Load Analysis and Consumption Profiling: An overview

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Abstract. Accurate power management in smart and micro grids rely on consumption data analysis to forecast energy needs of consumers. Since demand forecast is necessary to the correct operation of the grid, load analysis and profiling methods are used to generate realistic consumption data. The objective of this paper is to investigate load classification and profiling approaches used to model consumption.
Load analysis is helpful as well to identify factors influencing energy consumption, such as consumers' activity levels and weather conditions. It has been found that houses in urban areas consume more energy, while renewable energies integration is more important in rural areas.
The early approach used for load profiling was Prevalent Engineering Practice (PEP), based on the yearly maximum demand. Due to its unrealistic load curves, bottom-up and top-down approaches are used instead. Although both approaches generate realistic load curves, they have some design limitations discussed herein. Other options for load profiling include mathematical approaches, such as Gaussian distribution function. However, it is important to avoid over-fitting the Gaussian function to keep the model general.

Keywords: Load Profiling; Bottom-up Approach; Top-down Approach; Gaussian Distribution; Load Curve; Load Classification.

1 Introduction

Smart and micro grids combine Renewable Energy Sources (RES), storage and Advanced Metering Infrastructure (AMI) to decrease CO_2 emissions and provide advanced power management capabilities [1-2]. Therefore, power generation, delivery and utilization is improved using optimization techniques [2]. One of the main objectives of these grids is to align demand with supply and schedule power generation based on energy needs as well as power cost and availability. Estimation of load demand cannot be done arbitrarily since both overestimation and underestimation are dangerous to energy generation and conversion systems [1, 3]. Load forecasting and profiling algorithms are hence used to accurately model consumption using historical and real-time data.

The objective of this study is to investigate the research progress in load profiling approaches and assess their performance. First, we discuss the different factors that influence energy consumption then summarize common load types and clusters. Finally, we discuss common load profiling approaches and their limitations. The detailed performance comparison of load profiling algorithms, load factors and clustering algorithms are omitted to conserve space.

2 Factors influencing Power Consumption

Consumer profiling is an important step for load shifting and reduction, and the result is a mathematical model to generate load curves. Load analysis is also helpful to identify factors influencing power consumption. Figure 1 shows an example of a load curve based on the average hourly consumption in Morocco in year 2010 for the four seasons according to data provided by reference [4].

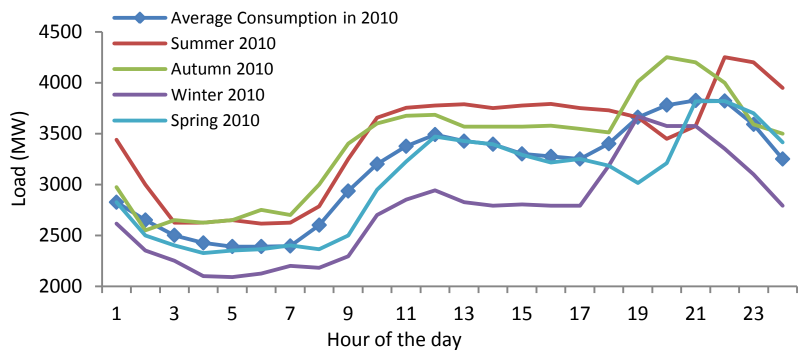

Fig. 1. Residential Consumption in hourly resolution in Morocco for year 2010

According to figure 1, residential consumption varies between seasons, but also throughout the day. The lowest consumption levels are observed in early mornings when people are sleeping. Consumption slowly increases between 7:30 and 10:00 when people get ready for work. A morning peak is observed between 10:30 and 11:30, explained by housework activities. Afternoon and evening peaks highlight the after work, diner and bed time activities. Hence, consumption variations depend on **consumers' behavior** and **activities**. It is noteworthy that the load curve in Morocco is similar to other countries on many aspects, such as Singapore [5] and UK [6], with some small differences specific to each area.

Energy consumption is also affected by the **geographical location**. It has been found that houses in rural areas consume less power compared to the ones in urban areas [7]. Consumers in rural areas use mostly firewood and gas for heating and cooking, with an important RES share. Furthermore, consumers in urban areas use HVAC (Heating, Ventilation and Air Conditioning) systems and more electric appliances.

Another factor introduced by the geographical location is the **weather condition**. Consumers living in countries with a hot climate tend to use air conditioning [8], so a midday peak is observed until temperature decreases. Load curves in countries with a cold climate have a peak whenever temperature drops below a certain value due to heating systems. Hence, load curves follow the patterns of temperature throughout the day. Countries with tropical climates, such as Singapore [5], have a relatively stable temperature, so the impact of temperature is negligible.

