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Energy management in a microgrid using a multiagent system

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Contents

Chapter 1

Introduction

The renewable energy sources developed rapidly over recent years. Production of the energy by many of them is, however, very volatile. This is one reason why the idea of dispersing the sources, within the power grid, is believed to be economically profitable. It is essentially connected with the prosumer concept [34], that is an entity that not only purchases energy, but can also produce and export it to the power grid. With such configuration there appears need for new, efficient, and reliable management systems.

Traditional energy management systems with centralized structure fail to provide well-suited solution to recent distribution generation concepts. This is caused mainly by the traditional system assumption of unidirectional flow of energy, from the distribution companies to the loads, located in the leaves of the distribution grid. Generation of energy inside the distributed grid ruins this assumption, as the energy flows bidirectionally. Thus, need for a new management systems appears [27]. A microgrid can be treated as an aggregated prosumer, which consumes or produces energy. Prosumer-like networks are mainly energy self-sufficient and may work in a so-called island operation mode, but periodically they may buy or sell energy from or to the higher level grid (distribution network).

Efficiency of these subnetworks depends mainly on the power balancing systems. As generators are dispersed in the grid, the idea of a decentralized management system arises as a natural solution. Recently, decentralization of decisions in computer networks is realized more and more often by multi-agent systems [28]. This paradigm is also applied in the energy management system considered in this paper. Agents are associated with devices, like power sources, loads, and energy storages. They have their own knowledge and individual goals defined. Agents communicate with others in order to ensure security of the energy supply, and to reduce (minimize) unplanned shortages or surpluses. Thus, both sides, the supply and the load devices, take part in resolving imbalances of the energy. This forms a distributed energy management system.

The developed multi-agent system aims to balance the differences in short time intervals. Agent-based Power Balancing System for the Microgrids follows the idea given in [20, 21]. The deviations are caused by unpredictable level of dispersed, renewable sources of energy, and by variations of the actual demand.

An auction is a well-suited solution to solve the problem with decentralized, autonomous parties that tend to realize only its own goals. As in the actual trading, particular entities can reach sub-optimal allocation of the goods in the competitive environment, even without the assumption of the shared knowledge. Thus, in the Agent-based Power Balancing System for the Microgrids, the bargaining of the unbalanced energy is performed to minimize differences between actual energy production and consumption. As short reaction time as possible is looked for to suppress imbalance, and to lower the costs borne by devices owner. Thus, a quick auction type has been chosen, viz. the reverse one-side auction. The goal of the paper is to discuss application of this auction algorithm and to present results of its implementation in a simulated microgrid.

Chapter 4

Generators of supply and demand

4.1 Introduction

Countries are strongly supporting installation of new ecological electricity sources to stop the global warming by decreasing emission of greenhouse gases to the atmosphere. Poland is a country that bases its energy production on the coal (over 98%), but the changes are visible – in the end of 2012 there were wind farms for totally 2189 MW, which is an increase of more than 36,9% in comparison with the previous year [32]. The drawback of the green energy is the unpredictability of its production due to weather changeability. This poses a challenge for Energy Management Systems (EMS), that have to compensate for sudden changes.

During creation and testing of an EMS it is necessary to simulate its runs for longer periods and multiple instances, in order to gather statistically significant information on time and accuracy of balancing the energy. Both the consumption and weather conditions have to be simulated. Available meteorological data are usually insufficient for such simulations. Considering a rather short period of measurements of weather data, a method for generating artificial weather data was necessary. A bootstrap [9] is a method for simulating 'artificial' data set by resampling original data and to create an arbitrary number of new data, whose statistical distribution are similar to the original ones. The main problems spotted in early tries of using this method to generate time series were lack of continuity between the parts of data and inability of recreating long-range trends and dependences. The Matched-Block Bootstrap (MABB) method proposed in [10], and later described in

[7] introduced matching the blocks (a piece of time series of certain length) to select the consecutive block in the new series. [29, 15] introduced the k-nearest neighbor bootstrap, where blocks from the k best matching years are sampled randomly. In work [31] proposed to use squared differences of the last values in the blocks as a matching factor, which influences probability of choosing the block. In the present article we propose to use a fitness proportionate selection method (also known as roulette wheel) [6] to choose blocks for creating the simulated data. It is a non-parametric and computationally non-demanding method to create input data of required length, using a limited number of original data. Results of application of the new method to real data are included.

Simulators of consumed energy described in the literature are usually simple as main effort is channeled toward creating management systems for the next generation of electric networks. They usually are based on general profiles collected from few devices. Each device has its own profile of energy requirement that varies in time. The amount of energy used by given equipment can be measured, but the general, statistical data of how frequently and how long people use devices are missing. Attempts have been done to measure the average amounts of power that different groups of consumers use during longer period. A report about the energy usage in Spain [1] is the most complete in that field (in [33] the short summary of the [1] in English is presented). Due to huge differences in culture, climate and wealth of the regions, the results of such research cannot be directly used in simulation of grids in different geographical locations, making the ability to simulate systems in defined localizations difficult.

4.2 Supply simulation

Data sets The data sets were obtained from LAB-EL Elektronika Laboratoryjna [14], a producer of weather parameters measuring equipment, which has a meteorological station near Warsaw, in Central Poland. Out of many parameters measured, particularly interesting for this study were the irradiance, temperature and wind speed.

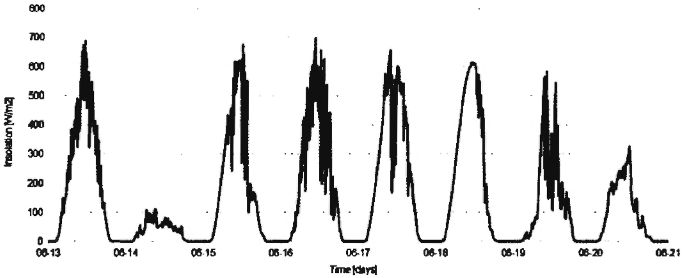

Figure 4.1: Example of measured sun irradiation during few days in June 2010.

4.2.1 Generator architecture

The MABB is used to create new time series from the existing one. It is expected that they should have similar statistical properties as real measurements. The method concatenates blocks (which are pieces of time series of certain length) to create a new series of data of required length. Weather time series are subsequent measurements with time indication. These types of data are continuous in time. To keep the connection between the concatenated pairs, the joining points should be as close as possible, so blocks with similar values at the end and beginning should be chosen with higher probability. A sample of original and bootstrapped time series is presented in Fig. 4.2. The upper time series of wind speed data is the original one and the lower is a series made of concatenated parts from the upper one. Equal length blocks are taken.

