 2021), finance and economics (Axtell & Farmer, 2022; Segovia et al., 2022; Zehra & Urooj, 2022), and others, have made use of ABMS. The past two decades represent a fast development of ABMS in management and business studies because of characteristics including heterogeneity, a bottom-up viewpoint, non-linearity, learning agents, and a complex system approach (Zehra & Urooj, 2022). Vijayan et al. propose an extendable agent-based computational model for assessing household electricity consumption patterns in cities of developing nations. They demonstrated the model using an urban precinct in India as a representative case. It simulates the monthly electricity consumption of an urban precinct in Nagpur by combining the significant factors impacting household electricity consumption in developing nations with the household's electricity consumption process in relation to outdoor weather conditions and the heterogeneity in occupants' behavior (Vijayan et al., 2024).

Using sociodemographic criteria, Gonzalo et al. employed the ABMS technique to create zones within the London metropolitan region. In order to replicate the hourly power consumption for domestic energy, electric vehicle charging, and heat pumps, a heterogeneous set of agents with an occupancy profile is created for each zone. This model focused on electric vehicles and showed their residential usage as a total amount of power used (Bustos-Turu et al., 2016). In order to assess the economic feasibility of different available storage technologies using a simulation-based method, Zheng et al. created an agent-based stochastic appliance level demand model to randomly generate demand profiles for a single representative US household. They then created dispatch strategies based on available demand response tariffs (Zheng et al., 2014). A multi-agent system architecture was presented by Wang et al. to investigate residential power usage under various price schemes (Wang et al., 2018). In the study, an ML-based simulation framework for exploring two fairness constructs of dynamic pricing for residential electricity with behavioral agent-based models based on social theory combined with active learning is described (Thorve et al., 2024). In the case study, four demand response algorithms were used to simulate a single family with a single occupancy pattern type. Elie et al.

suggested methods for achieving sustainable building performance by using the building's inhabitants as agents and their thermal comfort as an objective function for optimization (Azar et al., 2016). The suggested model's main goal is to integrate building performance with human activities. Zhang et al. investigated an office building's power usage using an ABMS model (Zhang et al., 2011). An ABMS model was presented by Lin et al. to investigate the power consumption of office buildings using a tiered pricing structure (Lin et al., 2018). Lin et al. looked at smart charging techniques by using multi-ABMS to analyze the charging patterns and penetration rates of electric vehicles (Lin et al., 2016). The use of the ABMS concept in relation to smart power markets and grids was studied by Philipp et al (Ringler et al., 2016). Multi-agent deep reinforcement learning optimization for immediate form multi-home energy administration, including EV charging schedules, was proposed in this study in (Kaewdornhan et al., 2023) in order to exchange information and reach the best possible decision. The SHEM multi-agent system (MAS) was proposed by (Wu et al., 2014) as a way to plan equipment operations and develop a prototype that can meet user requests for instant demand management. Using a novel fuzzy energy factor in the FLC approach for rapid demand management was also created and validated. In (Jabash & Jasper, 2020), an intelligent multi-agent Adaptive Neuro-fuzzy inference approach embedded in HEMS is given for the effective management of ESS, scheduling devices, and integrated green energy. This study (Wang et al., 2023) focuses on how to accomplish a significant savings by using multi-agent deep reinforcement learning to choose the best course of action using efficient power transactions and DSM methods.

3. Research Method

This section discusses the proposed ABMS framework. Three agents make up the architecture of the framework: the utility agent, the household agent, and the appliance agent. Fig.1 illustrates the hierarchical connection between the Household and Appliances agents.

