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Research Paper

Design and deployment of a novel decisive algorithm to enable real-time optimal load scheduling within an intelligent smart energy management system based on IoT

Challa Krishna Rao [a,b,*], Sarat Kumar Sahoo [a], Franco Fernando Yanine [c]

[a] Department of Electrical Engineering, Parala Maharaja Engineering College, Berhampur, affiliated to Biju Patnaik University of Technology, Rourkela, Odisha, India
[b] Department of Electrical and Electronics Engineering, Aditya Institute of Technology and Management, Tekkali, Andhra Pradesh, India
[c] Faculty of Engineering, Universidad Finis Terrae, Providencia, Santiago, Chile

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ABSTRACT

Consumers routinely use electrical devices, leading to a disparity between consumer demand and the supply side a significant concern for the energy sector. Implementing demand-side energy management can enhance energy efficiency and mitigate substantial supply-side shortages. Current energy management practices focus on reducing power consumption during peak hours, enabling a decrease in overall electricity costs without sacrificing usage. To tackle the mentioned challenges and maintain system equilibrium, it is essential to develop a flexible and portable system. Introducing an intelligent energy management system could pre-empt power outages by implementing controlled partial load shedding based on consumer preferences. During a demand response event, the system adapts by imposing a maximum demand limit, considering various scenarios and adjusting appliance priorities. Experimental work, incorporating user comfort levels, sensor data, and usage times, is conducted using Smart Energy Management Systems (SEMS) integrated with cost-optimization algorithms.

1. Introduction

The escalating consumption of electrical equipment in recent years has heightened environmental concerns, prompting the scientific community to prioritize alternative energy sources (Agyemang et al., 2021). Addressing the challenge of ever-increasing electricity demand is complex. Residents in underdeveloped nations grapple with frequent unplanned load shedding due to inadequate power supply during peak hours, forcing them to spend money on battery storage and fuel generators, which has a detrimental effect on economic growth (Bashir et al., 2021). Simultaneously, power plants face underutilization challenges as they require additional infrastructure investment to operate during peak hours. A reliable power network is crucial to balance energy supply and demand across production, transmission, and distribution sectors (Bhasin and Bhatia, 2011). The advent of smart grids facilitates peak load shifting, fault management, and rapid response to outages, ushering in a swift transformation in the energy sector. Furthermore, it encourages consumers to harness alternative renewable energy sources, reducing electricity costs and maximizing available power resources (Shah et al., 2022).

Demand-side Energy Management employs programs like Demand Response, offering an effective strategy that benefits both utilities and consumers. Smart meters play a pivotal role at the consumer level, contributing significantly to electricity control in the energy sector (Mohammadi et al., 2021). Two-way communication between utilities and customer premises enhances the flexibility of energy management schemes based on the served consumer category. Consumers are classified into residential, commercial, and industrial groups, each with distinct tariff rates, including Time-of-Use (ToU) and penalty charges based on factors such as demand and power factor (Almaiah et al., 2022). Industrial clients, being high-priority locations, pay higher rates, while residential customers enjoy lower rates (Balasaraswathi et al., 2020).Load shedding, a consequence of insufficient electrical generation, remains a significant challenge. In traditional systems, power outages occur when generated energy falls short of customer demand (Bashar et al., 2021). Load shedding is strategically implemented by

* Corresponding author at: Department of Electrical Engineering, Parala Maharaja Engineering College, Berhampur, affiliated to Biju Patnaik University of Technology, Rourkela, Odisha, India.
E-mail address: krishnarao.challa@gmail.com (C.K. Rao).

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utilities to balance the system and minimize outages, shifting energy use to off-peak times (Krishna Rao et al., 2023). With the increasing need for energy management systems, the focus is on optimizing power usage at consumer sites and enhancing resource management (Beştepe and Yildirim, 2022). Smart Energy Management Systems (SEMS) aim to maintain supply-demand equilibrium by ensuring adequate power access while reducing energy consumption during peak periods (Bhardwaj et al., 2022).

Power scheduling during peak consumption considers various constraints, categorizing appliances into schedulable and non-schedulable, as well as interruptible and non-interruptible types (Asif et al., 2021). Climate conditions influence the energy consumption of heating, cooling, and ventilation systems, with environmental weather sensor data offering valuable insights for effective planning and electricity reduction. Table 1 summarizes existing works on building energy management systems (Blasi et al., 2022).Extensive literature explores algorithms in demand-side energy management systems connected to Demand Response (DR) approaches. While appliance operation management is a frequent topic, automation is not always implemented (Afzal et al., 2021). Efficiency assessments of Energy Management

Table 1
Demand-SIde Energy Management Strategies and Its Importance (Shah et al., 2022).

DSM Strategies	Features	Merits	Demerits	Remarks
Peak Shaving	Cutting back on energy use during high demand to prevent supply overstretching	- Ways to address daily electrical demands - Lower cost per kWh of electricity	- Customers may face financial difficulties - Violation of consumer conveniences	Mostly suitable for highly predictable systems like traditional grids arranged vertically
Valley Filling	Increasing demand during times of high electricity generation	- Abolishes burdens associated with energy restrictions - Reduces dump energies - Customers benefit from cheap energy cost	- Requires soon-to-be-used storage facilities - Load categories need flexibility and criticality indication	Energy losses are prevented through valley filling, but customer satisfaction is put at risk
Load Shifting	Attempts to lessen the disparity between profiles with high and low demand	- Lessens the need for system expansions or upgrades	- Mostly advantageous for utilities - Like a blend of valley filling and peak shaving	Load leveling techniques may display traits found in other DSM techniques
Load Leveling	Shifting demands from one load to another based on criticality factor	- High level of system autonomy attained	- Only possible with flexible and important load classifications - Displays traits found in other DSM techniques	Load leveling techniques may display traits found in other DSM techniques
Energy Arbitrage	Economically saving less expensive energy sources to consume or sell when prices are higher	- Boosts the dependability of the supply system - Reduces wasted energy	- Requires effective energy storage handling - Events of fully charged ESS may favor dump energies	Very suitable for intermittent RE systems
Strategic Conservation	Utility-based DR initiative to encourage users to alter consumption patterns	- A plan for using energy efficiently - Focuses on less energy use	- Demand predictions impacted by consumer preferences - Typically focuses on less energy use	Focused on encouraging less energy use
Strategic Load Growth	Adoption of smart energy appliances to handle anticipated increase in energy needs	- Reduces waste energy - Saves money on energy	- Only possible with dump-loading systems - Must be combined with other tactics for effectiveness	Raises utility revenues while enhancing consumer productivity
Flexible Load Scheduling	Plan with incentives for system dependability degradation but no clear shapes	- Good for enhancing DG system autonomy	- In systems with uniform tariffs, like standalone, may not be possible - Most effective in multi-tariff integrated systems	Most effective in multi-tariff integrated systems
Valley Filling	Increasing demand during times of high electricity generation	- Customers benefit from cheap energy cost - Reduces burdens associated with energy curtailments - Significantly reduces dump energies	- Soon-to-be-used storage facilities - Energy losses are prevented, but customer satisfaction may be at risk	Load categories indicate the degree of flexibility and criticality required
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Systems involve comparing power consumption, room temperature, outside temperature, and client usage patterns before and after deployment (Pawar and Vittal, 2017). Strategies such as changing TV settings, reducing standby power, and adjusting refrigerator capacity have proven effective in significant energy savings. Real-time scheduling systems prioritizing appliances during peak periods also contribute to overall energy reduction. Evaluations include assessing communication delays in energy management setups and physically demonstrating DR program-based energy management at the appliance level (Raghul et al., 2022).Recent research emphasizes developing intelligent energy management systems using environmental sensors and user comfort data (Hamdani et al., 2021). These systems factor in occupant preferences and sensory inputs to dispatch control operations, ensuring user comfort and optimizing energy usage (Lekvan et al., 2021). Rule-based intelligent systems, relying on practical information, aim to provide a dependable energy profile, guarantee customer comfort, and reduce power costs (Peña et al., 2022). Implementing demand-side load management techniques, driven by specific rules and aiming for customer satisfaction within budget constraints, can improve forecasting and future energy usage patterns (Piatek et al., 2021).

