Residential Energy Management: a Machine Learning Perspective

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Mahmood Reaz Sunny*, Md Ahsan Kabir†, Intisar Tahmid Naheen‡ and Md Tanvir Ahad§
*Dept. of Electrical and Electronic Engineering, Uttara University, Dhaka, Bangladesh
†Dept. of Electrical, Electronic and Communication Engineering,
Military Institute of Science and Technology, Dhaka, Bangladesh
‡Dept. of Electrical and Computer Engineering, North South University, Dhaka, Bangladesh
§Electrical and Computer Engineering, The University of Oklahoma, Oklahoma, United States of America

***Abstract*—In smart grids, residential energy management is a vital part of demand-side management. It plays a pivotal role in improving the efficiency and sustainability of the power system. However, challenges such as variability of consumption profiles require machine learning to understand and forecast residential demands. Moreover, machine learning based intelligent load management is required for effective implementation of demand response programs. In this article, applications of machine learning algorithms in residential demand forecasting, load profiling, consumer characterization, and load management are comprehensively discussed. The article also examines the characteristics and availability of relevant databases, and explores research challenges and possibilities.**

***Index Terms*—Machine learning, residential energy management, smart grids, load forecasting, demand response**

I. Introduction

Residential consumption takes up a significant portion of total electrical energy demand. Thus, effective management of residential energy consumption can have a positive impact on the overall power system efficiency. Residential energy management (REM) systems improve usage efficiency by shifting and curtailing demands. The aim of residential energy management is to create optimal consumption profiles which benefit all parties involved, i.e. prosumers, consumers and utilities [1]. By reducing the overall energy consumption, REM reduces activation of thermal and nuclear power plants during peak demand periods.

Smart grid (SG) is a platform to bring together renewable energy resources, modern communication and control technologies, and active customer participation to build a sustainable, smart, efficient and clean electrical power and energy system. In smart grids, REM plays a vital role in reducing electricity costs and environmental pollutions and serves as enabler of virtual power plants, micro-grids, community energy storage and decentralized electricity markets.

Demand response (DR) refers to changing the usage patterns of electricity end-users in response to variations in the electricity prices over time. Residents can reduce their electricity costs by changing the pattern of their home electricity usage [2]. Moreover, a power system is most efficient when fluctuations in demand is kept at a minimum. Hence, DR is widely used to alter the timing of load usage, level of instantaneous demand or the total electricity consumption [3]. The most common DR programs include time-of-use pricing (TOUP), critical peak pricing (CPP), extreme day pricing (EDP), and real time pricing (RTP). In TOUP and CPP, the electricity prices may be calculated quarterly. On the other hand, electricity prices in RTP may vary hourly, as it reflects the generation costs for the generating utilities [2]. In REM, an energy management controller (EMC) is used to control the residential loads with the DR information consisting of electricity prices and incentives. The EMC transmits control signals to smart appliances at home via home area network (HAN).

A micro-grid is defined as a small network of electricity consumers and local producers that is usually connected to the national grid but can operate as independent network of electrical energy [4]. Local generation may consist of renewable and intermittent energy resources such as solar PV and wind. Environmental conditions effect the electricity generation from solar PV and wind, which in turn effects energy prices. Prosumers with renewable energy installations find difficulty in predicting energy production. Moreover, residential usage patterns are also variable and depend on geographic locations, socio-demographic conditions and seasonal variations. Prosumers also need to analyze current and predicted information such as electricity tariffs, generation and demand in order to participate in energy exchange programs in demand side management (DSM). The decision making process is quite complicated for most people to handle manually and the need for data analysis and synthesis is paramount. One of the solutions to integrate and streamline the energy management processes is to apply machine learning (ML), deep learning (DL), and big data analytics.

Various literature reviews have been conducted on residential energy monitoring, building energy management, and smart meter data disaggregation. In [5], building energy management architecture was discussed. In [6], energy usage pattern based on occupant behavior was reviewed. Review articles such as [7] focused on intrusive load monitoring, whereas [8] focused on non-intrusive load monitoring based disaggregation methods. Smart meter data analytics were reviewed in [9]. Above mentioned surveys however, do not focus on residential end-users. Moreover, these articles do not include discussions on publicly available residential energy databases. This study provides a basic overview of machine learning in section

II. Then, applications of various established and proposed machine learning techniques in three major areas of residential energy management are discussed in section III. Section III also includes a discussion on publicly available residential energy datasets. The article is concluded with a discussion on challenges and prospects of machine learning based residential energy management.