4.2.2 Determining block length

Choosing the proper length of blocks is important. It is strongly related to the type of time series that is considered. The matched block bootstrap method requires fixed time period blocks to be chosen from different years, that will be later on concatenated together to create artificial wind speed data of the required length. In a literature the short-term wind speed forecasting for wind reaches from 1 to 10 hours ahead [38]. This gives the boundaries to the

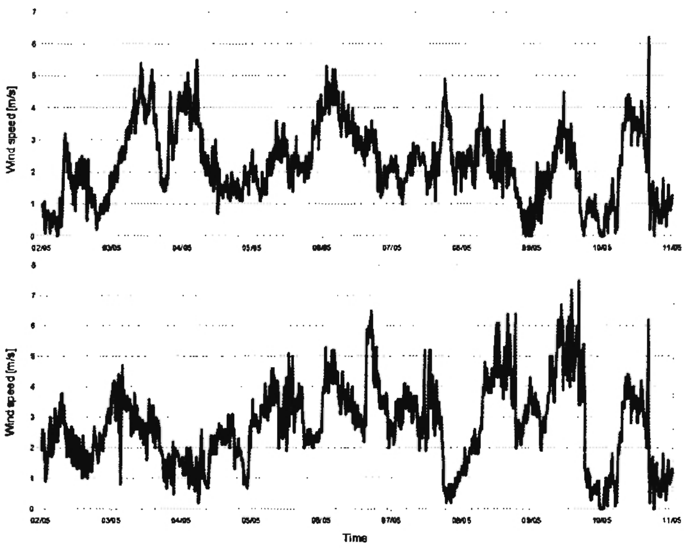

Figure 4.2: Example of original data (upper) and generated by bootstrap (lower).

search for the optimal length of time period used in the proposed method. The autocorrelations of data were calculated for a number of different periods. The outcome was that the loss of correlation rises with the time shift, so the period length of 5 hours has been arbitrary chosen. The correlation values between 5 hour blocks are presented in Fig. 4.4 The matching factor (called also a "feature" in literature) of blocks is defined as the squared difference between the end of the blocks at the same time of a year:

$$d_{i,j} = (r_{i,t} - r_{j,t})^2 \tag{4.1}$$

where i and j are the numbers of the year, and $r_{i,t}$ and $r_{j,t}$ are the last values in the blocks from the years i and j, respectively.

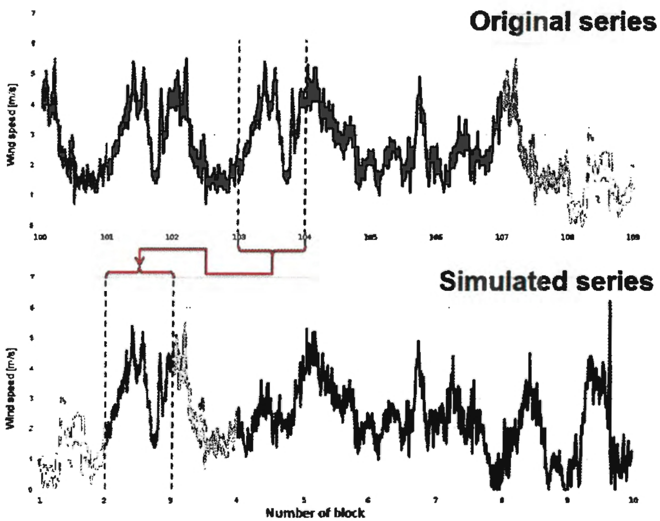

Figure 4.3: The schema of the Matched block bootstrap presented on wind example. The upper time series is the sample of wind speed data, the lower is a bootstrapped time series.

It is different with the irradiance data. Data of irradiance are time series with clear cycles of 24 hours. The most intuitive approach was to define a block as a 24 hour period starting from 0:00 and finishing at 23:59. The problem is that values near to the end and beginning of the block have always value 0. That makes the methods of matching consecutive blocks by similarities of the end parts obsolete and equivalent to the random draw with uniform distribution. The matching factor is therefore defined as the value of correlation between irradiance sequences in two subsequent days of the same year, calculated as ensemble estimates. This correlation is also used as a probability of taking the next day from the same year in the selection method with the inversion operation, described in the next section. The correlation estimates between subsequent days is presented in Fig. 4.5.

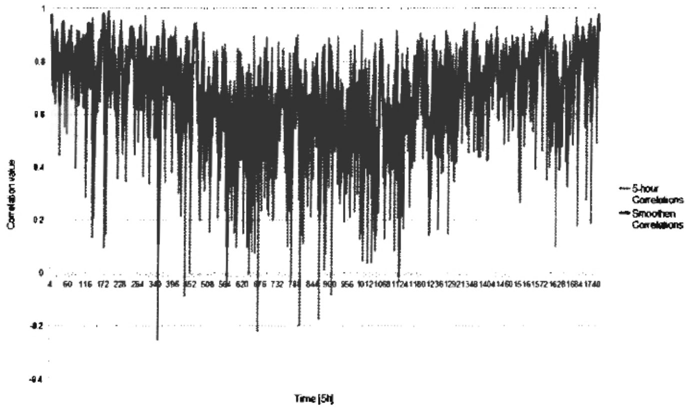

Figure 4.4: The correlation between blocks of 5-hour length for wind data.

4.2.3 Fitness proportionate selection

The MABB method implemented for the purpose of this research is a modification of the one described in [31]. The idea in their paper is to choose the next block out of k nearest neighboring blocks, as proposed by [15]. However, Lall & Sharma used equal probabilities for the choice, while the former authors use uneven probabilities, dependent on a match of the blocks. Our idea is to use the fitness proportionate selection for choosing the subsequent blocks out of the candidates from all years. The method groups the time series by month, day and time. Each year of real measurements is treated as a separate source data. The next block is chosen from the set of blocks with the same time stamp.

The fitness proportionate selection method (often called the roulette wheel) was introduced as a genetic operator for choosing individuals for creation of a set of descendants in genetic algorithms. It assigns a probability to each individual considering its value of a so-called fitness function, which in our case will be connected with the matching factor. The better the match of the individual, the higher is its probability to be chosen. The

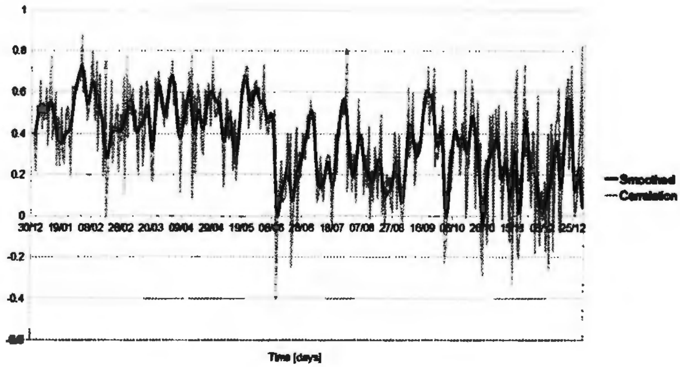

Figure 4.5: Estimates of correlations between two subsequent days for solar irradiance, averaged over all available years (from 2004 to 2012); to increase readability smoothed values of correlation are also presented.

sum of probabilities of choosing all individuals has to be equal to 1, which requires a normalization of the fitness function values. The main feature of the roulette wheel is that even the least fitted individuals have still a small chance of being chosen. This gives better variability to create a series of fairly well matching blocks. This is a desired feature in the generation of time series data, as a small amount of unusual weather conditions improves relevance of testing cases, and therefore its statistical properties in the probability distribution tails. To create the weather generator, two functions were proposed for transforming the matching factor (smaller factor value means better matching) into a fitness function (higher value means better fitness). One is using the inversion operation, the other is using a fuzzy set negation operation, where the factor is normalized and subtracted from 1. In both cases it is then normalized to the [0,1] range. The squared difference is taken as the matching factor. The methods are described in more details in the following subsections.