Utilizing load shedding and demand-side load scheduling, a model for optimal energy management aimed at reducing system running costs is described (Pong et al., 2021). The approach introduces a distinctive Demand Response (DR) calculation process tailored for both residential and commercial settings, taking into account consumers' usage patterns and temperature settings (Pawar, (n.d.)). The resulting system demonstrates adaptability and DR capability, particularly in predicting peak load shed. Within a multi-agent Energy Management System (EMS) architecture, inclusive of scheduling algorithms and DR mechanisms, An energy management system for a smart home functions in part because of sensor data and client intent. Additionally, this method has been applied to control renewable energy sources integrated into the smart grid (Rehman et al., 2021). The optimization of financial benefits for household energy management is achieved through the scheduling and control of home appliances using mixed-integer linear programming models. The incorporation of a DR approach, paired with a battery-based storage system, led to a significant reduction in power costs (Ahmad et al., 2022).

A strategy involving DR coupled with a battery-based energy storage system notably decreased power prices, with the proposed approach facilitating a prompt return to normal functioning after a DR occurrence and showcasing a substantial decrease in power usage (Zhang et al., 2022). A hierarchical control method, considering temperature levels and load flexibility, is introduced to provide demand-side management services. This strategy allows for variable load scheduling and minimal operating costs when combined with building thermodynamics and the HVAC system (Demirezen et al., 2020).An array of communication technologies, including power line carriers, ZigBee, and Wi-Fi, provide the basis of energy management systems. Effective communication between the utility gateway and consumer loads is crucial for appliance operation using specific operating techniques (Mazhar et al., 2022). The integration of the Internet of Things (IoT) into Smart Energy Management Systems (SEMS) allows for remote operation and monitoring of appliances, enhancing overall energy management effectiveness (Gupta et al., 2022). A study involving communication protocols and linear optimization methods proposes new models, providing a practical resolution to demand-side energy management challenges through the examination of information models and communication technologies for distributed energy systems (Khan et al., 2022). While existing energy management methods primarily target residential customers and organize appliance operations based on utility signals, there is a need for an adaptable system with reliable communication capable of handling power-intensive loads for various users (Raza et al., 2020).

The primary focus of the proposed technique in this study is the design and production of real-time hardware prototypes. Unlike existing strategies that prioritize appliance functionality, this work introduces a customizable smart energy management system (Rao et al., 2021a). With user-configurable priority features and cost-optimization strategies, the system maintains portability to suit diverse users without compromising convenience. SEMS's architecture includes reliable self-diagnostic tools for straightforward scalability and true communication at the appliance level. The recommended SEMS is also connected to the IoT ecosystem for remote monitoring and additional data analyses (Lilis et al., 2017). The model considers Time of Use (ToU), sensory information, multiple adjustable priority settings, and demand limit restrictions during testing. The hardware display of the model is configured in a lab setting, and the SEMS may be applied to maximize the use of electricity from independent systems, such as solar and wind power plants (Rao et al., 2021b).

The organization of the literature in this paper is as follows: Section 2 provides a summary of the recommended architecture and a breakdown of the suggested system. Section 3 covers the recommended control approach and the application of various optimization techniques. Section 4 thoroughly explains the experimental setup and general system organization. Findings and observations regarding the created control systems are presented in Section 5. The final section, Section 6, concludes the paper.

2. Illustration of the energy management system

The proposed Smart Energy Management System (SEMS) and its main algorithms are covered in detail in this section.

2.1. Outline of the energy management system

The conceptual layout of the suggested Smart Energy Management system is shown in Fig. 1. An essential part of the entire system, the SEM unit gives users and other end users the ability to monitor and operate. The electrical properties of linked appliances are locally controlled by Smart Sockets, which receive command signals from the SEM unit (Huang et al., 2016).Moreover, the SEM unit makes connections between a user and a utility by acting as a gateway. In this instance, the gateway obtains from the utility data on the allowed maximum demand limit and enters it into the SEM unit. Conversely, the utility aggregates and assesses energy usage data from each SEM unit in a city to adjust the maximum demand limit for individual users. This collected data serves billing purposes, and residents receive electronic bills accordingly (Kumar and Saravanan, 2019).

2.2. The structural design of smart energy management

The SEM Gateway comprises the following key components

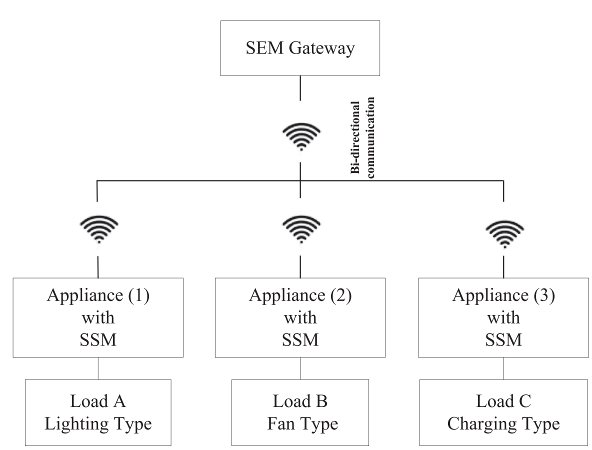

Fig. 1. Block diagram of Smart energy management system (Bhardwaj et al., 2022).

2.2.1. Central controller for the SEM gateway

The primary control element is the SEM, utilizing a decisive algorithm as its decision-making mechanism. Acting as the intermediary between the utility and the user, the SEM system's brain determines whether to turn ON or OFF a specific set of consumer data based on the received utility signal and domestic user load priority selections (Zachar and Daoutidis, 2018). To prevent tariff fees, the SEM unit notifies the user when activating a high-power-consuming device during peak load times. All load controllers equipped with the XBee unit are mandated to have an LCD, responsible for collecting energy usage data from each device. This enables real-time monitoring of energy use, adjustment of appliance priorities based on needs, and provision of real-time energy use data (Rao et al., 2022).

2.2.2. Communication module

A wireless connection is established between a coordinator and a router in the communication module. The communication unit in this case is an XBee Series-2 device, connected to both ends of the SEM system to facilitate communication. One XBee module functions as a router, while the other serves as a coordinator within a load controller. The coordinator and router are interconnected in the SEM system to enhance performance in terms of power usage and data transmission. Using the power consumption data obtained by the SEM unit, the coordinator uses control signals to the router in order to carry out the power negotiation methodology (Qureshi and Jones, 2018). With regard to communication technologies, ZigBee seems to be a good option for this application because of its low cost, low power consumption, and simplicity of deployment when compared to other technologies like Bluetooth, Wi-Fi, and Power Line Carrier (Abate et al., 2019).

3. Algorithm for Demand Side Energy Management

The proposed SEMS management system employs smart plug units to enable individual consumer devices to connect to the Gateway and communicate via XBee units in AT mode. In this recommended approach, the SEM gateway receives energy consumption data from each installed smart socket and the utility's authorized maximum demand limit. SEM schedules each appliance effectively using a reliable power negotiation technique (Alavi et al., 2018).

The Smart Socket Module (SSM) and SEM Gateway in the proposed SEMS incorporate the following algorithms to regulate demand-side energy management for efficient power utilization:

- Central Controller Gateway
- Demand Response utilizing a decision-making technique
- Self-diagnostic function for non-responding appliances
- Smart Plug (Appliance end)
- Organization of commands sent from the device end
- Cost Optimization Method

The SEMS main controller's decision algorithm, which supervises all control activities, is the cornerstone of the proposed SEMS approach.

3.1. Decisive algorithm through demand response

The recommended SEMS technique features a decisive algorithm that prioritizes customer appliances and operates at the highest level during insufficient energy supply from the utility to meet the maximum demand. Fig. 1 illustrates a comprehensive flowchart of the recommended SEMS approach using the power intercession method. This section provides a detailed, step-by-step explanation of the approach.

