Intelligent Techniques for Smart Home Energy Management Based on Internet of Things (IoT) Paradigm

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Abstract

Over the past decade, Internet of Things (IoT) plays a crucial role in promoting the smart city development. IoT provides smart solutions for transportation, agriculture, healthcare, industrial, educational, environmental and many other domains. One of the main objectives of IoT is to contribute in energy management solutions that guarantee the efficiency of energy use, thereby maximizing productivity, minimizing energy costs, reducing environmental effects and handling associated challenges. This paper contributes to the understanding of various methods used to utilize the energy consumption in smart homes. These methods can be concluded in the following; extracting appliances usage patterns, applying scheduling algorithms based on the simulation of Demand Response (DR) analysis and finally building a predictive models about the predicted energy demand in a timely fashion. Studies applied in any of these methods have shown significant results in energy saving.

Keywords: *Internet of Things, Home Energy Management, Smart Grid, Demand Side Management, Demand Response, Usage Patterns, Energy Prediction.*

1. Introduction

WITH THE rapid growth of population, there is an expeditious rise in energy demand all over the world. Energy is consumed by mainly four sectors; residential, commercial, transportation and industrial. The residential demand for a sustainable and reliable energy increases day by day, consequently increasing the pressure on power plants, utilities and natural resources. In 1949, the residential sector in the United States consumed 5,599 Quadrillion Btu of power energy. In 2011, the consumption has been increased to be 21,619 Quadrillion Btu [1]. This is around 300 percent increase in energy consumption. Moreover, Traditional electric power systems are facing several challenges such as system stress conditions in peak hours causing supply limit and blackouts in large areas [2]. Therefore, Energy management solutions should be provided. The main objective of energy management is to guarantee the efficient use of energy, thereby preventing the fluctuation of energy prices and reducing the emissions of carbon dioxide CO_2 for a cleaner environment [3].

With the emergence of IoT [4], a traditional city will be revolutionized into a smart city. The IoT plays a vital role in the smart grid technology. The smart grid is defined as a network of utilities and substations that carry electricity from power plants to dwellings in a bidirectional way. It combines billions of smart appliances, smart meters, actuators and sensors providing precise information for both producers and consumers [5]. One of the important functions of smart grids is the Demand Side Management (DSM) [6]. DSM is designed to influence the use of electricity by consumers in such a way to reduce the demand load stress on utilities and achieve reliability targets [7]. In this paper, we focus on energy management in the residential sector. The studies done in this sector are summarized in three methods as described in fig. 1

- Smart home energy scheduling.
- Extracting usage patterns.
- Predicting energy demands.

The organization of this paper is as follows: Section II presents a background on the work done in energy management. Section III provides the main concepts of smart home energy scheduling. Section IV studies the techniques done in extracting usage patterns. Then, predicting energy demands techniques are studied in section V. Finally, the conclusion and future work are drawn in section VI.

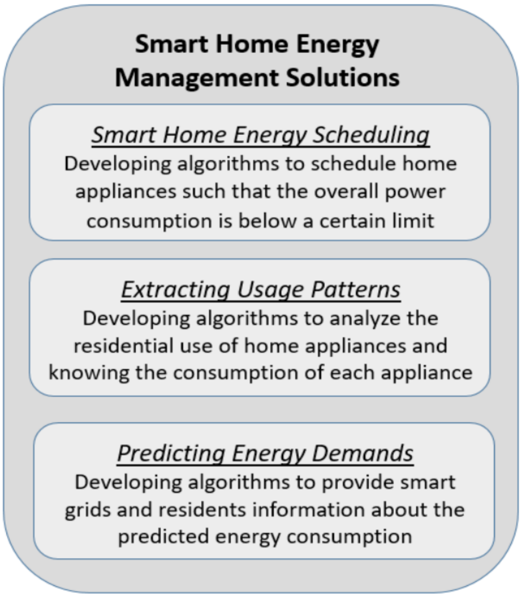

Figure1.Smart Home Energy Management Solutions

2. Background

Nowadays, Energy management in smart home has been attracting governmental, academic and industrial sectors. All of these sectors have been focusing on finding solutions for a smarter city and enhancing quality of life. Moreover, providing a cleaner environment and preserving natural resources.

