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Short-term smart learning electrical load prediction algorithm for home energy management systems

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HIGHLIGHTS

- A smart learning short-term electricity prediction for households.
- Developed to serve energy management systems.
- Dependent only on the given electrical load profiles.
- Simulink model for real-time simulation with energy management systems.

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ABSTRACT

Energy management system (EMS) within buildings has always been one of the main approaches for an automated demand side management (DSM). These energy management systems are supposed to increase load flexibility to fit more the generation from renewable energies and micro co-generation devices. For EMS to operate efficiently, it must learn ahead about the available supply and demand so that it can work on supply–demand matching and minimizing the imports from the grid and running costs. This article presents a simple efficient day-ahead electrical load prediction approach for any EMS. In comparison to other approaches, the presented algorithm was designed to be apart of any generic EMS and it does not require to be associated with a prepared statistical or historical databases, or even to get connected to any kinds of sensors. The proposed algorithm was tested over the data of 25 households in Austria and the results have shown an error range that goes down to 8.2% as an initial prediction.

1. Introduction

Energy management systems (EMS) represent a main tool for demand side management automation. Nowadays, the financial incentives are the main driving factor that motivates the users to shift their loads. However along with the increase of integration of renewable energies and micro co-generation, an automatic load planning and management system is necessary to increase the grid stability and decrease the burden of DSM on the consumer [1–3].

If the user is depending only on the public grid as a sole energy source, the EMS can shift the load according to the received DSM messages such as a time varying price signal [2,4,5]. Yet, if the user is depending on the public gird along with local energy supply such as a PV system, a need for power and energy demand prediction algorithm within the system will rise. Through providing a prediction for the next few hours up to the next day, the prediction system can show out to the EMS the period in which there is an energy surplus or a deficit. Consequently, the EMS can reschedule the shiftable loads to increase the self-consumption and minimize the imports out of the public grid. Also, it can easily assist the EMS in recognizing the valleys and peaks within the daily load profile to enable peak load shaving. Thus, several EMS and load shifting strategies can benefit out of the proposed system [6–10].

In large scale, from cities and on, prediction could be much easier than in case of buildings or households. The high quality produced prediction on large scale occurs as all the fluctuations of the grid customers add up to provide a more stable profile, but on the small scale every different users' actions affect the forecast significantly. Thus, most of the researcher approaches tend to use artificial intelligence (AI) methods along with a prepared statistical or historical databases, and it was also accompanied in some approaches with temperature and motion sensors to capture the users' behavior. Such approaches are always computationally expensive for the EMS and its not generic for every household (i.e., it requires the

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EMS to be preset according to its location, number of occupants and their life style). Also, these approaches still do not guarantee a global optimal solution, and in some cases (e.g., peak shaving) the EMS does not require a highly accurate prediction, but rather a prediction that identifies different peaks and valleys.

The main goal of this paper is to present a simple prediction system that can easily be integrated and implemented in any EMS within a smart home and which can operate efficiently and accurately while using minimal amount of data, minimal computational power, and without any additional user behavior capturing sensors, or even outdoor temperature sensor. Since the algorithm is designed to work as a part of an EMS, the algorithm works only on predicting the non-shiftable loads which are not controlled by the EMS. The EMS is supposed to be aware already and fully controlling all the shiftable loads, thus no prediction would be needed. Furthermore, the algorithm is self-learning, which means it adjusts itself to the user behavior not only in the next day prediction (i.e., every 24 h), but also on hourly basis to minimize the generated error. Through producing such efficient prediction, the algorithm minimizes risks of any applied demand-side management strategy.

The developed prediction algorithm does not require a prepared historical electrical profile for operation, before being installed in an operational EMS. It continuously acquires data to generate its own database and produces prediction immediately after only four days of operation. The algorithm simply works on clustering the load profile into four load levels, then through measuring the duration and probability of occurrence of each load, it generates the prediction of the next day. The probability of occurrence matrix is created for each hour and day of the year. Thus, the algorithm automatically learns about user consumption for every hour of the day, weekends, weekdays, and yearly official holidays without pre-adjustments or associating any additional databases. Also, it is associated with a live correction algorithm which corrects the day ahead prediction on hourly basis to make up for the continuously changing user behavior.

