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Smart grid data analytics framework for increasing energy savings in residential buildings

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ABSTRACT

Human energy consumption has gradually increased greenhouse gas concentrations and is considered the main cause of global warming. Currently, the building sector is a major energy consumer, and its share of energy consumption is increasing because of urbanization. This paper presents a framework for smart grid big data analytics and components required for an energy-saving decision-support system. The proposed system has a layered architecture that includes a smart grid, a data collection layer, an analytics bench, and a web-based portal. A smart metering infrastructure was installed in a residential building to conduct an experiment for evaluating the effectiveness of the proposed framework. Furthermore, a novel hybrid nature-inspired metaheuristic forecast system and a dynamic optimization algorithm are designed behind the analytics bench for achieving accurate prediction and optimization of future energy consumption. The main contribution of this study is that an innovative framework for the energy-saving decision process is presented; the framework can serve as a basis for the future development of a full-scale smart decision support system (SDSS). Through the identification of consumer usage patterns, the SDSS is expected to enhance energy use efficiency and improve the accuracy of future energy demand estimates. End users can reduce their electricity costs by implementing the optimal operating schedules for appliances, which are provided by the SDSS.

1. Introduction

Human energy consumption has gradually increased greenhouse gas concentrations in the atmosphere and is considered the main source of global warming. Because of global warming and the accompanying climate change, conserving electricity is imperative. End-use energy efficiency can contribute more than 50% to the total global energy conservation [5,40,53]. Clearly, even a small reduction in the energy consumption of buildings can have appreciable economic and ecological impacts for the society [43]. Improving electricity use efficiency can gradually mitigate the contribution of human energy consumption to global warming and climate change [15,50,54].

The construction sector is a major energy consumer, accounting for approximately 40% of the global energy consumption and 30% of CO_2 emissions [7,19,35]. Its share is increasing because of urbanization [59, 60]. In the United States, commercial and residential buildings account for 40% of the nation's total energy consumption, and this figure is steadily increasing [1,40]. In Europe, buildings constitute 40% of the energy consumption and 36% of CO_2 emissions [36]. Accordingly, improving the energy efficiency of buildings is necessary for controlling energy costs, reducing environmental impact, and increasing the value and competitiveness of buildings.

In Taiwan, the total energy consumption has increased steadily over the past two decades, with an average annual increase of 3.52%. The electricity consumption has increased annually by 4.52% on average. Specifically, in 2012, the residential sector formed 10.88% of the total energy consumption; the energy and industrial sectors consumed 45.25%; the transportation sector accounted for 11.89%; the agricultural, forestry, and fishery sectors consumed 0.89%; and the services sector consumed 11.04% [2]. Compared with other sectors, the residential sector is currently a major energy consumer. Moreover, the introduction of the green building certification system in Taiwan has raised public awareness about energy efficiency. Hence, identifying and optimizing the electricity use of equipment and appliances in residential buildings are desirable.

The smart grid system offers a promising solution to the rapid increase in power demand [3,20,24,56]. Smart grids can potentially improve the reliability and quality of electricity generation; reduce peak demand; reduce transmission congestion costs; increase energy efficiency; increase environmental benefits accruing from increased asset utilization; improve capability to accommodate renewable energy; and enhance security, durability, and ease of repair in response to malicious attacks or adverse natural events [25,31]. Because a smart grid involves the use of information and communication technologies for all aspects of electricity generation, delivery, and consumption, it

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minimizes environmental impact, enhances markets, improves reliability and service, reduces costs, and improves efficiency.

A smart meter, which is a key component of a smart grid system, is an electrical meter that records energy consumption at intervals of an hour or less and sends the information to a utility center for monitoring and billing purposes. Smart meters can provide customers with detailed electricity consumption data in real time or in near real time. Consumers can use the smart grid system for monitoring and tracking their energy consumption. In accordance with global trends, Taiwan, which imports 97.49% of its energy needs, has already begun replacing conventional meters with smart meters [38]. The objective is to improve energy use efficiency and reduce CO_2 emissions.

Recent studies have investigated various aspects of smart grid systems, such as challenges faced in, concerns related to, advantages of, and suitability of the use of smart meters for power grids [23]; information and communication technologies used in such grids [52]; supervisory control for such grids; and data acquisition in the grids [32]. Researchers in other studies have constructed an energy consumption management system [18,27,28], an automatic monitoring system [37], demand response in electricity supply [12,26,41], and a building automation system [6,18,43]. These studies have mainly focused on technical aspects, such as developing smart grid platforms and facilities for improving the performance and reliability of energy systems.

A literature review shows that many researchers have investigated energy management systems from a macro viewpoint of utilities and power companies, and few studies have presented dynamic operating strategies for home appliances for effectively saving energy costs. Therefore, this paper proposes a real-time smart grid data analytics framework for effective energy-saving systems at the appliance level for residential buildings; the framework is presented from the end-user perspective. The framework has a layered architecture and includes a smart grid, a data collection layer, an analytics bench, and a web-based portal.

The main contribution of this study is the development of an innovative framework for energy-saving decision processes. The proposed framework is expected to serve as a basis for the future development of a full-scale smart decision support system (SDSS). The SDSS integrates data analytics and dynamic multi-objective optimization models to generate energy consumption patterns and alternative energy-saving solutions at an appliance level. The SDSS is expected to identify consumer usage patterns, accurately estimate future energy demand, and improve the efficiency of energy use by end users. In particular, end users can reduce their electricity costs by using optimal operation schedules for appliances, automatically provided by the SDSS.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature on energy management systems. Section 3 presents the residential building considered in the experiment and the design of a smart grid big data analytics framework with three main layers. Finally, Section 4 concludes with remarks and recommends future works.

2. Literature review

Recently developed energy consumption management systems have enabled end users to effectively use electricity [28,30,60]. For instance, Zhou et al. investigated a real-time energy control approach for a home energy management system in the United Kingdom [60]. A demand response mechanism was proposed to enable households to avail of demand response services. Half-hour-ahead rolling optimization and a real-time control strategy were combined to achieve household economic benefits and the capability to cope with complex operating environments. Simulation test results indicated that the proposed control approach could optimize the schedule for home appliances and battery charging/discharging behavior, even if the forecast data were inaccurate.

Aghemo et al. proposed a building automation and a control system that can manage the lighting plants and air-conditioning system in buildings to increase user comfort and reduce operation and maintenance costs [6]. Arghira et al. proposed a stochastic method to predict the energy consumption for the next 24 h [9]. Basic predictors that have been presented and tested in the literature include "will always consume," "will never consume," and autoregressive moving average parameters.