Step 1: The initial step in the SEM decisive strategy is to gather information on the power consumption of each device in a specific sequence. A load controller starts a self-diagnostic procedure if it doesn't react.

Step 2: After organizing power usage information based on client priorities, the SEM Gateway checks for violations of the demand limit, such as the sum of apparent power exceeding the MDL.

Step 3: Before instructing other devices to switch off, the SEM Gateway commands the activation of as many high-priority appliances as possible to ensure the MDL is not exceeded.

Step 4: Each activated appliance undergoes a peak load analysis by the decision-making algorithm, activating the load controller to warn the customer of excessive energy usage during peak load hours. The buzzer and LED are activated for one second to alert the customer.

The cumulative power consumption of all appliances surpasses 25 % of the highest apparent power recorded in the previous month.

Step 5: The SEM Gateway pauses for 30 seconds after transmitting correct command signals to each device before sampling the next batch of data. Customers can adjust device priority during this time, repeating steps 1 through 5 as needed.

Fig. 2 provides a comprehensive overview of the decision-making process in the SEM for 'n' loads within a household. The flow chart incorporates variables "J" and "P," which increment based on priority for variable "J" and follow a predetermined sequence for variable "P" to systematically gather energy usage data from all appliances. In the event of a disruption, the load controller may fail to respond even after the resumption of data flow. In such cases, the SEM Gateway initiates a self-diagnostic method by continuously querying the load controller for a response over the next five seconds and beyond. This process continues for the specified six-second waiting period. If the lack of activity is attributed to a temporary issue, The necessary information is returned by the load controller. The SEM Gateway then moves on to submit inquiries to the following load controllers. If a load controller remains unresponsive even after five seconds of continuous polling, the SEM assumes the controller is permanently inactive. Consequently, requests are directed to other load controllers, ensuring that the system's overall performance is not adversely affected by a few idle load controllers.

3.2. Cost optimization algorithm

The cost optimization algorithm plays a crucial role in mitigating energy expenses for consumers, particularly under Time of Use (ToU) tariff structures. The objective of the load scheduling algorithm development is to achieve reduced energy expenses. However, the applicability of this algorithm varies among household devices, contingent upon the consumer's preference for allowing schedulable processes on their devices, as illustrated in Fig. 4. This technique is employed by the load controller in any device amenable to scheduling. Thus, the load allocation technique used in the load controller of a scheduler works in tandem with the SEM calculation processes to regulate all schedulers. In Fig. 3, TPCODL illustrates the ToU Tariff for the 2023 financial year, pertinent to Low Tension businesses. The load scheduling algorithm is designed with this ToU pricing in mind to optimize cost savings. Each scheduled device equipped with a SEM unit receives time information. A load controller, scheduled as an appliance, utilizes the time zone to determine the device's operational state. The daily usage pattern of a customer defines the appliance's daily use requirement.As depicted in Fig. 6, the algorithm is configured to activate the appliance during the optimal period between 22:30 and 06:30, allowing the user to benefit from an incentive of Indian Rupees 1.50 per unit. However, irrespective of the required operational period, the appliance must be turned off during peak load hours to avoid penalties. If the necessary operational time exceeds eight hours, the device may run from 10:00–18:00 without receiving rewards or penalties during off-peak load hours. Otherwise, the device is set to operate between 22:00 and 6:00, earning a reward during this timeframe before being turned off. The SEM decisive algorithm has the capability to prevent an appliance from operating for the required duration on any given day if the generated power is insufficient. In such instances, the algorithm ensures that the deficit is compensated the following day by allowing the appliance more time to run. The unmet requirement from the previous day is added to the

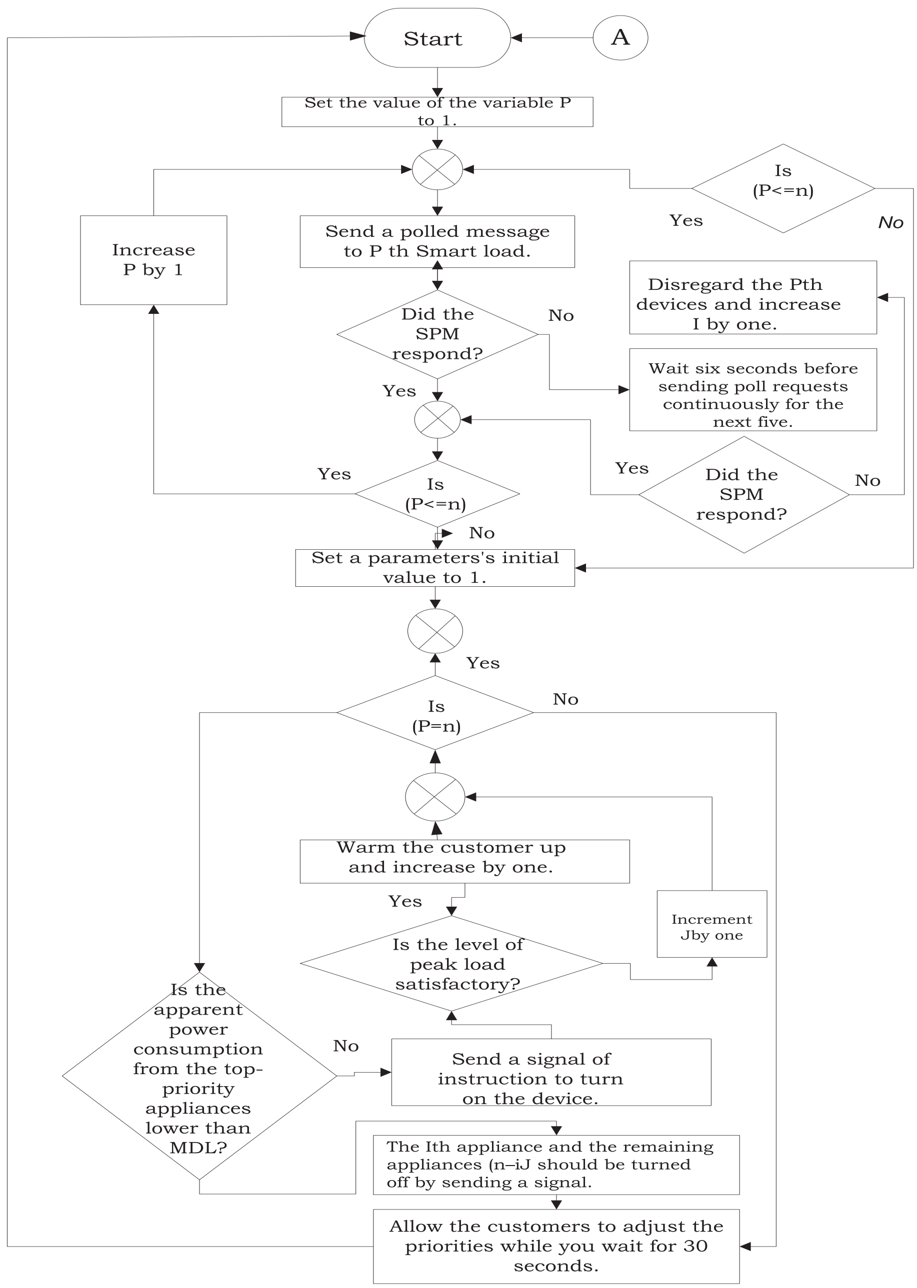

Fig. 2. Decision algorithm with self-diagnostic capability (Ahmad et al., 2022).

demand for the current day, updating the daily demand every day at 10:00 PM.

3.3. Controller Activities at the Device End

Fig. 6 presents a flowchart outlining the algorithm, with further details explained in subsequent sections. The algorithm concentrates on the actions occurring at the device end, namely the smart plug's internal operations. The Smart Plug decision-making mechanism continuously reviews any requests from the coordinator end for power usage statistics. The microcontroller unit connected to the smart plug, as depicted in Fig. 5, computes and sends data on real power, power factor, voltage, and RMS current. The coordinator sends a command signal to the smart plug, which then triggers the relay to change an appliance's state. Additionally, the coordinator sends signals to the Smart Plug to communicate any cautions related to usage.