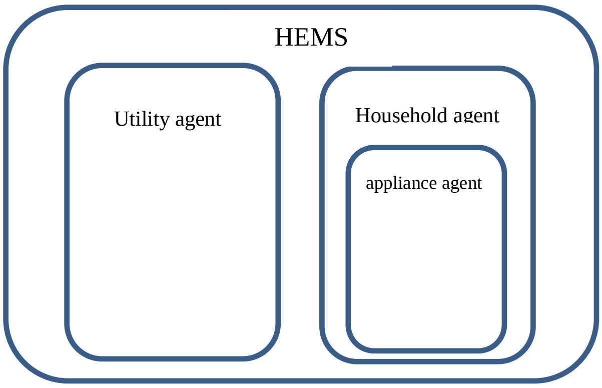

Fig. 1. Hierarchical connection

The appliance agent has the parameters such as appliance types, appliance power & price. The type of appliances, clustered in (Simsar et al., 2023) according to their inherent characteristics, is identified and shown in Table 1. The appliances that are in the first cluster are known as essential loads and should be run immediately; these are the base loads that can be predicted a day ahead, including different types of lamps, heating or cooling appliances such as air conditioners or water heaters, and cooking appliances. The appliances that are in the second cluster are known in two categories: 1) These loads can be scheduled on the optimal decisions. These devices can shift their run time within user-defined time or optimally defined time, such as a dishwasher, washing machine, etc. 2) Appliances that should always be plugged in (fridge, phone, garage door, Wi-Fi modem, water pump, etc.). The price of these loads in the case of the variable price scenario, is greater than the first cluster of appliances in the peak time. The appliances that are in the third cluster are known as items that are mostly recreational or non-essential, such as an outdoor hot tub, straightening iron, water feature, game console, etc., which can be placed in lower priorities. The price of these loads in the case of the variable price scenario, is greater than the second cluster of appliances in the peak time. This agent models the appliance behavior at a microscopic level and interacts with upper agents to simulate steady or intermittent load over time.

The household agent consists of three types of households, which are a group of individuals in a house with parameters such as number of members ($Hcount$) and mean hourly energy consumption ($MeanHourlyHsCon$). t establishes the amount of time that each type of household consumes each appliance wich is determined by H1(h), H2(h) & H3(h). Equations 7, 8, and 9 represent household types. Table 1 summarizes each appliance's consumption according to the type of household. A low-consumption household is represented by H1, a medium-consumption household is represented by H2, and a high-consumption household is represented by H3. In the case of the variable price scenario for appliances, the household's hourly consumption is compared to the $MeanHourlyHsCon$, and if the $MeanHourlyHsCon$ is greater, the appliance is switched off. This agent interacts with the appliance agent for outputs, e.g., triggers to switch on/off a device, while it provides a central role in computing the occupancy of individuals' overtime.

The Utility agent, has the parameters such as The maximum and minimum total hourly consumption based on the available capacity of the utility, which determines peak and off-peak hours of consumption. This agent interacts with the household agent in order to determine peak load times and peak load shedding during peak times.

Over the course of three months, the suggested framework creates the load curve for a specified number of homes on a 24-hour scale. Our implementation is agent-based and hierarchical.

Table 1
Clusters of Appliance.