Chen et al. presented a smart appliance management system that can recognize electric appliances in home networks by measuring the energy consumption of the appliances through a current sensing device [16]. This system can search the corresponding cluster data and eliminate noise by applying the current clustering algorithm thereby achieving accurate recognition of electric appliances and error detection. Radulovic et al. presented guidelines for linked data generation and publication, together with one complete example in the domain of energy consumption in buildings [45]. Their findings can facilitate researchers and practitioners in exploiting linked data technologies.

Bapat et al. developed a Yupik system that enables users to respond to real-time changes in electricity prices [10]. The Yupik system combines sensing, analytics, and integer linear programming to generate appliance usage schedules, which may be used by households to minimize energy costs and potential lifestyle disruptions. Similarly, Lima and Navas integrated automated remote metering and submetering of electricity into a structured knowledge tool [28]. This integration environment received electricity meter measurements.

Lach et al. proposed an automatic monitoring system for reducing the energy consumption of a typical home; the system involves using Wi-Fi-technology-enabled smart switches [37]. Multiple sensors are used for the automatic monitoring and control of the environment according to the user preference, which was ascertained from the user profile. Reinisch et al. proposed a Think Home system that entails using multi-agent techniques to reduce energy consumption [47]. The Think Home system contains a large knowledge base, which is used to achieve energy efficiency and user comfort.

Lee et al. proposed a green construction hoist that applies an energy regeneration system for reducing its operating energy requirements [39]. The energy regeneration system was customized to improve its energy-saving efficiency. Zeng et al. investigated the application of several energy management strategies to hybrid electric wheel loaders. The strategies included an engine optimal control strategy, a minimum motor power control strategy, a motor optimal control strategy, and an instantaneous optimal control strategy [57]. Ramos et al. proposed a data-mining-based methodology to identify typical load profiles of medium voltage consumers and to develop a rule set for the automatic classification of new consumers [46].

Regarding time series (TS) energy data prediction, Chou and Telaga proposed a novel approach to using large data sets for identifying anomalous power consumption in building office spaces [17]. The two stages of the anomaly detection approach were consumption prediction and anomaly detection. Daily real-time consumption was predicted using a hybrid neural net autoregressive integrated moving average model. Anomalies were then identified by applying the two-sigma rule for comparing actual and predicted consumption. The research contributed to the formalization of a methodology for real-time detection of anomalous patterns in large data sets. The prediction stage facilitates building managers in planning their future energy consumption, and the anomaly detection stage enables them to identify unusual consumption of electricity by tenants.

To date, most studies have focused on establishing a system for predicting the baseline of future electricity consumption through stochastic methods and regression analysis, and few studies have proposed dynamic operating strategies, which enable effective energy use and cost saving, for home appliances. Therefore, this paper describes a procedure and the components required for an energy-saving decision support system.

The smart metering infrastructure system collects real-time data for home energy use. Bluetooth is used in home area networks for wireless communication. Real-time data are dynamically analyzed using an advanced artificial intelligence and a multi-objective optimization algorithm, and a list of energy-saving alternatives is provided. Finally, web-based technology is used to enable users to visualize the real-time data.

3. Framework design for smart grid data analytics

In this study, to provide efficient information to end users, a framework for a smart grid big data analytics system was developed. The framework can efficiently retrieve, continuously analyze real-time electricity consumption data, identify power consumption patterns, predict future energy consumption, and provide optimal operation schedules for appliances. The framework was verified by installing a smart grid metering infrastructure in a residential building.

The metering system was installed in a typical three-story building in Xindian District, New Taipei City, Taiwan. Fig. 1 shows an axonometric view of the experimental building, with each floor height measuring 3 m. The residential building was occupied by a family of five (three children and their parents). Fig. 2 illustrates the building layout, which had a total area of 350 m^2. Table 1 shows the appliances and electricity equipment used in each floor of the building. Their positions are mapped to the corresponding floors in Fig. 2 by using the assigned number of the appliances and equipment in the "location" column of Table 1.

The first floor mainly consisted of an office area, where the owner ran his business, and a test area, where the owner conducted experiments for his business. The second floor mainly comprised a kitchen area, a dining area, a reading area, and a living area. The third floor mainly consisted of a master bedroom, bedroom for the owner's daughters, bedroom for guests, and a study room.

The layered architecture of the proposed smart grid big data analytics framework for improving energy savings in residential buildings includes a smart grid and data collection layer or a data layer, an analytics bench, and a web-based portal.

3.1. Data layer

The data layer is a database management system containing real-time electricity data, appliance information, unit price of electricity, and data obtained from an analysis (the data include future electricity prediction and electricity-saving alternative data). Additionally, electrical parameters such as voltage, current, power, frequency, and power factor are retrieved from a database management system. Electricity data are retrieved from smart meters and transferred to a dedicated server through the communication network. The smart meter data are streamed at 1-min intervals, producing 1440 data points daily for each smart meter.

The smart grid data metering infrastructure was installed in the experimental building. It can be depicted schematically according to the physical location and function of the different segments: (a) the residential metering and submetering infrastructure, (b) the communication network, and (c) the data management system (Fig. 3).

(a) Metering and submetering infrastructure

The metering and submetering infrastructure comprised smart meters and submeters with bidirectional communication resources for collecting, transferring, and controlling information. The submetering process involves installing additional metering resources in each electrical appliance or equipment. The collected data are sent through the communication network to the database management system and then fed to the analytics bench for further analysis. Fig. 4 illustrates the physical configuration of the metering system in the second and third floors.

The metering infrastructure has the following elements:

o Three-phase smart meters and single-phase submeters

The specifications of the three-phase smart meters are as follows: (1) voltage rating: AC 0–380 V; (2) power consumption: <1 V A; (3) impedance: >230 kΩ; (4) accuracy: precision level less than 0.5; (5) current rating: 60 A; (6) frequency: 40–60 Hz; (7) communication: two-way RS-485, MODBUS-RTU protocol; (8) working power range: AC 80–260 V/DC 5 V; (9) working environment: −20 to 55 °C; (10) storage environment: −30 to 75 °C; (11) dimensions: 116 mm × 94 mm × 58 mm; and (12) weight: 0.25 kg. Single-phase submeters measure six sets of equipment