Consumption differs also according to the **building type** between residences, offices and universities [9-10]. Energy consumption in offices and universities accounts between 30 and 45% of the global energy demand. Concerning universities, a peak is observed during the day till late afternoon in academic and administrative areas. Another peak is observed in the residential area till late night, when students are back to their rooms [9]. In office buildings, however, a peak is observed between 10:00 and 16:00, then consumption is relatively low and constant afterwards [10].

Finally, energy consumption differs between appliances according to their **brand** and **machine cycle**. A study conducted by Pipattanasomporn et al. [11] shows that consumption is different for the same appliance in different brands. For example, LG washing machines consume less power than the brand GE. It has been shown also that the initial state of the machine affects its power consumption. For example, a cold oven consumes more energy to reach the temperature set by the user.

3 Types of Loads

Classification of loads define energy consumption levels and possibilities of shifting appliances to other periods. It is also useful in understanding the nature and behavior of connected loads. Loads can be classified based on their energy consumption into three major groups: brown goods, white goods and small appliances [12, 13]. Brown goods include relatively light electric devices, such as equipments for offices and entertainment. The second group includes heavy electric devices and major appliances, such as HVAC systems. This group is difficult to model mathematically due to its stochastic behavior. Small appliances refer to light electric devices that are not used frequently, such as blenders and mobile phone chargers.

Loads can also be classified according to their Demand-Response (DR) opportunities and constraints. Some loads can be shifted from the current time period to a later one. Other loads cannot be shifted either because of their machine cycle or the user comfort levels, such as fridges and lighting. The following categories are identified: storage, shiftable, non-shiftable and thermal loads [13]. Clustering loads is used to generate models and extract characteristics for DR applications.

4 Load Profiling Algorithms

To avoid demand underestimation and overestimation, load profiling algorithms are used to model load curves and identify factors of influence. For this purpose, following is a list of common methods for data extraction [14]:

Load curve and Net Load Curve methods: demand of consumers is modeled using the system load curve. Even though these methods are not costly, the accuracy of the generated curve is very low since it does not depict consumption details.

Similar Load Curve and Adjusted Load Curve methods: historical load data is used to model consumption for different consumers' clusters, seasons and days. Demand forecast for a time period is therefore based on historical data on the same time span. The accuracy of the generated curve is higher compared to the first methods.

Dynamic Load Curve method: daily consumption measurements sent by smart meters are used for load profiling. Even though the generated curves are highly accurate, this method remains unattractive to utilities due to AMI installation costs.

Thanks to the balance between cost and accuracy, adjusted load curve method is used to build reference load curves for consumption profiling. One of the early approaches of demand estimation in Low Voltage Networks (LVN) is the Prevalent Engineering Practice (PEP) [15]. This method estimates the maximum load demand in a time window, such as 1 year, based on the maximum yearly demand. It assumes that an individual peak is strictly less than the sum of the total demand at a time T.

A limitation of PEP is the 1-year span used for data forecast, while control is done every 30-min or less. The generated load curve is therefore unrealistic. Also, PEP is not useful for consumption profiling of low-demand periods. To overcome these limitations, other methods were proposed, such as bottom-up and top-down approaches.

4.1 Bottom-up Approach

Introduced in 1980 by Piller et al. [12], this approach builds the consumption curve from the list of individual appliances. The impact of consumers' behaviors and activity levels on the consumption are therefore highlighted [5]. The behavior of stochastic devices, such as fridges, is considered with no need of mathematical modeling. Figure 2-Left shows the flowchart of the general bottom-up approach.

In order to build the load curve, nominal and standby wattages, saturation level and frequency of use of each appliance should be known [5]. The saturation level of an appliance is the probability of availability in dwellings. It is obtained by dividing the number of units of that appliance in the grid by the number of connected households. The frequency of use, on the other hand, depends on the number of individuals in the house and their activities. The energy consumption of an appliance is then computed using all the parameters above (equation omitted because of space limits) [5, 16].

For an example, Table 1 summarizes details about common appliances and their activity levels in the city of Ifrane. In order to gather this data, residents of an average neighborhood were surveyed about electric appliances usage during a day. The appliance activity level is the probability of turning ON an appliance at a given hour, and it is used to compute the frequency of use and start probability of appliances. Because of space limitation, appliance activity levels at peak hours are shown.