In the governmental sector, the Australian government invested AUD 490 million in the Smart Grid Smart City project (2010-2014). It is one of the largest smart grid projects that was deployed across eight local government areas in New South Wales (NSW) [8].

In the academic sector, the IEEE had a partnership with the International Telecommunication Union (ITU) working on the transition to smart cities [9]. The Seventh Framework Programme (FP7) for research of the European Commission has introduced RERUM framework, which will be deployed for several smart city applications to evaluate the security and privacy mechanism [10]. Also, they have introduced the ALMANAC project which integrates IoT with metro access networks providing smart services to citizens [11]. The Future Internet Research and Experimentation initiative of the European Commission has deployed several IoT devices in Smart Santander project to support services and applications for smart cities [12].

In the industrial sector, Fujitsu is working on the development of energy management systems for participating in the emergence of smart cities [13]. In addition to many industrial companies have been paying attention for the development of smart city such as IBM, Intel and Cisco [9].

3. Intelligent Techniques for Smart Home Scheduling

There is a crucial need for dynamic pricing technique to regulate electricity consumption and minimize stress load over electric power plants. Dynamic pricing leads to introduce DR strategy in dwellings. DR is defined as the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time [14]. There exists different forms of dynamic pricing like Critical Peak Pricing (CPP), Time-Of- Use pricing (TOU) and Real-Time Pricing (RTP). CPP refers to the rate of the prices are substantially raised when the utility observes an emergency conditions during a specified time and needs to reduce the load [14]. TOU pricing refers to the rate of the prices depending on the current period of time where the twenty-four hours of a day are partitioned into a number of periods and the price of each period is constant and predetermined [15]. RTP refers to the rate of the prices based on an hourly rate [16].

With the help of Home Energy Management Systems (HEMS) [17], customers can schedule and manage their appliances load. HEMS guarantees that the total power consumption of all home appliances are below a certain limit. This can be achieved by controlling home appliances while taking into consideration customer preferences [2]. In addition to the ability of the customers to control their appliances. Therefore, smart home energy management systems are the key enablers for the scheduling mechanisms.

Researchers have categorized home appliances in different ways. The authors in [9] have categorized the appliances into unmanageable load and manageable loads. Manageable loads are subcategorized into shift-able load that runs on shift basis like washing machine and dishwasher, interruptible load that can be turned off for a specified time during running time like water heaters and weather-based load like air conditioners and heaters.

The authors in [18] have categorized the appliances into Automatically Operated Appliances (AOAs) and Manually Operated Appliances (MOAs). AOAs are the appliances that can operate automatically without the customer interference like washing machines and air conditioners while MOAs are the appliances that are turns on or off manually by the customer like television and vacuum cleaner.

The authors in [19] have categorized the appliances into Schedule-based Appliances with Interruptible Load (SAIL), Schedule-based Appliances with Uninterruptible Load (SAUL), Battery-assisted Appliances (BAs) that are supplied with an internal battery, and Model-based Appliances (MAs).

In general, most of the researchers develop home energy scheduling algorithms for the appliances that can be automatically operated and runs on shift basis like washing machine, dishwasher, dryer, microwave, oven, refrigerator, heaters, air conditioners, electric kettle and electric vehicle. The primary aim of home energy scheduling algorithms is to schedule home appliances efficiently in such a way that can achieve the following objectives: minimizing energy consumption, satisfying customers preferences and comfortability, optimal utilization of home resources, and reliable shifting of appliances load, thereby, reducing electricity bills.

4. Intelligent Techniques for Extracting Usage Patterns

Recently, Inflation rates in electricity have made home residents pay much attention to their energy consumption. However, the only meter they know about their consumption is their electricity bill. When it gets high or low, they have no idea what made their bill raised or reduced. A detailed electricity usage analysis is needed to monitor home appliances consumption. With the arrival of smart grid technology, smart meters have been introduced into the market. In this regard, sensors are deployed on each home appliance where they can send data about their electricity usage to smart meters on time based-interval. Now the role of data mining techniques comes on the spot, where we need to have useful information from this massive raw data [20]. Extracting usage patterns focuses on providing vital information to residents about how their energy consumption are distributed among home appliances based on their behavior. Researchers have worked on extracting useful information about consumed energy from these data.