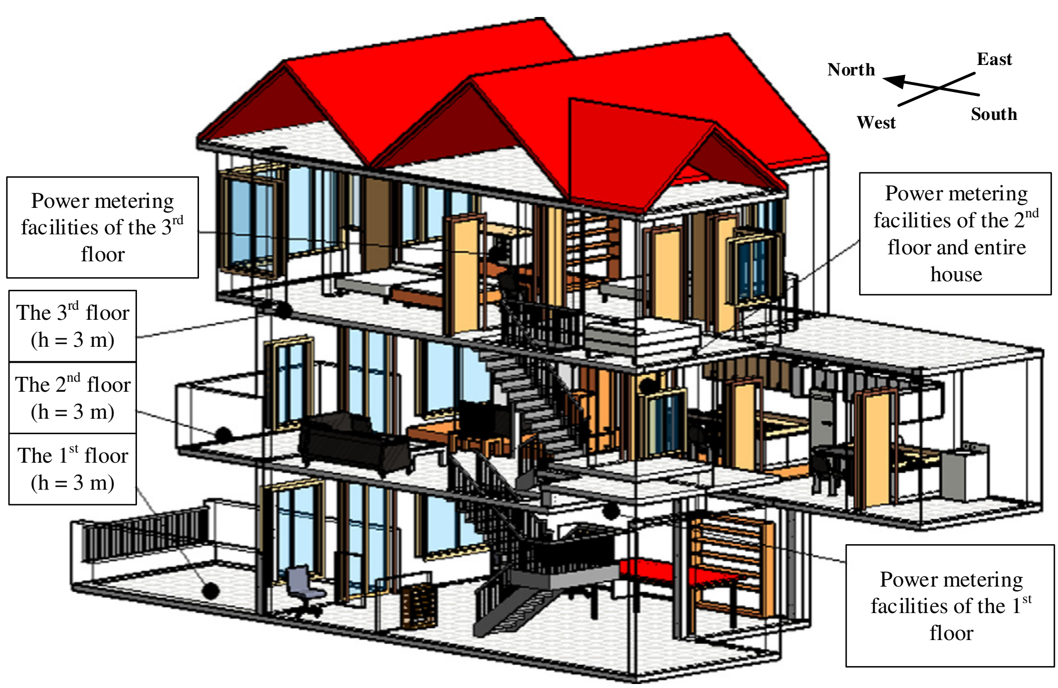

Fig. 1. An axonometric view of the residential building.

Fig. 2. Building layout and location of appliances and electricity equipment.

Table 1
Building appliances and electricity equipment.

No.	Name of equipment	Quality	Area	Location in Fig. 2
1st floor				
1	Fan	2	Office area	(1)
2	Computer	2	Office area	(2)
3	Desk lamp	2	Office area	(3)
4	Wall lighting	1	Office area	(4)
5	Cell lighting 1	1	Office area	(5)
6	Cell lighting 2	1	Test area	(6)
7	Specialized machines	?	Test area	(7)
8	Dehumidifier	1	Test area	(8)
9	Cell lighting 2		Balcony	(9)
2nd floor				
10	TV set	1	Living area	(10)
11	Cell lighting 1	1	Living area	(11)
12	Electric fan 1	1	Living area	(12)
13	Cell lighting 2	1	Dining area	(13)
14	Oven	1	Dining area	(14)
15	Microwave	1	Dining area	(15)
16	Rice cooker	1	Dining area	(16)
17	Hot water machine	1	Dining area	(17)
18	Hot water heater	1	Dining area	(18)
19	Stereo	1	Dining area	(19)
20	Cell lighting 3	1	Kitchen area	(20)
21	Refrigerator	1	Kitchen area	(21)
22	Small lighting	1	Toilet	(22)
3rd floor				
23	Cell lighting	4		(23) (24) (25) (26)
24	Wall lighting	4		(27) (28) (29) (30)
25	Computer	1	Studying area	(31)
26	Lamp	1	Studying area	(32)
27	Air conditioning	1	Bedroom	(33)

energy data with the same input circuit including voltage, current, power, frequency, power, and power consumption. The general measurement module specifications are voltage (80–250 V), current (20 mA to 40 A), and accuracy (1%).

o Smart Internet Protocol power controller

The functions of the smart Internet Protocol (IP) power controller are (1) energy management, (2) remote control (e.g., supporting web control and Transmission Control Protocol (TCP) command control), (3) local control (e.g., manual switch control for local use), (4) monitoring (e.g., monitoring real-time status through a web browser and an LED indicator), (5) environment control (e.g., control based on external temperature and humidity sensors), (6) power budget management (e.g., control of daily/weekly/monthly consumption), (7) alert notification (e.g., supporting email notification and TCP trigger command in case of any event), and (8) data logging (e.g., supporting local data storage in the SD card for querying and downloading).

Fig. 5 shows the configuration of the smart IP power controller. Its specifications are as follows: (1) CPU: 32-bit ARM-7 (80 MHz); (2) RAM: 16 MB SDRAM; ROM: 8 MB flash ROM; (3) Ethernet LAN: 10/100 Mbps; Port: RJ-45 connector; (4) Ethernet protocols: Address Resolution Protocol (ARP), IP, Internet Control Message Protocol (ICMP), User Datagram Protocol (UDP), TCP, Hypertext Transfer Protocol (HTTP), Dynamic Host Configuration Protocol (DHCP), Point-to-Point Protocol over Ethernet (PPPoE), and File Transfer Protocol (FTP); (5) input power: 110–240 V AC/15 A/50–60 Hz; (6) outlet ports: two ports controlled by a dual switch relay (≈240 V AC/15 A); (7) power information: current, voltage, frequency, active power, power factor, energy, and power consumption; (8) support application programming interface (API) for the system integrator; (9) maximum current: 15 A; (10) operating temperature: 0–60 °C; storage temperature:

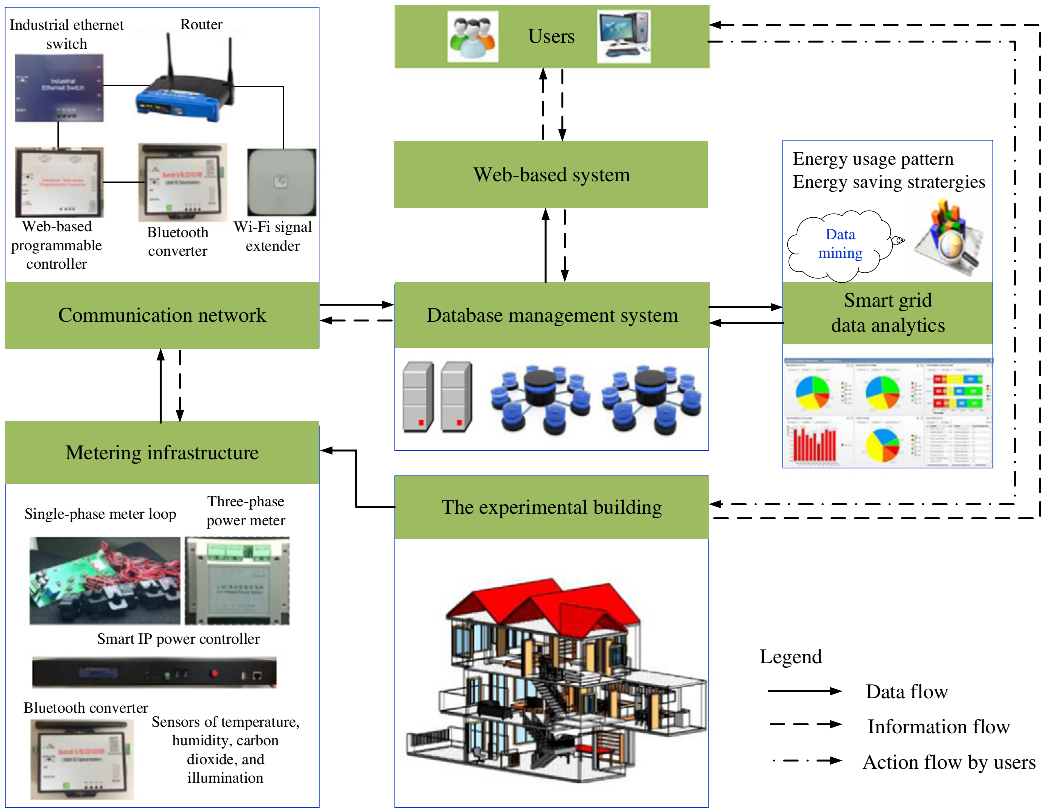

Fig. 3. Smart grid metering infrastructure in the building.

−10–70 °C; (11) dimensions: 35 cm × 11 cm × 4 cm (W × D × H); and (12) weight: 1.38 kg.

- o Bluetooth converter

Bluetooth is a wireless communications system commonly used to exchange data over short distances [11,22]. Its main features are low power consumption, fast data exchange, and widespread availability. The IEEE standard for Bluetooth is IEEE 802.15.1 [42]. A wireless Bluetooth network is connected to the smart IP power controller for data transmission and Internet access.

- o Temperature sensors for measuring the indoor and outdoor temperatures of the building
- o Humidity sensors for measuring the indoor and outdoor humidity levels of the building

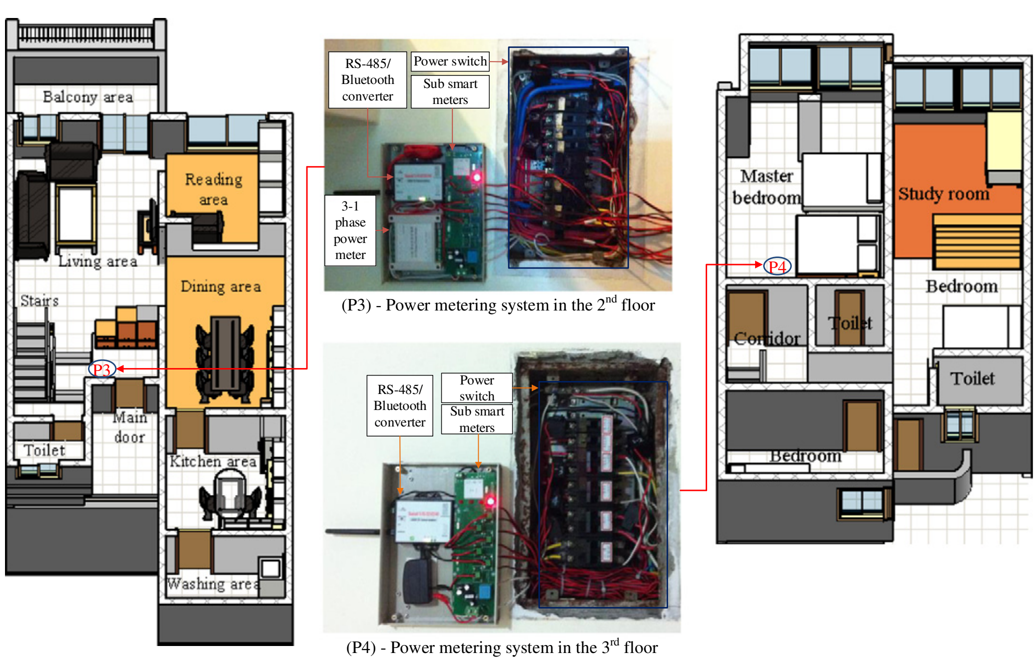

Fig. 4. Configuration of smart grid metering infrastructure in the second and third floors.