Appliance	Type	power(kwh)	H1(h) [a]	H2(h) [b]	H3(h) [c]
Corded Electric Handheld Leaf Blower	3	2.5	0.25	0.33	1
Curling Iron	3	0.035	0.22	0.3	0.7
Drill	3	0.85	0.1	0.17	0.24
Electric Blanket	3	0.2	1	1.5	3
Electric Mower	3	1.5	0.25	0.7	1
Electric Shaver	3	0.02	0.03	0.12	0.3
Game Console	3	0.2	1	2	5
Hair blow Dryer	3	2.5	0.15	0.22	0.3
Heated Hair Rollers	3	0.4	0.25	0.35	0.75
Outdoor Hot Tub	3	0.5	0.25	0.5	0.75
Power Saw	3	0.275	0.07	0.1	1.14
Straightening Iron	3	0.3	0.15	0.22	0.3
Strimmer	3	0.5	0.25	0.7	1
Treadmill	3	0.9	0.5	0.75	1
Water Feature	3	0.035	6	16	24
Air Purifier	2	0.03	2	8	18
Bathroom Towel Heater	2	0.15	1	5	8
Coffee Machine	2	1.5	0.13	0.33	0.5
Computer (Monitor & Printer)	2	0.2	1	3	8
Cordless Drill Charger	2	0.15	0.03	0.08	0.2
Clothes Dryer	2	5	0.2	0.4	1
Dehumidifier	2	0.35	4	13	24
Dish Washer	2	1.5	1.4	2	4
Electronic Alarmclock – Radio	2	0.005	24	24	24
Espresso Coffee Machine	2	0.9	0.017	0.025	0.05
EV Home Charger	2	3.4	8	12	24
Laptop Computer	2	0.1	1.5	2	2.5
Microwave	2	1	0.17	0.25	1
Furnace Fan Motor (Intermittent)	2	0.35	5.3	8	13.83
Projector	2	0.27	0.75	2	5
Crock Pot	2	0.25	6	8	10
Humidifier (Portable)	2	0.1	2.67	11	18
Iron	2	1	0.04	0.2	0.34
Kettle Boiler	2	1.35	0.14	0.2	0.33
Laser Printer	2	0.8	0.1	0.4	0.75
Mobile Phone Charger	2	0.007	1	2	4
Nintendo Switch AC Adapter	2	0.04	2	3.5	6
Paper Shredder	2	0.22	0.05	0.08	0.25
Power Shower	2	7.5	0.08	0.25	0.33
Rice Cooker	2	0.8	0.33	0.42	0.68
Scanner	2	0.018	0.015	0.03	0.08
Sewing Machine	2	0.075	0.13	0.47	2
Slow Cooker	2	0.18	6	8	10
Steriliser	2	0.65	0.03	0.06	0.5
Vacuum Cleaner	2	0.8	0.067	0.15	0.2
Washing Machine A+++	2	0.5	0.24	0.75	1.33
Washing Machine B	2	1.8	0.24	0.75	1.33
Water Dispenser	2	0.1	3	7	10

Appliance	Type	power(kwh)	H1(h) [a]	H2(h) [b]	H3(h) [c]
Air Conditioner (Room) 6,000 BTU	1	0.75	8	12	24
Air Cooler	1	0.08	4	6	24
AV Receiver	1	0.45	2	5.8	8
Ceiling Fan	1	0.065	0.5	4.64	24
Cooker Hood	1	0.2	0.5	0.8	3
DVD Player	1	0.06	0.3	0.58	2
Electric Pressure Cooker	1	1	0.08	0.5	1
Electric Tankless Water Heater	1	3.8	1	3	5
Electric stove	1	2	0.23	2	3
Energy Saver Lamp	1	0.06	3	5	8
Evaporative Air Conditioner	1	2.6	0.5	2	7.23
Extractor Fan	1	0.012	0.3	0.8	1.1
Fan (Portable)	1	0.115	0.5	2	4.64
Food Blender	1	0.39	0.1	0.13	0.17
Fridge A+	1	0.335	6	12	24
Fryer	1	1.15	0.33	0.67	2
Garage Door Opener	1	0.3	0.16	0.4	0.6
Halogen Lamp	1	0.018	0.56	4	6.67
Heater	1	1.2	1	5	8
LCD television	1	0.17	2	5.8	14.67
LED television	1	0.12	2	5.8	14.67
MI Box	1	0.007	2	5.8	8
Furnace Fan Motor (Continuous)	1	0.35	24	24	24
Night Light	1	0.001	4	8	10
Oven	1	2.15	0.23	2	3
Sandwich Maker	1	1	0.27	0.3	0.4
Space Heater	1	5	1	5	8
Stereo	1	0.03	0.5	3	5.67
Stove Hood	1	0.03	0.5	0.8	2.5
Toaster	1	1.35	0.13	0.2	0.33
Tower Fan	1	0.06	0.5	7.5	24
Video Cassette Record DVD	1	0.04	1.67	3	6.67
Water Heater Typical Family(4)	1	3.8	0.74	3.33	5
Water Pump (Deep well – higher powered)	1	1.1	0.33	0.5	1.67
Water Pump (Deep well – moderate power)	1	0.5	0.33	0.5	1.67
WiFi Booster	1	0.002	12	18	24
Home Phone	1	0.005	24	24	24

[a,b,c] Publications of Managerial Focus of Comprehensive Statistics Report about the Electricity Power Distribution Sector 2021.