4. Practical Implementation of SEM

This section outlines the laboratory setup and improvements made to the SEMS.

4.1. General setup of SEM

Fig. 7 provides an overview of the entire SEM system set up in the laboratory, featuring common loads such as lights, fans, and charging laptops. The algorithms embedded in the SEM are designed to function during demand response events, instructing devices based on assigned priorities while considering the maximum demand limit. These algorithms schedule appliances, taking into account the Time of Usage, to

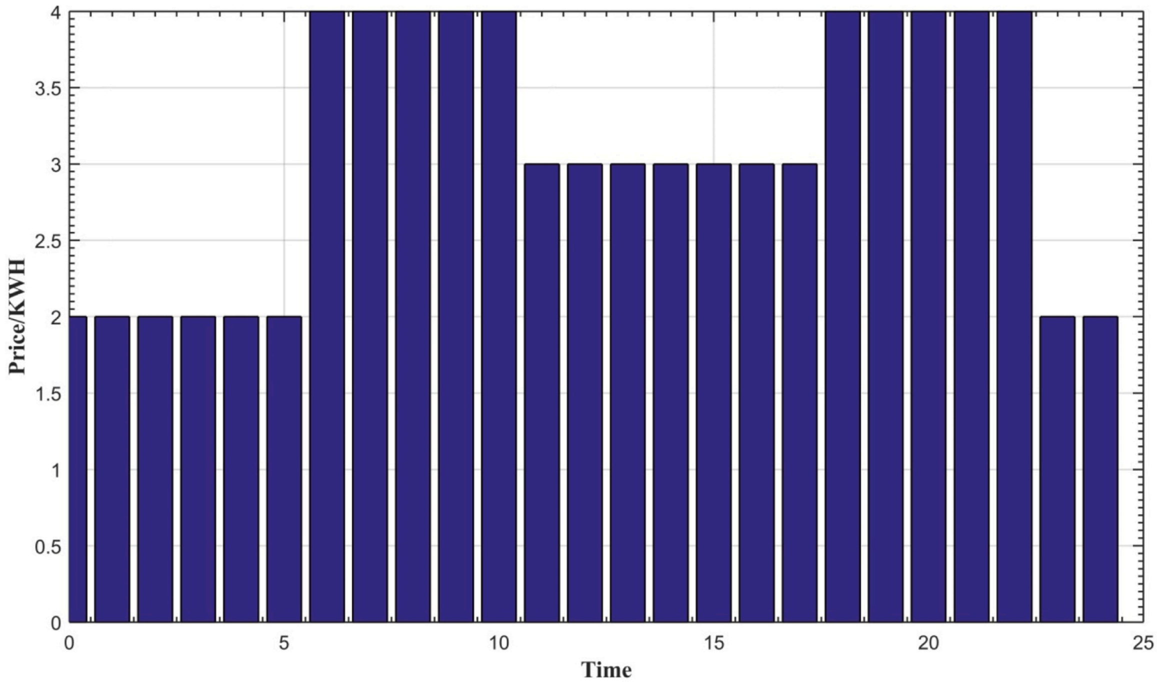

Fig. 3. The Time of Usages Tariff for Consumers (Lekvan et al., 2021).

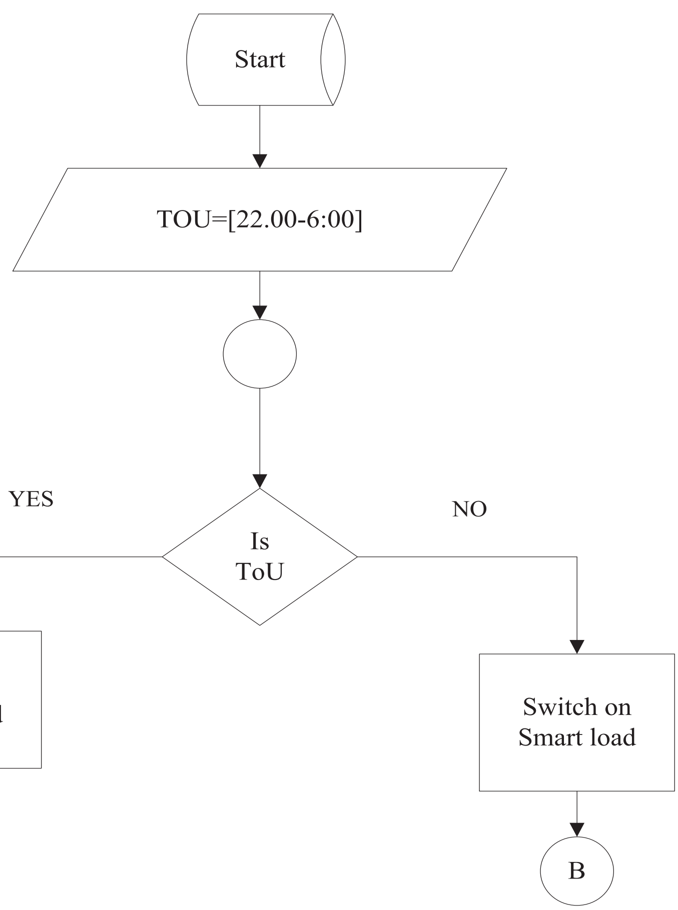

Fig. 4. The load controller of a schedulable device (Rehman et al., 2021).

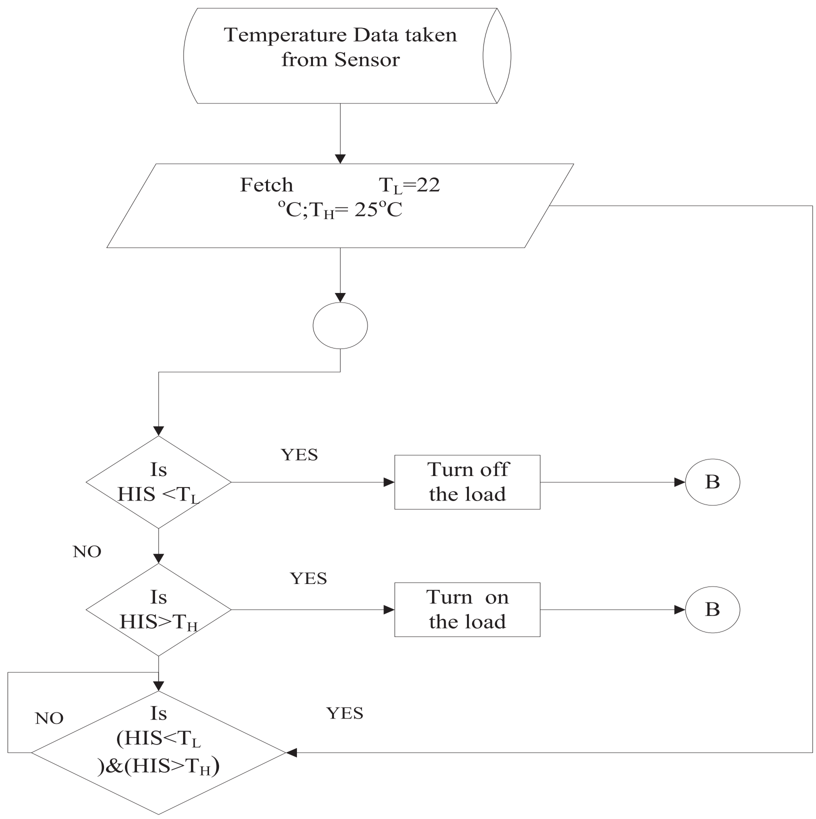

Fig. 5. Temperature controller of a schedulable device (Krishna Rao et al., 2023).

optimize energy consumption and fit within the lowest slab rate.

In the laboratory experimental setup, a bank of incandescent lights is designated as Load-A, while Load-B is represented by a fan with a variable speed feature connected to humidity and temperature sensors. This arrangement aims to demonstrate the integration of algorithms with user comfort conditions. Load-C, a charging laptop, has been purposely selected to illustrate how charged loads can be scheduled, taking the Time of Use (ToU) into account.