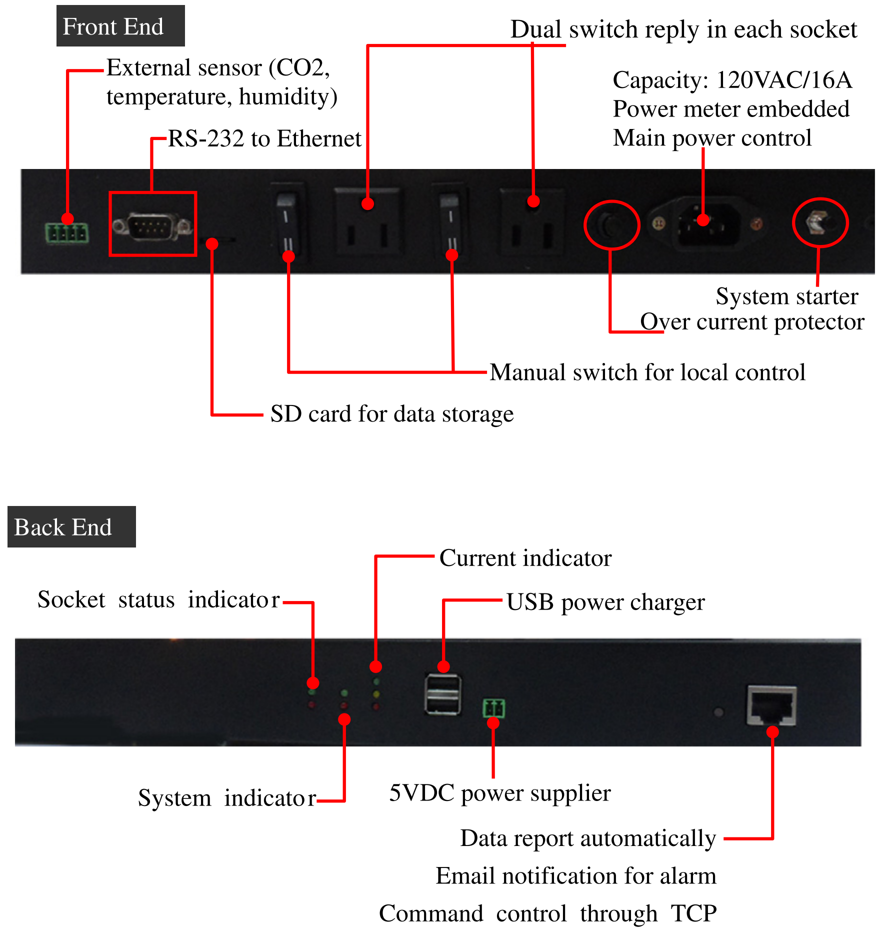

Fig. 5. Configuration of smart IP power controller.

o CO_2 sensors for measuring indoor CO_2 emission
o Illumination sensors for measuring the indoor and outdoor illumination intensities of the building

(b) Communication network

The communication network, which transfers information collected by the metering systems to the database management system, includes a router, industrial Ethernet switch, web-based programmable controller, Bluetooth converter, and Wi-Fi signal extender. Fig. 6 presents the physical connections among the components of the communication network.

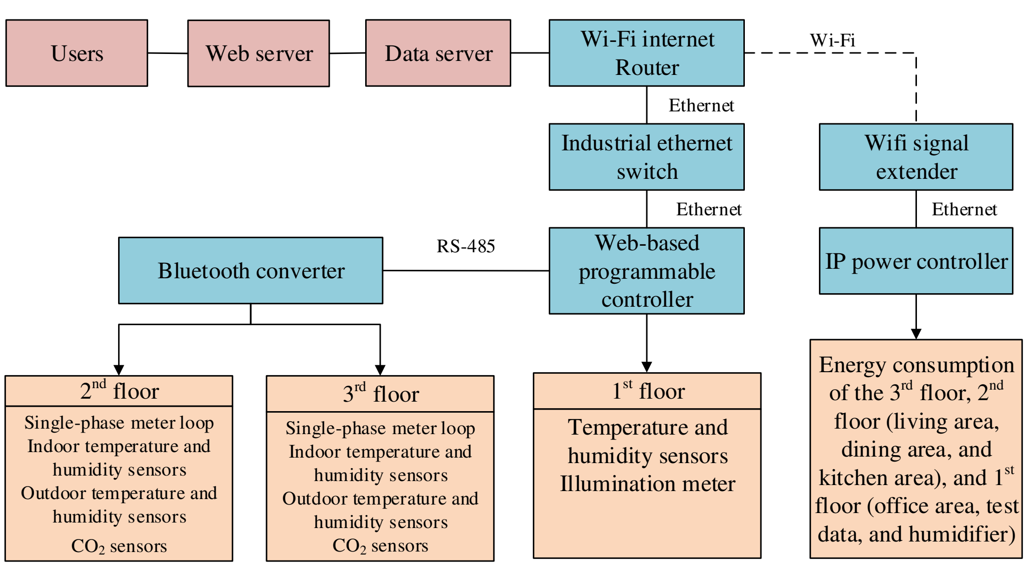

Fig. 6. Schema of communication network.

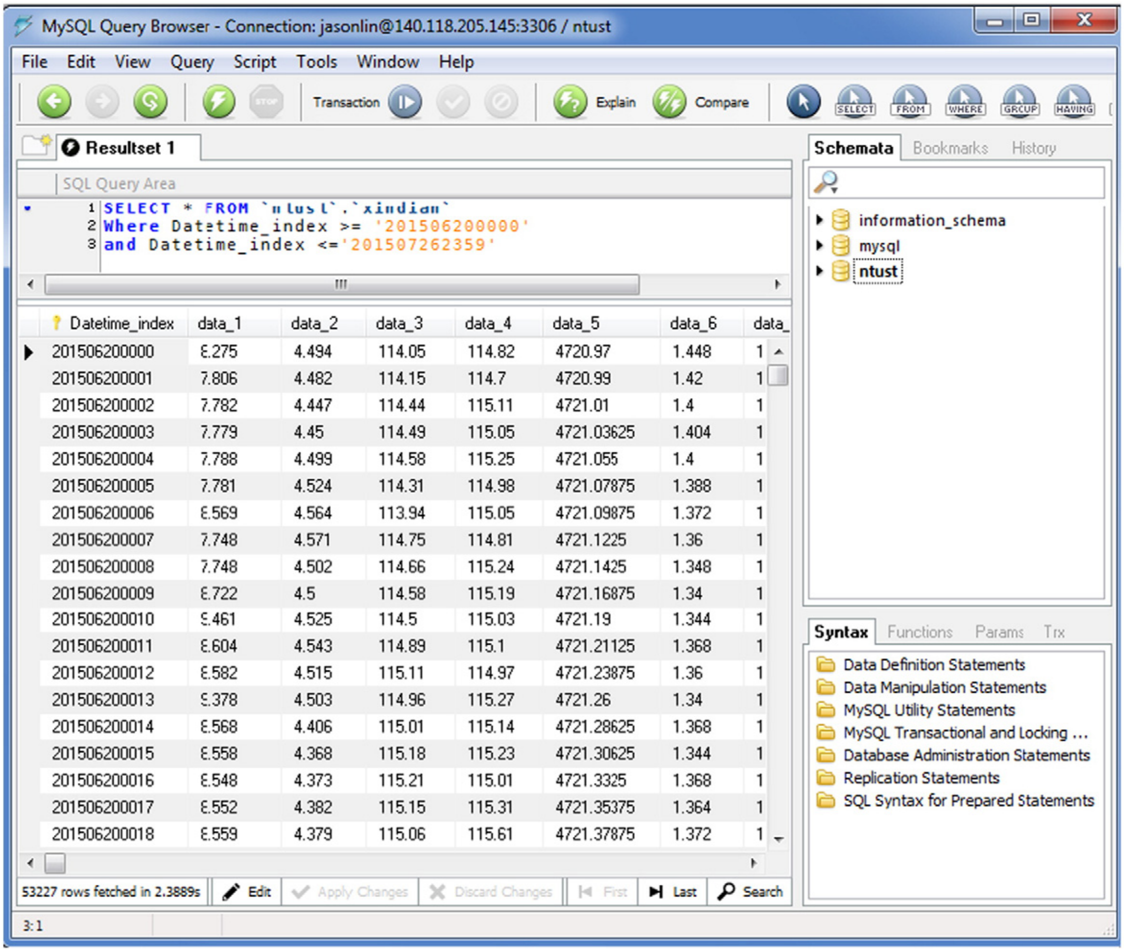

Fig. 7. MySQL — database management system for building energy consumption.

