Modeling of power consumption in a small microgrid

Weronika Radziszewska[1], Zbigniew Nahorski[2]

Abstract

Development of energy management systems and models of power grids are popular topics of many research projects. Unfortunately, quite often the behavioral tests with load data are not present. It is due to the difficulty of representing and collecting data about the power usage. To obtain such data it is required to deeply analyze operation lifecycle of certain devices and information about statistics of human behavior, as well as the patterns of people actions. Although many devices time profiles have been published, they lack characterization of variability of behavior and uncertainty. The paper presents some alternative ways to model power usage: probability profiles, rules and a mix of them. The purpose is to create a simulator for testing performance of energy management systems in a small microgrid.

1. Introduction

With the development of new technologies and with the digitalization of many areas of life, the number and variety of electrical devices grows. In larger grids, the influence of single device activity is limited, as the total grid is aggregated so much that small fluctuations often do not appear in the aggregated result. But in smaller ones, like microgrids, this effect becomes much more prominent. This implies that there are more dynamically changing conditions, to which small power grids should preferably adjust. This can be done by introducing intelligent methods of power management. Development of such methods requires appropriate models, as experiments usually cannot be run on existing structures. The models should possibly resemble the real world situations, which requires a thorough understanding of what the consumers do. Some aspects of consumer behavior can be described by patterns (e.g. day/night), but influence of random human behavior is always profound.

With the development of smart grids, there appeared systems that allow gathering on-line information about the amount of power usage. This can help users to smartly save power by shifting its usage towards the time when it is cheaper due to a time of a day or a better availability of power from renewable power sources. This idea is called Demand Response approach to power management [6]. Many studies have been started recently to profit from measurements provided by smart meters, particularly in the residential sector, see e.g. [3]. Within them intensive research have been conducted to identify periods when different devices are active during the measurement time. For this, the measured power is disaggregated to the devices that are generating it. Presentation of these methods can be found in [3, 8, 10]. Simulators described there perfectly reproduce the power usage of the chosen devices, when their activity times are known [3]. But very little is known on patterns of using devices by people. Here, we focus more on human aspect – on modeling how people switch on or of a device. This is connected with creating a simple simulator to represent operations of chosen devices by rules.

Supplementary results of the mentioned above studies are energy consumption profiles of different devices [1, 7, 9]. They were used to categorize devices. [8] classify them as resistive, inductive, capacitive, and non-linear. Zeifman et. al. [15] divide them to permanent, on/off, multistate, and

[1] Systems Research Institute Polish Academy of Sciences, Warsaw, Poland, Weronika.Radziszewska@ibspan.waw.pl, Department of Computer Modelling

[2] Systems Research Institute Polish Academy of Sciences, Warsaw, Poland, Zbigniew.Nahorski@ibspan.waw.pl, Department of Computer Modelling

variable. None of these classifications suits good enough a simulation of human patterns of using electrical appliances.

The problem addressed in this paper pertains to simulation of the electric energy loads in a research and educational center which is now under construction. It was needed to examine an energy management system proposed to be tested in the center. This task is different from those considered in the literature mentioned. First of all, it is not a residential sector and patterns of devices usage depend on many persons and on events taking place in the center. In particular, a considerable part of energy usage in the center is due to intensive computations, see e.g. [11]. Moreover, the center was only in a design stage, so no measurements have been available to help in simulation. Finally, to better test the management system, simulation of the electric energy load with a random behaviors is needed. In this paper data structures that can store characteristic power consumption of different devices are outlined. An idea of a simulator is presented.

2. Modeling power consumption

The power consumption is triggered by human actions. Very often people do not know how much power is used for their activities. A good example of that is power usage in the stand-by mode of the devices: people think it is negligible, but in reality such usage can reach up to 50% of actual usage of this appliance [13]. Recent studies described in [5] show that average user is underestimating power usage of some of his appliances while overestimating others. During that study the power usage of electric clothes dryer was severely underestimated, whereas the power usage of a laptop was slightly overestimated.