The authors in [21] extracted sequence patterns of home appliances to understand their usage behavior more clearly. This was achieved by using Prefix Span as a sequence-pattern mining algorithms on Spark as a distributed platform and applying it on the smart grid smart city dataset mentioned in Section II. The SGSC dataset records data about customer ID, reading date and time, plug name, reading value, calendar key and record count. The records per each day in the week is extracted and the algorithm is applied on. Then, it is applied on the whole dataset. Results show that some patterns extracted in the whole database cannot be extracted in the week day database.

The authors in [22] introduced two types of usage patterns, Time-slot Probability Usage Pattern (TPUP) and Daily Behavior-based Usage Pattern (DBUP). TPUP divides a day in a number of time slots then calculates the probability if the appliance will be operating in this time slot. The results of TPUP reveals information about the usage time distribution of each home appliance instead of the resident usage behavior, so that the user can acquire a detailed information about the consumption of each appliance and which one consumes more or less than other ones. On the other hand, DBUP is designed for mining daily behavior-based usage patterns where clustering algorithms are applied to group the usage behavior of similar days together. It begins by considering each day usage sequence is a cluster and the distances between those clusters are calculated by using a similarity function in the clustering process. This similarity function is calculated based on the time space points. The results of DBUP reveals information about the number of times the appliance is used, its start time and duration.

The authors in [23] extracted diurnal load profiles which is the value of the average consumption daily load divided by the maximum peak load. Then demonstrate its use in two cost-reflective product offerings, a Network-type and a Retail type product bundle.

This was achieved by using Principal Component Analysis (PCA) and Self-Organizing Mapping (SOM) and applying it on the SGSC dataset mentioned in Section II. Results have shown that customers have a great intention to lower their electricity bills since that up to 12% reduction were achieved in peak demands.

The authors in [24] recognizes the state of appliances by monitoring the circuit-level electrical consumption from the distribution board providing consumption information in real time. They built their model based on the assumption that they know the household appliances on two assumptions. The first is getting the state of the appliances by using smart meters and the second is the way of using appliances is directly related to user behavior so if the user has a regular life cycle, we will have a regular usage pattern. The authors used classification algorithms such as Bayes, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) to develop their model and experimented them on two real dataset extracted from smart home consisting of 18 combinations of states and 48 state changes for about 3 hours. The developed model produces the number of states of each appliance associated with its power consumption.

However, data mining is a key enabler in the process of extracting usage patterns. Although researchers have different objectives about the implemented models but most of them have agreed that data mining algorithms are very effective to achieve this. The main objective of the mining process is to provide useful findings about the usage whether it was about the user behavior or about the consumption of each appliance.

Table.1 The work done in the extraction process

Ref	Technique	Dataset	Objectives
21	Sequence-Pattern Mining Algorithms	SGSC	Extracting sequence pattern.
22	Classification Learning Algorithms: decision tree(4.5), decision table and bayes net	Data extracted from six appliances which are microwave, dish-washer, washer, dryer, light, oven and air-conditioner in smart home	Extracting TPUP and DBUP
23	PCA and SOM	Data set collected from dwellings [31]	Extracting diurnal load profiles.
24	Bayes, KNN and SVM	Data extracted from smart home	Extracting the number of states of each appliance associated with its power consumption.

As illustrated in table 1, the objectives of the extraction process are concluded in the following points:

- Extracting Sequence Patters: defining the usage sequence of appliances, i.e. [[Washing, Dryer], [Washing, Dryer], [Washing], [Washing, Dryer], [Dryer], [Dryer]] is a sequence pattern providing information that the dryer is always used after the washing machine.

- Extracting TPUP: defining the time slot when each home appliance is mostly used such that the coffee machine is mostly used in the interval from 7 to 8 am.
- Extracting DBUP: the same as TPUP but on daily base such that similar behavior days are grouped together.
- Extracting diurnal load profiles: calculating this percentage is very useful to smart grid as it provides information about the variation in the electricity imported.
- Extracting the number of states: providing residents real time information about how many times each appliance is used in a given time interval and the total power consumed in each state.