The specifications of the web-based programmable controller are as follows: (1) CPU: 32-bit ARM-7 Winbond CPU (80 MHz); (2) RAM: 8 MB SDRAM; (3) ROM: 4 MB flash ROM (2 MB for user programming); (4) operating system: uC-Linux, which provides and API and common gateway interface for customer programming Ethernet; (5) port type: RJ-45 connector; (6) speed: 10/100 Mbps (autodetecting); (7) protocols: ARP, IP, ICMP, UDP, TCP, HTTP, DHCP, PPPoE, DDNS, NTP, FTP, and Telnet; (8) modes: TCP Server/TCP Client/UDP; (9) setup: HTTP browser setup (Internet Explorer & Netscape), Console; (10) port: RS-232/422/485 × 1 port (3000 V DC photocoupler isolation protection); (11) speed: 300 bps to 230.4 Kbps; (12) power: DC 9–30 V, 2000 mA, and 500 mA at 12 V; (13) operating temperature: 0–70 °C; (14) storage temperature: −10 to 80 °C; (15) dimensions: 150 mm × 110 mm × 20 mm (W × D × H); and (16) weight: 170 g.

(c) Data management infrastructure

The data management infrastructure includes a data server and desktops. The MySQL system stores all the data from the smart grid system installed in the experimental building. Information on electricity consumption is retrieved from smart meters and transferred to a dedicated server through the communication network. The data stream from smart meters arrives at 1-min intervals, producing 1440 data points daily for each smart meter. Fig. 7 illustrates a sample of data stored in MySQL.

To provide readers with detailed technical and scientific information, Table 2 lists the hardware and software used for performing the experiment in the residential building. The hardware comprised the communication system, smart meter system, environmental sensor system, and server system, and the software programs used for processing data were MATLAB, the web server (e.g., XAMPP controller), and MySQL.

Table 2
Facilities and equipment used for setting the experiment.

Facilities/Equipment	Quality
1. Hardware	
Communication system	
Wi-Fi internet router	1
Signal extender	6
IP power controller	2
Industrial Ethernet switch	3
Industrial — web based programmable controller	11
RS-485/Bluetooth converter	22
Control box	2
Smart meter system	
Three-phase smart meter	1
Single-phase meter loop	2
Environmental sensor system	
Environmental CO2 sensor	3
Temperature and humidity sensor	4
Illumination sensor	2
Server system	
High performance computer	1
Data server	1
2. Software	
MATLAB	1
Web server	1
MySQL	1

3.2. Analytics bench

The analytics layer constructs computational models by integrating data analytics and dynamic multi-objective optimization modules for continuously analyzing real-time electricity consumption data at the appliance level received from the smart meters and submeters. It then generates energy consumption patterns, alternative optimal schedules for home appliances, and percentage of electricity cost saved. This section presents the data analytic procedures. The future electricity consumption of appliances is estimated and optimized by using advanced data mining (DM) techniques, TS analysis, and the dynamic multi-objective optimization algorithm.

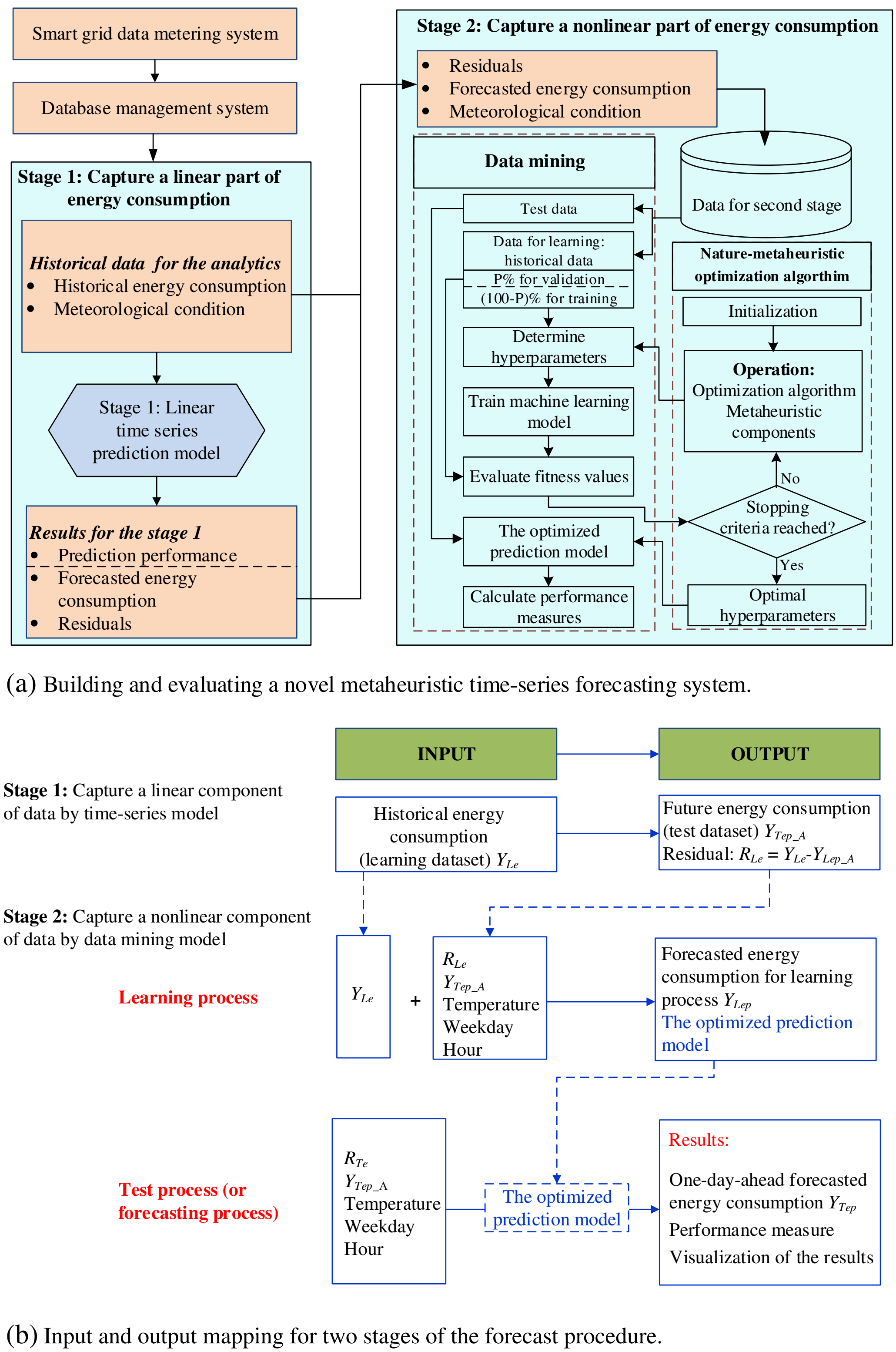

Fig. 8. A novel metaheuristic time series forecasting system.