4.2. User-end interface through the LCD

An LCD included within the SEM unit shows important electrical properties including energy usage and load prioritisation. Users can adjust the priority of appliances to suit their preferences using the available switch buttons. Fig. 8 provides a visual representation of the SEM unit's experimental lab setup.

4.3. Smart plug serving as a load controller

Fig. 8 showcases the laboratory setup featuring a "smart plug," incorporating three identical load controllers. These general-purpose plugs are utilized to test the essential electrical characteristics of connected loads for sub-metering applications and to switch loads in response to control signals. The smart plug module includes an XBee Series-2 module for two-way communication, a 20 A relay module for switching tasks, a LEM LV-25 P and LA-55 P current and voltage sensor unit, an ATMEGA328 microprocessor unit, and loads connected to the smart plug. The SEM unit's coordinator sends control signals to the router, which in turn receives data in string format, as depicted in Fig. 9. To obtain the actual values of electrical parameters, these string-formatted values are then translated into suitable decimal forms.

4.4. Communication unit

The SEM employs two similar XBee units to facilitate communication via ZigBee, with one serving as the coordinator in the Home Energy Management (HEM) and the other functioning as a router in the smart plug at the load end. In the laboratory setup, ZigBee messages are transmitted in Application Transparent mode.Table 2

The SEM coordinator initiates a message containing a data request to the integrated routers of connected loads, specifically the energy consumption data gathered by the smart plugs, ensuring the correct order. After the string-formatted data is received from the router, the SEM unit coordinator sends the control signal to the SEM unit. The received data is then converted to the equivalent decimal format to obtain accurate values for the electrical parameters, as outlined in Tables 3 and 4.

4.5. User priority setting options that can be configured

The priorities of appliances may change periodically based on the user's preferences and needs. For example, lights may be preferred over the air conditioner at night, while the air conditioner could be more useful during the day. Therefore, priority settings are designed to be flexible and can be altered by the customer at any moment to accommodate shifting requirements. The client has the freedom to adjust the priority settings on an LCD monitor in real-time, providing them with flexibility in managing their energy consumption according to their preferences.

4.6. IoT-based energy monitoring system

The integration of smart meters in housing complexes enables real-time monitoring of energy usage. After establishing a successful Ethernet shield connection, the generated SEMS data can be seamlessly transferred to the server. A data monitoring system or dedicated devices

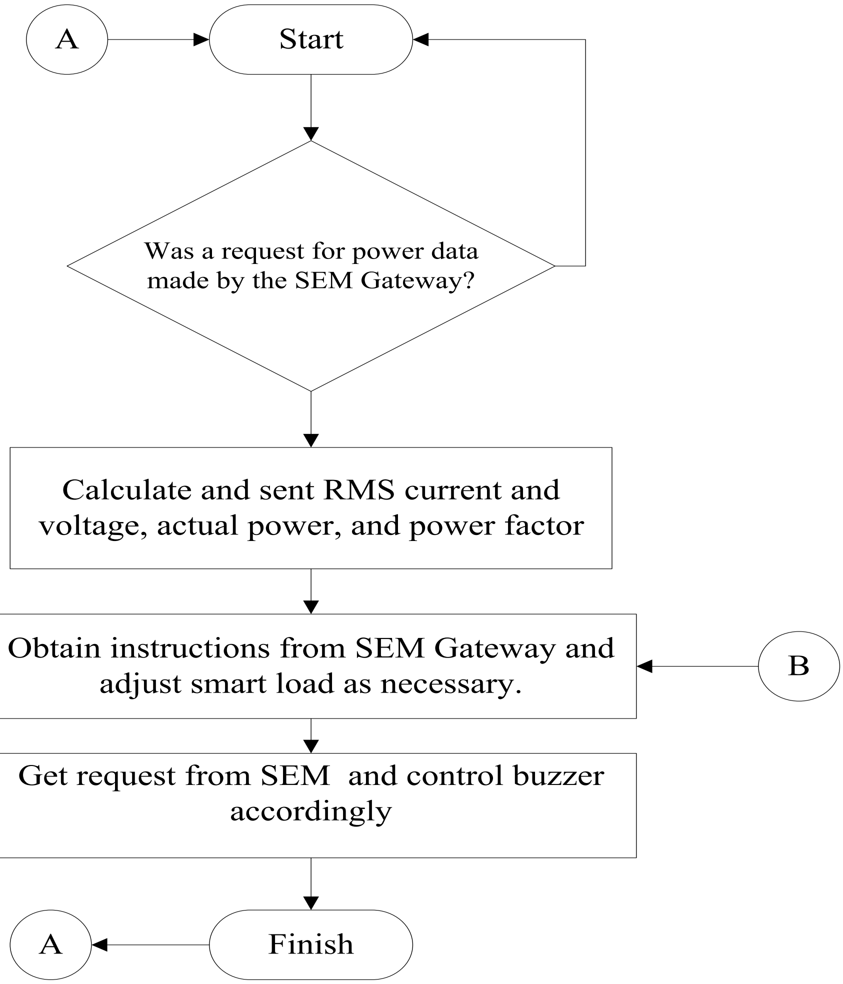

Fig. 6. Implemented algorithm in the smart plug module (Bashir et al., 2021).

can be utilized for monitoring and tracking additional data. Fig. 10 provides a comprehensive graphical overview of the entire system.

To delve into energy system management, substantial amounts of metering data can be collected. Various research teams are actively engaged in exploring solutions for energy costing, machine learning applications, big data analytics, and the development of real-time energy management systems. The server and database management system employed by the energy monitoring system facilitate data gathering and real-time monitoring. Access to the web portal is restricted to authorized individuals with the correct login credentials, ensuring a secure and controlled environment.

5. Demonstrations and result analysis

This section presents and analyzes outcomes from multiple scenarios to showcase the effectiveness of the energy management system. Experiments are conducted using various appliance settings, a user comfort scenario, and a cost-optimization approach.

5.1. Test-I: operational plan for a load with an established precedence - active utilization of "Load A" (One Light)

In this scenario, the luminous lights are given top priority and designated as Load A, with a mid-priority assignment for a fan load (Load B). Battery charging, being of lower priority, is given little consideration. The SEM load scheduling procedure for this case is depicted in Fig. 12, and a step-by-step breakdown of the load preparation with selected priorities is provided:

Step 1: The SEM unit transmits a data request signal "PA."

Step 2: Load 'A' responds by providing details such as RMS voltage and current, power factor, apparent, real, and reactive power, and energy consumption.

Step 3: SEM sends an information request signal "PB."

Step 4: Load 'B' responds by providing information on its power consumption.

Step 5: SEM sends a data request signal "PC."

Step 6: Data about the power consumption of load 'C' is returned.

Step 7: According to Table 2, the requested power amount is less than the permitted maximum demand. The decision process determines that all three loads should remain "Switched On." The SEM unit uses command signals in the form of the strings "paag," "pbbg," and "pccg" to turn on the relays for all three loads because the total power usage is less than the upper limit of the demand.

