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Home Energy Management System and Internet of Things: Current Trends and Way Forward

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Abstract: Managing energy in the residential areas has becoming essential with the aim of cost saving, to realize a practical approach of home energy management system (HEMS) in the area of heterogeneous Internet-of-Thing (IoT) devices. The devices are currently developed in different standards and protocols. Integration of these devices in the same HEMS is an issue, and many systems were proposed to integrate them efficiently. However, implementing new systems will incur high capital cost. This work aims to conduct a review on recent HEMS studies towards achieving the same objectives: energy efficiency, energy saving, reduce energy cost, reduce peak to average ratio, and maximizing user's comfort. Potential research directions and discussion on current issues and challenges in HEMS implementation are also provided.

Keywords: Home energy management, energy management review, smart home, internet-of-things, renewable energy storage, energy scheduling, energy monitoring

1. Introduction

Energy management system (EMS) has becoming essential with the objective of cost saving, and indirectly will save the energy and protect our mother earth from climate change. The average earth's level of carbon dioxide emissions for 2019 is 409.8 parts per million (ppm) [1] and the highest record in human history is 415.26 ppm on May 2019 [2]. Hence, it is the responsibility of human race to fight global warming and everyone can contribute little by little with renewable energy (RE) usage and efficient utilization of energy to reduce the wastage as much as possible. It was reported from the electrical consumption in the United States of America, that at least 30% of electricity is wasted in the residential consumptions [3]. This can be reduced with the help of EMS, and indirectly will reduce the energy cost while maximizing user's comfort. EMS is beneficial for both commercial or industrial field and domestically, aims at monitoring, controlling, managing, and saving of energy. In the industrial field, it will cover the retail, factory, and local grid coordination. Domestically, it will manage the community for coordinated operation with large system, energy saving and demand side management. Domestic EMS also encompass of home sphere, known as home EMS (HEMS), for appliance scheduling, energy and price forecasting, and renewable energy source integration. Thus, with the paradigm of the new communication and network, variety of things and objects are networked together. Each are equipped with microprocessors and transceivers, to communicate with each other and intelligent services can be provided autonomously to the users. The internet of things (IoT) is a convergence of various domains with

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heterogeneous technologies to interconnect things through the Internet for monitoring, detection and controlling multiple devices remotely. With the help of IoT, big data technologies and machine learning, HEMS promises to contribute to a greater energy efficiency.

A basic illustration of smart home environment is shown in Fig. 1. It comprises of a number of IoT sensors and actuators for lighting, pressure, motion, temperature and humidity; a computational system with wireless technologies such as Bluetooth, ZigBee, Wi-Fi, and IPv6; control systems such as remote controls, computers, smartphones and tablets; computation system for analysis and decision making; and remote and in-house visualizations for monitoring. Many challenges faced by previous studies on constraints for deployment of IoT in energy systems, such as sensing, connectivity, power management Big Data, IoT computational requirements and capabilities, complexity, and security challenges. These challenges with the recommended solutions have been discussed in depth by Bedi et al. [4].

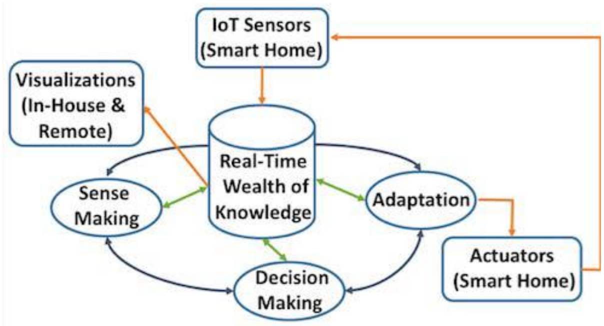

Fig. 1 - Smart home environment, as illustrated in [4]

This paper will be focusing on the HEMS, its current challenges, trending solutions and its way forward. The review will consider recent manuscripts with noteworthy contributions from the literature. Considering recent research, this study is expected to provide an overview of the most recent advancements in HEMS and IoT technologies. The analysis performed in this study highlights the issues and challenges in current HEMS implementation to provide insights into potential research directions. The main contributions of this study are summarized as follows:

- Related studies on recent trends in the smart home and HEMS with the IoT are provided. The objective, features, tools and potential improvements of each study are summarized and presented in a table.
- Potential research directions in HEMS with the IoT and Big Data technologies using promising algorithms are presented.
- The issues and challenges in the current HEMS implementation and the improvement of current methods to support smart home advancement and energy efficiency are discussed.