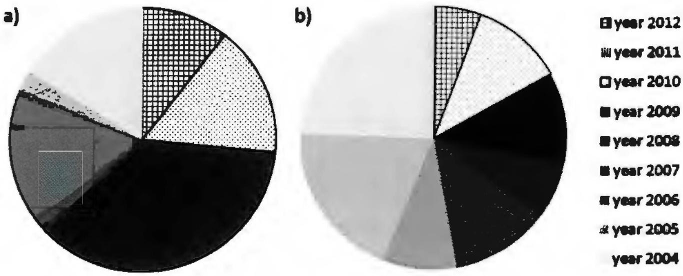

Figure 4.6: Examples of fitness proportionate selection with inversion operator for irradiance for a) 10 Jan 2011 and b) 10 June 2011. Segments represent the probability of choosing the block from a given year

4.2.4 Fitness proportionate selection with inversion operation

The smaller the squared difference between the blocks ends $d_{i,j}$, the higher the probability of choosing the block should be. In the first selection method the following operation is applied:

$$D_{i,j} = \frac{1}{d_{i,j}},\ d_{i,j} \neq 0 \tag{4.2}$$

To get probabilities, these values have to be normalized to the range [0,1]. The normalized values are denoted as $p_{i,j}$:

$$p_{i,j} = \frac{D_{i,j}}{\sum D_{i,j}} \tag{4.3}$$

Each value represents the probability of choosing the j-th block as the succession of the i-th one. The smaller the difference $d_{i,j}$ is, the biggest the probability $p_{i,j}$ of choosing the block as a succession. Examples of the sample fitness proportionate selections with the inversion operation are presented in 4.6.

Fitness proportionate selection with the inversion operation has a major drawback. The difference between consecutive blocks from the same year is always 0, and cannot be inversed. To solve this problem, the decision is done in two steps. The first step of the decision is, if to continue with the next block from the same year or not. The probability of choosing the block from the same year is defined by the absolute value of correlation between the currently chosen block and the successive one. The answer yes terminates the procedure. If the answer is no, then in the second step the inversion selection procedure is applied without the successive block from the same year. If the difference between the blocks is less than or equal to 0.1 (the accuracy of the measurements), the value $D_{i,j} = 10$ is chosen.

4.2.5 Fitness proportionate selection with negation operation

To avoid problems with undefined values, another fitness proportionate selection, with negation operation, is introduced. In this method the squared difference between blocks is transformed according to the following equation:

$$n_{i,j} = \frac{1}{N-1}(1 - \frac{d_{i,j}}{\sum d_{i,j}}) \tag{4.4}$$

N is the number of possible choices of blocks. The values $n_{i,j}$ are normalized to the range $[0, 1]$. Each normalized value is the probability for choosing the block from a given year (denoted as i). In this case the decision is taken in one stage. An example of an outcome of this method is presented in 4.7. This selection rule gives more even distribution of probabilities that the previous one.

4.2.6 Irradiance generator

Irradiance is the power of electromagnetic radiation per unit area incident on a surface. The irradiance was measured using meter LB-900 [14]. The sensor is equipped with photodiode sensitive to visible light. Data are available for 9 full years (from 2004 till 2012), in a 10 minute interval. Exemplary sun irradiance for a few days in June 2010 are depicted in Fig. 1, where the changeability of the solar power measured by the sensor can be seen. Cloud cover is an important factor that influences the amount of sun radiation reaching the ground level. The influence of cloudiness is big and cloudy days can be in the vicinity of sunny ones, which makes the irradiance modeling not that straightforward. Unfortunately, there are very scarce data about the

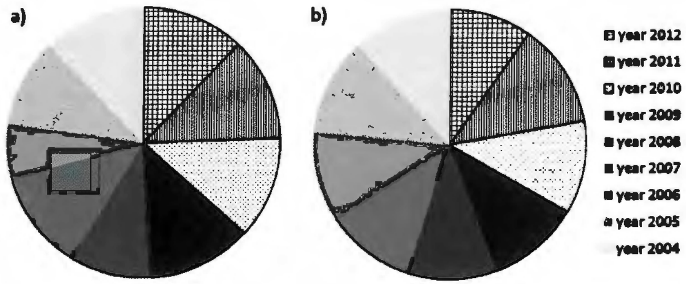

Figure 4.7: Examples of fitness proportionate selection with negation operation for irradiance for a) 10 Jan 2011 and b) 10 June 2011. Segments represent the probability of choosing the block from a given year.

type and dynamics of clouds that could be used for modeling purposes. Due to the fact that clouds move and have different transparency, there is lack of mathematical methods for irradiance simulation. In [25] the irradiance is forecasted using the Weather Research and Forecast (WRF) model, where radiation interactions with air, steam, clouds and climate profiles of ozone and aerosols are considered. The location described in the article is the Atacama Desert, where the influence of clouds and humidity is extremely limited. In this article we use the data about the irradiance measured directly, so no model for cloud cover is necessary.

Temperature is an important factor for photovoltaic panels efficiency. A change of temperature has a small, but still visible impact on the electricity production of the panel. A difference in temperature of 60 degrees Celsius (from -25 to +35) makes a difference of 500W in produced power for 15kW panels, presented in Fig. 4.8. For comparison, the change of irradiance necessary to cause a similar effect is 30 W/m^2. The dynamic of temperature changes is slow and shows very strong seasonality, with averages similar in different years. Taking into account its small impact on panel production and visible seasonality of the data, it was decided not to include the strict dependence on the temperature in the generator, and use only the average temperature for the considered day of the year.

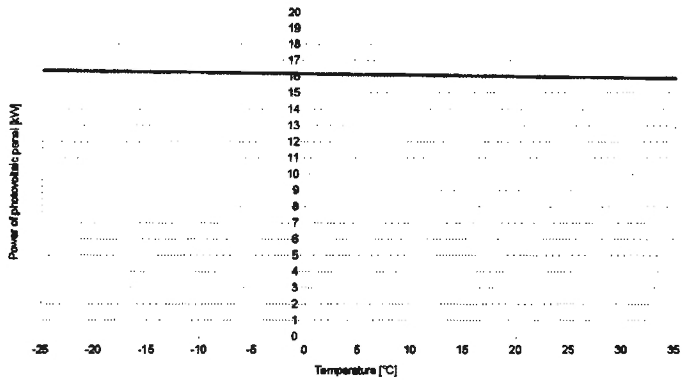

Figure 4.8: Change in production of electric power by the photovoltaic panel in different temperature.

Generated data of solar irradiance statistics are depicted in 4.9. The sample mean, standard deviation, skewness, autocorrelations and histogram are close to their counterparts from real values.

