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Standby Power Reduction of Home Appliance by the i-HEMS System Using Supervised Learning Techniques

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Abstract: Electricity consumption in homes is on the rise due to the increasing prevalence of home appliances and longer hours spent indoors. Home energy management systems (HEMSs) are emerging as a solution to reduce electricity consumption and efficiently manage power usage at home. In the past, numerous studies have been conducted on the management of electricity production and consumption through solar power. However, there are limited human-centered studies focusing on the user's lifestyle. In this study, we propose an Intelligent Home Energy Management System (i-HEMS) and evaluate its energy-saving effectiveness through a demonstration in a standard house in Korea. The system utilizes an IoT environment, PID sensing, and behavioral pattern algorithms. We developed algorithms based on power usage monitoring data of home appliances and human body detection. These algorithms are used as the primary scheduling algorithm and a secondary algorithm for backup purposes. We explored the deep connection between power usage, environmental sensor data, and input schedule data based on Long Short-Term Memory network (LSTM) and developed an occupancy prediction algorithm. We analyzed the use of common home appliances (TV, computer, water purifier, microwave, washing machine, etc.) in a standard house and the power consumption reduction by the i-HEMS system. Through a total of six days of empirical experiments, before implementing i-HEMS, home appliances consumed 13,062 Wh. With i-HEMS, the total consumption was reduced to 10,434 Wh (a 20% reduction), with 9060 Wh attributed to home appliances and 1374 Wh to i-HEMS operation.

Keywords: HEMS; home appliance; energy consumption; standby power; supervised learning

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1. Introduction

Background and Study Objectives

The world is facing environmental challenges such as resource depletion and global warming due to energy overuse. Electricity consumption in buildings in OECD countries is increasing every year, and electricity consumption in buildings accounts for 55% of global electricity consumption [1]. Countries are developing policies to minimize energy waste by establishing energy-saving policies and systems.

Recent scientific research has developed numerous methodologies and technologies to mitigate energy and environmental impacts. Over the past decades, energy systems used in buildings have been utilized to improve human comfort and convenience. However, in terms of home energy management, they have been used at a simple monitoring level. There are three main types of power loads in a home. Base loads are loads that are not subject to load usage scheduling, such as microwave ovens, TVs, computers, and other essential loads that consume low power or are not responsive to electricity prices. "Curtailable load" refers to power loads that vary in energy consumption. Examples include temperature-controllable appliances like water heaters, air conditioners, and heaters. These appliances are major contributors to peak loads due to their high power usage and frequency. Lastly, "Deferrable Load" refers to loads with flexible usage times, allowing adjustment based on electricity prices. Electric vehicles (charging) fall into this category. Home energy management systems (HEMS) are a growing technology as a solution for reducing electricity usage in homes and efficiently managing power consumption. Electricity consumers can minimize energy costs through active demand management. In addition, IoT technology, which embeds sensors and communication modules in various objects to send and receive data over the Internet, has recently provided many services [2].

However, products that use electricity consume standby power even when turned off. Standby power is the power consumed by an electronic device when it is connected to an external power line and is not performing its main function or waiting for an operating signal from the outside. In Korea, household electricity consumption is estimated to be 80,996 MkWh in 2022, and the proportion of standby power is estimated to be about 0.86%. This is equivalent to 5% of a household's monthly electricity bill [3].

In the case of Smart HEMS, the energy consumption used in the home is minimized to reduce the cost of electricity [4]. These technologies are evolving as new technologies for energy conservation. Typically, the power used in offices and homes is controlled by smart controllers and applications, and power wastage is reduced through transformer alternators, voltage alternators, and circuit breakers [5,6]. In addition, Ab-HPMS (Appliance based control for home power management system), which controls the power consumption of energy-saving appliances, was developed to improve energy efficiency while securing user convenience. Appliance-based control plays a crucial role in home power management systems, enabling efficient energy usage and remote monitoring. Various systems incorporate this concept, such as a power management system with a battery that controls loads based on energy information [7], a smart home module allowing appliance control and real-time energy monitoring [8], and a transformer less power controller providing low standby power and adjustable power levels based on appliance needs [9]. Additionally, an intelligent home appliance power control system utilizes socket controllers to detect loads, automatically turning off standby appliances to save energy [10]. Furthermore, a power control system for home appliances predicts operating patterns based on sensor data and controls appliance drives accordingly. These systems collectively enhance energy efficiency, user convenience, and remote management capabilities in modern households.

Current research is actively exploring various developments in both hardware and software domains. Ghazal, M et al. used smart plugs in homes in the UAE to control energy consumption by monitoring household energy consumption through an application [11]. Deep learning technology can be used as a way to predict energy consumption in smart homes. Electricity demand forecasting in smart homes helps to reduce energy wastage and improve energy consumption efficiency. The use of LSTM, Bi-LSTM, and GRU algorithms in electricity supply and production has been reported for demand forecasting methodologies [11,12]. The smart home control platform in the study by Josimaret et al. proposed a smart home customized automatic control scheme using IoT and machine learning [12]. Zhao et al. proposed a machine learning method to effectively mine and analyze intelligent home user behavior patterns to improve personalized services through behavior pattern analysis. It has the ability to analyze preferences and provide targeted services based on behavior patterns [13]. Xing hua et al. improved the existing behavioral pattern analysis method by mining and analyzing smart home user behavior patterns using a two-layer neural network and Apriori algorithm based on cloud computing [14].