The rest of this paper is organized as follows. Section 2 discusses the recent trending solutions for HEMS and IoT technologies in literature. Section 3 focuses on potential directions with current promising algorithms. Section 4 discusses the issues and challenges of current methods. Section 5 concludes the work. Nomenclature is included, listing the acronyms and notations used in the paper.

Nomenclature	
AMI	Advanced Metering Infrastructure
BOA	Butterfly Optimization Algorithm
DHAN	Dynamic Home Area Network
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
ECG	Electrocardiogram
EMC	Energy Management Controller
EMS	Energy Management System
GA	Genetic Algorithm
HAN	Home Area Network
HEMS	Home Energy Management System
IAT	Intelligence Awareness Target
IE2S	Intelligence Energy Efficiency as a Service
IoT	Internet of Things
IST	Intelligence Service TAS
MAS	Multiagent System
MQTT	Message Queuing Telemetry Transport
NA	Nomadic Agency

NILM	Nonintrusive Load Monitoring
PV	Photovoltaic
RE	Renewable Energy
RL	Reinforcement Learning
SHMS	Self-learning Home Management System
SoC	System on Chip

2. Current Trends of HEMS-IoT

A smart home is facilitated by a HEMS which allows the end-users to monitor and manage their energy usage inside a home, with the assistance of hardware and software or mobile applications. Other than energy efficiency and cost savings, a smart home promotes services with targeted user's satisfaction. Early study on the HEMS found that the conventional architecture has some limitations in terms of scalability, reusability, and interoperability [5]. The cost of implementing HEMS is also very expensive and lead to the disturbance of the spread of a HEMS [5]. Existing smart homes are also limited by a scarcity of operating systems to integrate the devices that constitute the smart home environment. These devices use independent IoT platforms developed by the brand or company that developed the device, and they produce these devices based on self-service modules. A smart home that lacks an integrated operating system becomes an organizational hassle because the user has to manage the devices individually. Rapid and large-scale development of smart home and IoT-related technologies have caused many problems, such as inefficient operating systems, excessive network traffic, and energy wastage [6]. IoT devices for smart homes also have limited resources. To overcome this limitation, it is important to consider other data handling alternatives, such as machine learning and big data, to collect, manage, and analyze large volumes of data [6-9]. A few initiatives can automatically, and without much user intervention, handle and operate decisions of smart home devices connected to a domotic control system [7]. A domotic is referring to home automation for smart home. A HEMS-IoT will monitor domotic devices and sensors in real time, provides energy saving recommendations and facilitates interactions between devices and users.

2.1 Photovoltaic

An IoT-based HEMS with lightweight photovoltaic (PV) system over dynamic home area networks (DHANs) enables the construction of a HEMS to be more scalable, reusable, and interoperable. Previously, in smart grid, communications infrastructure is constructed with the installation of smart meters and smart gateways to collect and analyze real-time data. This is considered as partial IoT because only the metering and gateways are intelligent. There are several limitations in this architecture, such as low scalability, low reusability, and low interoperability. Therefore, a distributed system architecture was proposed to develop a fully IoT-based system [5]. It consists of smart objects by adaptive middleware architecture, dynamic network configuration by DHANs and enhancement of scalability and reusability by flexible platform design. The HAN was configured using reusable nomadic agencies (NA), that is the applications of middleware in user's smart phones. The overall architecture of the proposed system has several user-centric service domains, where the services are provided autonomously based on the contextual information related to users and environment. The NA will be in-charged of the interconnection between a central management server and an end device, and the HAN can be dynamically configured using the user's NA without fixed gateways. The system also has information fusion scheme, to manage all processes of information convergence, search similar domains and manage interconnection of other domains. The adaptive middleware scheme was applied to the energy saving device, with awareness of user's state and environment, and the middleware will be reconfigured based on the information. The energy saving scheme with interaction based on IoT will interact between devices, user's behavior patterns and user's preference. The tested configurations of DHANs are using home appliances, a PV system, a NA, and a central management server. For the PV system, a real-time energy production can be monitored, as well as the outside temperature, humidity, and the state of PV panels (degradation, failure, and surface temperature). There are two methods for the DHANs communications, a direct method, and an indirect method with behavior-based routing scheme. For direct method, the system will construct a peer-to-peer network between a PV system and a user's NA via Bluetooth technology. Thus, after the pairing process, a user can directly monitor a PV system through mobile phone. For indirect method, the system will construct a client-to-server network between PV system and the central management server and user's mobile phone will be utilized as the nomadic gateway. However, due to the short communication range, the information of the PV system will not be transmitted to the central management server if the PV system is installed in a space where the users did not access. To solve this, the authors in [5] proposed an information aggregation scheme. It is done using the NA in the autonomous mode. The processes involved dynamic decision of the head-device in the machine-to-machine zone, connection between the head-device and the NA and connection between the PV system and the NA.