II. Machine Learning Techniques

Machine learning (ML) refers to the ability of systems to learn and improve from experiences or data without being explicitly programmed. In general, data or examples are observed to learn patterns and then, improved decisions are made using the learned patterns or features. ML algorithms are generally categorized as: *supervised learning (SL)*, *unsupervised learning (USL)*, *semi-supervised learning (SSL)*, and *reinforcement learning (RL)*. These categories are briefly discussed below.

A. Supervised Learning

In supervised learning, the output for given input is known and the algorithm learns the mapping function from input variable to output variable, shown in Fig. 1. A full set of labeled data is used to train a supervised learning algorithm. Prediction and classification problems are generally solved using supervised learning algorithms. Some popular supervised learning algorithms are linear regression, support vector machine, neural networks, decision trees, random forest etc.

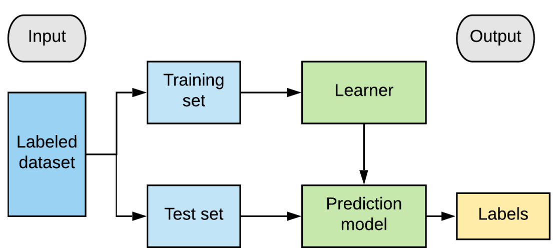

Fig. 1. Supervised learning

B. Unsupervised Learning

In unsupervised learning, unlabeled data is used as shown in Fig. 2. Unsupervised learning algorithms extract useful features and patterns in the given data. Afterwards, data can be organized in various ways. One of the most common applications of unsupervised learning is clustering, where the algorithm looks for data that are similar to each other and groups them together. Unsupervised learning is also used to detect anomalies and to reduce the number of features. Unsupervised algorithms such as k-means clustering, hierarchical clustering, and principal component analysis (PCA) are widely used in energy management research. Recently, unsupervised learning is being used in power systems and smart grid security [10].

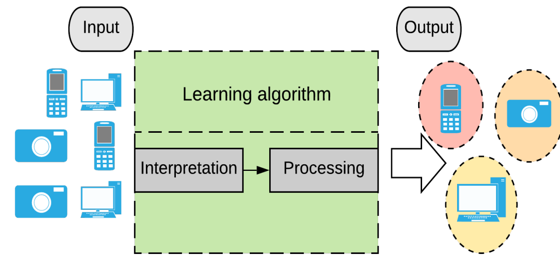

Fig. 2. Unsupervised learning

C. Semi-Supervised Learning

Semi-supervised learning algorithms are trained on a combination of labeled and unlabeled data. Typically only a small portion of the data is labeled, as shown in Fig. 3. Many of the real-world machine learning problems fall under this category. Transductive support vector machines (TSVM), artificial neural network are examples of commonly used semi-supervised learning algorithms.

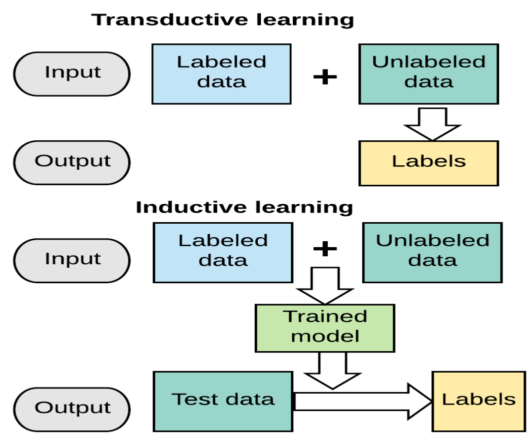

Fig. 3. Semi-supervised learning

D. Reinforcement Learning

Reinforcement learning trains an algorithm with a reward system. An agent (learning algorithm) performs an action in an environment (object), shown in Fig. 4. The environment provides feedback consisting of next state and reward. The agent updates its knowledge and evaluates its last action based on the reward. Examples of reinforcement learning algorithms include q-learning, state-action-reward-state-action (SARSA), deep q network (DQN). Reinforcement learning can be used in cyber-physical power systems [11], and in smart grid security [12].

III. Applications of Machine Learning Techniques in REM

Various machine learning techniques have been applied in residential energy management. Major application areas can be identified as *analysis of load profiles*, *prediction of energy consumption*, and *intelligent load management*.