J, Menaka et al. proposed FPS-Tree (frequent pattern stream tree) algorithm and efficiently modeled home behavior patterns using sensor data to detect activity recognition and power consumption in smart homes to operate power management system [15]. Mohd's research introduced a time series-based sequence prediction algorithm, M-Speed, to analyze the behavioral patterns of residents using the on-off status of devices and detect daily life activities in smart homes. M-speed had an accuracy rate of 96.8% for smart home activities [16]. Moreover, the integration of IoT technology in legacy air conditioning systems can significantly enhance energy management efficiency [17,18]. By utilizing IoT sensors and actuators, along with sophisticated control algorithms, energy consumption can be optimized without compromising user comfort [19]. Previous studies have attempted to provide energy management and personal health, safety, and convenience services through the combination of hardware and software in smart homes by predicting human behavior. However, there is a lack of research on energy saving demonstration and analytical data for sensor-based intelligent control solutions.

In this study, we propose an Intelligent Home Energy Management System (i-HEMS) and verify the energy saving effect of the proposed system based on the general energy usage of a standard house and the demonstration of the proposed system with IoT sensing and behavioral pattern algorithm.

2. i-HEMS System Description

i-HEMS monitors the energy consumption of devices such as home appliances, air conditioning, and lighting used in the house. It provides energy consumption monitoring results and conducts environmental monitoring and human behavior pattern analysis through environmental monitoring sensors and human body detection sensors. It is an intelligent power management and environmental management system that can efficiently save power in the home by turning on/off power devices or controlling operation modes according to user-set schedules and behavior pattern algorithms.

The configuration of the i-HEMS system is shown in Figure 1. The main components are IoT broker (Main panel), energy smart device, Wifi–environment sensor modules and a multi control module. The IoT Broker communicates with the energy smart device, Wifi–environment sensor module and multi control module to control the device according to the behavior pattern algorithm, schedule and environmental conditions based on the measurement data. The energy smart devices directly implement power supply and disconnection and power metering functions. In addition, power data are transmitted wirelessly to the IoT Broker. Wifi–environment sensor modules provide IoT broker with information on indoor temperature, humidity, illumination, and human presence through human body detection sensors. Table 1 shows the specifications of each sensor type. The multi control module is a controller that controls the on/off settings of electrical appliances based on IR. IoT broker and HEMS software (Ver 1.0) have the functions of extending the interface of energy smart devices, relaying energy smart device communication, and collecting and transmitting data. Each function receives data through the Zigbee communication module and controls electric air conditioners, TV, etc., through the IrDA (Infrared Data Association) communication module.

The i-HEMS system can manage the power consumption of the house and conduct behavioral pattern analysis according to the environment, and can control remote devices including on/off. In addition, it can reduce energy consumption by actively reducing the unnecessary use and standby power of electrical appliances without user intervention. In addition, by providing users with real-time electricity usage data and analysis data, it is possible to expand awareness of energy conservation. The controlled device in this study is a home appliance scheduler that prioritizes user convenience. User convenience entails scheduling the device to operate effectively based on external temperature changes or established habits. Additionally, an intelligent system is employed to control the device intelligently when a person is not detected via a human sensor. The product under the base load learns the user's usage schedule and performs power control according to the learned user's schedule, and cuts off standby power during non-use periods. The product under the curtailable load learns the user's schedule and setting conditions and controls the setting conditions according to the schedule. In addition, the device's operation is controlled by determining the user's presence or absence through the human body detection function. To process big data measured from external weather, indoor environment monitoring data, and energy smart device measurements, we used "hadoop" and "Spark", which are open source frameworks that can effectively handle large amounts of data. The distributed filesystem enables the distributed storage, analysis, and visualization of data.