A case study was done by John Borland [10] on island nano grid, using rooftop solar PV, battery storage discharge and thermal storage. The island is using 100% renewable clean energy; sun light and heat with multiple storage for all daily energy needs on sunny and partly cloudy days. The study has achieved the clean energy usage in 336 days and 92% of the time in 2018 and 2019, and only 8% grid-buy electricity was used as back-up on rainy and cloudy days. The EMS for this island is using smart IoT devices for home automation and energy usage monitoring and control. The IoT devices ensures lowest daily cost of electricity and resilience 24/7 home safety and security. To manage the massive data collected from various types of wireless sensors in the residential units of smart homes, Big Data technology can be utilized. Predictive analysis and advanced methods can be used to monitor and analyze large amount of data to obtain actionable information in the form of reports, graphs, and charts. The analysis is in real-time, thus can assist the homeowners and utility eco-systems providers to get significant insights on energy consumption of smart homes. With the assistance of data analytics engine, the utility providers can make use the available power consumption data to provide flexible and demand response supply. Having the close interaction with the utility providers, the homeowners as the consumers can optimize their power consumption based on consumption behavior and reduce their electricity bills. The load consumptions in residential areas are heavily depending on the cumulative power consumption over period, peak power consumption, weather conditions and consumption slab rates. An effective cost-saving system and energy management solutions can be achieved using a combination of IoT technology and Big Data analytics to provide seamless remote access control of home devices to the consumers via computers or mobile phones.

2.2 System on Chip

A data acquisition using System on Chip (SoC) module is an IoT object with unique Internet Protocol address, used to collect energy consumption data from each devices in each smart home and transmit the data to a centralized management server for processing and analysis [9]. A system with SoC modules was proposed in [9] with functional requirements and business processes such as consumption analysis for monitoring, asset efficiency analysis, root cause analysis, predictive analysis, remote and local device controlling, and bill tracking utility. The sensors, actuators and solid-state relays were used to monitor and control the air conditioning units, interfaced with the microcontroller to measure the ambient conditions. A SoC high end microcontroller was used as edge device data acquisition module that manages the heating, ventilation, and air conditioning unit. The middleware module has several software tools to provide different services, such as Message Queuing Telemetry Transport (MQTT) protocol server as a communication medium, storage server as data warehouse, analytics engine server to make smart decisions from the received big data and a webserver JavaScript. The system was evaluated on the MQTT server and webserver scalability, and speed for storage server, which is reported to be acceptable for up to 4000 concurrent users.

2.3 Machine Learning: Real Time Monitoring

Another work on Big Data and machine learning-based HEMS is observed in [7] using J48 algorithm in Weka API to learn user behaviors and their energy consumption patterns, then classify the houses according to the energy consumptions. The user preference-based energy saving recommendations are generated by RuleML and Apache Mahout, tools for scalable machine learning algorithms in Big Data analytics. This HEMS-IoT architecture was built with seven layers functionality: presentation layer (integrates user and system through mobile or web application), security layer (guarantees secure data collection from device layer), IoT services layer (as a link between application and management layer), data layer (stores the generated data from the device layer; manage information on recommendations, service profiles, sensed data, device profiles and user profiles), communication layer (establish communication protocols for the devices), and lastly, device layer (provides data linkage and reception from the devices, and controls sensors, actuators, controllers and gateways). A case study was conducted for 10 houses in a Mexican residential complex, of two different types, with sensors and smart plugs. The sensors sent and collected more than 2500 data per day to the data layer, which occurs every 30 seconds. The HEMS-IoT system was evaluated with User-Centric Evaluation Framework for Recommender System [11] which investigates the system from the user's perspective, and achieved satisfactory results for the user-centered evaluation and reduced energy consumption. The authors have concluded three fundamental factors for achieving energy consumption reduction: smart home inhabitants must be committed to change their energy consumption habits, follow-ups on the system's energy-saving recommendations, and users are allowed to modify the operating parameters of the devices from the system according to their needs.