Since the bottom-up approach is based on real data about appliances and consumers' behaviors, it generates realistic load profiles suitable for the study of micro-grids. In order to calculate required parameters, surveys should be conducted first to gather data about consumers' activities [5]. Non-homogenous Markov-Chain could be used to model the stochastic behavior of individuals and transitions between states [5]. Since data preparation is an important step in load profiling algorithms (see figure 2), clustering appliances, as discussed in Section 3, could be used for this purpose.

Table 1. Details about Common Appliances and their Activity Levels in Ifrane, Morocco.

Appliance	Saturation	Nominal Wattage (W)	Standby (W)	Appliance Activity Level			
				H-10	H-11	H-12	H-13
TV	1	105	8	0,245	0,546	0,578	0,596
Fridge	1	350	N/A	0,995	0,995	0,995	0,995
Oven	0,85	2150	8	0,002	0,052	0,052	0,004
Clothes washer	0,81	1200	N/A	0,41	0,41	0,37	0,37
Lighting	1	55	N/A	0,001	0,001	0,001	0,001
Iron	0,74	1000	N/A	0,004	0,004	0,001	0,001
Phone charger	1	7	N/A	0,13	0,23	0,35	0,125
Laptop/Desktop	0,825	100	2,5	0,0012	0,0012	0,0036	0,004

Paareto and Lund in [16] use this technique in their proposed 2-step bottom-up approach for micro-grid scheduling. Before execution of the bottom-up algorithm, fluctuations are first analyzed to cluster appliances and define their start and standby times. Social random factor, seasonal and hourly probability factors are then calculated to depict features of the load curve. The first factor models the social impact on the load curve; the second factor models the impact of seasonal changes on consumption, while the last factor describes the activity levels at home.

Researchers in [17] propose a 2-step bottom-up approach as well for office load profiling. First, consumers are classified based on 4 usage profiles: Transient- when a user is a away from his desk; Strict hours- when a user is working; Extended hours- when a user works outside the official hours; Always on- a station should be kept on. These clusters are then used to generate a combined load curve for all profiles.

Even though this approach generates realistic profiles, it has many limitations. From the load data collection in the city of Ifrane, it is found that the algorithm accuracy relies on the availability and correctness of the data. The significant amount of required data imposes a computational complexity and overhead. Additional surveys are needed to properly model consumption on national and special events.

4.2 Top-down Approach

The top-down approach is another load profiling algorithm that starts with a load curve instead [18]. As illustrated in Figure 2-Right, this algorithm analyzes synthetic or measured load data to generate realistic load profiles. The resulting curve is then validated using a reference load curve.

This approach uses statistical functions to derive load patterns. First, the load histogram is normalized by the Cumulative Distribution Function (CDF), then a load distribution function is applied to find an appropriate modeling function. Since load duration has an exponential behavior, an exponentially distributed random variable is combined with the load duration function to generate the curve. Since the power factor is appliance-dependent, active and reactive power correlation is analyzed. Finally, the modeling function is validated using a reference load curve for adaptation.

Even though this approach does not require extensive data about appliances and consumers' activities, it lacks auto-correlation within a single load profile and is not as popular as the previous algorithm. Although the bottom-up approach outperforms this method in peak and curve modeling [19], this approach has less computational time and overhead.

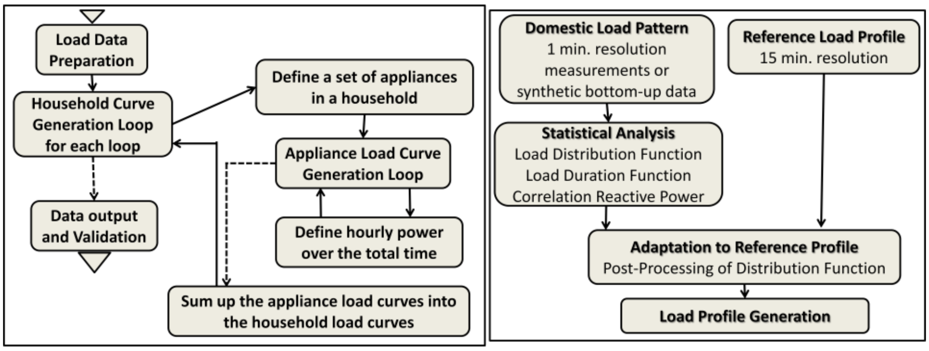

Fig. 2. Left- Flowchart of the Bottom-up Approach; **Right-** Flowchart of the Top-down Approach

4.3 Other Mathematical Approaches

Mathematical modeling is also an alternative for load profiling. For example, Gaussian Distribution Function is used to model the load curve by adapting its parameters to the characteristics of the curve [6, 19]. These parameters are: **a**- controls the height of the curve; **b**- controls the position of the peak center, and **c**- is the width factor.