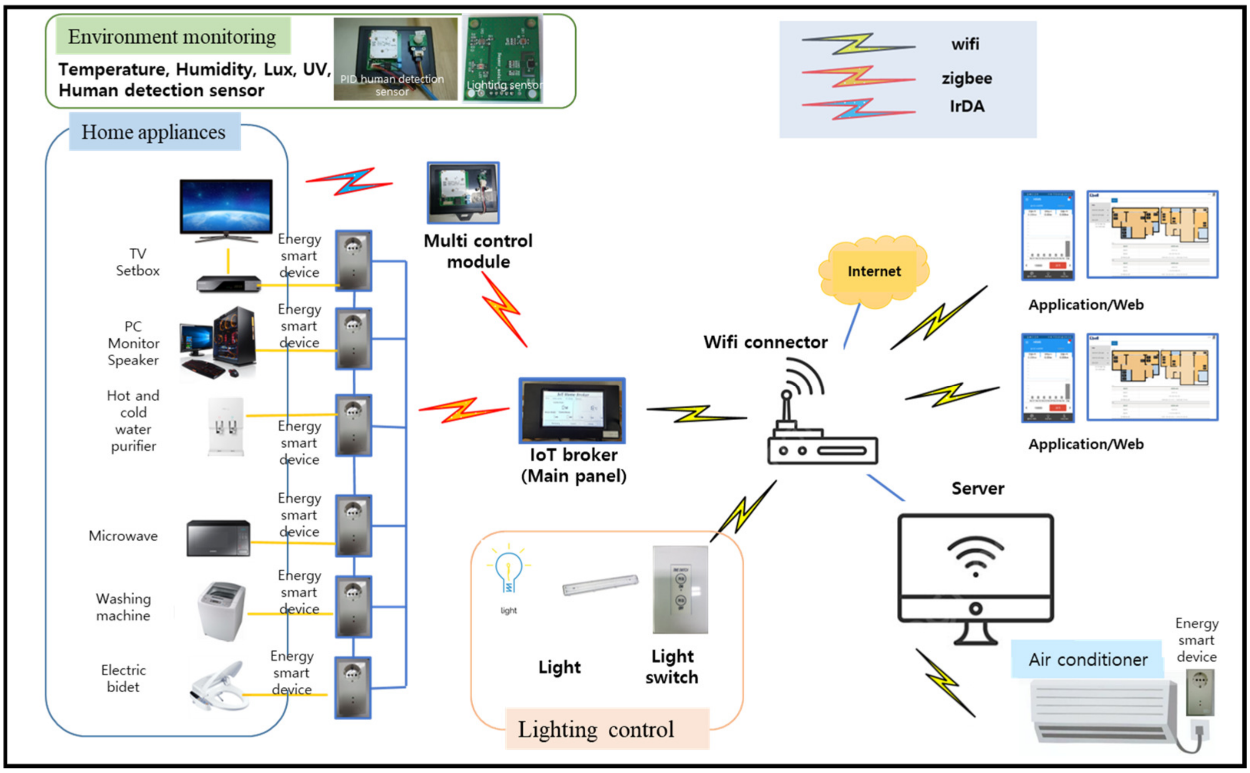

Figure 1. Hardware configuration of the i-HEMS.

Table 1. i-HEMS environment sensor modules specifications.

Items	Types	Range
Temperature	SHT31 Humidity and temperature sensor	(0~125) °C, Accuracy ±0.3 °C
Humidity		(0~100)% R.H. Accuracy ±2% R.H.
Light	Silicon Labs Si1132 UV index and Ambient Light Sensor	(1~128) Klx (100 mlx resolution)
Motion sensor	Passive Infrared Sensor	Sensitivity range: 110° × 70° detection range, 7 m

For example, at 0 o'clock every day, i-HEMS Server sends three types of data to HDFS: power usage data for each plug on the day, weather data from the Korea Meteorological Administration, and measurement data for each environmental sensor on the day, and "hadoop" distributes the files to the master, slave01, and slave02 clusters block by block. For big data analysis, we used "Spark", an in-memory processing method that is 5 to 50 times faster than MapReduce of "hadoop". In addition, Zeppelin is used to check the analysis results of "Spark", with visual results such as graphs at a glance.

Figure 2 shows a block diagram for the power management and control of the i-HEMS system. The power usage information of the device, based on the user's usage event, is transmitted to the IoT Broker through Zigbee communication and then sent to the web and server for storage as data. The stored power data are sent to the IoT Broker for the determination of the power device control algorithm.

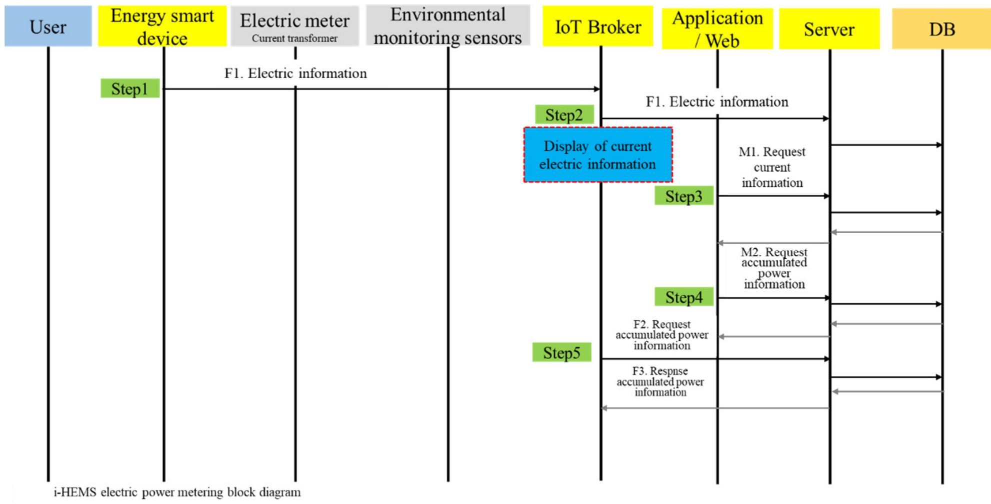

Figure 2. i-HEMS electric power metering block diagram.

3. Methods

In this study, the energy-saving performance of i-HEMS was verified by comparing the relative power usage before and after the system application using a standard experimental house of 59 m^2. The standard experimental house is located at Latitude 36°54′04.9″ N, Longitude 127°32′29.7″ E. The experimental period was conducted from 4 July to 10. In Case 1, i-HEMS monitored power 24 h a day without any algorithmic control. The i-HEMS collected learning data based on the behavioral patterns of the occupants for three days. In Case 2, according to the analysis of the behavior pattern of the resident in Case 1 for 3 days, the time when the resident was in the room was identified and the standby power was turned on when the resident was in the room, and the power was turned off when the resident was not in the room. The monitoring results of Case 1 without standby power and Case 2 with standby power were compared to see the power savings.