2.4 Machine Learning: Situation Recognition

As current smart homes are limited in terms of operating systems to integrate the devices that constitute the smart home environment, it becomes necessary to build an integrated management system that connects IoT devices to each other. To efficiently manage the IoT, three intelligent models were proposed in [6] as IoT platform application services for a smart home. The models are namely the intelligence awareness target as a service (IAT), intelligence energy efficiency as a service (IE^2S), and intelligence service TAS (IST). IAT will manage the "things" stage, acquire a situational awareness of the data values generated by the things (sensors) using intelligent learning to collect data according to the environment. There are four major types of lifestyle patterns and user activities defined in IAT, and IAT will be aware of the situation and only process the required data. The study divided IAT devices into sensor IAT (stationary), smart phone IAT (non-stationary) and smart appliance IAT (collects data at the level of things and provides service at the level of service). IE^2S does the role of a server (IoT platform), processes the data collected by the IAT and integrates things and service levels intelligently. On the things level, IE^2S will perform two functions through machine learning, namely situation recognition and user consumption pattern discovery. On the service level, IE^2S will analyze the learnt data, and provide services according to the situations. The service command data is transferred from IE^2S to IST, which the actions were defined by the IST system. IST will help to provide, control, and manage the service stage. For implementation, the work used an Arduino board as the sensor board, with three sensors (sound, motion, and rotary). MQQT protocol was used between the Arduino board and the server. The Arduino will use IAT algorithm to continuously monitor the situation with low processing cost. The server uses the Mobius international standard platform and the IE^2S algorithm. The received data from IAT will be converted into a database on Mobius server. The TensorFlow engine will learn the data using Jupyter editor with the Anaconda package. The advantage of this study is that it can resolve network congestion and energy wastage problems by introducing a systematic planning to use the energy according to IoT usage patterns and reduce the unnecessary network tasks.

2.5 Context-awareness

An IoT architecture with context-awareness in terms of minimum and maximum power, time of use, kind of devices and type of devices (interruptable, non-interruptable, flexible and not flexible), was introduced by Pérez-Camacho et al. [12] to analyze and control the way of household appliances consumption occurs in a context. It is also aimed at reducing energy consumption, costs, peak average ratio and maximizing users' comfort. The HEMS architecture consists of a control unit and three modules: programming, monitor and prediction. It was designed based on the IoT data flow architecture and considered the constraint of the environment as well as user preferences. The IoT architecture has the data flow through five layers: sensor layer architecture with data acquisition using a non-invasive potentiometer (Arduino Uno and SCT-013 sensors); physical layer with ambient intelligent which extracts the context and process sensor and user data; extracted-data-to-information-module layer, which gathers all the context data; behavioral awareness layer which processes the data and discover the related behavior; digital layer where a logical object is created representing the real objects; and lastly the meta-layer, where all the logical objects data from digital layer will be processed according to the particular objective of the problem to be solved. The problems became a multi-objective optimization problem and are solved using metaheuristics and an electric consumption model. It is deemed that the methodology in the work will allow the developers to identify every requirement needed in the current world HEMS.

2.6 Demand-side Management

In software applications development, the simulation of complex individual interactions will be supported by the agents. The agents for various applications such as scheduling, strategic planning, resource, control, and real-time planning are useful for HEMS as a self-learning system. To adapt with the changes in environment, implementation of multiagent system (MAS) allows flexible modifications to the agent behaviors. MAS in self-learning home management system (SHMS) was proposed by Li et al. [8] with rule-based classifiers technique and machine learning in the supply and demand side management (DSM) system, experimented at the housing development in Singapore as the test bed. DSM is one of the HEMS functions, mainly used on demand response and load management. The demand information will be collected by the DSM to dictate power usage in an optimized manner. For example, the load shifting can be implemented to enable usage of electricity market during peak and off-peak hours. The main components in the SHMS are the DSM system (household appliances) and supply side management system (renewable energy, battery storage, main grid and electric vehicle) to provide economical and energy efficient whenever activated by the HEMS. Other components are price forecasting, price clustering and power alert system, with machine learning functionality to optimize the residential household through electrical distribution optimal algorithms. A MAS communication framework was established in the SHMS, which assigned each plugs and system into an agent with its own unique Internet Protocol address that exist in the network. Then, the data from the smart plugs are transmitted to the respective EMS to decide the next step.