5. Intelligent Techniques for Predicting Energy Demands

The surge in energy demand has increased the need of predictive models to meet the expected demand. It is necessary for the smart grid to know the estimated energy demand. Load prediction can support decision-making process for the smart grid [25]. Understanding residential behavior studied in the previous section is a key factor to predict residential energy consumption. Most of the research done in the predictive method is to provide short-term energy demand forecasting. That means predicting the energy demand for the next hour and the next 24 hours as well so that it can adapt itself with residents behavior. This assumption can provide prediction after short number of days. However, having a bulk of previous historical data can enhance prediction accuracy. One of the advantages of the prediction model is to be integrated with home energy management systems. If there is an expected deficit, HEMS can reschedule appliances load or depend on another energy source such as solar planets. Moreover, it can decide then which appliance will operate at a given time taking into account residents preferences. Thereby, decreasing the dependence on smart grid [26].

The authors in [26] have presented a predictive model that can be integrated with HEMS. The proposed model works on predicting the non-shift able load appliances only under the assumption that HEMS is already managing the shift able appliances. The algorithm works on Load Monitoring and Prediction (LMP) function that operates on mainly four functions summarized in the following:

- The 24-hour prediction: classifies electrical load into four classes: high load, upper average load, lower average load and low load.
- Duration calculator algorithm: calculates the maximum and mean time of occurrence of each load level.
- Derivatives clustering: calculates the rate of change of clustered data.
- Live correction algorithm: predicts the electrical load in the next few hours.

The authors have used the dataset of the research project ADRES-CONCEPT [27]. The dataset carries the readings of 30 dwellings for two weeks in summer and two weeks in winter. The algorithm is implemented on matlab integrating with Simulink model. Prediction error analysis after applying live correlation algorithms ranges from 8.5% to 37.3% for summer and from 7.5% to 43.4% in winter.

The authors in [28] have proposed a predictive model by using classification-learning algorithm. The classification task has two classes only which are the on and off classes. It is designed to predict whether a home appliance will be working on the next hour or not.

That means if the appliance is working, it will be in the on class, and if not it will be in the off class. Since the time space is 24 hours a day, it can also be used to predict for the next 24 hours. The authors have used the dataset of IRISE project which is a part of Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe (REMODECE) project [29]. The records of the dataset are the consumption of each home appliance captured every 10 minutes for a one year. The authors have applied decision tree (C4.5 algorithm), decision table and bayes net on the dataset. Interested results were found where the highest accuracy are obtained when using C4.5 algorithm and decision table. C4.5 algorithm has more accuracy when applied on shift-able appliances such as washing machine and decision table has more accuracy when applied on regular consumption appliances such as lighting and random consumption appliances such as oven.

The authors in [30] assumed that residents daily activities have a great impact on energy consumption. Therefore, they used temperature, power and motion sensors placed on the ceilings to track residents location. Each sensor has a unique ID. The sensor gather data about current date and time, sensor ID and a message. The message varies based on the sensor type where temperature sensors send temperature degree message, power sensors send reading watt message and motion sensors send a status on or off message. Unlike work done in [28] where the authors objective is to predict the total home energy consumption not each appliance consumption. They have implemented both linear and non-linear regression learning models for predicting energy. They applied their work on real dataset collected from four dwellings in two different areas Kyoto and Tulum [31], and found that the linear regression learning models are preferable for energy prediction in smart environments.

The authors in [32] proposed an Artificial Neural Network (ANN) algorithm for predicting the total power consumption of a building. The algorithm first calculates the predicted energy consumption for each end user in the building. Then, the building total power consumption is their aggregated value. The applied model has selected the following factors for feeding the ANN:

- Weather conditions: temperature always has a great impact on power consumption through Heating, Ventilation, and Air Conditioning (HVAC) systems.
- Calendar: power consumption depends on the day and time. Prediction is obtained every 15 minutes per hour. Thus, 96 predictions are obtained to calculate prediction daily.
- Type of Day: since the consumption through week days differs from the those in holidays.
- Unpredictable Factors: factors that may affect power consumption such as failure in HVAC systems or another.

The applied work have been applied on Universitat Politcnica de Valncia (UPV) which is about 66 buildings with classrooms and offices included. The proposed method is applied on the end users first that are the classrooms and offices. Then, their value is aggregated to calculate the total consumption. The authors have used two error indexes to evaluate the prediction error which are the Mean Absolute Percentage Error (MAPE) and the Energy Mean Error (EME). MAPE has shown error equals to 4.88 and EME has shown error equals to 5.95.