In this study, the general household appliances of the TV, washing machine, computer, bidet, water purifier, and lighting, which are environmental control devices, were studied. The details of the appliance groups are shown in Table 2.

Table 2. Schematic of home application specifications in field test housing.

Items	Types	Install Location	Common Operating Schedule
TV Set top box	HD32″ Stand, Voltage: (220~240) V, 50/60 Hz Electric consumption 48 W Standby mode power consumption 0.3 W	Room	07:00~09:30 19:00~23:30
Personal computer	INPE_G4400(3.3 GHz)/4 G/500 G Voltage: 220 V/60 Hz	Room	19:00~21:00
Monitor	24″ Monitor, Voltage: 220 V/60 Hz	Room	19:00~21:00
Hot and cold water purifier	Cold water tank:3.8 L, Temperature: (2~8) °C Hot water tank: 1.8 L, Temperature: (82~92) °C Heater types: Sheathed heater Voltage: (220~240) V, 50/60 Hz	Kitchen	07:00~09:30 19:00~23:30
Microwave	Volume:23 L Voltage: 220 V/60 Hz, Output: 700 W, Electric consumption 1100 W	Kitchen	19:00~19:10
Washing machine	Electric consumption 480 W	Balcony	19:50~20:10
Electric bidet	Electric consumption 1170 W Voltage: 220 V/60 Hz, Heater capacity:1100 W	Toilet	07:00~09:30 19:00~23:30

The measurement error and hardware operation status of each instrument and sensor of the prototype developed in this study were reviewed through preliminary experiments. The measured values of the Energy Smart Device were compared with a calibration standard device with higher precision and accuracy to verify the homogeneity and performance of the product for power measurement. The calibration AC power meter was the PM 3000A model from VOLTECH (Abingdon, UK). In addition, the temperature and humidity sensors were checked for measurement errors under temperature and humidity conditions in a constant temperature and humidity chamber. In the case of the human body sensor, the measurement error depending on the position of the human body sensor was also reviewed in advance. The reliability of the i-HEMS measurements was preliminarily validated. Figure 3 shows the exterior and floor plan of the standard house test building and the installed appliances.

Figure 3. Schematic of the field test housing specifications.

4. Learned Home Appliance Operating Pattern

In this study, we proposed a behavioral pattern algorithm through learning using power usage monitoring data and human body sensing data as a standard primary scheduling algorithm and a secondary algorithm. The most important factor in an energy-saving system that automatically cuts off standby power is to determine when to return to operation from standby mode. When the standby power is cut off, the home appliances cannot be controlled wirelessly or wired, which causes inconvenience to the user. A basic way to do this is to set a time schedule to automatically enter and return to standby mode after a certain period of time. In intelligent learning methods, Supervised Learning uses schedule input as the basic input. To predict the user patterns of occupants, we explored the deep connection between power usage, environmental sensor data, and input schedule data based on a Long Short-Term Memory network (LSTM) and prepared an occupancy prediction algorithm. The smart meters in the i-HEMS provide data on daily household load consumption, but to achieve effective results with the proposed HEMS, data on load usage patterns at the device level was needed. Therefore, the standard Korean household appliance usage patterns were used as the basic scheduling algorithm. Using the occupant's appliance usage patterns and human body sensors, we developed a learning scheduling algorithm to identify the appliance usage patterns through the device operation and occupancy data of the i-HEMS users. As shown in Table 2, the usage schedule of each home appliance in Korea was used as a generalization condition.

The i-HEMS performs priority management based on user behavior analysis and power plug control. The system detects the first user's event. For instance, it identifies user interactions with household appliances like light switches, televisions, and personal computers. Additionally, it senses human presence using dedicated sensors. Energy-efficient devices achieve this by analyzing historical power consumption patterns and applying predefined rules. Figure 4 shows the sequence of shutting off the standby power and entering standby mode according to human recognition and user demand. In the case of the TV and Setbox, PC and Motor, Microwave and Washing machine, the standby power was programmed to be cut off if the power consumption of the object device was 12 W or less twice during the three-day study period. That is, the user's behavior was considered as ON when the user did a specific behavior, and as OFF when the user finished a specific behavior. Figure 3. Shows the i-HEMS flowchart of standby power reduction mode. For the electric bidet and water purifier, we set the same time based on the TV usage time when the room is occupied. It checks the minute-by-minute power usage history of the electronic device and judges that the device is used if the power measurement of 12 W or more is recorded for each minute, and judges that the device is not used if the measurement is less than 2 W. In addition, among the recently used data, if the measurement is used for each minute, the schedule for that minute is judged to be ON, and if the measurement is not used, it is set to OFF and saved. Figure 5 shows the operation signal before applying the standby power cutoff algorithm. In the case of the water purifier, it was observed that the power consumption varied significantly depending on the product operation logic to continuously store hot and cold water in the tank at a certain temperature. Figure 6 shows the power consumption change in a water purifier that is always running. In this study, an automatic learning pattern was applied. Figure 7 shows the system operation schedule derived through device learning in the test-bed. It can be seen that the operation of home appliances by occupants was concentrated in the morning before work and after work. This operation pattern was reflected in the i-HEMS, and the i-HEMS was programmed to cut off standby power through the energy smart device hardware control during the period when the system was off.