The main objective of the DSM is to achieve a balance between energy production and demand. It includes all demand-reducing measures, which are demand response (DR) and energy efficiency. DSM aims to seek balance between energy demand and supply on the side of utilities, but DR focuses on the consumer's side which encourages them to reduce their short-term energy demand [13]. DR programs persuade the consumers to participate in the electricity market via advanced metering infrastructure (AMI). An hour-ahead DR algorithm was proposed in [14] for HEMS with a steady price prediction model based on artificial neural network. This specific study is needed because the inherent nature in hour-ahead electricity price market, so the customer accesses only one price for the current hour. With the integration of forecasted future prices, multiagent reinforcement learning (RL) is adopted to make optimal decision for different home appliances in a decentralized manner to minimize the user energy bills, dissatisfaction costs and degree of discomfort. RL is an excellent artificial intelligence method, with a decision-making ability to solve problems without initial knowledge of the environment and its distinct features of model-free. The continuous changes in controlling the energy systems such as dynamic electricity prices, intermittent availability of renewable resources, and changes in energy consumption amounts, has demand a powerful tool like RL to optimize the energy systems. Several studies with RL adoption in the energy systems are reported in [14], but most studies did not consider how the learning algorithms will decide on the multiple kind of appliances, and all studies only uses day-ahead energy management. However, to deal with the uncertainty in prediction and dynamic constraints in energy generation, an hour-ahead DR has greater potential in balancing power systems, as presented by Lu et al. [14]. The simulations considered multiple kind of appliances, which are non-shiftable loads, shiftable loads and controllable loads. The study has significantly reduced the user's electricity cost as compared to a benchmark without DR.

Another energy management strategy using price-based DR program was developed in [15] for IoT-enabled residential buildings by fully utilizing the AMI, DR programs and IoT-enabled environments. The aim is to systematically manage the power usage by scheduling the energy usage to improve peak to average ratio, minimize cost of electricity and maximize user comfort for satisfaction of both users and distribution system operators (DSOs). In price-based DR program, the IoT-enabled users are stimulated to spontaneously manage their power usage in response to offered price-based incentives. The study has proposed a practical optimization model using different DR programs such as time-of-use pricing scheme, day-ahead pricing scheme, and real-time pricing scheme of the smart grid. The proposed framework in the study uses inputs such as available energy from power grid, power usage patterns, appliances power rating, DR programs and length of time operation. The residential building is enabled with IoT and equipped with energy management controller (EMC), home gateway, smart appliances, smart meter, remote control, indoor display, and wireless home area network. The smart appliances are categorized as power adjustable, time adjustable (interruptible and non-interruptible), and critical. The output of the framework will be a solution to an optimization problem, which the main problem is the energy management, on how to automatically respond to DR pricing signals to schedule power usage of residential buildings to ensure efficient energy management. Then, the residential building energy consumption, cost for consumed electricity, peak to average ratio and user comfort in terms of waiting time, are formulated. The overall energy management problem is formulated as an optimization problem with several defined constraints: power grid capacity (not overburdened and capable of taking part in power usage scheduling), equal net energy consumption before and after scheduling, status of activity (in-progress or completed), and same length of time interval before and after scheduling. The authors in [15] also adopted six benchmark strategies to solve the abovementioned optimization problem, which the proposed DR program leads to the lowest electricity cost, peak average ratio and stable power usage schedule, via the simulation results.

2.7 Human State Detection

Energy flow monitoring is useful to analyze the special-time or rush-time but requires and waste a large amount of energy. A specific strategy is needed in the smart EMS to distribute the energy efficiently. A smart control system that can detect human behavior was proposed in [16]. It is able to decrease the energy supply to idle devices and the connected extra devices by analyzing how many IoT will be used in a service. The system will detect the human movement and turn in activation state automatically, to ensure the efficient energy usage. The study detected the human behavior by analyzing electrocardiogram's (ECG's) patterns and has experimented two cases: human in normal state and activate state. The assumption is that minimal energy will be used in normal state and otherwise in activate state. Hence, to control the energy usage, human behavior plays very important role.

2.8 Summary

Table 1 summarizes the aforementioned studies with their objective, features, tools and potential improvements and sorts them according to the year of publication.