	Mean	Median	Autocorrelation	Skewness	Std. deviation
Inversion	189.2	118.7	0.958	1.03	190.0
Negation	190.	120.2	0.956	1.05	190.8
Real measurements	192.0	119.1	0.954	1.09	195.0

4.2.7 Wind speed generator

For the wind speed the statistics are presented in 4.10. The statistics for the generated and real data are very close. Comparison of frequency of wind speed values demonstrated that generated time series tend to be less extreme than the original one. As can be seen in 4.11 the wind speeds between 0.4 to 5 m/s tend to be equally frequent for all methods, but the wind speeds greater than 11 m/s appeared with much smaller probability using inversion selection method and did not appear at all in negation selection method. Because such values appear extremely rarely (few times in all real time series) it is not invalidating the method and does not influence the statistical qualities

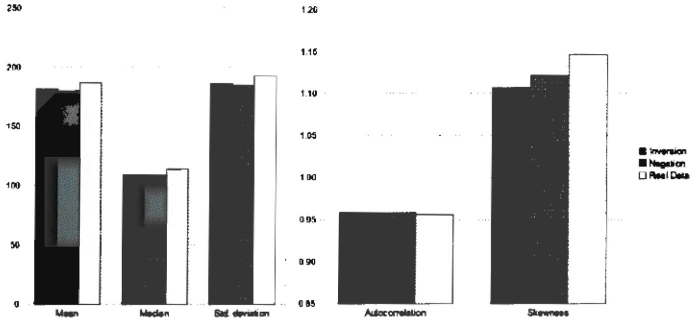

Figure 4.9: Comparison of medians, autocorrelation coefficients and skewness of the original and synthesized irradiance, with exclusion of zero values of irradiance.

of the methods. The results indicate that choice of the selection method is not very important. Inversion operation creates time series that have slightly better statistical qualities, but have a tendency to continue with the same year, if the correlation between the consecutive blocks in some time of the year is high. The negation operation chooses the blocks from different years more often. The method using negation operation is creating more typical and averaged time series, but the extremes still appear.

The amount of produced energy by a windmill depends on the wind speed, the size of the blades and the efficiency of the wind turbine. The required start-up wind speed for the turbine used in our study is 3 m/s, and the optimal wind speed is 11 m/s. The obtained data on the wind speed were available over 10 years, from 2002 to 2012. Wind does not change much between the 10-minute periods, in 19% of the measurements the wind does not change, in 21% it changes by 0.1 m/s. In rare cases the changes might reach even 1.2 m/s, which shows that although the wind is blowing with more or less constant speed, some sudden changes can happen. Central Poland is not a very windy region. Most of the time the speed of wind is between 2 and 4 m/s.

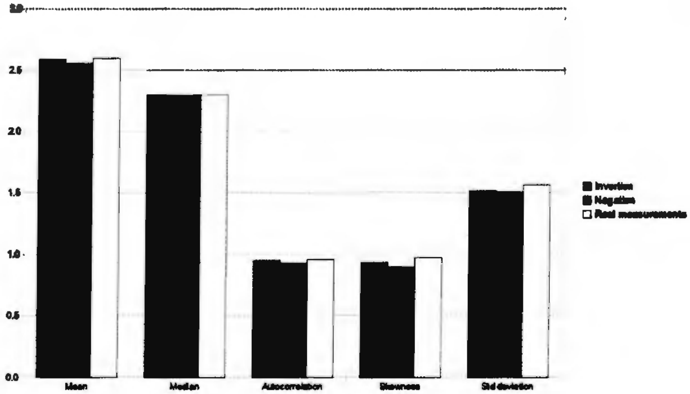

Figure 4.10: Statistics of generated wind speeds as compared with the real data statistics.

	Mean	Median	Autocorrelation	Skewness	Std. deviation
Inversion	2.59	2.30	0.95	0.94	1.52
Negation	2.56	2.30	0.93	0.90	1.51
Real measurements	2.60	2.30	0.96	0.98	1.57

4.2.8 Water flow generator

Research about water flow are extremely important as the water can become great destructive force so its level and dynamic should be monitored. There are a lot of publication about water forecasting and modeling of rivers and water reservoirs. Here the small poer source is considered so we focues on small river. For the requirements of the project the smal river in the vinciity of Warsaw was chosen: Świder. Świder is a river in Masovia and a tributary to the Vistula. It is a river of length about 89 km with average water flow of 4,86 $m^{(}3)/s$. Data were obtained from Institute of Geophysics, Polish Academy of Sciences. Data are form 48 years, from 1961 to 2009, one per day, indicating the amount of water flowing via the river.

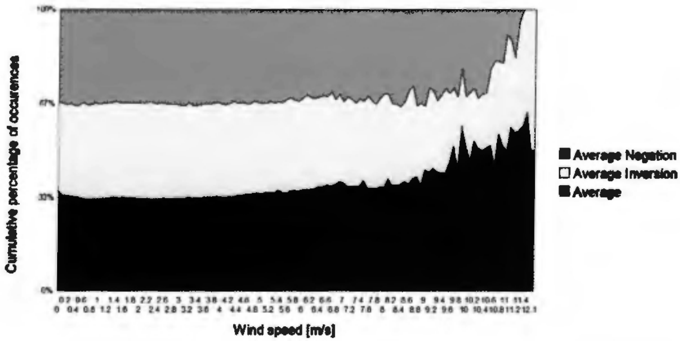

Figure 4.11: Proportion of occurrences of wind speeds in two generated and real measurement sequences.

	Mean	Median	Autocorrelation	Skewness	Std. deviation
Inversion	4.39	2.85	0.88	7.58	6.23
Negation	4.30	2.72	0.87	7.38	5.76
Real measurements	4.25	2.84	0.91	7.28	5.56

4.2.9 Conclusions

Testing is a crucial element of implementation of any computer program. It is particularly important for the multiagent systems that are simulating independent behaviors of the agents and should work continuously for longer time period. Energy management systems are dealing with all type of energy sources and power consuming devices. Many of them have certain work cycles, which depend on the time of the year, the day of a week, or the hour of a day. To perform such extensive testing, the problem of lack of frequent enough weather data is faced. The described generator provides data that include randomness and can produce series of any length. The advantage of this method is its simplicity, fast computation and good statistical properties. The main disadvantage is its high dependence on the amount of available measured data and their representativeness.

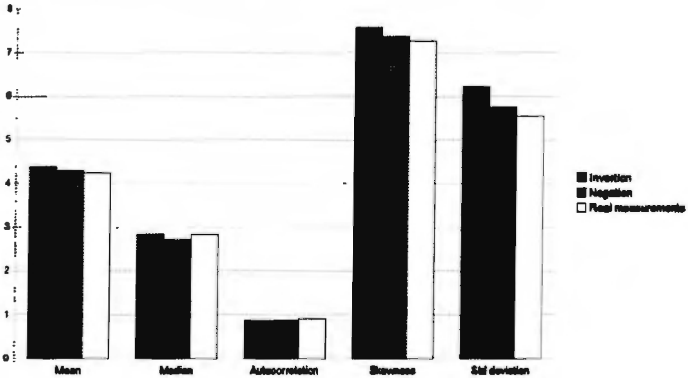

Figure 4.12: The basic statistic of generated and measured statistics of the water.

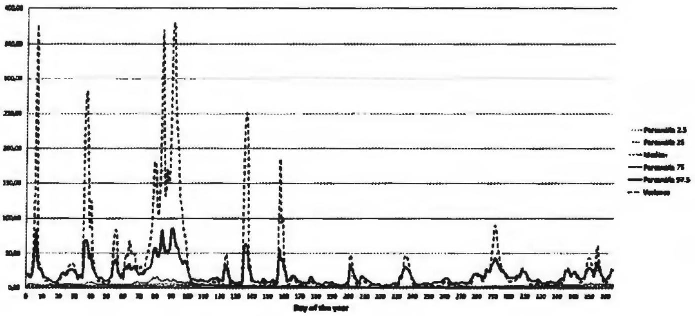

Figure 4.13: The percentiles and variance of the amount of water flowing throug the river Świder.

4.3 Power consumption simulator

Power production has to cover demand and has to compensate for power loses – this balance is crucial for the operation of the networks. If we look from the point of view of high voltage networks the problem can be solved on the level of automatic sensors that would measure certain parameters of the current. On this level the aggregation of consumers and producers is such that only the major imbalances are considered.