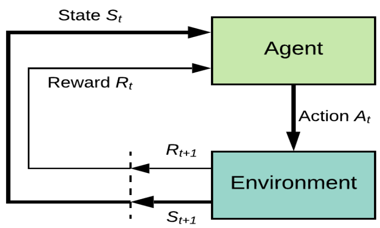

Fig. 4. Reinforcement learning

A. Datasets

Due to privacy and security concerns, the availability of public datasets are scarce. Only a few anonymized datasets are available for research purposes. One of the largest datasets available is from smart metering trials for electricity consumers in Ireland with more than 5000 participating residences. This dataset has been used for electricity theft detection, smart meter data compression and pattern extraction, residential energy usage forecasting etc [13]–[15]. This dataset can be acquired for research and teaching purposes via an on-line application process. A dataset containing the electricity consumption data of a house located in Sceaux, France has also been widely used for prediction and classification studies.

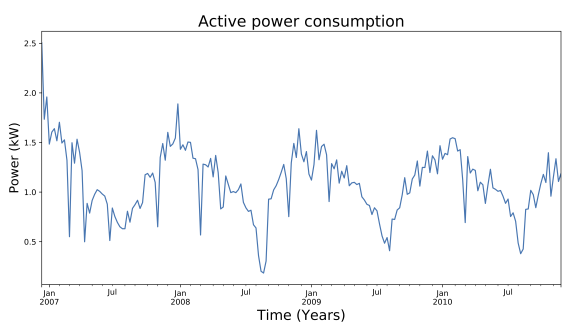

Fig. 5. Active power consumption data of a house in Sceaux, France

Another publicly available dataset consists of smart meter data collected from 5567 London households as part of the *low carbon london* project. Data was taken at half hourly frequency. Electricity consumption data was collected from two groups of customers; one group was subjected to dynamic time-of-use pricing where tariff prices were given to the customers a day ahead. The other group of customers were on a flat rate tariff. This dataset can be downloaded for free from its web-page. Pecan street dataset consists of minute-level electricity consumption data from 500 homes in Austin, Texas. This dataset contains both electricity meter level data and appliance usage data. Pecan street data is available for free to university faculty and students for non-commercial educational purposes. This dataset has been used in [16] to investigate customer responses in incentive-based demand response programs. In [17], pecan street data was used to develop framework for real-time control of aggregated residential energy sources in distribution micro-grids. Various miscellaneous works have been conducted based on pecan street data for short-term load forecasting, segmentation of residences, community energy storage feasibility study, and to develop models for electric vehicle charging demand. Ausgrid dataset consists of half-hourly electricity data for 300 homes with rooftop solar PV systems for a duration of three years. Ausgrid also provides a dataset consisting of monthly electricity usage data from 2657 solar homes and 4064 non-solar homes for the duration of eight years. This dataset is available for free. UMass Smart dataset contains a wide variety of data. For example, it includes minute-level electricity usage data of 400 homes for one day. Electrical (usage and generation), environmental (temperature and humidity), and operational (wall switch events) data are also available. Moreover, minute-level aggregated energy usage data along with ground truth occupancy status data are also present in this data repository. UMass data has been used for power consumption profiling studies in [18], [19].

TABLE I
PUBLICLY AVAILABLE DATASETS

Name	Description
Customer Behavior Trials	Smart meter data
Low Carbon London	Smart meter and time-of-use tariff data
Pecan Street	Residence-level and appliance-level data
Ausgrid Resident	Load and PV output data
UMass Smart	Electricity, occupancy, weather data

B. Analysis of Load Profiles

Residential load profiles typically vary more compared to industrial consumption behaviors. Residential usage also varies both daily and seasonally. Thus, a better understanding of the variability of residential loads is required. The first step towards load analysis is anomaly detection; because a trained machine learning model may become biased due to anomaly in training data. Various works have been done in the areas of bad data and energy theft detection. In [20], optimally weighted average method was used for data cleaning. Clustering methods have also been used to find missing data in [21] where clustering was used on segmented load profiles. In [22], Lambda architecture based on-line anomaly detection method was proposed in order to process real-time smart meter data. Supervised classification algorithms work well to detect energy theft, where the algorithm can be trained to understand abnormal energy usage behavior. In [23], a decision tree model was used to estimate expected energy consumption based on the number of occupants, types of appliances and weather conditions. Then, SVM was used to classify whether the consumer's energy usage pattern was normal or abnormal. Unsupervised machine learning methods can be very useful to detect energy theft, because of the scarcity of labeled data. Optimum-path forest clustering algorithm was proposed and compared with other unsupervised learning methods e.g. k-means, gaussian mixture model in