Table 1 - Summary of the HEMS-IoT studies with their objective, features, tools and potential improvements

Author [ref]	Year	Objective	Features	Tools	Potential Improvements
Kim, Byun et al. [5]	2015	- low-cost, scalable, reusable, and interoperable HEMS - energy saving	- connectivity: Bluetooth, client-to-server, machine-to-machine	- distributed system architecture, dynamic network configuration, contextual information, user centric service domain	- integration of social networking concepts
Al-Ali, Zualkernan et al. [9]	2017	- cost saving EMS, scalable and high-speed server	- big data, business intelligence, SoC data acquisition, scalable MQQT server up to 4000 concurrent users	- centralized management server, MQQT server, storage server, analytics engine server, JavaScript webserver, high-end microcontroller with functional requirements and business processes, unique Internet Protocol address	- Not discussed
Jo and Yoon [6]	2018	- integrated management system for interoperability of IoT devices, solve network congestion, reduce energy wastage	- intelligent models, machine learning for situation recognition and user consumption pattern discovery, MQQT protocol, four major types of defined-lifestyle patterns	- intelligent models (IAT for situational awareness, IE^{2}S as IoT server, and IST to manage services), Arduino board as sensor board with sound, motion and rotary sensors, Mobius server, TensorFlow engine, Jupiter editor, Anaconda package	- to improve prediction accuracy and collect actual data for system stability - to perform direct analysis and testing of the network - in-depth research on intelligent models and structured intelligent IoT platforms for smart homes
Li, Logenthiran et al. [8]	2018	- DR, load management	- multiagent system for self-learning HEMS, rule-based classifiers (K-means clustering) and machine learning (recurrent neural network) for price forecasting and price clustering, supply and DSM system, load shifting for peak and off-peak hours	- self-learning home management system with DSM and supply side management, having optimized RE, battery storage, main grid and electric vehicle, case study in Singapore	- not discussed

Table 1 (continued) – Summary of the HEMS-IoT studies with their objective, features, tools and potential improvements

Pérez-Camacho, González-Calleros et al. [12]	2019	- reduce consumption, costs, peak average ratio; maximize user's comfort	- context awareness, defined type of devices (interruptible, non-interruptible, flexible, not flexible), multi-objective optimization problem, meta-heuristics model	- HEMS architecture with control unit and three modules (programming, monitor, prediction), five data flow layers in IoT architecture, data acquisition using non-invasive potentiometer (Arduino Uno and SCT-013 sensors)	- creation of intelligent schedule which works with the probability of use, schedules and the time of consumption of every device
Lu, Hong et al. [14]	2019	- DR, load balancing, minimize user energy bills, dissatisfaction costs and degree of discomfort	- price prediction model using multiagent reinforcement learning, decentralized architecture, considers nonshiftable, shiftable, and controllable loads	- an hour-ahead DR algorithm for multiple appliances in home EMS, simulation using multiple kind of loads	- will consider usage patterns, working time, and the impacts of network congestion when implementing the presented DR algorithm in real physical applications
Borland [10]	2020	- renewable clean energy, lowest daily electricity cost, resilience 24/7 home safety and security	- island nano grid, rooftop solar PV, battery storage discharge, thermal storage	- case study at an island with RE using sunlight and heat with multiple storage	- to achieve 100% RE usage from current stage 92%
Hafeez, Wadud et al. [15]	2020	- DR, load scheduling, improve peak average ratio, minimize electricity cost, maximize user's comfort	- several DR programs (time-of-use pricing scheme, day-ahead pricing scheme, and real-time pricing scheme), optimization model (wind-driven bacterial foraging algorithm) - Categorized home appliances into power adjustable, time adjustable (interruptible and non-interruptible), and critical	- IoT-enabled DSOs and residential buildings utilizing AMI, EMC, home gateway, smart appliances, smart meter, remote control, indoor display, and wireless home area network	- to experiment on fog- and cloud-based energy management via scheduling using the DR - to use MILP-based efficient energy management modular framework for performance and sensitivity analysis
Ko, Kim et al. [16]	2020	- energy scheduling, energy efficiency	- ECG's pattern analysis for human state detection - decrease energy supply to idle services when human action is inactive	- smart energy management system with ECG's pattern analysis to detect whether a human is in an activate state or normal state	- not discussed

Table 1 (continued) – Summary of the HEMS-IoT studies with their objective, features, tools and potential improvements

Machorro-Cano, Alor-Hernández et al. [7]	2020	- Real time monitoring HEMS for IoT devices and sensors, minimal user intervention, energy saving, user's comfort, and safety	- machine learning (J48 and Weka API), Big Data (RuleML and Apache Mahout), user-centric evaluation	- seven layers functionality architecture for the HEMS-IoT, sensors and smart plugs in residential complex case study	- not discussed