The average consumption amount per household (HSC) depends on both the average consumption amount per home $(MeanHourlyHsCon)$ and the household population$(Hcount)$. The household population is determined by the Poisson distribution with $\lambda = 3$[1].

$$HSC = MeanHourlyHsCon * Hcount \quad (1)$$

$$Hcount = poisson(3) \quad (2)$$

3.1. Mathematical model of agent-based modeling

The mathematical model of the problem is as follows:

$$Z_{it} = \sum_{t=0}^{24}\sum_{i=1}^{3} power_i \times t \times Price_{it} \quad (3)$$

[1] Statistical Center of Iran

$$\min Z_{total} = \min \sum_{j=1}^{j} \sum_{i=1}^{3} \sum_{t=0}^{24} Z_{itj} \qquad (4)$$

$$C_{it} = \sum_{t=0}^{24} \sum_{i=1}^{3} power_i \times t \qquad (5)$$

$$\min C_{total} = \min \sum_{j=1}^{3} \sum_{i=1}^{3} \sum_{t=0}^{24} C_{itj} \qquad (6)$$

$$\sum_{d=1}^{31} \sum_{t=0}^{24} \sum_{i=1}^{3} C_{dit1} \leq Np \quad j = 1 \qquad (7)$$

$$Np < \sum_{d=1}^{31} \sum_{t=0}^{24} \sum_{i=1}^{3} C_{dit2} < p \quad j = 2 \qquad (8)$$

$$p \leq \sum_{d=1}^{31} \sum_{t=0}^{24} \sum_{i=1}^{3} C_{dit3} \quad j = 3 \qquad (9)$$

In this model, $power_i$ (Kw/h) indicates the amount of power consumption of each appliance. $Price_{it}$ shows the cost per kilowatt of energy consumed by cluster of appliances i at time t. C_{it} determines the daily consumption of a household. C_{total} shows the total daily consumption of households. Z_{it} determines the daily cost of a household. Z_{total} shows the total daily cost of households. C_{dit} determines the monthly consumption of a household that if it is more than p, it is a high-consumption household, if it is less than Np, it is a low-consumption household, and if it is between the two, it is an average-consumption household. J stands for household, i for appliance, and t for the amount of time (hour) the equipment has been turned on.

3.2. Simulation procedure

This section explains how to use ABMS libraries to implement the suggested agent-based model for household electricity consumption with a time unit of day in AnyLogic 8 Professional 8.7.11. A flowchart of this procedure is shown in Fig. 2. To compute electricity consumption per minute, three agents of appliance, household, and utility are included in the design of the home energy management system. Also, Table 1 lists the three types of appliance agents and the amount of energy consumption by the three types of household agents. The number of the appliances is the same in different types of houses. An initial population of the house agents is configurable through user inputs. The behavior of appliance agents is encapsulated within the house agent. The house agent may switch on or off the appliances, using the probability distributions assigned to each appliance and conditional transitions. In order to investigate changes in domestic load and for demand-side or demand-response management, the utility agent aggregates the consumption of the households within and is made to communicate with external modules, such as transmission grids and power distribution. The classification of households as high-, low-, or average-consumption is based on the quantity of electricity used. The utility calculates the amount of electricity consumed by all households per hour and compares it with the amount of energy delivered from the producer and determines the peak hours. The lower the amount of electricity consumed during peak hours, the better for the utility.

