THE APPLICATION OF ARTIFICIAL INTELLIGENCE IN THE PROCESS OF OPTIMIZING ENERGY CONSUMPTION IN INTELLIGENT AREAS

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Abstract: The text describes the optimization task of renewable energy sources distributed to electrical microgrid of fictitious intelligent area that consists of intelligent buildings. Firstly, to solve this task a general optimization heuristic method of simulated annealing will be described. Testing was performed on the analytical functions but those will be only covered marginally. Of the tests on the approximation functions the method of simulated annealing would be the most suitable algorithm for the optimization task. Furthermore, two experiments were introduced. The first lies in the application of cluster analysis on daily diagrams of electricity consumption in intelligent buildings. Because the modeled year history of hourly electricity consumption is represented by multidimensional data this data forms the training set during the adaptive dynamics submitted to a competence model of neural network by days. After the network adaptation process the Kohonen's map during the adaptive dynamics will be drawn, from which required clusters can be read. In the second experiment a sorting design of the resources for typical days of a week is performed in the computer program UniCon.

Key words: *Artificial neural network, self-organizing map, simulated annealing, cluster analysis, type daily diagrams, load prediction, unit commitment, intelligent building, renewable energy, micro grid*

Received: March 31, 2017
Revised and accepted: August 8, 2017

DOI: 10.14311/NNW.2017.27.023

1. Introduction

The objectives of sustainable development (Sustainable Development Goals – SDGs), which were adopted at the UN Summit in September 2015, are a joint development program for all the countries in the world. They include a commitment to eradicate extreme poverty, ensure peace and common prosperity, build partnerships but also to protect the environment. "Sustainable development is development that meets the needs of current generations without compromising those needs of the future

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generations, and without it happening at the expense of other nations" [2]. Energy is one of the three largest cost items in the manufacturing process, and therefore this topic draws attention.

This article is focused on the basic item which is energy management and monitoring. Actually it deals with monitoring and control of the operation of the selected Smart Object (complex of intelligent buildings of residential or office features and of a wide character range of facilities) and their technologies. An intelligent building can be defined as follows: *"Intelligent building is a dynamic and responsive architecture, structurally functional methods of design and building technology, which provides productive, economical and environmentally acceptable conditions to each resident through continuous interaction between its four basic elements: building (material, structure, space), equipment (automation, control systems), operation (maintenance, management and operation) and the relationships among them."* [5]

In this case the electrical energy is distributed in an electrical microgrid of the renewable energy resources. The basic strategy of the energy management is to monitor and evaluate consumption of the electricity on the buildings. Subsequently, we will speak about optimization of energy costs based on the analysis of the energy performance of building operations including sorting the resources on typical days of a week (Wednesday and Saturday). Part of the optimization task will be the justification and then application of the heuristic technique of simulated annealing to solve a particular case (this experiment) with a specialized computer program with the source from C++, which will be presented below.

In this case electrical energy is integrated in the microgrid of renewable energy resources in the composition of: wind energy, water energy, cogeneration, biomass and energy network.

Solar energy represents the vast majority of energy, which is located on the ground and uses. At the outset, it is necessary to emphasize that all the energy on the Earth comes from the sunlight. The area of the Czech Republic is yearly hit by solar radiation of about a million times more solar energy than our annual electricity consumption. Solar radiation can be efficiently transformed into heat, of course the conversion into electricity is more expensive. It can be *directly* generated by using photovoltaic panels, *indirectly* via wind, hydro or thermal power plants burning biomass or biogas. Within the conditions of the Czech Republic we focus on indirect conversion of sunlight so that we approached the reality as much as we can. That means that a brief justification of a particular piece of the electrical microgrid fictitious field of intelligent buildings is in place.

The defining aspect of the application of renewable energy is solar energy, which then affects the components such as biomass, wind energy, hydropower energy and energy of the environment, with the exception of geothermal energy. To understand the nature of the application of renewable energy sources (RES) in the experiment some *basic characteristics of solar energy* are presented.