When the only sources of power were huge electric power plants management of power in the network was relatively easy. The flow of energy was mainly unidirectional and the power production was centralized, which made it easier to manage the power production. But the constantly growing demand for power forced network to undergo constant modernization. When demand was rising, the prices went up; they increased even more when the world became aware of the ecological problems, in which energy producing sector has its part. Introducing more ecological solutions lead to fragmentation of power sources which requires more advanced power balancing systems.

The undergoing changes are not just in the area of energy production. Increasing prices and ecological awareness changed the way that people think about consuming energy. The energy usage is now an important factor that influences the purchase of new appliances, it is partly due to clear labeling of the average energy usage. The technology of production of most of daily use devices is evolving toward more energy saving solutions, like for example incandescent light bulbs are being replaced by the fluorescent lamps and by light-emitting diode lamps (LED).

With the development of smart grids the ideas for optimizing energy consumption went even further: to ensure the stable current parameters and rational prices for power the consumers have to actively take part in managing the energy usage. Demand Side Management (DSM) emerged as a new interdisciplinary research area. DSM considers some main issues as: convince people to take part in energy optimization, find the best way to communicate them the current status of the network, develop appliances that would be optimizing power without the human intervention.

First issue is about showing people the future problems and make them realize that they can make a difference. But such actions would require adjusting peoples lifestyle to the current situation. If there is a peak of demand, the more people agree to shift their energy consumption (by e.g. not switching home appliances or postponing their lunch) the cheaper and easier would be to cope with peak effects (usually additional power sources have to be switched on just to cover short term demand increase). Second problem is the communication of the network status: how the users know that there is a deficit of power? The most popular way of informing people is by presenting them prices. When there is peak of consumption the price of energy is high and it is lower when there is an excess of energy. That idea was behind introducing peak and off-peak tariffs.

To simplify the consumption management there is an idea to create intelligent appliances that would be proctively delaying or modifying their operation cycles to reduce the power peak. Such devices exist (e.g. washing machines of Miele), but they are still very unpopular due to: lack of trust of people (they do not like the feeling that something is happening outside of their knowledge), high prices and service unavailability in the network (power grid is not yet sending signal to the appliances).

The greatest obstacle of DSM technologies is the lack of preparation of legislation that would allow introducing: retail market, clear rules about exchange of information from smart grid, simpler rules of installation micro sources (both renewable and not-renewable), etc.

The problem of demand management is extremely important as the consumption control and forecast facilitates the power balancing. The context of this work is developing intelligent Energy Management System (EMS) for the research and conference center. The center is the group of few buildings that have connected different power sources [26, 37, 24, 22]. The EMS includes different modules as short-time balancing, planner, model of the network, models of the devices, etc. To test the implemented system of power balancing it was necessary to create a simulation of the operation of the research and conference center which implies simulating power demand in frequent intervals for each node of the network. Simulation of energy consumption is more complex, because there is usually a large number of heterogeneous loads considered. Consumers can be considered at different aggregation levels: from models of single devices, to nodes of the network, whole buildings and bigger structures, as areas and cities.

In a houschold, small microgrids or single buildings it is most common to consider single devices, as oven or microwave [33]. Data about their power usage can be measured, which gives exact information about the dynamic of changes, but considering the large numbers of devices of the same type, broad testing is required to derive the generic usage of some appliances. The authors of this work were unable to find any studies about the characteristic power usage of basic devices. An exception here is a computer, its power usage can be measured on-line using simple software. In larger networks, at levels of groups of houses, general profiles are used (e.g. in [35]). In large networks profiles are grouped by sectors. such as commercial, residential. industrial.

For some purposes the general profiles are sufficient. e.g. in [36] they are used to verify the design of the network. The application had to be made to test the designed system of conference and science center to identify possible overloads or violation of constraints. For that purpose only eighteen exemplary load-flow calculations were designated, with 19 profiles for different categories of loads. Authors of [36] parametrized test by: season (summer/winter), hour (from 11 a.m. to 1 p.m.), type of the day (weekday/holiday), weather conditions (windless and sunless day/windy and sunny day), demand (maximum or minimum) and the state of energy storage units (OFF/charge/discharge). Such parameters combined with power profiles were sufficient to cover all extreme situations, like e.g. extremely high consumption with no production from renewable sources. The tests confirmed that the network was well designed and there is no threat of overload. But such load profiles are not good enough to test the dynamic behavior of the microgrid: values of a profile are 1-hour averages, so there are only 24 different load values for a day.

Profiles for a big group of consumers can be easily derived. as any outstanding or uncommon behaviors tend to be compensated by each other, so they do not vary very rapidly. On country scale, they can be easily obtained from large power producers. Profiles show cycles of daily and weekly changes that reflect the human activities. Night is usually the time of lower energy usage, and peak usage is around late afternoon. Weekends and holidays are introducing disturbances to the working day cycles. Moreover, seasonal differences are visible, caused by different demands: changes in the outer temperatures (e.g. large amount of power is used for air-conditioning), long holiday seasons and changes in labor structure [1].

By contrast, in microgrids, each consumer has a relatively larger influence on the profile than in large grids: a 4kW induction cooking plate will not be visible in profile on the regional level, but can dominate the energy usage in a single household. When a single domestic device can make a change its switch on and off time is visible in the power usage. Averaging power consumption is such situation introduce imbalances, because the usage is changing very dynamically and the most effective would be controlling changes in real time. Thus, profiles are not sufficient for microgrid simulation purposes, because their resolution is usually too small (every hour or half an hour).

The most comprehensive research about the structure of energy usage has been done in Spain [1]. Users presented in the report are divided in 5 groups: residential, commercial, touristic, large consumers and others, with the total contribution of power usage 20%, 6%, 0.5%, 25%, and 48.5%, respectively. These values might differ among regions and countries and depend on the method of categorization. The authors emphasize the big differences in the energy usage between user groups, as for example households, tourist facilities or companies. Other factors that influence the amount and structure of power usage are e.g. seasons of the year (in case of Spain there are 2: summer and winter, but it may differ in other climatic zones), days of week, times of day, months, holiday distributions, structure of labor and economic situation. It demonstrates the difficulty to obtain one reliable description of consumer structure even within small area.

The EMS considered in this work governs a relatively small microgrid. The maximum necessary load does not exceed 900 kW. In this situation, a room where a computer lesson takes place can use easily 4.5 kW, which can be visible in overall balance. Such lessons can be planned and entered to the Planner (see 3.3.2) that would inform energy management system about an increase in power. Power usage of computers in a room, projector, air conditioning and lights are gathered and their average power usage is placed in the schedule for a specific time with a duration of e.g. 1.5 hour. The important thing to remember is that Planner plans energy for the rooms, but one room can be connected to few different nodes: one node would be light, other computers and other general use sockets.

For the Short-Time Balancing System (see 3.3.3), the execution of the task "computer lesson" would mean the increase of power on two nodes of network, the one that would power the computers (which is reserved, i.e. the node has priority in receiving power) and the other for lights and additional equipment. That means that two agents would "sense" the increase of power usage and start the balancing procedure.

The goal was to create a load simulation device that would consider the information from Planner (scheduling in which locations the increase of power is expected), but also simulate the general operation of the devices in micro-grids (e.g. lights in the corridor, air-conditioning) and simulate randomized behavior of people (e.g. switching on and off computers, making coffee). Because Planner and Short-Time Balancing System are operating on different levels the simulator has to operate on the level of single device, and have information to which node device belongs and in which location it is.