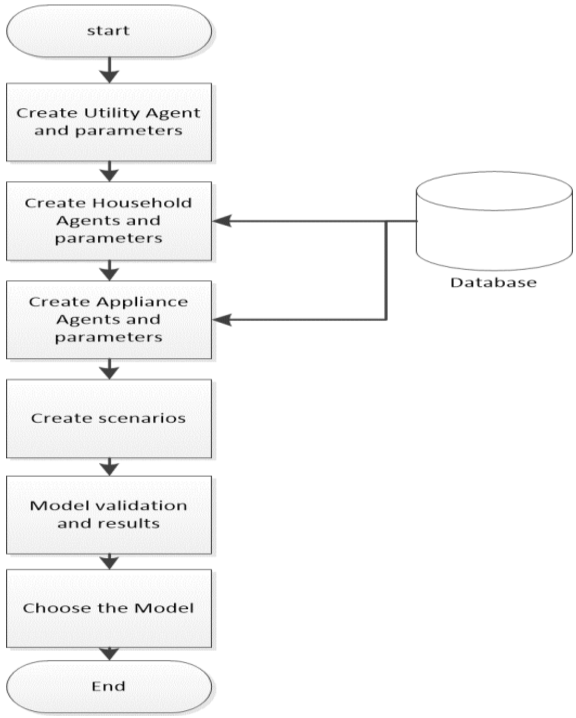

Fig. 2. Flow chart for model initializations

3.3. Agents behavior

The behavior of appliance agents is encapsulated within the household agent; hence a hierarchy is formed.

3.3.1. Appliance agent

According to Figure 1, in the off state, the appliance is off and waiting for a message to turn on based on the probability of the appliance turning on. Regardless of the type, the appliances are turned on and turned off after the working time has elapsed. In this case, the price of electricity consumed is p_{tj}, which depends on t, the type of time of consumption (peak or off-peak), and j, household type (low consumption user, medium consumption user, high consumption user). The price of electricity used under a fixed pricing scenario is determined by the household type and the time of consumption. If the variable price scenario is in effect, the price of electricity used depends on the kind of household j, the type of appliance i used in the home, and the type of time of consumption t. For every one of the 85 appliances that are switched on, this cycle is repeated. During the on-to-off transition, the quantity of consumption is determined hourly, daily, monthly, and quarterly. The bill cost is obtained based on the price p_{tji}, which is determined.

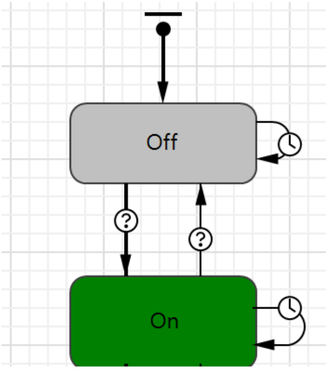

Fig. 3.Appliance behavior

3.3.2. Household agent

The state diagram for the household agent is presented in Figure 2. If the monthly electricity consumption of the household is greater than the maximum amount set by the utility, the household is a high-consumption household; if it is less than the defined minimum amount of electricity consumption, the household is a low-consumption household; in between this range is average consumption, and the pattern of calculating the cost of electricity consumption is different for each type of household.

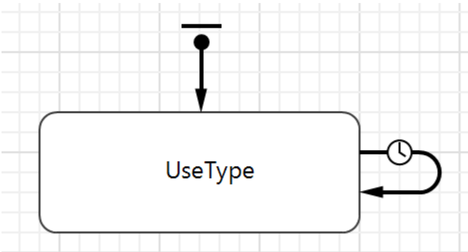

Fig. 4. household behavior

3.3.3. Utility agent

The utility agent state diagram is shown in Figure 3. As the ruling authority, the utility agent establishes the peak states and sets the daily minimum and maximum power consumption amounts.