3.2.1. Data mining techniques and time series analysis for identifying energy use pattern

The data analysis scheme employed involves using DM techniques and TS analysis for identifying energy use patterns at appliance level. The scheme helps users understand and monitor their appliances so that they can take appropriate steps to reduce their electricity costs. TS analysis comprises methods for analyzing TS data for extracting meaningful patterns. The TS forecasting model predicts values on the basis of previously observed values. The various model-fitting methods include autoregressive integrated moving average (ARIMA) and neural network autoregressive methods.

The energy consumption data are the TS data for both linear and nonlinear components. Therefore, hybrid linear and nonlinear models effectively capture energy consumption patterns. Artificial neural networks (ANNs) and support vector regression (SVR), for instance, are widely used nonlinear models that can handle nonlinear components, whereas ARIMA or seasonal autoregressive integrated moving average (SARIMA) method is usually used to fit linear components in the linear and nonlinear models.

Models integrating ARIMA and ANNs have been extensively used by researchers [29,33,34,48,49,58]. Khashei and Bijair proposed a novel hybridization of ANN and ARIMA models for TS forecasting. The advantage of the ARIMA model in linear modeling is its effectiveness in identifying and magnifying the existing linear structure in data. The ANN model is used to capture the nonlinear part, which comprises the residuals from the first stage of ARIMA modeling [34]. However, sufficient data are required to construct an effective hybrid model. Other problems with ANN models are their numerous parameters, uncertain solutions, and potential to overfit.

SVR was proposed by Vapnik [51] to avoid the drawbacks of ANNs. SVR is a nonlinear alternative to ANNs. Researchers have effectively used SVR to solve numerous regression problems [8,13,44]. The hybridization of ARIMA and SVR has been effectively applied to TS forecasting, such as stock markets [21,44] and electricity prices [14].

However, the main problem with SVR is that setting the hyperparameters requires an experienced practitioner. Inappropriately chosen kernel functions or hyperparameter settings may lead to extremely poor performance. Therefore, a novel hybrid model combining a TS model such as ARIMA and nature-inspired metaheuristic optimized model such as SVR is proposed for forecasting the energy consumption of residential buildings. The fine-tuned machine learning model (e.g., SVR or least squares SVR) is used to address nonlinearity, and the TS model (e.g., ARIMA or SARIMA) is used to address the nonstationary linear component.

Fig. 8 shows the process involved in constructing and evaluating the proposed novel metaheuristic TS forecasting system. The first stage of the TS system, such as ARIMA, involves modeling the linear component. At the second stage, the residuals from the first stage, outdoor temperature, type of day (i.e., weekday or weekend), and hour of day (i.e., 0, 1…23) are used as inputs for the metaheuristic optimized model. The forecast accuracy of the proposed system can be improved by separating the linear and nonlinear components.

Compared with other models in the literature, the proposed hybrid TS forecasting system has two major advantages. First, the proposed system can automatically connect to the MySQL database management system. Consequently, the system can directly read, access, and analyze the energy consumption data from the MySQL and store analytical results in the MySQL. This automatic process may reduce the computing time for the forecasting process.

The second major advantage of the system is its high prediction accuracy. The proposed system integrates the linear TS prediction model and the nonlinear metaheuristic optimized model. Consequently, the system can accurately capture energy consumption patterns, and its prediction performance is higher compared with the single TS models reported in the literature. In addition, the nature-inspired metaheuristic optimization algorithm is integrated into the system to automatically fine-tune the hyperparameters of the machine learning model, thereby improving the prediction accuracy of the system.

3.2.2. Dynamic multi-objective optimization algorithm for allocating energy use

The dynamic multi-objective optimization algorithm is used to optimize appliance operating schedules. Users can compare alternatives to determine when appliances should be turned on or off. Each solution is an alternative (nondominant) energy-saving strategy.

An objective of this phase was to simultaneously optimize the total energy consumption, appliance-level electricity usage and electricity cost. The first constraint is the electricity pricing policy, which is categorized by season, type of day (weekday, weekend or holiday), and time of day (peak and off-peak time). Table 3 shows the time and cost breakdown for each rate [4]. The second constraint is the available/desired operating time for the appliances and the status of the occupants of the residential building. Fig. 9 illustrates the dynamic multi-objective optimization module used for optimizing energy use and electricity cost.

Swarm intelligence (SI) and bio-inspired computation have attracted considerable attention. In the fields of optimization, computational intelligence, and computer science, bio-inspired algorithms, particularly SI-based algorithms, are commonly used [55]. Examples of SI-based algorithms are the bee algorithm (BA), particle swarm optimization (PSO), cuckoo search, and firefly algorithm (FA). Optimization algorithms used for solving real-world problems include genetic algorithms, PSO, the FA, and the BA.

3.3. Web-based portal

The web-based portal is the interface layer that enables a user to interact with the energy-saving decision support system. Fig. 10 shows

Table 3
Electricity pricing methods in Taiwan (Unit: New Taiwan Dollar).