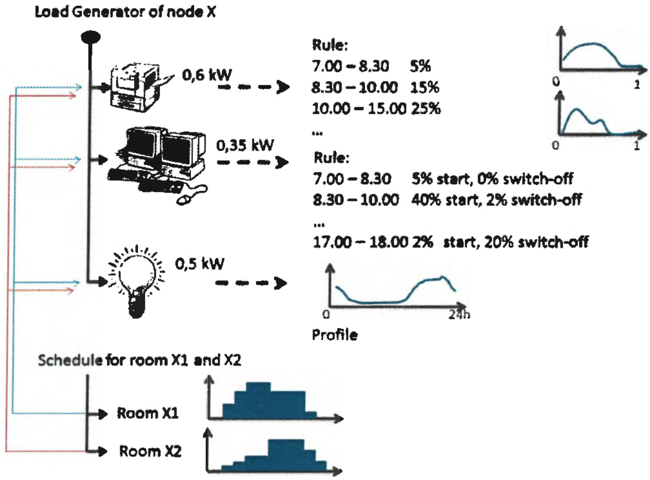

Figure 4.14: A diagram of different possible descriptions of energy consumption.

Simulating the power usage of each device gives much higher accuracy, makes the simulation less abstract and gives possibility to base the model on existing devices, whose parameters might be measured or found in the literature. In [34] a detailed analysis of representative office environment was conducted to test the model designed. 500 electrical devices were identified, mostly user dependent.

4.3.1 Description of consumer behaviour

The modeling of users behavior regarding the use of electric equipment is the most difficult part of simulation. It is due to a number of factors:

- there is a great variety in peoples' actions due to personal differences, habits, location, time, etc. - research made in one place location will be not useful in others. This forces to make research on a larger scale and more detailed considering the social group, place and time.

- 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 – the change of technology is extremely fast, even when the people behavior is predictable, the devices their use are constantly being modernized, which for devices as washing machines or fridges is a mater of years, in the area as computers and cell phones might be a matter of year or two, the point is that once described set of devices might change in few months and for sure it will change in few years. Only the trend of that change can be generally anticipated.

Devices consume power because people placed them there, switched them on and use them. The load simulator, in reality, tries to mimic the patterns of human behaviour. It cannot model the whole complexity of human reasoning, but can derive general patterns and statistical distribution of certain human actions.

4.3.2 Concept of the simulator

The simulator is designed to generate load data for each node for a certain period of time, with a given start date and a time. Generated data are stored as test scenarios which allows to repeat the test with different configuration of sources. The schema of the system is presented in Fig. 4.15.

Data that have to be available for the simulator consists of the schedule made by the Scheduler, the list of nodes with information how many and what type of devices are connected to them, the mapping between devices, nodes localizations (e.g. rooms), the profiles of nodes and individual devices that are connected to a node, and the rules for devices without profiles. The outcome of the simulator are power values aggregated for each consumption nodes of the network, with the sampling frequency defined by a parameter.

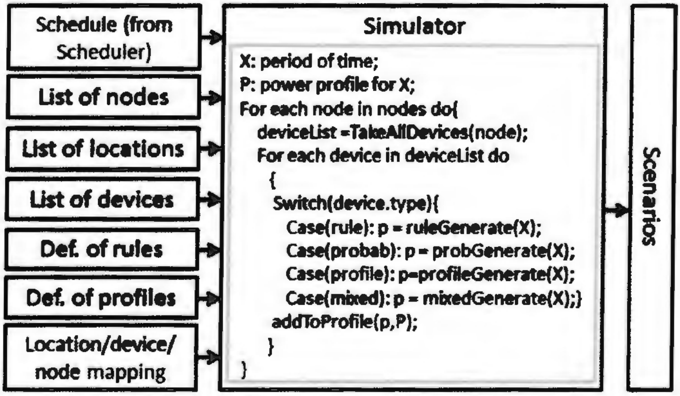

Figure 4.15: Concept of the Simulator of consumption with data sources, outcome and general description of the algorithm.

The simulator processes each node separately in order of their numbering. It queries all the devices connected to the node and then generates for each device the load for the requested time period. Then it sums up all power consumptions of the loads connected to the node, at each sampling time. Each device is processed depending on the type of the device, and the load is generated from the profile or from the rule. The most important factor is the date and the time, as both rules and profiles are parametrized by them.

The devices have defined their type, which defines a way of generating the consumption. The types are:

- Profiles
- Probability profiles
- Rules
- Combined rules with short profiles

Generating methods are described in following sections.

4.3.3 Profiles

Usage of energy by some devices can be described as a profile, which is an approximation of a function of energy usage of the device. Device profiles are made to represent energy usage by a device during a certain time period. Such profiles come from real measurements and are applicable for the devices (or group of devices) that have stable and defined work cycles. Examples may be a dishwasher, a fridge or a freezer. Profiles are also reliable when there are many small consumers of energy, for example light bulbs. In this case a single device has little influence on the overall power consumption and multiple small deviations tend to level the usage.

Profiles define the average, typical behavior and are not suitable to describe events that happen with low frequency or of extreme power usage. For example, the profile of a coffee machine is repeatable and can be measured, but the information of how often and when users make coffees has to be derived from statistical behavior. Simulators based on profiles encounter troubles to represent small variability in the generated data, even when random disturbances are introduced.

Simulator might increase the diversity of generated data by using multiple profiles for a single device, e.g. there might be 10 profiles for a computer. It can be switched on for 1 hour or for 24 hours, might be used for energy demanding calculations or might be in a sleep mode for most of the time. This approach would require a large number of different profiles that would represent certain cases and still would not show all possible combinations.

Each device in the microgrid is connected to the node of the network. Nodes group devices according to their function and location in the building. These profiles were used for calculations of power flow in the network and to calculate possible violation of power constraints in the initial stage of designing the grid. The power consuming nodes were initially divided to general 17 categories:

- air condition in the rooms (1)
- ventilation in the rooms (2)
- preparation of the meals (3)
- powering of the elevators (4)
- external lighting of the buildings (5)

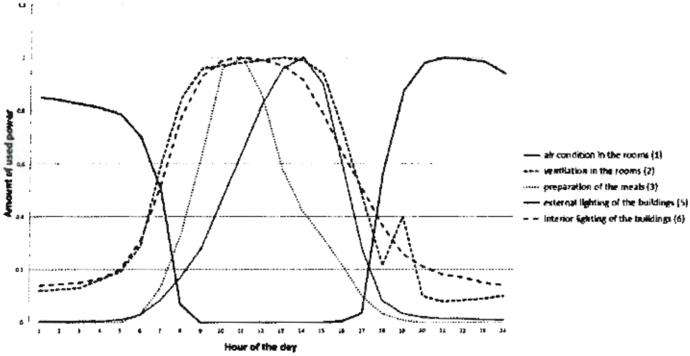

Figure 4.16: Examples of profiles for chosen categories of devices.