[24]. In this study, the load profile is modeled as gaussian distribution and anomaly can be detected if the distance is greater than a pre-specified value. Smart meter data have been used in clustering algorithms to classify residences and their load profiles. Popular unsupervised algorithms, e.g. k-means, hierarchical clustering and self-organizing map have been used in [25]. It was suggested in [26] that smart meter data with sample rate of 30 minutes would be reliable for most analytical purposes. A modified k-means clustering algorithm was used to address time-dependent smart meter data in [27].

Research on residential load data has been limited thus far, and is also a difficult task because of the inherent variability. As more and more smart meters are being installed world-wide, further research efforts are necessary on real-time bad data detection, and on real-time load analysis. Two-stage analytical methods, where features from the data are extracted at first, and then fed into a clustering algorithm need to be further investigated due to promising results in terms of speed and efficiency.

C. Prediction of Energy Consumption

Electric power utility companies have been using short, medium and long-term demand forecasting for a long time to support their generation and distribution operations. However, studies on low-voltage distribution-level or individual customer-level forecasting are not so common. In recent years, individual consumer-level load forecasting have received increased attention. The approaches for residential load forecasting can be broadly categorized according to the level of intrusiveness. The measurement devices and sensors can be deployed with various levels of intrusiveness to the residents. In general, two broad categories are defined: *intrusive load monitoring* (ILM) and *non-intrusive load monitoring* (NILM) [7]. ILM uses sensors throughout the residence to gather appliance usage statistics, and weather information. NILM refers to collection of energy usage data from a smart energy meter or a central data logger in a residence [28].

In order to predict appliance usage and energy consumption, significant research work has been devoted to recognize the patterns and behaviors of different household appliances. To aid in appliance recognition, more than a thousand of electrical appliance signatures are available in *Tracebase* database, recorded from 122 appliances spread into 31 categories [29]. In [30], energy consumption of appliances was measured every 10 seconds and appliances were classified using k-nearest neighbors (k-NN) and gaussian mixture models (GMM). The work compares k-NN and GMM with appliances divided into 6 categories. The outcome shows a 85 % success rate in correctly identifying appliances based on their usage patterns using k-NN method. Random forest classifiers have been used to achieve 99.8 % accuracy in recognizing appliances on 14 categories in [31]. Different algorithms such as bagging, bayesian network, j48, naive bayes, random committee, random forest and random tree were compared in [29], [32]. The correlation between behavioral patterns and appliance energy consumption along with anomaly detection was explored in [33]. The work compared performances of bayesian belief network (BBN), support vector machine (SVM), and artificial neural network (ANN) techniques in terms of predicting energy usage based on number of appliances available in the household. The study in [34] proposed a model to predict the probability of an appliance to switch on or off in the next hour. Beyond the simple on/off events, appliance usage patterns were categorized using clustering methods in [35]. Hidden semi markov model (HSMM) was used in [36] to recognize patterns in dynamic residential energy usage. The work showed 30 % energy savings while maintaining optimal comfort levels for the occupants. In [37], both linear and non-linear regression learning models were utilized to predict energy usage patterns based on known occupant behaviors. The authors suggested that linear models show better results although only for short time periods. This is due to the fact that in longer time periods, residents' behaviors tend to change quite significantly.

Although ILM provides in-depth information regarding appliances, there are some disadvantages, e.g. expensiveness, intrusiveness of sensors, large data management, and scalability challenges. NILM with the help of smart meters presents less accurate but less intrusive way of measuring and predicting energy consumption. Smart meters enable distribution system operators to understand and predict individual consumer demands. Smart meters also provide high resolution load data which improves forecast accuracy. However, variability in residential load profiles still remains a significant problem. A study used variants of regression, ANN and SVM algorithms on datasets of two commercial buildings and three residential buildings. It was found that the algorithms predicted the demands for the commercial buildings more accurately. Deep learning techniques such as factored conditional restricted boltzmann machine (FCRBM) showed better forecast accuracy compared to artificial neural network, recurrent neural network and SVM in [38]. The Irish dataset was used in [15] to address over-fitting challenges in training a forecast model. A spatio-temporal forecasting method was used on the pecan street dataset in [39] factoring in the interactions of neighboring residences with the target residence. Clustering was used to forecast residential load pattern based on contextual information e.g. weather, special events, economics and day types in [40]. A case study demonstrated that forecast accuracy can be improved by grouping consumers based on their usage patterns [41]. In [42], persistent forecast, flat forecast, ARIMA, neural network were used to forecast residential loads and it was found that an ensemble of the models produce the most accurate results.