The highest demand is indicated to be 196 W in Fig. 11. All three loads were turned on from 9:17:45–9:20:45, as the highest power usage was below the MDL (maximum demand limit). At 9:20:45 PM, two additional incandescent lamps are switched on, causing the power bank's overall power usage to exceed the MDL. In response, the SEM controller promptly eliminates the battery charging load (Load C). Furthermore, by turning on the additional bulb, the lighting load's power usage increases at 9:21:30 PM. The controller additionally disconnects the second load (Load B) in order to preserve supply and demand balance, as the lighting load uses 60 W of the 196 W MDL total. Following a drop in Load A usage, Load B and Load C are turned on in

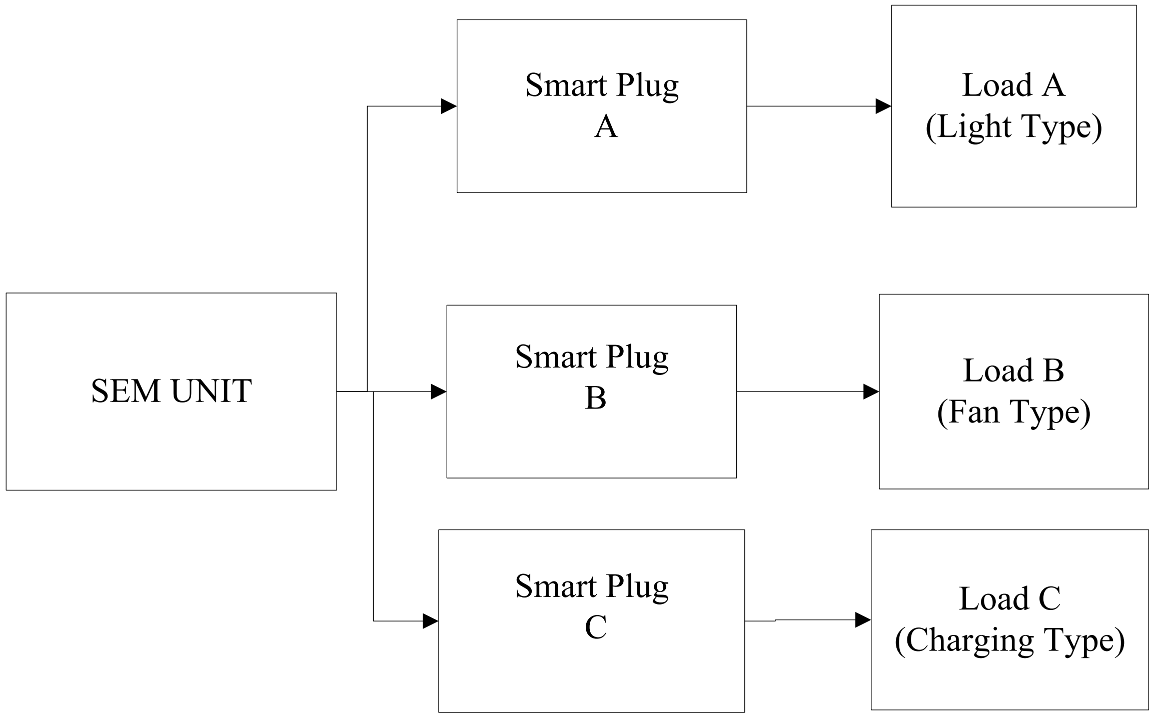

Fig. 7. Practical implementation of a smart energy management system.

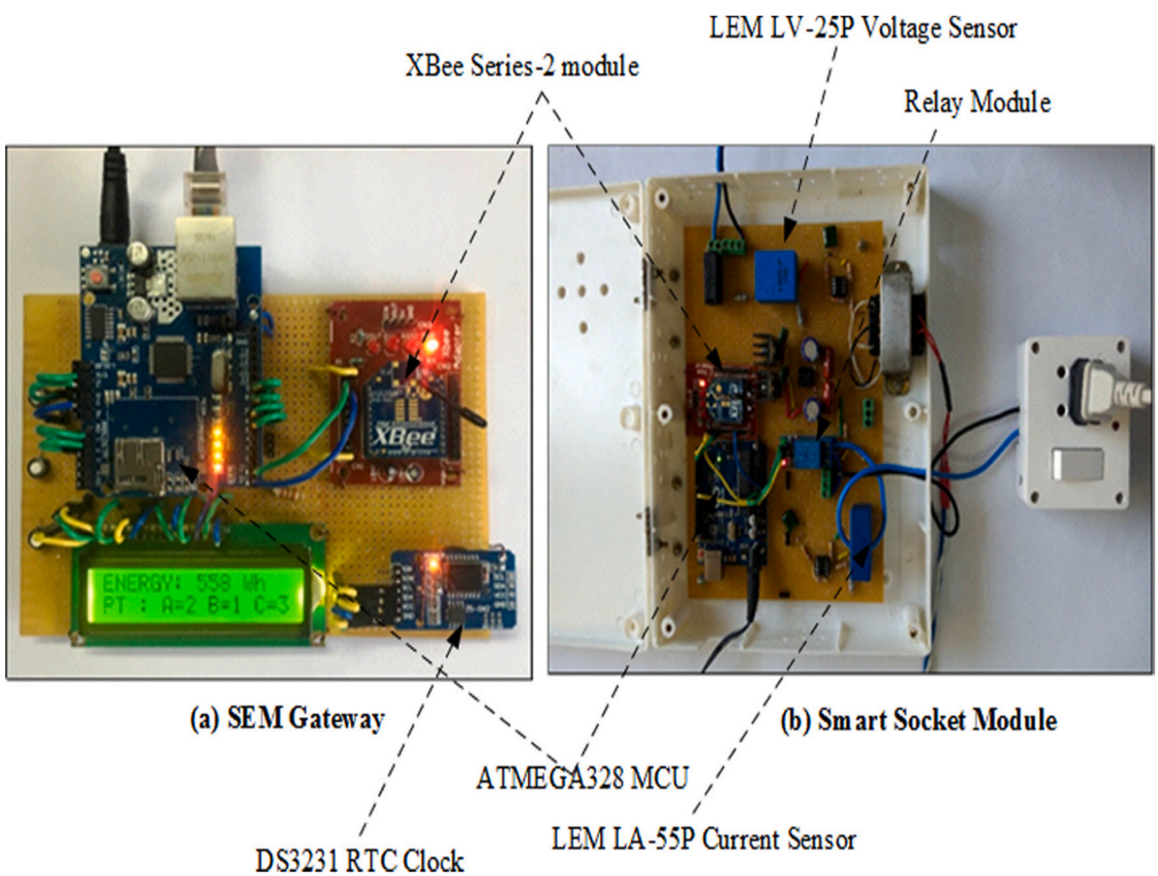

Fig. 8. Laboratory implementation of SEM and Smart Plug.

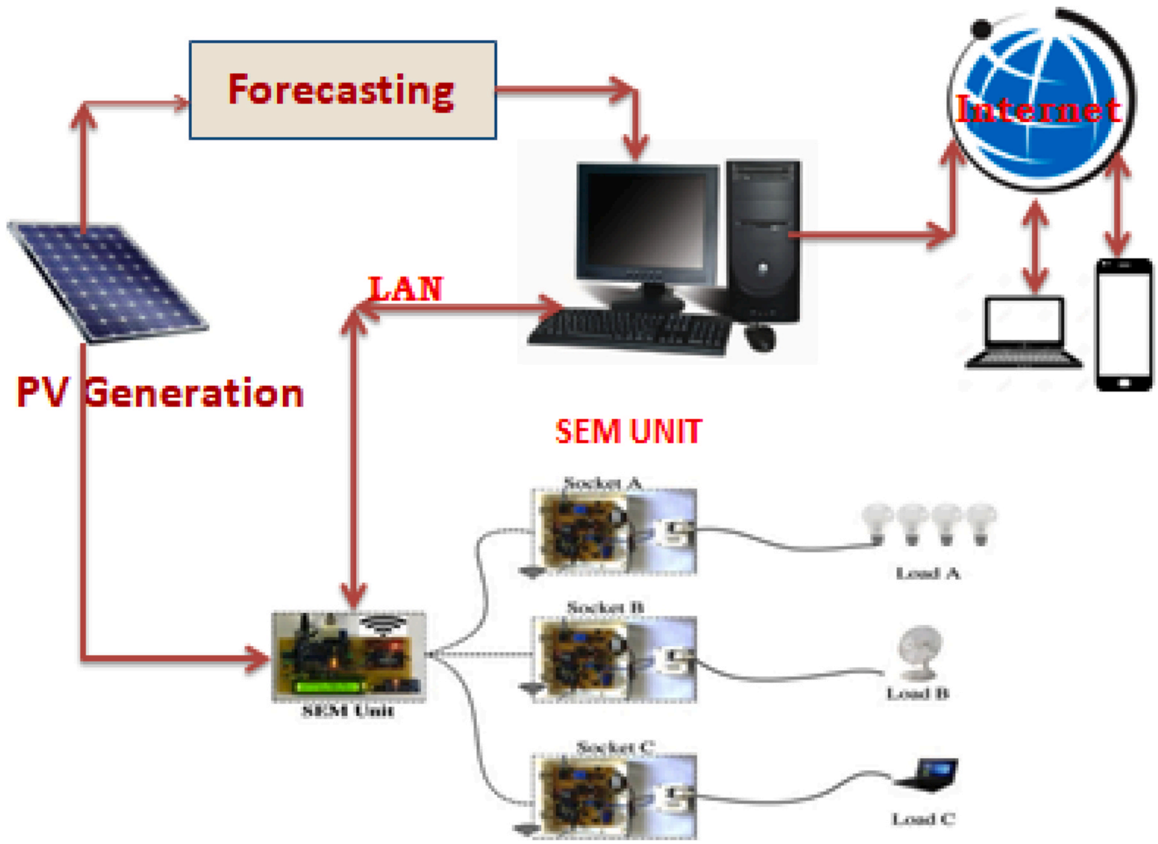

Fig. 9. IoT-based Energy Monitoring System.