Classification					Summer (Jun. 1~Sept. 30)	Non-summer (All other days)
Non time-of-use rate	Non-commercial building	≤120 kWh per month		Per kWh	1.81	1.81
		121–330 kWh per month			2.64	2.33
		331–500 kWh per month			3.90	3.20
		501–700 kWh per month			5.09	4.18
		701–1000 kWh per month			5.94	4.85
		>1000 kWh per month			6.71	5.28
Time-of-use rate	Monday to Friday	Peak period	07:30~22:30	Per kWh	3.62	3.56
		Off-peak period	00:00~07:30 22:30~24:00		1.65	1.58
	Saturday	Partial-peak period	07:30~22:30		2.58	2.50
		Off-peak period	00:00~07:30 22:30~24:00		1.65	1.58
	Sunday and Off-peak day	Off-peak period	00:00~24:00			

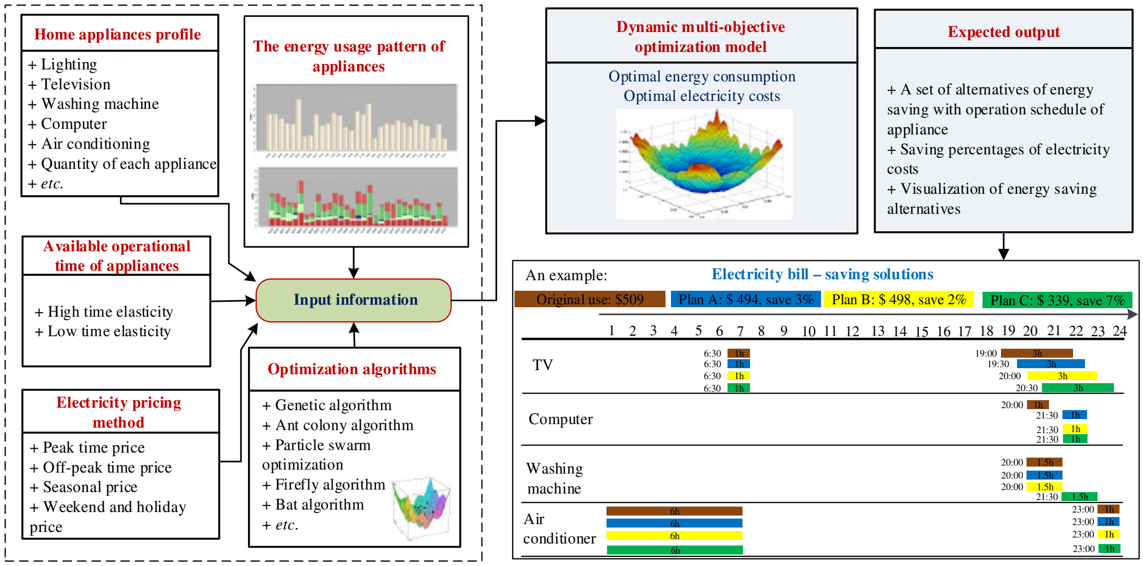

Fig. 9. Dynamic multi-objective optimization model.

the expected interface of the SDSS. The system supports consumer needs by providing (1) real-time electricity consumption; (2) monthly consumption records; (3) monthly comparisons; (4) maximum, average, and minimum consumption; (5) consumption forecasts for the current month and the resulting expenditure; (6) alternative operation schedules for home appliances with optimal electricity costs; and (7) the electricity cost saved by using alternative operation schedules.

4. Conclusion

This paper presents a framework for an energy-saving decision-support system. The metering infrastructure was installed in a residential building for performing experimental simulations. The layered architecture of the proposed framework includes a smart grid big data collection layer, an analytics bench, and a web-based portal. In particular, a novel hybrid nature-inspired metaheuristic forecast system and a

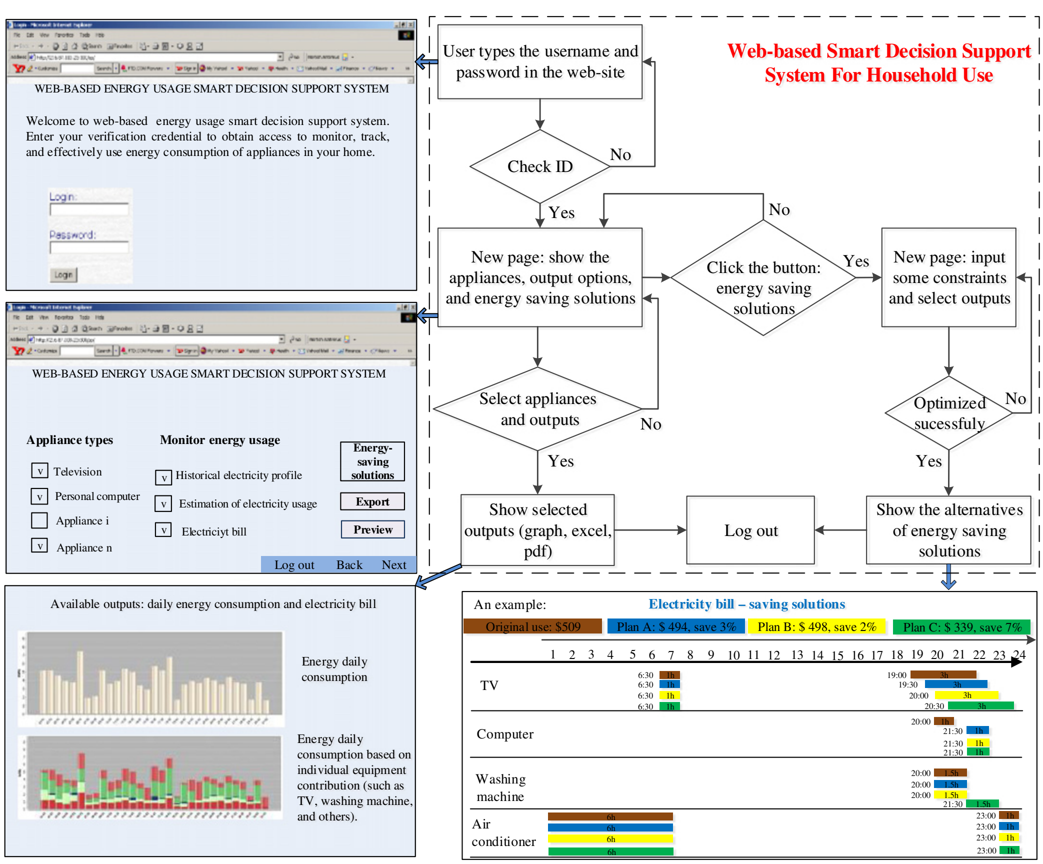

Fig. 10. Web-based SDSS for household use.

dynamic optimization algorithm are designed behind the analytics layer to enable accurate prediction and optimization of energy consumption.

The main contribution of this work is the development of an innovative framework that can serve as the basis of a full-scale SDSS, which can be used for determining an appropriate energy-saving strategy. The SDSS can identify and allocate energy use through machine learning and constrained optimization. Specifically, it integrates data analytics and dynamic multi-objective optimization modules for generating energy consumption patterns and alternative energy-saving solutions at home appliance level. The SDSS can help improve the energy efficiency of end users. Notably, end users can reduce electricity costs by using the system to automate the operating schedules of appliances, lighting systems, heating, ventilation, and air conditioning.

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