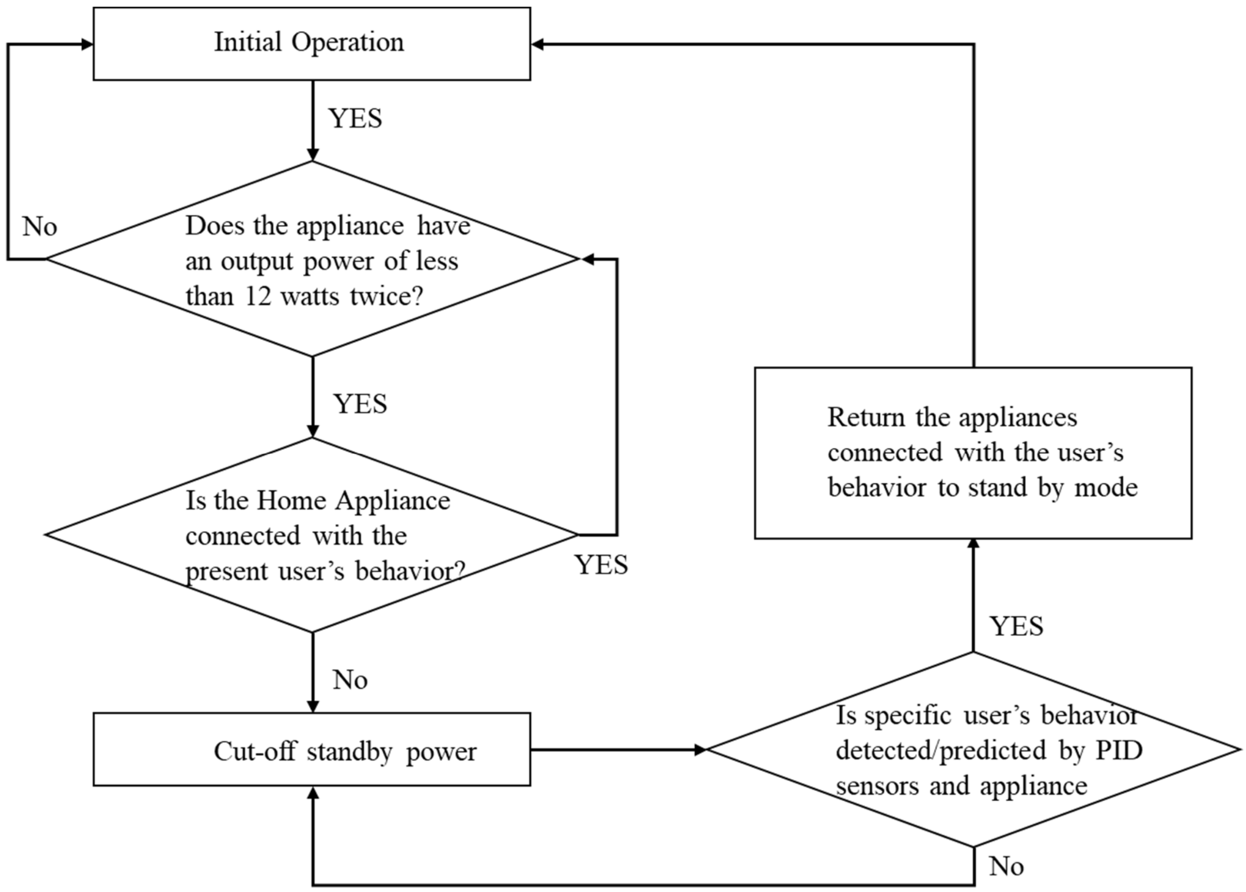

Figure 4. I-HEMS flowchart of standby power reduction mode.

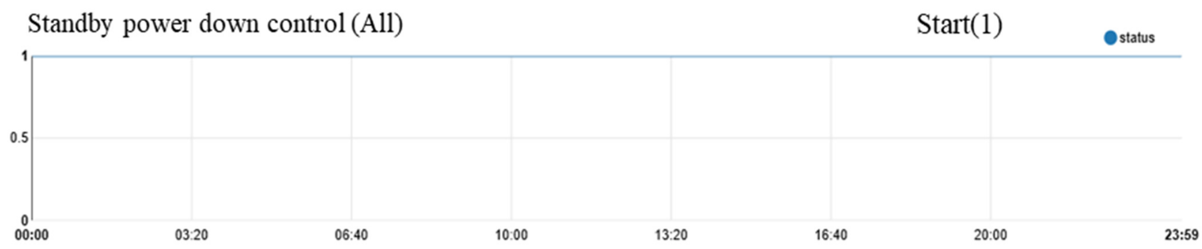

Figure 5. Before applying the standby power-off algorithm, on/off signal (0: off, 1: on).