Table 2
Device state of operation behind Load arrangement.

Devices	Device Status	Priority	VA Power (kW)	Power Demanded (kW)	MDL (kW)	Device Position
Load-A	Switch On (One Light)	High	0.02	0.185	0.196	Turn On the Switch
Load-B	Switch On	Medium	0.08	0.185	0.196	Turn On the Switch
Load-C	Switch On	Low	0.085	0.185	0.196	Turn On the Switch

Table 3
Device state of operation behind Load arrangement.

Devices	Device Status	Priority	VA Power (kW)	Power Demanded (kW)	MDL (kW)	Device State of Operation
Load-A	Switch On (Two Lights)	High	0.04	0.205	0.196	Turn On the Switch
Load-B	Switch On	Medium	0.08	0.205	0.196	Turn On the Switch
Load-C	Switch On	Low	0.085	0.205	0.196	Turn Off the Switch

priority order. Table 2 provides the SEM system's appliance scheduling and power usage information for this specific instance.Fig. 12

Test-II: Operational Plan for Dynamic Utilization "Load A" (Two-Light)

Table 4
Device state of operation following Load arrangement.

Devices	Device Status	Priority	VA Power (kW)	Power Demanded (kW)	MDL (kW)	Device State of Operation
Load-A	Switch On (3 Lights)	High	0.06	0.225	0.196	Turn On the Switch
Load-B	Switch On	Medium	0.08	0.225	0.196	Turn On the Switch
Load-C	Switch On	Low	0.085	0.225	0.196	Turn Off the Switch

In Test-II, the operational plan involves dynamic utilization of "Load A" with two lights. The specifics of this test scenario, including the apparent power consumption and scheduling decisions, are not provided in the current text. If additional details or a breakdown of this scenario are available, they can be included for a comprehensive analysis.

5.2. Test-III: Order of Load Precedence (Low) for Load A, (Medium) for Load B, and (Highest) for Load C

Similar to Test-I, Test-III visually demonstrates the different ratings of significance for the loads. In this case, Load A is assigned a low priority, Load B a medium priority, and Load C the highest priority. The SEM compares the overall apparent power of the three loads (196 W; 060 + 080 + 085 W) with the 196 W demand limit, as shown in Fig. 12. The top two priority loads' combined power usage (080 + 085 = 165 W) is less than the maximum demand limit. As a result, the SEM sends a signal to loads C and B to turn on while turning off load A's relay.

In Fig. 12, a decisive algorithm-based appliance operation with assigned priority orders is illustrated. Consider a situation where the

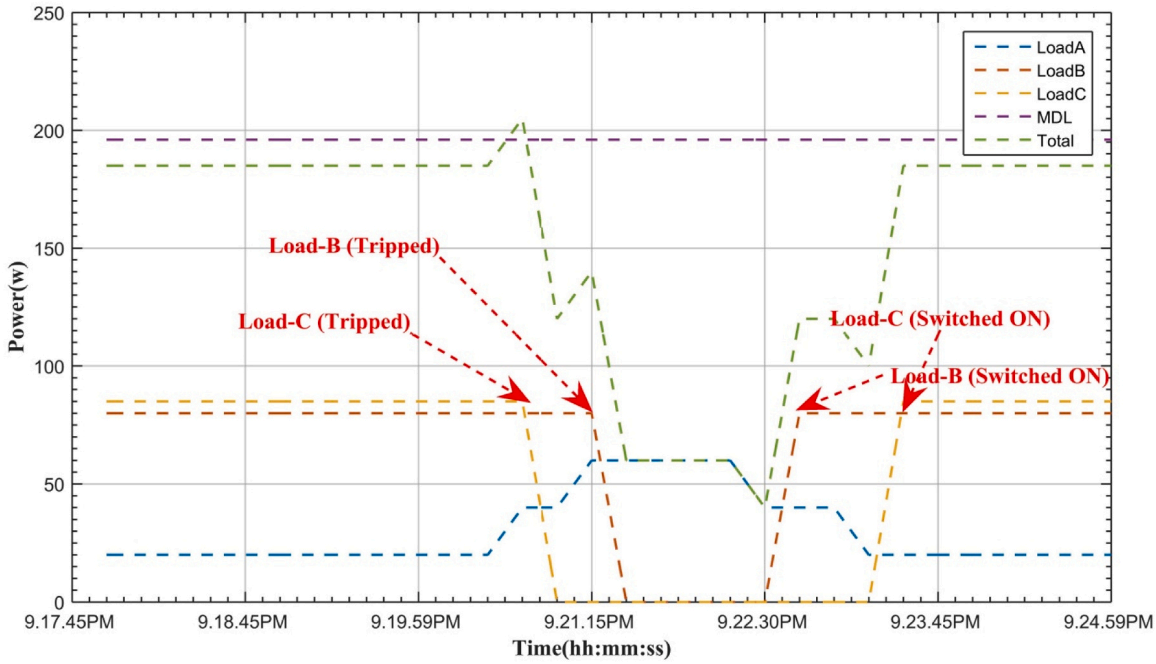

Fig. 10. The high-priority devices with MDL limitation.

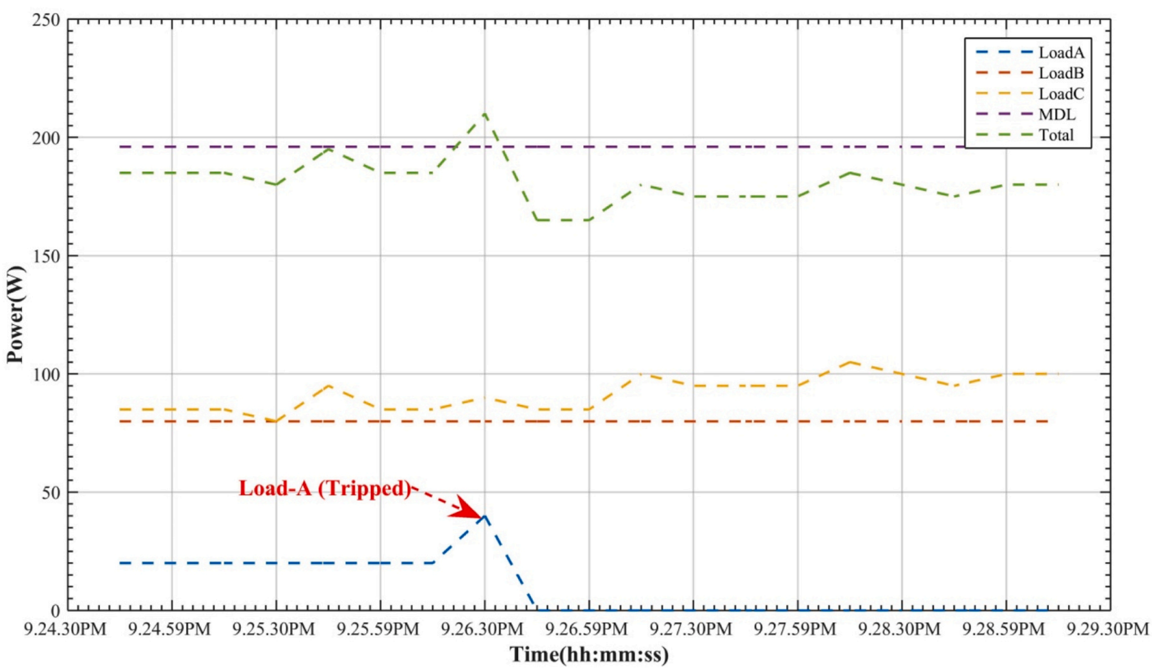

Fig. 11. The high precedence devices with modifications in the order of precedence allowing for MDL limitation.

user intends to activate each of the three loads. Since there is no violation of the maximum demand limit, all loads are initially turned on. It is observed that as Load A consumption rises, Load A itself is tripped off at 9:26:15 PM to prevent an MDL violation, given its lower priority in the scenario depicted in Fig. 13.