The authors in [33] developed an algorithm for predicting the usage of dwellings appliances in the next 24 hours. The developed algorithm processes on the following three prediction levels:

- Status Prediction: predicting whether the device will operate the next day or not using prediction sequence algorithm.
- Time Prediction: predicting the number of times the appliances will operate and at what time by adding a normal function with variance minutes for every start time of the device.
- Duration Prediction: predicting the duration that the appliances are turned on by calculating the mean value of previous duration associated with each device.

The introduced model has been developed with the Bright Energy Equipment (BEE) project considering only three devices for a one year: oven, air conditioner and dishwasher. The results obtained show accuracy in status prediction up to 95% and time prediction error varies from 13 to 91 minutes and duration prediction error varies from 8 to 22 minutes. The algorithms proposed in the prediction model along with the datasets used and the results achieved are summarized in table 2.

Table2.Intelligent Techniques for Predicting Energy Demands

Ref	Technique	Dataset	Results
26	Load Monitoring and Prediction	ADRESCONCEPT Project [27]	Prediction error analysis after applying live correlation algorithms ranges from 8.5%to 37.3% in summer and from 7.5% to 43.4% in winter seasons.
28	Classification Learning Algorithms: decision tree(C4.5),decision table and bayes net	IRISE Project[29]	More accuracy obtained when using C4.5 algorithm with shift-able appliances and when using decision table with regular and random consumption appliances.
30	Linear and non-linear regression Learning models	Dataset collected from dwellings [31]	More accuracy obtained when using linear regression learning models
32	Artificial Neural Network	Data set collected from UPV	MAPE has shown error equals to 4.88 and EME has shown error equals to 5.95.
33	Status, time and duration prediction	Data set collected from BEE	Status prediction accuracy up to 95%.Time prediction error ranges from 13 to 91 minutes. Duration prediction error ranges from 8 to 22 minutes.

These results show that it is impossible to provide a predictive model with 0% error so researchers focus on how to increase accuracy percentage. Based on our study increasing the training number of days can give us a better accuracy [32], [33]. Although there is an extensive focus in this area, but still several challenges are to be addressed.

Some of these challenges can be pointed out in the following: what if the dwelling's residents are changed given that prediction is totally dependent on the user behavior, how to train a large number of dataset effectively and meeting performance challenges, how to respond with sudden failures and how to meet scalability challenges in terms of both performance and accuracy.

6. Conclusion and future work

This paper presents an overview and future work of the research done in the field of energy management in the residential sector. Saving energy has become an important global direction to focus on and find solutions for. A lot of efforts have been done in this area by the academic, governmental and industrial domains. SGSC is one of the huge projects that have been implemented in the residential sector. A lot of various methods and algorithms have been applied but all of them have a one unified objective, which is reducing energy consumption in dwellings. Thereby, achieving the following objectives; reducing load stress on smart grids, preventing blackouts and reducing the emission of carbon dioxide CO_2.

In the context of scheduling method, researchers focus on scheduling home appliances with shift able load like washing machine, dishwasher, dryer and oven so that HEMS can schedule their operation time in such a way that the total power consumption is below a certain limit.

In the context of extraction method, researchers agreed that energy consumption is directly related by the user behavior with home appliances. The objective of the extraction process differs from one another. The most effective method is to provide residents analyzed information about the consumption of each appliance and the peak time period when each appliance is mostly used.

In the context of prediction method, researchers found that developing a model for predicting home energy consumption with minimal error percentage is not an easy task since user behavior is hard to predictable. For that reason, most of the work done is to provide methods for short-term forecasting that means predicting energy demand within the next 24 hours so that the system can adapt itself providing more accurate prediction results. Although previous work have shown significant results for energy saving, but a lot of work is still missing in this area like integrating HEMS with other energy sources like wind or solar systems, meeting the challenges of scalability and reliability of smart grids and integrating the mentioned methods together for achieving better results. In our future work, we will introduce a model that integrates both the usage patterns model with the scheduling model through HEMS. In this work, we will extract usage patterns data and provide it to the HEMS, so that the HEMS will gain information about user preferences from the extracted data instead of making the user insert his own. Also, it can adapt itself with the change of user behavior.

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