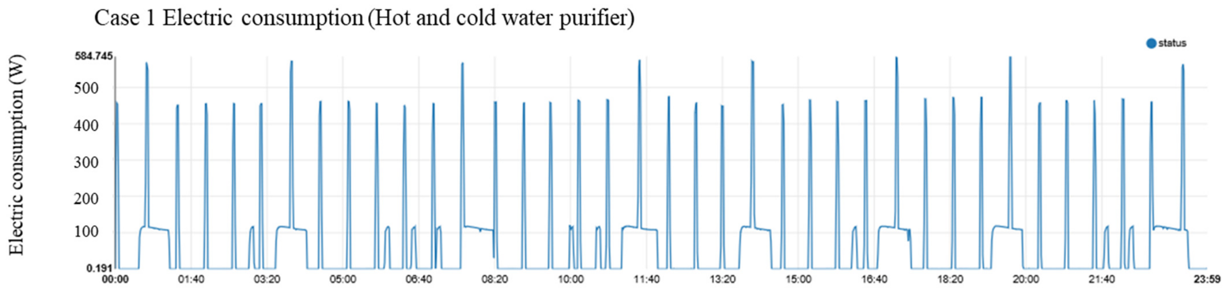

Figure 6. Results of electric consumption of hot- and cold-water purifier (Case 1).

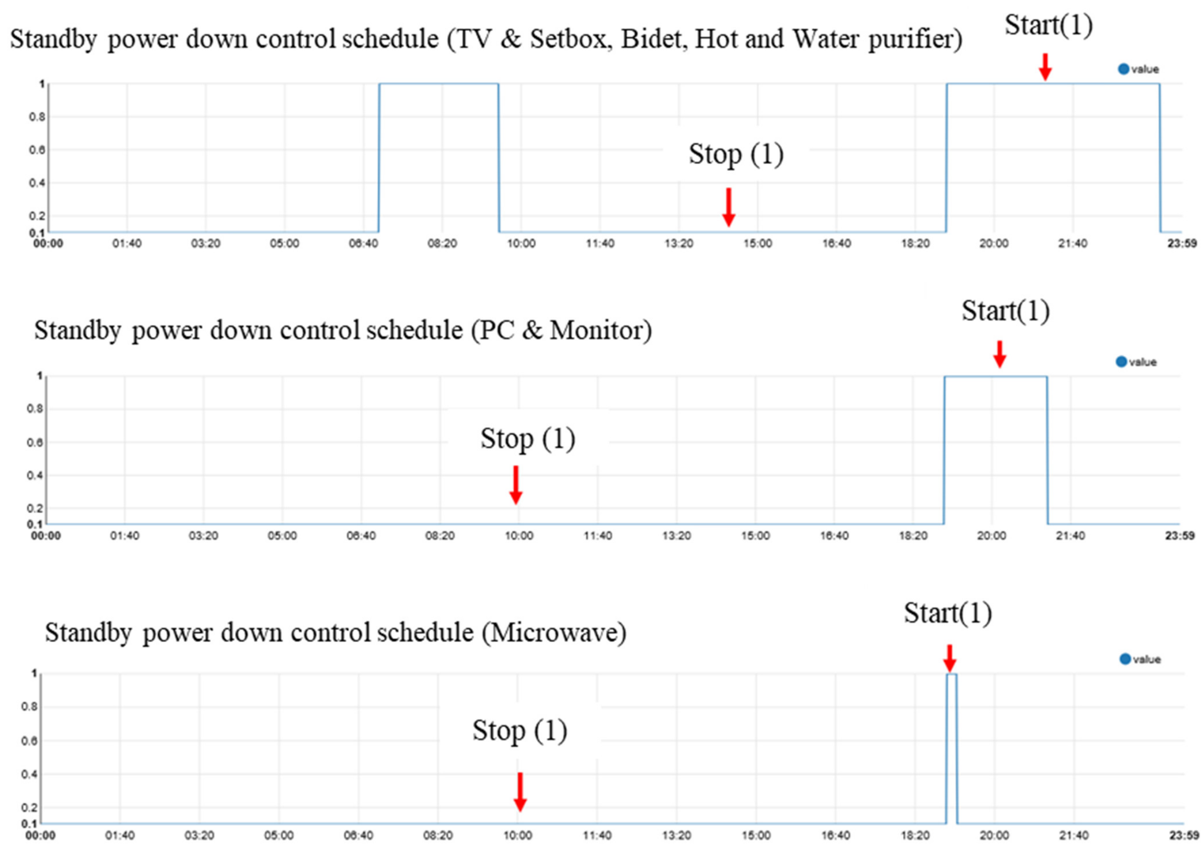

Figure 7. Learned standby power down control schedule.

5. Electricity Consumption Reductions

By identifying the behavioral patterns of the residents of the demonstration house over a three-day period, we compared the power consumption before and after the application of the behavioral pattern analysis algorithm. Figure 8 shows the change in power consumption by applying the behavioral pattern algorithm for each home appliance over the course of a day. According to the user's behavior pattern, the standby power was turned off when not in use, and the power consumption was measured as 0 W. It can be seen that the change in power consumption of the water purifier in Case 1 in Figure 6 changed significantly from the change in power consumption in Case 2 in Figure 8.