Modeling of users behavior regarding the use of electric equipment is especially difficult due to some obstacles that have to be overcome:

- there is a great variety of peoples' actions due to personal differences in habits, location, time, etc. — a research made in one location may be not useful in others. This forces to make research on a larger scale, categorized by social group, place, time, etc.;
- people do not like to be interrogated — questions about how they use electric equipment during the day would reveal their daily activities, in such case it is unlikely to obtain honest and exact replies;
- behavior of people might be extremely erratic — group of people might have a tight schedule, but their detailed actions will be different each day, that suggest a probabilistic or fuzzy models of such actions;
- constant evolution — change of technology is extremely fast, even when people behavior would be predictable, the devices they use are constantly being modernized, in the area of computers and cell phones changes are introduced every few months; as a consequence measured and described usage of power can be outdated soon enough to be unusable.

The power usage of a device can be measured, which gives a lot of information about change of its operating point in time. That would allow making a detailed description of the power consumption. Such description can well define devices which operating cycle is not changeable: for example a toaster. In this case small changes, like the length of toasting, can occur, but that would be just small prolongation of the operation time. But such devices are in minority, usually the conditions of the environment are introducing significant changes in the operation cycle. For example operation of washing machine depends not only on the program, but also on the weight and dirtiness of the laundry and softness of the water. What is more important, it is difficult to measure the frequency when and in what conditions the device is being switched on. That requires long term

observations of different users to derive typical patterns and deviations from the patterns of using the device.

Correlations between operation of different devices also exist. People often act in sequences, for example switch on a television set and make popcorn. The problem of finding this correlations is that people do not think about them, they just do it because it is their custom or a desire of the moment. Description of such relations is difficult and little research is done to discover and formalize them.

Another aspect that has to be considered while describing the consumption is the aggregation level of the power usage. When a city is modeled, the profile of its usage is a sum of all sectors, like commercial, residential, industrial and others. Such data are dominated by daily and weekly cycles. When a village is considered, the aggregated profile encompasses private houses, farms and small factories, characterized by much bigger variability. To model power usage of a household, single devices are considered. In such low level modeling each day is usually different. All of this examples have different aggregation level and their properties and dynamics are distinct, so the method of description has to be different. The big aggregates tend to have less variability between the same times and days of the week during the year, in such case their consumption can be described by profiles. When a single device is considered, the description has to be more detailed, also the distribution of device usage and its operating point must be properly simulated, to achieve useful operation rules or probability profiles. In the next section some methods of describing the power consumption for simulation purpose are presented. Fig. 1 presents a simplified schema of the described methods.

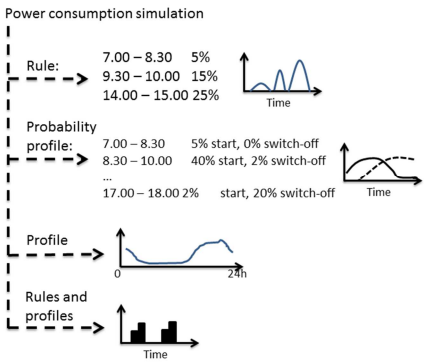

Figure 1: A diagram of different descriptions of energy consumption

3. Profiles

Usage of energy by some devices can be modeled as a profile, which is an approximation of a device energy usage in time. In the digital technology, profiles are defined in a certain time period. The shorter the period, the more exact the representation is. Discrete-time real measurements are divided into time periods $(t_1, t_2, \dots, t_n \in T)$ and then the values that have been measured within this time period are averaged to give one value representing this period of the operational cycle of the device, for period t_i the value is x_i.

Profile can be describes as: $p(x) = [x_1, x_2, x_3, \dots, x_n]^T$. Examples of devices, for which profile modeling can be applied may be a dishwasher, a fridge, heat pumps, a meteorological station or a freezer. Profiles can be also used to represent the sum of small power consumption of devices, for example a set of light bulbs in a large corridor. In this case the small changes in operation of single element does not create big deviation from the profile and with a large number of devices the deviations can level out. Some examples of profiles are presented in Fig. 2.