5.3. Using perceived sensor data to set user preferences

Heating and cooling units, designed to operate within specific temperature ranges, frequently cycle on and off to maintain the desired temperature. For instance, an air conditioner starts its compressor when the interior temperature reaches the set point and it stops when the target temperature is achieved. Nevertheless, the air conditioners effectiveness may be lowered by repeated brief cycles. Conversely, longer cycles can enhance efficiency. The recommended approach allows users to specify a wider temperature range, improving appliance efficiency and reducing energy consumption.

The load controller, when receiving a signal from SEM to activate a heating or cooling device, checks for deviations from the comfort criteria. It manages the appliance to maintain the temperature within the user's specified comfort levels. In this example, using heat index in Celsius, humidity, and temperature sensor data, along with threshold

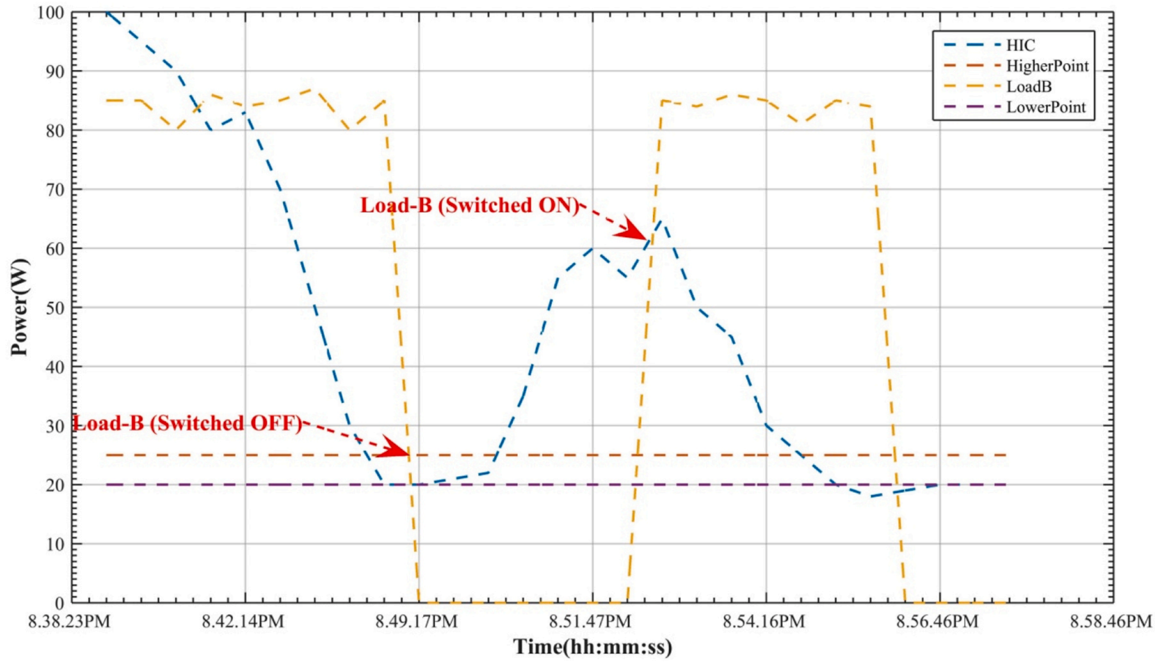

Fig. 12. The user comfort level with the detected value.

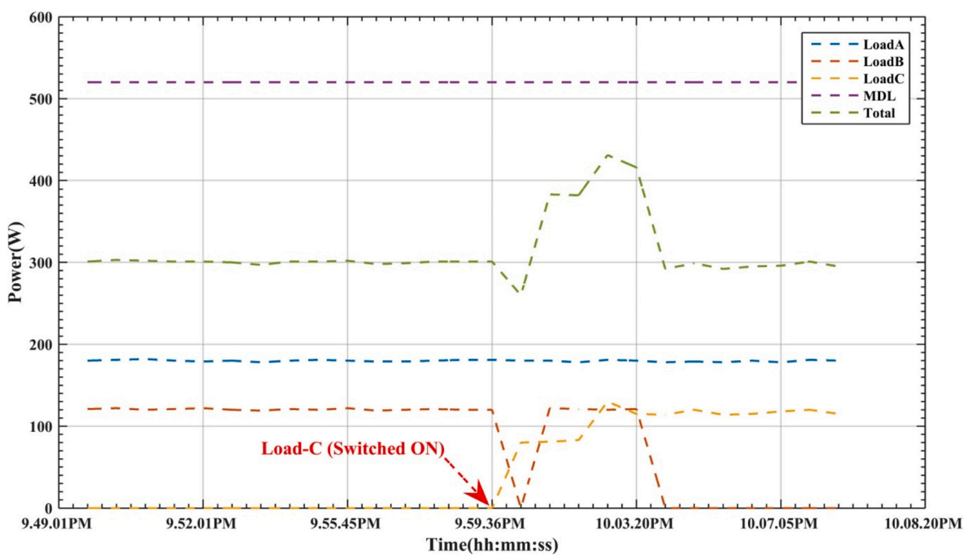

Fig. 13. The scheduling operation with ToU.

values, the load controller ensures that the fan load is turned off when the outdoor temperature is below 21 °C and turns it on when the temperature exceeds the upper limit of 25 °C (as illustrated in Fig. 10).

5.4. Scheduling allowing for time of use (ToU)

There are two types of home appliances: schedulable and non-schedulable. The suggested controller schedules loads that can be moved to off-peak hours in order to minimise power expenditures during Time of Use (ToU) tariff periods. Utilizing data from both the Real-Time Clock (RTC) module and peak usage data from the utility, the controller makes informed decisions. In Fig. 11, the load scheduling choices for the ToU pricing scheme are illustrated. For instance, battery charging is shifted to off-peak hours, starting at 10 PM, to reduce power costs.

6. Conclusion

In the laboratory setting, the hardware for the Smart Energy Management System (SEMS) prototype has been successfully developed and constructed. Rigorous tests have been conducted to validate the effectiveness of the controller's power optimization algorithms. Using XBee Series-2 modules, the SEM controller and smart socket unit enable wireless ZigBee communication, integrating cutting-edge self-diagnostic technology to create a dependable network. Three distinct loads are used in the initial testing to demonstrate the customisable priority features. Customers are provided with the flexibility to modify the priority order for appliances, enhancing user control. The paper presents multiple experimental scenarios to illustrate how higher-priority appliances can operate during Demand Response (DR) situations while adhering to Maximum Demand Limit (MDL) constraints. Furthermore, the SEM controller employs cost-optimization methods to plan the utilization of specific equipment during off-peak hours, considering the Time of Use (ToU) tariff to reduce electricity costs. The system actively informs consumers of increased power usage during peak hours through audible and visual indicators such as a buzzer and LED notifications. To gather detailed information on the power usage of specific loads, an Internet of Things (IoT) environment is established, connecting to a secure internet gateway. With possibilities for additional data analysis, the system includes a database for the energy management system and a Graphical User Interface (GUI). It displays the daily and monthly power consumption of specific equipment, providing users with valuable insights into their energy usage patterns.

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CRediT authorship contribution statement

Challa Krishna Rao: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sarat Kumar Sahoo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Franco Fernando Yanine:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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