- interior lighting of the buildings (6)
- teleinformatic equipment of the buildings (7)
- other consumers (8)
- power feed of boilers (9)
- power feed of circulation pumps (10)
- power feed of cafe equipment (11)
- power feed of hydrophore (12)
- power feed of waste water pumps (13)
- power feed of meteorological station (14)
- power feed of heat pumps(15)
- power feed of the buildings (16)
- power feed of science experiments (17)

During development of the system new categories were added:

- power feed by single hotel room (20)
- power feed by double hotel room (21)
- power feed by empty hotel room (22)

The categories had defined daily profiles, which assigned the percentage of power use by the node with hour of the day, example of the profiles are presented in Fig. 4.16.

The list of categories was made for the defined system, but can be easily expanded if needed. General profiles are useful when considered very regular power feeds or ones that are a sum of power feed of devices that require relatively small power, like for example light bulbs. That is why for generation profiles are used for such categories as heat pumps, meteorological station or lighting. Categories like other consumers or preparation of meals are too general to be fully useful. The main limitation of the profiles is that they have defined one value per hour, which is not frequently enough if the quasi real time processing is considered. Also lack of information about the variance within the hour period makes it difficult to add some randomization in the profile.

Using of the profile is very simple, the algorithm just chooses the proper value from the profile based on hour of the day, adds some small value to randomize the power usage and returns the usage.

4.3.4 Probability profiles

Profiles are very suitable, and adequate to represent devices which are dependent on time of the day (e.g. light, ventilation). When device shows big variance in the operating time profiles become imprecise and not useful. The main example for device that cannot be described by the profile is a computer, it is a device that if once switched on usually stays on for a long time, even when it is not used. This is due to: long starting and stopping time; the long time needed of switching on and off the programs that are needed during work; and the false assumption that the components of the computer get used more quickly during the switch on and off phase [3]. 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 group of people would schedule

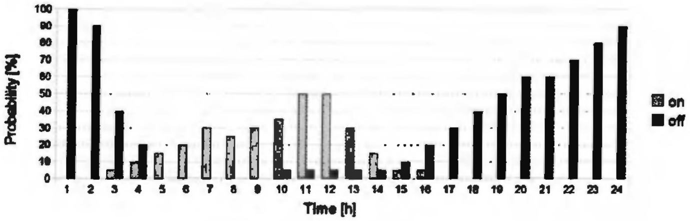

Figure 4.17: Examples of probability profiles for switching on and off of the device.

time consuming operations for night time and then do not switch computer at all. During short brakes at work people often do not bother to switch off the monitor or printer, not mentioning the computer.

For such devices some other way of describing power consumption had to be defined. We propose here describing one device with probability profiles: in this case the profile is not showing the total power consumption at certain time of the day, but the probability of switching the device on and off. For each case of device at least two profiles are needed: one for switching on the device and one for switching it off. Example of the profiles for a device is presented in Fig. 4.17, it shows that at 4 pm this device can be switched on with 5% probability (if at the time it is inactive) and will be switched off with 20% probability (if it is active).

There might be multiple profiles for a single type of device representing different possible behaviors, but each device have to have one pair for probability profiles (if it is described using this category). In the beginning program reads the profiles from database, then calculates which part of the profile apply to the current time (in general situation profile can be defined for shorter periods of time than 1 hour). Then, a random value is generated and, depending of the state of the device, this value is compared to the value of probability of switching on or off of the device. If the device is on and stays on, the value of it energy consumption is changed by adding or subtracting some value from the last state (or average state if the device was just switched on), this value takes values from Gaussian distribution.

The example of working generator for one chosen node is presented in Fig. 4.18. It is the node that has 12 computers and one projector connected

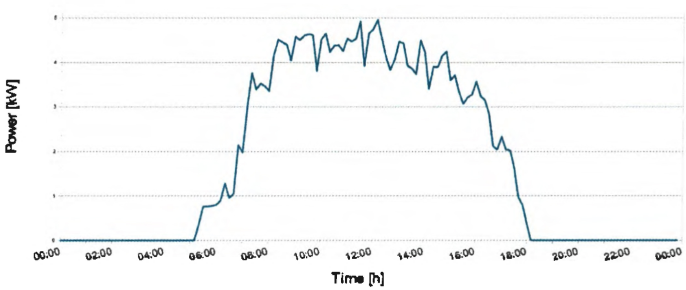

Figure 4.18: Examples of probability profiles for node 189.

to it. Computers are defined by 5 pairs of probability profiles. Consumption of projector is defined by the rule.

4.3.5 Rules

The power consumption of devices that do not have typical profiles and are not working for long time have to be described differently. An example of such device is microwave, it is switched on for short moments, maximum few times a day, usually in the afternoon or evening. The method of describing that behavior may be a probability distribution of switching on the device. That means describing loads by a set of rules. This type of description is introduced in [1] according to the Spanish behavioral data. The work of appliances like dishwashers, ovens, etc. is described by the probability of their operating in a certain time. For example, an electric kitchen (a stove) is mainly used around 9:00, 13:00, and 21:00 hours with the respective probability around 20% at the 21 o'clock, 10% at the 13 o'clock, and 2% at the 9 o'clock [1](page 100). To simulate the consumption data some random generators has to be used to ensure that each generation will be different, but that the average operation time is within some defined limits. User has to be able to define that the microwave operates by average twice a day from 10:00 to 16:00 and on average it is heating up food for 2 minutes.

This type of description might be giving large variability in consumption generation, but this is the expected behavior. Obtaining such rules require detailed studies on a large enough sample, which is difficult and costly to conduct. The advantage of using such approach is that, by increasing the certainty of the behavior, the rule can be easily adjusted .

Rule is defined by the set of parameters:

- duration – a value describing the average duration of the active period of given device,
- time from earliest time of the day that the device can start working,
- time to – latest time of the day that the device should stop working,
- amount amount of power that device uses during the activity period.
- number of times a value describe how many times the device is active in a given time frame,
- deviation of time – deviation of the switch on time of the device,
- deviation of amount – deviation of the amount of power the device use,
- deviation of duration – deviation of the length of the active time of the device,
- deviation of number of times – deviation of the number of times the device is switched on during given time frame.

The example of the simulation using rules is presented in Fig. 4.19. To this node are connected just four projectors that are 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,

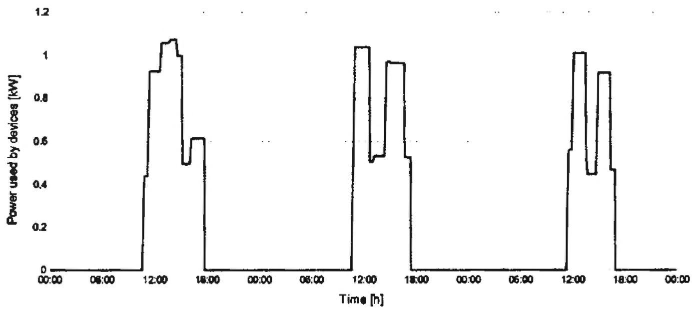

Figure 4.19: Examples of simulated power consumption for node 124.

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

The values for the presented example are input by the common sense, as unfortunately no research has jet been made about the frequency of using the projectors.