Profiles describe the typical, average behavior and should not be used when power usage dynamics has to be considered or when a device has very erratic behavior. For example, a weekly profile of a washing machine would be extremely not accurate, as the times and frequency of switching it on vary during the week. The main limitation of the profiles is that their resolution of data is limited. Often half an hour or one hour time periods is assumed, which is often not enough when a quasi real time processing is considered. On the other hand, for some purposes such information can be sufficient and then it is very effective structure to work with. Usual lack of information about the variance within the time period makes it difficult for a simulator to add some randomization in the profile.

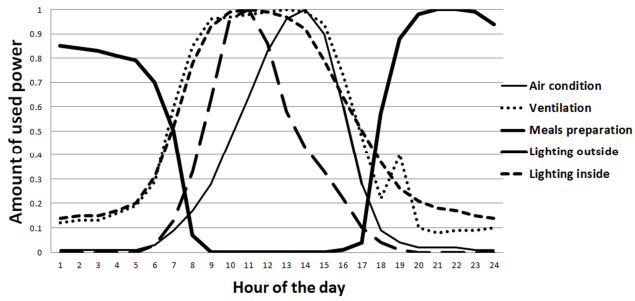

Figure 2: Examples of profiles for chosen categories of devices

4. Probability profiles

Profiles are very suitable and adequate to represent devices which are dependent on time of the day (e.g. light, ventilation). When the power consumption of a device is very volatile during the operation time, the profiles become imprecise and not useful. The main example of a device that should not be described by a profile is a computer — it is a device that once switched on usually stays on for a long time, even when it is not used. This is caused by long starting and stopping time; long time needed for switching on and off the programs; and the false assumption that the components of the computer get used more quickly during the switch on and off phase [1]. When computer is not occupied by the tasks it can enter an idle mode in which it uses around one third of the average power consumption. Users tend to switch on the computer when they come to work and switch it off in the afternoon when they go home, but some groups of people would schedule time consuming operations for night time and then do not switch computer off at all. During short breaks at work people often do not bother to switch off the monitor or printer, not mentioning the computer. So, operation of a computer can vary a lot among different people and different jobs.

For such devices deterministic profiles are not adequate. A proposed solution, that can be used in consumption simulation, is to use probability profiles. In this case, the profile does not present the total power consumption at certain time of the day, but a probability of switching the device on and off, i.e. a probability of incrementing or decrementing the total power used. During the device operation, some random fluctuation of power may be also introduced, if it better corresponds to the device work patterns. It is convenient to use at least two profiles, one describing probability for switching the device on ($p_{on,i}$) and one for switching it off ($p_{off,1}$). Such profile can be describes as: $p_p(x) = \begin{bmatrix} p_{on,1}, p_{on,2}, p_{on,3}, \dots, p_{on,n} \\ p_{off,1}, p_{off,2}, p_{off,3}, \dots, p_{off,n} \end{bmatrix}^T$. Examples of profiles for a device are presented in Fig. 3. As can be noticed, at 4 pm the device considered there can be switched on with 5% probability (if at the time it is inactive) and can be switched off with 20% probability (if it is active). There might be multiple profiles for a single type of device, conditioned on different situations or days of the week.

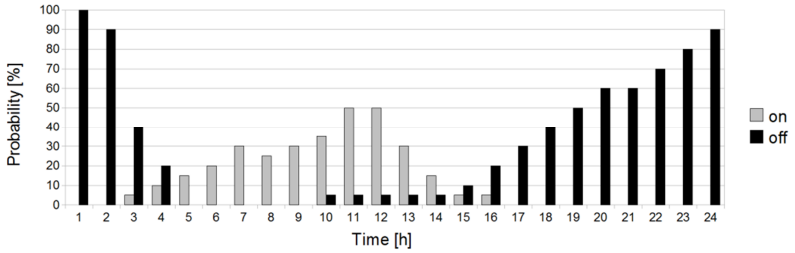

Figure 3: Examples of probability profiles for switching on and off of the device

5. Rules

The power consumption of the devices that do not have typical profiles and do not usually operate for a long time, has to be described differently. An example of such device is a microwave. It is switched on for short moments, maximum few times per day, usually in the afternoon or evening. The time period when the device is working, is called here an activity period. The most exhaustive research results concerning power consumption were presented in [4]. Authors described distributions of devices operation. The power usage in Spain are divided on sectors. Then typical devices which consume powers are defined and their typical operation cycles described. In the residential sector the devices were home appliances like oven, washing machine, television set, etc. The description is focused on typical times when devices are active (e.g. electric kitchen is usually used around 9:00, 13:00 and 21:00 o'clock), probability of using them (e.g. 20%, 10% and 2%, respectively). In our system, to simulate consumption data, a random generator has been used to ensure that each generation will be different, with the expected operation time within some defined limits. This type of description gives large variability in consumption generation. To obtain such rules, detailed studies on a large enough sample has to be done, which is rather complicated and costly to conduct.