3. Its Way Forward

Current trends of the HEM systems involving around machine learning, Big Data, and intelligent scheduling, which intrusively manage and monitor the electrical loads, and can react to DR programs for DSM effectively. Moving forward, a nonintrusive method as an alternative to EMS has gained a considerable attention in the research field of smart grids. The evolutionary computing-based nonintrusive load monitoring (NILM) is a viable load aggregation technique and cost-effective. It is considered and addressed as a multi-objective combinatorial optimization problem that breaks down the circuit-level power consumption to the appliance level power consumption. A trainingless multi-objective evolutionary genetic algorithm (GA)-based NILM for DSM was presented in [17], on a smart IoT-oriented home EMS. Unlike the conventional NILM, this new method does not require training and retraining stages, as well as hyperparameter tuning procedure for the load classifiers in the artificial and deep neural networks. The HEMS in the work consists of three entities: power company-owned smart meter for composite power consumption data transmission and to receive DR signals for DSM; residential environment to monitor different types of electrical appliances; and the EMC with NILM, which act as home gateway, and implemented in Phyton to measure the circuit-level to appliance-level breakdown using plug-panel current and voltage sensors. It is different from the current practice of using plug-load smart plugs or power meters. The disaggregation of electric-energy consumption into power consumption is based on the electrical characteristics, extracted from the individual electrical appliances using data acquisition device. The NILM is consists of the data acquisition device, feature extraction for creating feature space, and load identification that is solved by the GA. In conventional NILM, a preliminary experiment will label the monitored electrical home appliances with user intervention, where their rated power consumptions are measured to train the artificial intelligence models. In the trainingless and fully nonintrusive NILM, only the types of enrolled electrical appliances are needed which will be used as labels in GA. The database will use the historical data from the recorded states such as signals from infra-red remote controls and Wi-Fi flows, to analyze and interpret the occupant energy-use patterns in the environment. The data will be used to consider load combinations of electrical appliances using data-fusion analysis for the real-consumed power, estimated using the new NILM approach. The authors have achieved up to 6.35% improvement for the load-identification using the trainingless multi-objective GA-based NILM.

Another multi-objective optimization method was proposed by Xiuwang et al. [18] which also focuses on energy consumption cost and user satisfaction. To increase the convergence speed, the optimization algorithm is based on an improved version of the butterfly algorithm [19], proposed by the authors. The IoT-based model HEMS was developed based on Radio Frequency Identification for automatic monitoring of the household appliances. The system considers two categories of household appliances: controllable (irregular electricity time, interruptible and uninterruptible) and uncontrollable (uninterruptible). A prediction for the renewable energy output power is studied based on the historical usage data of controllable appliances. The mathematical model for user's demand is based on the power consumption of appliance operation, period of appliance process and running time for the appliance. The inputs will be the on-off appliance state at a time, number of time slots, time resolution in minutes, value of power consumption at a time, limit summation power consumption for the appliance and limit of the time for the appliance in hour. The cost function will study the users' satisfaction and electricity cost, to ensure the power supply for the users' load demand can be supplied by the power grid, battery, and renewable energy generation. There are three constraints in the cost function, as identified by the authors: demand, battery capacity and power trade-off. The butterfly optimization algorithm (BOA) is used in the study, to solve complicated problems meta-heuristically. It is a type of swarm optimization algorithm, introduced in 2019 by Arora and Singh [19]. Butterfly is chosen for its unique characteristics, specifically the sense of smelling at long distances, and its ability to precisely sense, locate and separate different fragrances. The search agents in the BOA population is the group of butterflies, and its cost of the objective function will vary according to butterflies' location. BOA is a type of swarm optimization algorithm, where each agent will share their experiences by distributing the fragrance over the distance with other group of butterflies. Global search point phase is when the fragrance was sensed from a movement of one butterfly to the other, and local search is when other movement was made. This random generated process is the basis of BOA method, a trade-off between smell senses and fragrance. The optimization process for the improved BOA [18] will start with initializing a swarm of butterflies, followed by the evaluation of the fitness function containing grid power, batter power and situation of the optimized appliances. The grid power and battery power will be reevaluated on the basis of the predicted data from the renewable energy, power generation and family load. If the solution provides the constraints for the participated appliances in scheduling and the storage battery, the DR will be granted only when the home load can cope, followed by location update for each butterfly. Else, the optimization process will have to restart at reinitializing the butterflies' swarm. This new BOA has illustrated improvements compared to the original BOA, in the system efficiency, specifically in energy consumption cost and user's satisfaction. This promising multi-objective optimization method can be a new paradigm for the HEMS-IoT system with the ever-changing appliances.