2. Literature review

Prediction can be divided into long-term and short-term load profile prediction. The long term load prediction is used for understanding the nature of the overall grid customers, developing the grid infrastructure and future generations plans, but the short term prediction is used by the power generation sites as it helps in setting up the least-cost strategy for the short-term generation plans [11–15]. But for the EMS, load prediction has a crucial role in the load shifting decision, as a false prediction might lead to an EMS failure.

For households, long-term prediction is not of a need as the most of the presented EMS in the literature can operate with a 24-h ahead prediction [1,2,16,17]. Thus, a short-term prediction would be sufficient for an EMS.

The common methods used for prediction can be classified into statistical methods and artificial intelligence methods [18]. The artificial intelligence methods include Support Vector Machines (SVM) [19], Neural Networks (NN) [20], fuzzy logic [21], and genetics algorithm [22], but the statistical methods are the techniques which try to relate the load demand to its causal factors through mathematical models. An example of these methods could be the multiple regression methods, Kalman filters, and Auto Regressive Moving Average (ARMA) [23,24].

Several researchers have based their electricity prediction on NN [25–29], as it does not request a definition of the relationship between the inputs and outputs. NN learns itself through the historical data, which increased its popularity in modeling nonlinear patterns [20,30]. Yet, NN training time might vary from a model to a model, also it is exposed to over-training [31]. Furthermore, the NN cannot guarantee generating an optimal global solution. In addition to that, its performance and reliability within an EMS running system cannot be guaranteed [32]. Furthermore, most of the NN prediction methods have associated the input electricity load profile with outdoor temperature, indoor temperature, or motion sensors within the household, so that NN can correlate the electricity load profile along with these data.

For short-term district level or upper level loads, NN method was providing an acceptable results when associated with the outdoor temperatures as presented in the paper of Mirhosseini [33], where a maximum prediction error of 4.94% was achieved. Yet, on a single family household the fluctuations are high enough to lead to a significant error. Another proposal was presented by Chen and Cook [34] to generate behavior-based energy prediction. In the author's used smart home, sensors were installed everywhere in the household to gather data about resident's motion, environment temperature, light level, water and electrical energy consumption. Since the author has installed numerous sensors, he used the minimum-Redundancy–Maximum-Relevance (mRMR) algorithm to extract the most important features out of the sensors' generated data, in another words, to know the features based on which the prediction shall be created. Then based on these features, two main prediction learning models were used, the linear regression model and the SVM regression model to generate the prediction.

While in Bao's approach [35], all household devices were connected to the prediction system to collect information about the current user behavior, then based on it, a 24 h prediction is produced. The author has based his user behavior prediction on two models, the Day Type Model (DTM) and the Semi Markov Model (SMM). It was found throughout the author's research that the devices which have been used regularly would be better modeled using the SMM, like the TV, while the devices that are irregularity used would be better represented through the DTM, like the hair dryer or the coffee machine. This is because the DTM group similar days of use of each device based on the weekday and season classification.

Several papers were presented that used the previously mentioned approaches, or other AI learning algorithms along with statistical approaches to predict even the operation of each single device within the household to build up the whole load profile [36,37]. Consequently, the research approaches were always tending to collect massive amount of information about the user and the surrounding environment, yet the prediction error was lying within the same range.

3. Methodology

3.1. Algorithm overview

The main function that runs the overall algorithm is called Load Monitoring and Prediction (LMP) function. It is presented in Fig. 2. Through this figure, it can be noticed that there are several functions based on which the algorithm operates. The four main functions based on which the LMP operates are the 24-h prediction function, duration calculator function, derivatives clustering function. and live correction function. The 24-h prediction algorithm works toward producing an initial day-ahead prediction every 24 h, the remaining functions work together to correct this prediction throughout the day. In the upcoming sections, details about the operation methodology of each function will be presented.

3.2. 24-Hours prediction algorithm

The 24-h prediction algorithm has been designed to accept, electrical load profile as an input and generate a day-ahead initial