A rule is defined by a set of parameters:

- duration – a value describing the average duration of the activity period of a given device,
- time from – the earliest time of the day that the device can work,
- time to – the latest time of the day that the device can work,
- amount – amount of power that device uses during the activity period,
- number of times – a value describing how many times the device is active in a given time frame,
- deviation of duration – deviation of the length of the activity period of the device,
- deviation of time – deviation of the switch on time of the device,
- deviation of amount – deviation of the amount of power used by the device,
- deviation of number of times – deviation of the number of times the device is activated during a given time frame.

An example of simulation using the above rules is presented in Fig. 4. There are four projectors connected to this node, all defined by the same rule:

- duration: 120 [min];
- time from: 09:00:00,
- time to: 17:00:00,
- amount: 0.1,
- number of times: 5,
- deviation of duration: 20 [min],

- deviation of time: 20 [min],
- deviation of amount: 0.1,
- deviation of number of times: 2.

An algorithm simulating such device has to resolve one complication: the device might be switched on multiple times, but the activity periods should not overlap. In this example it is preferred that projector is switched on for two hours, but the situation when it has to be on for twice as much is also possible. To realize that requirement the algorithm uses heuristic method of choosing the time period, by shifting the activity time of the device in such a way that it starts immediately after the overlapping activity period (in case of a forward shift) or that it ends immediately before the activity period (in case of a backward shift). This algorithm is not guaranteed to simulate requested number of activity periods, but it prevents overlapping and distributes the activity periods not uniformly.

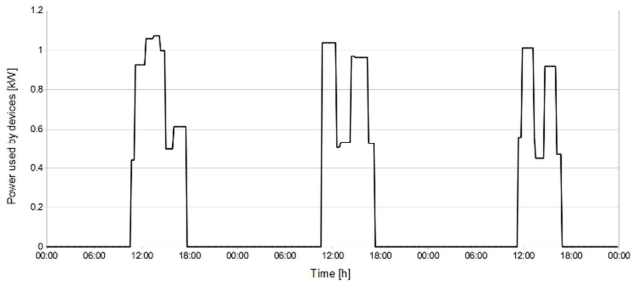

Figure 4: Examples of simulated power consumption in a node when using rules

6. Combination of rules and profiles

Profiles and rules are suitable to represent only a subset of power consuming devices. There also exist devices for which simulation of power usage can benefit from both such descriptions. These are the appliances that are started by humans, but once switched on, they have a fixed operation cycle. An example is a coffee machine. An user switches it on, but the cycle of coffee making is almost the same for all types of coffees. Rules can define a probability of starting an action at certain time. When a device is active, the power consumption during its activity time is described by its profile.

Profiles here are by default short, contrary to profiles from section 2.1, so they are described as a list of couples containing a minute and a value. The minutes represent moments of changes. Starting from an initial time (in this case from 0), the next minutes show how much time later the change in power occurs. Value may represent the percentage of the maximum power usage or absolute power usage of the device.