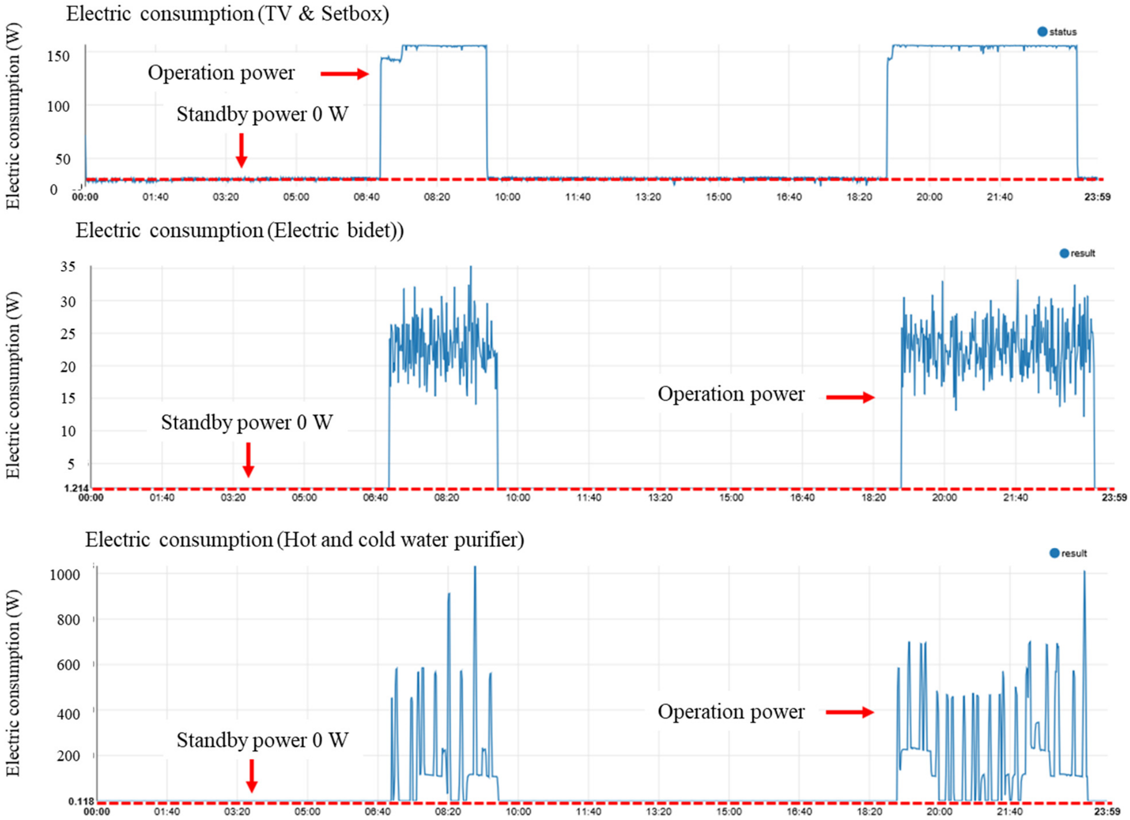

Figure 8. Results of the application power consumptions (Case 2).

Table 3 shows the electricity usage of each appliance for 3 days in Case 1 before the algorithm was applied and 3 days after the algorithm was applied in Case 2. The device with the largest reduction in electricity usage was the water purifier, which was reduced by 54% from 4904 Wh in Case 1 to 2694 Wh in Case 2. The power consumption of the TV and setbox, PC and monitor, and Microwave, which are subject to base load, also showed a significant reduction. The electric bidet, hot and cold water purifiers, and electric devices that require temperature control with a 'curtailable load' were the most significant contributors to the reduction in power usage. In contrast to the constant use of electricity even at night when users were not using it, i-HEMS's user pattern recognition allowed it to cut off the power when not in use, significantly reducing power consumption. Figure 9. shows the results of daily power consumption. The washing machine and lighting, with the same usage time and frequency, did not change in power consumption. However, the reduction in power consumption varied among devices with different usage loads, depending on the duration of use and operating conditions.

Table 3. Result of daily power consumptions.

Category	Case 1 Electric Consumption (Wh)				Case 2 Electric Consumption (Wh)			Sum (B)	Reduce Rate (A/B)
	4 July	5 July	6 July	Sum(A)	7 July	8 July	9 July		
TV and setbox	534	548	521	1603	352	357	353	1063	33%
PC and Monitor	438	437	437	1313	206	205	205	617	54%
Hot and cold water purifier	1663	1611	1630	4904	927	881	885	2694	45%

Table 3. *Cont.*

Category	Case 1 Electric Consumption (Wh)				Case 2 Electric Consumption (Wh)			Sum (B)	Reduce Rate (A/B)
	4 July	5 July	6 July	Sum(A)	7 July	8 July	9 July		
Microwave	416	389	418	1223	337	337	337	1013	18%
Washing machine	406	405	406	1217	406	407	407	1221	−0.2%
Electric bidet	184	178	187	549	63	61	64	188	66%
Lighting	751	752	751	2254	754	754	757	2264	−7%
i-HEMS		-			458	458	458	1374	-
Sum	4392	4320	4350	13,062	3047	3004	3009	10,434	20%