Algorithm of generating such data has one major complication: the device might be switched on multiple times, but the periods of switching on should not overlap. In this example we would like that projector is switched on for two hours, we can imagine the situation when it has to be on for 240 min, or 250 min, but we would not like to see it on for 30 minutes. That is why we prefer that the time periods in which the projector is switched on are not overlapping. To realize that requirement the algorithm uses heuristic algorithm of choosing the time period, the time period when the device is active is called activation period. The outline of the algorithm of simulating the devices power consumption from the rule is presented in Alg. 1. The most interesting part of it is the function correctOverlap, which is in more detail shown in Alg. 2. Method iterates through all the set activation periods and checks for overlaps, if the overlap is found it randomly choses if the chosen time should be shifted backward in time or forward. Shifting means moving the chosen start time of the device in such a way that it starts immediately after the overlapping activation period (in case of forward shift) or that it ends immediately before the activation period starts (in case of backward shift). The trick is that each time the shift is made the activation period counter is reseted to initial value, which forces the program to check from the beginning for overlaps. This algorithm uses random shifting and is not guaranteed to simulate requested number of activation periods, but it prevents overlap and does not distribute the activation periods which would look artificial.

Algorithm 1 ruleGenerate()

```
Create empty profile
Find rule for this device
Draw number that indicates how many operation cycles has the device
for i = 0 ; i < numberOfTimes ; i++ do
    duration =chooseDuration()
    chosentime = chooseTime()
    chosentime = correctOverlap()
    addToProfile(duration. chosentime)
end for
```

4.3.6 Combined rules with short profiles

The requirement was that the simulator developed should be as general as possible, to be able to simulate the operation of most existing devices. That can be obtained by combining the ideas of rules and profiles. The example of such description for devices connected to one node is presented in Fig. 4.14. For devices described by a profile, such as a fridge or a freezer, the profile is used. Devices that are activated by a person and controlled by person's actions, are described by rules. Devices that would benefit from both are appliances that are operated by human, but if they are switched on they have some fixed operation cycle. Example of such situation is a coffee machine: user choses the time to switch it on, but the cycle of coffee making is almost the same for all types of coffees. Rules define a probability of starting an action at certain time. When a device is active, the simulator

Algorithm 2 correctOverlap()

```
counter ←0
for j = 0 ; j < i ; j + + do
  if counter>n then
    return null: {It is not possible to find time period when device will
    be switched on.}
  end if

  if chosentime overlaps with previously chosen operation times then
    if randomBoolean == true then
      chosentime ← ShiftForward()
      if chosentime outside of the time limits then
        chosentime ← ShiftBackward()
      end if
    else
      chosentime ← ShiftBackward()
      if chosentime outside of the time limits then
        chosentime ← ShiftForward()
      end if
    end if
    counter++; j←-1;
  end if
end for
return chosentime
```

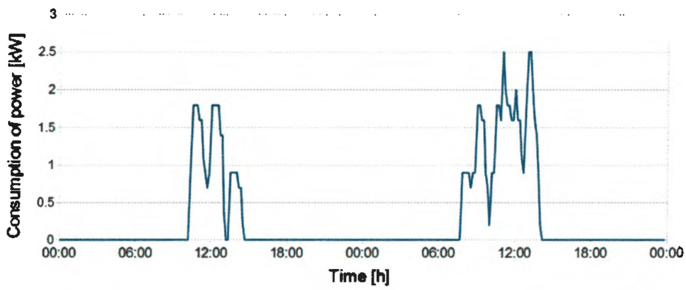

Figure 4.20: Examples of simulated power consumption for node 152.

generates consumption data according to its profile. A rule has the same set of parameters as in section 4.3.5.

Profiles are by default short and unlike in rules from section 4.3.3 they are described as a list of pairs: minute of change and value. The minutes are representing a moment of change: first minute is always 0 and the next entry is showing how many minutes later the change in power occurs. Value represents the percentage of the maximum power usage of the device. Example of the generated profile for node 152 is presented in Fig. 4.20, to this node 4 printers are connected, which have defined rules and profiles.

4.3.7 Conclusion

Testing is an important step in developing EMS, especially when systems work in a microgrid environment, where small changes in load have a big impact on overall balance. To have statistically significant data about microgrid operation, a large number of long-term tests has to be made. A real infrastructure for testing purposes is often not available. Detailed profiles of energy usage of devices can be measured, but they do not reflect the way people use devices. User behaviour is very varied and influenced by many factors. Simulator of energy consumption has to mimic this behaviour with all its impreciseness and unpredictabilities, which requires using probabilistic distribution combined with fixed profiles. Presented energy consumption simulator requires rules and profiles that define device's behaviour. Based on that it creates time series of energy consumption aggregated per node, which is a tool for EMS testing.

It is clear that more efforts should be made to examine the nature of different energy consumers to obtain the statistical distribution of loads considering different social and environmental factors. That would also help to find where energy is wasted and how to avoid it. The next stage of the research is exhaustive testing of the EMS and then connecting it to real devices.

Chapter 6

Conclusion

Impressive changes in electricity grid structures have been initiated by the emergence of new technologies, the new regulations to fight against the global warming, increasing demand for the secure supply of energy and rising prices of electricity. These changes gravitate toward development of renewable energy sources, prosumers and microgrids. Recent research results indicate that it is possible to create an energy self-sufficient community, that can be even selling surpluses of energy. The energy produced by renewable sources is, however, volatile, as it depends on changing meteorological conditions. Also the consumption of the energy in microgrids is proportionally much more volatile than in bigger grids. The problems caused by uncertain production and consumption can be overcome by using the computer based Energy Management Systems.

In this work, a modular distributed EMS is presented. The novelty of the solution presented is first of all in the complex treatment of the problem. It includes two modules dealing with balancing the power produced and consumed in the microgrid. One module solves in advance the task scheduling problem, in order to find a suboptimal way of shifting the loads to be possibly covered by the energy produced within the microgrid. The second module balances the power in the real time by activating both the generation and the load side of the microgrid. For this, it uses the multi-agent technology. Thus, both production and consumption of the energy in the grid self-adapt to the changing energy needs and supply. The reaction of the real-time system is accelerated by using short time forecasts of generation and demand of energy.

The main aim of the system is to optimize (generalized) costs of exploiting the electric energy in a Research and Education Center, which is simulated with a considerable high accuracy to allow for testing the EMS operation. As compared to the simple reduction of the energy bought, caused by straight exploitation of the renewable energy sources, application of the EMS provides savings due to making long-term deals with external power grid, which is cheaper in comparison to trading on the balancing (spot) market, and then possibly precisely following the contracted power trajectory, in spite of disturbances resulted from randomness in generation and demand of energy. In all decision making stages soft suboptimal algorithms are applied, as metaheuristic or multi-agent ones.

Although a Research and Educational Center is considered in the paper, the elaborated system and methodology is of a general character. Many solutions are opened and can be easily redefined. So, it can be applied as well for other grids.

To test the system the insolation, wind speed, water level and consumption simulators had to be designed and implemented. For weather data some specific requirements had to be met: data had to be adequate to the location of the microgrid and had to be calculated fast for long time (more than a year). For this purpose the Matched-Block Bootstrap was used. It is a fairly simple and fast method that generates data that have satisfying statistical properties.

Simulating power consumption proved to be more complex and much less researched problem than weather simulation. The most common method of describing the consumption are 24-hour or longer profiles, which is not enough for system that should balance continuous changes in power levels. Consumption simulator offers different, adjusted to the type of a device, ways of describing the behavior: profiles, probability profiles, rules and combination of rules with short profiles.

There are many aspects that were not yet studied in this work, like short term predictions, trading with external network, demand side management, island mode operation and many others. These are very interesting aspects of smart grids and very important ones. Up to now the research were blocked by lack of testing equipment and inaccessibility to existing smart grid installations.

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