In order to model the Spring load curve in figure 1, a survey should first be conducted to identify the number of rooms, $\mathbf{N_r}$, and residents, $\mathbf{N_O}$, in each house. These two values are needed to compute the parameters previously discussed. In general, a total of 5 Gaussian functions are needed to model the peak periods: morning, mid-day and evening. From figure 1, one can observe that the mid-day peak lasts longer than the morning and evening peaks. Different from published load curves in European and Asian countries [5-6], the Moroccan load curve is characterized by an important longer mid-day peak that lasts 6 hours, explained by housewives' activities done mostly on that period of the day.

According to results in [6], it has been found that the value of **a** depends on the number of rooms in the house, **b** depends on the activity level of residents, while **c** is inversely proportional to the number of occupants and rooms in the house. When computing the parameters to model the Spring load curve, it can be assumed that $\mathbf{N_r}$ ranges from 2 to 7, and $\mathbf{N_O}$ ranges from 2 to 9. For each combination of ($\mathbf{N_r}$, $\mathbf{N_O}$), an appropriate Gaussian function should be defined, and the sum of single household curves is the load curve of a neighborhood, city or a country depending on the scale.

Using the curve in figure 1 and data from surveys, the times for residents' activities could be defined as follows: $\mathbf{T_1=6}$ is the time at which the first person wakes up; $\mathbf{T_2=10}$ is the time at which the last person leaves the house; $\mathbf{T_3=16}$ is the time at which the first person is back home; $\mathbf{T_4=23}$ is the time at which the last person goes to bed. These values are used to compute **b** (equations omitted because of space limits).

Hence, surveys are still required to find the number of rooms, occupants and activities. Therefore, the accuracy of load profiles still depends on data correctness. Overfitting the Gaussian model is another problem raised by the correlation between parameters **a**, **b** and **c** and consumers' lifestyle. In the discussed example, $\mathbf{T_1}$, $\mathbf{T_2}$, $\mathbf{T_3}$ and $\mathbf{T_4}$ are extracted from the Spring curve, so the resulting Gaussian functions cannot be used to model consumption on other seasons. Also, having a function to describe each dwelling type involves a significant computational overhead.

Another method for load profiling is combining the mathematical model of every device and appliance in the grid to compute the net demand [19]. This method is suitable for micro-grids equipped with RES, so the green energy generation is considered in the load analysis step. However, stochastic appliances, such as ovens and fridges, are difficult to mathematically model, and surveys are still needed to form the list of appliances connected to the grid.

5 Conclusion and Future Work

An important feature of smart and micro-grids is the advanced management capabilities to enhance energy generation, delivery and utilization. Knowledge of demand is therefore a prerequisite to efficiently schedule operations. The estimation of energy demand should be done methodically and accurately since overestimation and underestimation are risky to the power grid. The objective of this paper is to investigate load profiling techniques and approaches used to model consumption.

Load curve analysis is helpful in the identification of factors influencing consumption, such as consumers' behavior and level of activities at home. Load clustering is useful as well in load profiling to classify appliances according to DR opportunities and energy consumption.

Many approaches were proposed for the modeling of load curves for demand forecast. One of the earliest methods used for this purpose is Prevalent Engineering Practice, which builds the load curve using the maximum yearly demand. The generated curve is unrealistic, and the approach is not useful to model low-demand periods.

Bottom-up approach is a popular load profiling method. It builds the load curve from appliances' wattage, saturation level and frequency of use. Even though the generated consumption data is realistic, there is a computational overhead due to the data size, and its accuracy depends on data availability and correctness. On the other hand, the top-down approach builds a load curve based on measured or synthetic consumption data using statistical analysis. It has less computational effort but lacks autocorrelation in a single profile.

Gaussian distribution function is also useful to model load curves by calculating its parameters. However, data about consumers' activities and appliances is still necessary, and there is a risk of over-fitting the function.

As future work, it is interesting to investigate the feasibility and accuracy of modeling load curves using Fuzzy Neural Network (FNN). Since load consumption is related to ambient temperature, number of rooms and occupants and activity levels at time T as discussed in Section 2, they could be used as inputs to FNN to generate aggregate consumption profiles for specific seasons or events.

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