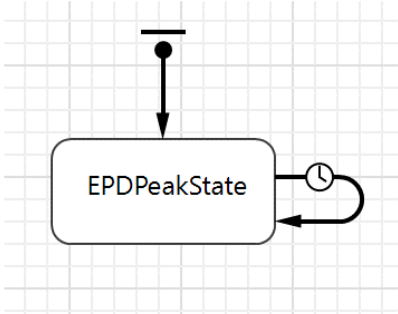

Fig. 5. Utility behavior

4. Scenario Analysis

To evaluate home energy consumption patterns and investigate the impact of particular factors, we created two scenarios. Scenario 1 is intended to simulate energy usage in a fixed-price setting. Scenario 2 simulates energy use in a variable-price setting.

4.1. Energy consumption simulation in Fixed-Price scenario

The price of electricity used under a fixed pricing scenario, as shown in Table 2, is determined by the household type and the time of consumption. Therefore, the price of electricity consumption for a household is higher during peak hours than at other times, and the price of electricity consumption during peak hours is higher for a high-consumption household than for a low-consumption household. During the on-to-off transition, the quantity of consumption is determined hourly, daily, monthly, and quarterly. The bill cost is obtained based on the price p_{tj}, which is determined.

4.2. Energy consumption simulation in Variable-Price scenario

As illustrated in Table 3, if the variable price scenario is in effect, the price of electricity used depends on the kind of household j, the type of appliance i used in the home, and the type of time of consumption t. For every one of the 85 appliances that are switched on, this cycle is repeated. During the on-to-off transition, the quantity of consumption is determined hourly, daily, monthly, and quarterly. The bill cost is obtained based on the price p_{tji}, which is determined.

Table 2
Price in fixed price scenarios

Fixed price scenarios	(T1,H1)	(T1,H2)	(T1,H3)	(T2,H1)	(T2,H2)	(T2,H3)	(T3,H1)	(T3,H2)	(T3,H3)
Price of App1, App2, & App13	120	159	183	300	397	457	600	794	913

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Table 4
Evaluation of simulation results

Scenarios	Hourly max consumption	Hourly mean consumption	Hourly MAD consumption	CostMonth.max	CostMonth.mean	CostMonth.deviation
Fixed prices	1307.21553	636.111635	184.9057655	421937755.3	201026954.1	119942838.4
Variable prices	754.21487	283.047607	77.52504767	40722728.92	20208926.52	11744029.21

5. Research results

The results are reviewed and analyzed according to repeated scenarios and indicators. For two distinct scenarios, the hourly consumption diagram illustrates the simulation results. The hourly consumption diagram is shown in Fig. 6 & Fig. 7. The graphic shows that in the case when appliance prices are changing, hourly consumption is reduced. It is quite difficult to perform the validation of ABMSs; to validate the model, every simulation scenario was run 30 times, with the system producing the necessary output each time. The "maximum hourly consumption" is one of the key indicators; it has dramatically dropped in the variable pricing scenario and has a reduced "standard deviation." Thus, it is possible to say that the "hourly consumption" diagram has smoothed out. All indicators in the variable-price scenario have decreased in comparison to the fixed-price scenario, as Table 4 illustrates. This means that a decrease in the hourly MAD consumption signifies a smoothing of the hourly peak diagram, while a decrease in the hourly max and mean consumption indicates a decrease in consumption. In a similar vein, the consumer's reduction in the monthly cost signifies their contentment. Consequently, the problem identified in the literature review—which is a win-win situation for the utility and the household—is thus resolved.

The model is validated through the following four steps: (1) micro-face validation; (2) macro-face validation; (3) input validation; and (4) output validation (Fraccascia et al., 2020). The micro-face validation criteria are satisfied because its mechanisms and characteristics are defined in a way that is consistent with the literature, and because it is based on the real household consumption system, it is consistent with the mechanisms of electricity consumption in the real world. The macro-face validation criteria are satisfied because the model aligns with real-world dynamics. This model is congruent with real-world dynamics since it is designed for cold weather and the peak times of the year, and it may be extended to different scenarios by adjusting certain parameters. Various strategies are adopted to meet the input validation criteria; the robustness of the model is tested by running additional simulations with randomness in the model inputs. In this model, input data is either taken from the real databases, and in the absence of data, random distributions are used to define the inputs. To validate the output criteria in this research, Table 4 presents the results.