In smart grids, increased distributed generation means accurate demand prediction in distribution sector is a necessity. A big data approach is necessary which incorporates weather information, smart meter data and load transfer data. Research efforts are also required to explore how to combine information and forecasts from different regions or voltage levels.

D. Intelligent Load Management

Intelligent load management includes comfort management, load rescheduling, demand response program management, and customer characterization. Firstly, comfort management increases the building energy efficiency, reduces the cost and carbon emissions. The management of customer comfort depends on the availability of smart devices or flexible appliances, and on algorithmic control of appliances, pricing contracts, and dynamic tariffs with real-time energy monitoring systems. The energy management system needs to be capable of integrating the new methodologies such as demand response, peak load shifting and selective consumption practices from distributed renewable generation. The efficient comfort management depends on dynamic load usage pattern and consumer behavior information. Consumer activities such as cooking, watching TV, or bathing are identified as time critical use of energy or non-flexible applications, whereas laundry, dish-washing etc. are considered as flexible activities [43]. Energy consumption behaviors were explored in [36] using Semi markov model. Energy-plus simulation results showed a 30 % reduction in energy consumption without hampering customer comfort for an indoor conference room. A total of 162 academic papers was reviewed in [44], where both residential and commercial building comfort optimization methods were summarized. The most commonly used computational optimization strategies were generic algorithm (GA), multi objective particle swarm optimization (MOPSO), multi islanded genetic algorithms (MIGA), CPLEX with linear programming, mixed integer linear programming (MILP), and predictive reactive algorithms. The commonly used control strategies were found to be agent-based, adaptive neuro-fuzzy inference systems. Moreover, [45] proposed a multi-agent control system with four types of agents (switch agent, central coordinator-agent, local controller agent and load agent) with particle swarm optimization (PSO) using a graphical user interference (GUI) to ensure the consumers' thermal comfort, visual comfort and air quality. [46] proposed a load control method which detects the peak load and curtails the unwanted load selected by consumer based on game theory. The study demonstrated that the management of customer comfort while reducing building power consumption is one of the biggest challenges for future smart home energy system.

Identification of socio-demographic information of consumers based on energy usage is a major area of research in load management. In [14], linear SVM was used to classify consumers into residences and small-and-medium-sized enterprises (SME). Location, floor area, age of customers and number of appliances were found to be significant factors in deciding the energy consumption in [47], where stepwise selection was applied. Income level and home ownership were found to have little influence on load consumption behavior. In [48], random forest was used to predict energy usage patterns based on a combination of socio-economic status and environmental factors.

In order to implement demand response among consumers and prosumers, evaluation of program suitability needs to be carried out. Moreover, understanding consumer behavior is necessary to develop policies, design tariffs, and conduct marketing campaigns. In [49], hidden markov model based spectral clustering was utilized to estimate variability of consumption along with occupancy status. Consumers with lower consumption variability are suitable for incentive-based demand response programs. On the other hand, consumers with high consumption variability are more likely to adopt price-based demand response programs due to their flexibility [50].

Data-driven deep learning techniques can be useful due to the high non-linearity of the data in consumer characterization problems. Further studies can be conducted to better understand the acceptance criteria for various demand response programs.

IV. Conclusion, Challenges and Future Research Trends

In this study, recent research trends involving various machine learning techniques in residential energy management have been discussed. Highlighted research efforts are geared towards creating a residential energy management system which is intelligent, automated, energy efficient and environmentally sustainable. There are still significant obstacles remain, e.g. the variability of residential load pattern, concerns over data privacy and scarcity of labeled data. A collaborative effort involving consumers, utilities, industries, academia and government institutions is needed to overcome the challenges. Moreover, a combination of weather data, voltage and power flow data, electricity consumption data from different zones, electric vehicle charging data, and survey data is required for further research in this domain. Recent progresses in distributed and parallel computing capabilities mean high resolution data will accelerate the research outcome in this sector.

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