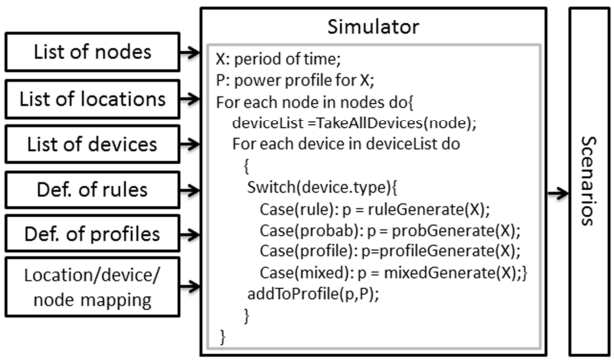

Figure 5: A general schema of a consumption simulator showing data sources, outcome and general description of the algorithm

7. Simulator of power consumption

Using the above presented methods of modeling the power usage, a power consumption simulator intended for a research and training center has been implemented. The simulator is designed to generate load data in a microgrid for a certain period of time, with a given start date and time. Generated data are stored as a test scenario. Multiple repetition of scenarios with random variations of the loads are possible, to allow for evaluation of different statistics of the microgrid performance. The schema of the system is presented in Fig. 5.

A description of the microgrid considered can be found in [14]. The grid consists of nodes that aggregate some group of devices. A node can supply power to few locations, e.g. few rooms, a corridor, few laboratories, hotel rooms etc. A device is connected to a certain node and to a location. Location is important, as power usage depends on the events that happen in it, like a conference in a conference hall. In the microgrid the power usage is considered at nodes, so the power from all devices has to be aggregated in the nodes. The simulator processes each node separately in the order of their numbering by querying all the devices connected to the node. Then the loads of all connected devices are generated in the requested time period and summed up to form the power consumption in the node for each moment. The loads are generated using profiles, probability profiles, rules, or rules and short profiles, depending on device types. The outcome is the power usage profile with required resolution, e.g. one minute. The example outcome is presented in Fig. 6 where 3 nodes were merged. In the presented example the first node has 24 computers and 2 projectors connected to it, the second aggregates 3 general devices and the third one has 4 printers connected.

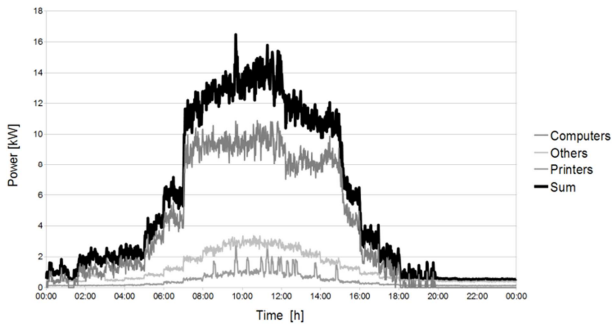

Figure 6: Example of the generated power usage for 3 nodes.

8. Conclusions

Power consumption and human behavior are very erratic and influenced by many factors. There are only scarce studies on typical usage of electric equipment or habits of using such devices. This makes it difficult to simulate consumption precisely enough. That is why simplified methods have to be used. There is no one unique way to model power consumption: profiles, probability profiles, rules, distributions, etc. were used for this purpose. A simulator of energy consumption ought to mimic consumers behavior with all its impreciseness and unpredictability, which requires using probabilistic or possibilistic distributions, possibly combined with fixed profiles. The presented energy consumption simulator is an attempt to look for a system that can describe the full range of behaviors and characteristic of electric devices. To improve the system, it is required to insert real world data of how the power is used by a single device, as well as categories of the devices. There are many different types and brands of devices with different power patterns. Concerning the rules of usage, many people do not want to participate in a study that requires revealing certain aspects of their private life. Thereby, approximations seem to be inherent parts of the approach presented.

Consumption is changing according to influences of different people, social and environmental factors. There is a number of unknown connections and correlations between operation of devices,

which are not included as far in our simulator. For example, in some countries switching on a toaster is positively correlated with switching on a coffee machine. Such knowledge would improve the forecast of power usage, allow making more exact models of power consumption and show where energy is pointlessly wasted. Moreover, having included advanced user behaviors it can be possible to test different demand-side management policies.

However, even such simplified modeling of consumers' behavior is sufficient in testing energy management systems and microgrids models, and the presented simulator gives enough varied power usage data to test energy management system, like the one described in [12], and actually applied in the considered case.

Acknowledgments

The research was supported by the Foundation for Polish Science under International PhD Projects in Intelligent Computing. The project is financed from The European Union within the Innovative Economy Operational Programme 2007-2013 and European Regional Development Fund. The results have been partially obtained in the Polish Ministry of Science and Higher Education grant number N N519 580238.

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