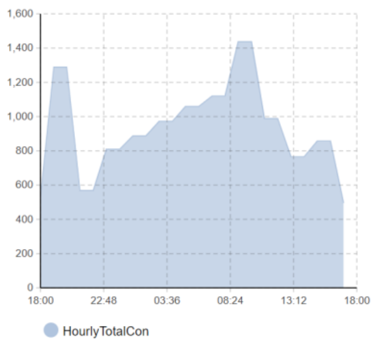

Fig. 6. Hourly consumption fixed-price scenario

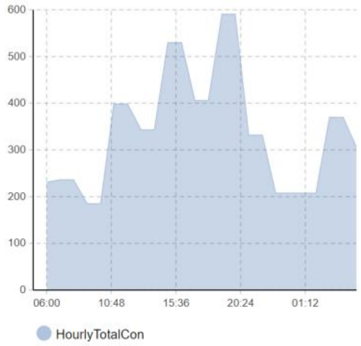

Fig. 7. Hourly consumption variable-price scenario

6. Discussion and Conclusion

Electricity is undoubtedly the most adaptable energy source in contemporary economies across the world and is strongly associated with both social and economic advancement. In this scenario, smart grid is an emerging technology that is related to different role players in different parts of energy systems. One fundamental aspect of smart grids is demand response. Increasing demand response efficiency requires an intelligent home appliance control system that prioritizes appliance startup based on efficiency and utilization requirements. Various signals, including price, are used by utilities to effectively control the demand response. Differentiating prices for various appliance clusters is one such pricing strategy. For demand response management, prior research employed an incentive-based pricing criteria in which home characteristics and time of use (ToU) were the only factors utilized to calculate the price. As an example, Thorve et al. simulate behavior adaptations in response to changes in electricity prices to study cost savings through monthly bills and peak demand reduction in synthetic household agents in a Time of Use (ToU) pricing scheme in Virginia, USA. Further, they can show that there exists a region in the parameter space that corresponds to a fair ToU pricing scheme for both entities: all income-stratified communities and power companies (Thorve et al., 2024). Unlike previous studies that used an incentive-based price criterion for load response management, where the price was determined solely based on time of use and household characteristics, in this study the cost of using each appliance, based on the time each cluster of appliances is used by each kind of household, has been considered. An extended agent-based model is established in this study to investigate the rules governing home energy use. The findings demonstrate the enormous potential of agent-based modeling in simulations of home energy usage. Three kinds of agents created. Among them, the household categorization is critical, the appliances are detailed, and the utility is specified as a government agency. The design of appliance operation is the key to successfully simulating household energy consumption. The results are reviewed and analyzed according to repeated scenarios and indicators. Two scenarios were taken into consideration for the simulation: fixed and variable pricing for appliances. For two distinct scenarios, the hourly consumption diagram illustrates the simulation results. The graphic shows that in the case when appliance prices are changing, hourly consumption is reduced. It is quite difficult to perform the validation of ABMSs; to validate the model, every simulation scenario was run 30 times, with the system producing the necessary output each time. The "maximum hourly consumption" is one of the key indicators; it has dramatically dropped in the variable pricing scenario and has a reduced "standard deviation." Thus, it is possible to say that the "hourly consumption" diagram has smoothed out. However, smart grid systems can benefit from this technique because the peak load consumption curve has been smoothed, and home power usage has been optimized by giving varying charges for the use of various clusters of appliances. Consequently, the problem identified in the literature review—which is a win-win situation for the utility and the household—is thus resolved. This study considers one utility, the competitive situation and different utilities could be taken into account for evaluation. Environmental and household economic factors, which were not included in this study, may possibly be the subject of future research. An additional area of study in order to optimize home consumption patterns might also focus on determining the right price for consumption of appliance clusters.

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