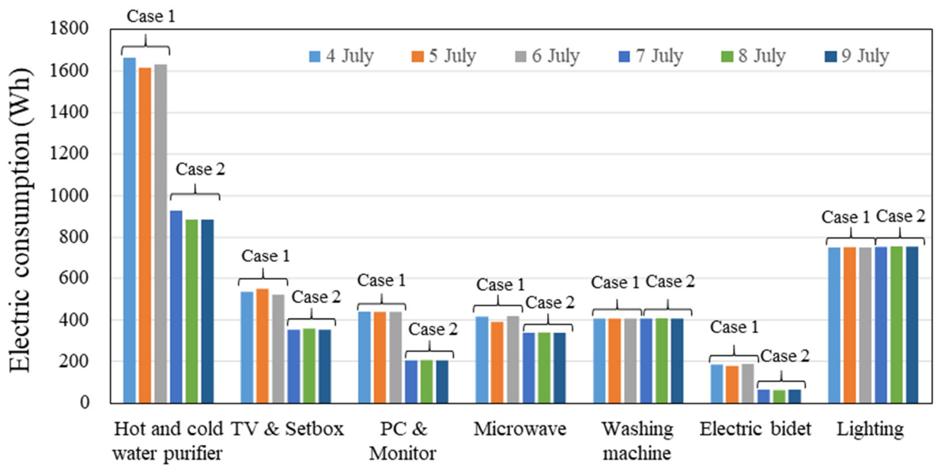

Figure 9. Result of daily power consumptions.

In Case 1, the total power consumption of home appliances before applying i-HEMS was 13,062 Wh, and in Case 2, the total power consumption of home appliances after applying i-HEMS was 10,434 Wh due to the standby power cut-off function through the operation of the behavior pattern recognition algorithm, which was reduced by about 20%. Of the 10,434 Wh of power consumption in Case 2, 9060 Wh is for home appliances and 1374 Wh is for i-HEMS operation (Figure 10.). In this experiment, we analyzed the energy consumption savings of home appliances by turning off standby power. In the future, we will study how performance is affected by load fluctuations in indoor air conditioning and heating systems in response to changes in the outdoor environment.

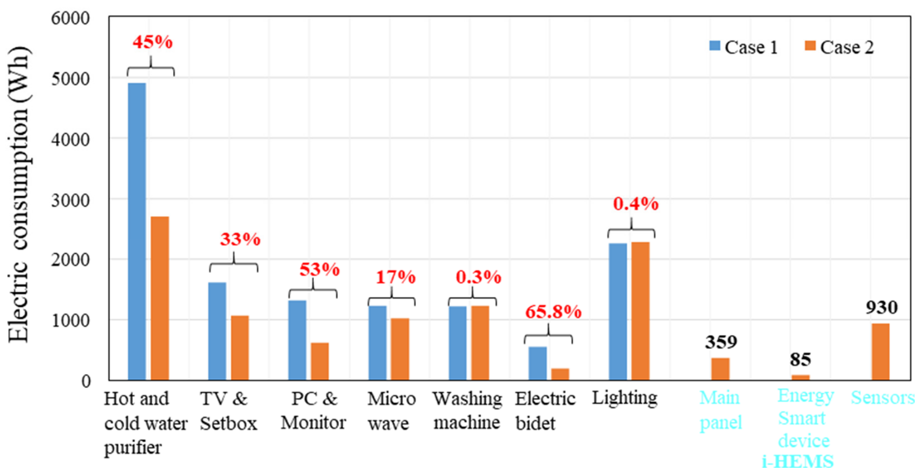

Figure 10. Result of power consumption with i-HEMS system.

6. Conclusions

The world is facing environmental challenges such as resource depletion and global warming due to energy overuse. Electricity consumption in buildings in OECD countries is increasing annually, and it represents 55% of global electricity consumption. Home energy management systems (HEMSs) are an emerging technology designed to reduce electricity usage in homes and efficiently manage power consumption. Previously, the power management system for home solar energy production and consumption was studied. A proposed system was developed to manage energy by aligning the load characteristics of home appliances with the behavior patterns of users.

In this study, we proposed an Intelligent Home Energy Management System (i-HEMS) and verified the energy-saving effect of the proposed system based on the general energy usage of a standard house. We demonstrated the effectiveness of the proposed system using IoT sensing and a behavioral pattern algorithm. We proposed a behavioral pattern algorithm for learning using power usage monitoring data and human body sensing data as the primary scheduling algorithm and a secondary algorithm. The most crucial factor in an energy-saving system that automatically cuts off standby power is determining when to resume operation from standby mode. The average power consumption of the plug over 3 days was analyzed. We analyzed the behavioral patterns by identifying the residents' occupancy time using an IoT broker and induction sensor for 3 days.

(1) In Case 1 we did this before the algorithm was applied, and 3 days after the algorithm was applied in Case 2. The device that showed the most significant reduction in electricity usage was the water purifier, which decreased by 54% from 4904 Wh in Case 1 to 2694 Wh in Case 2.

(2) The total power consumption of home appliances before applying i-HEMS was 13,062 Wh, and in Case 2, the total power consumption of home appliances after applying i-HEMS was 10,434 Wh due to the standby power cut-off function through the operation of the behavior pattern recognition algorithm, which was reduced by about 20%. Of the 10,434 Wh of power consumption in Case 2, 9060 Wh is for home appliances and 1374 Wh is for i-HEMS operation.

As we move toward a low-carbon society, it is expected that blocking standby power will become a necessary requirement for households.

Author Contributions: Conceptualization, B.P. and S.-h.K.; methodology, B.P. and S.-h.K.; formal analysis, B.P. and S.-h.K.; data curation, B.P., S.-h.K. and B.O.; writing—original draft preparation, B.P., S.-h.K. and B.O.; writing—review and editing, B.P. and B.O.; supervision, B.P. and B.O. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the supporting project involving a confidentiality agreement.

Conflicts of Interest: Author Byoungchull Oh was employed by the company International Climate & Environment Center. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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