4. Issues and Challenges

With the rise of smart cities and smart homes, there is an increasing need for a smart energy management system. However, a large-scale implementation is limited due to the high deployment cost, high complexity, and high maintenance technology. Massive amount of data collected throughout a country from different cities possess different multiple issues in data storage, organization, and analysis [9]. The IoT and Big Data are a solution to these issues, because the energy consumption can be analyzed and classified efficiently, user behavior pattern can be identified, and comfort at home can be increased [7]. But with the rapid development of both technologies comes a coexistence challenge, the connectivity standards for IoT applications are not comprehensive. They can be classified into three broad categories: service related, communications-related, and data-related [4]. The connectivity protocols for data transmission also differs in many IoT applications, such as Wi-Fi, Bluetooth, Bluetooth Low Connectivity, and ZigBee, which developed heterogeneous connectivity scenario [7]. There will be interferences resulting from the interaction between the wireless connectivity sharing same frequency band (i.e.: 2.4 GHz) that can degrade the network's quality of service significantly. To manage the different IoT devices, an integrated operating system is needed to allow the devices in a smart home to mutually cooperate with each other [6]. Failed to manage the IoT devices will lead to excessive traffic on the smart home network and energy wastage. Scheduling the IoT devices are important to reduce energy wastage so that it is only activated when needed. Efficient energy can be achieved by operating the IoT according to the energy flow with self-organization network and artificial intelligence to improve prediction and establish efficient maintenance schedule [16]. For the method, handling large data problems is inefficient and impractical using the deterministic optimization, thus metaheuristic optimization has become an optimal approach [12]. However, some GA-based strategy may lead to unguided mutation that makes the loads unbalanced [15]. Other algorithms like binary particle swarm optimization have limitations such as increased model complexity and computation overhead with the shorter timeslots schedule. A new optimization method like BOA in [18] is worth to be explored further.

The challenges in implementing artificial intelligence in the electrical power system are the design for automation of heterogeneous devices to adapt with the power consumption and the pricing signals. Distributed network structure and computing algorithm is necessary in accelerating a flexible and self-healing system, but it has triggered many security issues in the smart grid that may lead to infrastructure failure, privacy breach, disturbance and denial of service [20]. On the HEMS side, a need of intelligent environment to solve appliances load scheduling remains an open issue [18]. Other problems are grid power dispatching under single optimization framework with dynamic costs, minimizing the peak average ratio, lowering the cost, and reducing the energy consumption while maximizing user's comfort. Electrical consumptions are varied according to the hour of the day, the day of the week, and seasonal. DR programs can help with coping the ever-rising electricity demand, but there is a lack of user knowledge in the DR, and less users participate in the program. The EMC can help to overcome this, where the electricity cost can be lowered effectively and automatically. The output of EMC will be an optimal power usage schedule for residential building smart appliances, but at high capital cost. Hence, DR program is still preferable to attract users to actively participate due to the minimal cost without sacrificing user's comfort. Current proposed DR programs are still on one-day ahead, but an hour-ahead is found to be better for balancing the power systems. This is due to the uncertainty in the algorithm prediction and dynamic constraints related to the energy generation. There is also limitation on study with different kind of loads such as electric vehicle or thermostatically control load, which should be considered by future research [12, 14, 15] to train the learning algorithm on decision making when dealing with different types of appliances.

5. Conclusions

Realizing a practical approach of HEMS with the vast growth of heterogeneous IoT devices coexisting in the same system with different standards and connectivity is one of the challenges in the smart home development. The urgency to address this important issue to provide an efficient energy management and reduce energy wastage has become the motivation of this study. Here, a review on the noteworthy work on HEMS was conducted. Recent trends on the smart home such as distributed architecture, centralized server, intelligent models, self-learning HEMS and various DR programs are explained in this paper. Future research directions in HEMS with the IoT and Big Data technologies using promising algorithms were also discussed. The main issue related to the development of HEMS is to optimally schedule the home appliances to achieve close to zero energy wastage. This becomes the main objective because energy generation from the grid is precious, costing extremely high carbon dioxide emissions to our mother earth. The RE usage can help with the environment using its clean energy production, but somehow will lead to wastage as well if not properly managed and scheduled. DR programs is beneficial to the users due to its low-cost implementation without sacrificing user's comfort. However, balancing the load of the power systems remains an open issue globally, due to many uncertainties in the intelligent algorithm and dynamic constrains in the energy generation. This review is expected to aid researchers in addressing important issues in achieving successful EMS for home sphere and together we can protect the world for longer stretches of our generations in the future.

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