Let us start with the fact that the overall flow of energy radiated from the Sun is 3.85×10^{26} W. The power density of the energy on the surface of the Sun is $6 \times 19^{7}\,\mathrm{W/m^2}$. The surface temperature of the Sun considered as a black body is about 5700 K. The solar radiation reaches the surface of the Earth atmosphere perpendicularly throughout the year, however, it is not constant and varies around approximately 3 % according to the relationship, where n is the order of a day in the year and The radiant energy that reaches the Earth surface is in the form of diffuse solar radiation and direct sunlight. The diffuse light is not directional in nature but direct solar radiation is directional. It means that direct solar radiation is dependent on the angle of incidence. In technical considerations it must be accepted that a certain portion of direct radiation that is reflected from nearby surfaces has to be necessarily added to diffuse radiation. Then the the total solar radiation relationship can be mathematically expressed as follows:

$$G = G_{\mathrm{b}} + G_{\mathrm{d}}\ [\mathrm{W/m^2}],$$

where G_{b} is direct radiation, G_{d} is diffuse radiation. *Index d* stands for omni-isotropic solar radiation and *index b* denotes that direct sunlight is of a directional character.

Direct solar radiation that impinges on the surface perpendicular to the direction of propagation $G_{\mathrm{bn}}\ [\mathrm{W/m^2}]$ can be theoretically set for the given area from the value of radiation, which impinges on the outer surface of the atmosphere from the following relation:

$$G_{\mathrm{bn}} = G_{\mathrm{on}} \cdot \exp\left(-\frac{Z}{\varepsilon}\right),$$

where Z [-] is a coefficient of air pollution and ε [-] is a factor dependent on the height of the Sun above the horizon and the altitude. The coefficient of air pollution can be determined from a long-term measurement as e.g.

$$Z = \frac{\ln G_{\mathrm{on}} - \ln G_{\mathrm{bn}}}{\ln G_{\mathrm{on}} - \ln G_{\mathrm{b0}}},$$

where $G_{\mathrm{bo}}\ [\mathrm{W/m^2}]$ is direct solar radiation passing through "clean" air (Z = 1, intangible atmosphere) and

$$\varepsilon = \frac{9.38076\left[\sin h + \left(0.003 + \sin^2 h\right)^{0.5}\right]}{2.0015\left(1 - L_V 10^{-4}\right)} + 0.91018,$$

where L_V [m] is the altitude of a place, and h is the height of the Sun, Z is the contamination factor, which is usually set between 2 to 5 or more.

Then it is possible to say that the power and energy of solar radiation that is impinging on the surface are affected by several factors (such as latitude of the location, screen orientation towards the cardinals = azimuth area, inclination of the surface towards the horizontal plane), and factors that cannot be changed such as the motion of the Earth relative to the Sun, i.e. time. Then the total solar radiation $G_{\mathrm{T}}\ [\mathrm{W/m^2}]$ impinging on the general area is according to the relation $G_{\mathrm{T}} = G_{\mathrm{bT}} + G_{\mathrm{dT}} + G_{\mathrm{rT}}$. Direct solar radiation in the area of $G_{\mathrm{bT}}\ [\mathrm{W/m^2}]$ determines the relative position of the Sun and the Earth and from the geometry of solar radiation it is possible to determine the angle of incidence θ of the rays according to the relationship $G_{\mathrm{bT}} = G_{\mathrm{bn}} \cdot \cos\theta$.

The diffuse solar radiation for a given area $G_{\mathrm{dT}}\ [\mathrm{W/m^2}]$ can be determined as the scattered isotropic radiation coming from the spatial park of the sky according to

$$G_{\mathrm{dT}} = \left(\frac{1 + \cos\beta}{2}\right) \cdot G_{\mathrm{d}}$$

and the radiation reflected from the nearby surfaces

$$G_{\mathrm{rT}} = \rho_g \cdot \left(\frac{1-\cos\beta}{2}\right) \cdot (G_{\mathrm{d}} + G_{\mathrm{b}}),$$

where G_{b} [W/m^2] is direct solar radiation of the horizontal plane, G_{d} [W/m^2] is diffuse solar radiation of the horizontal plane, ρ_{g} is the reflectance of the horizontal plane, usually it is considered $\rho_{\mathrm{g}} = 0.2$ and β is the inclination of the collector.

For standard engineering calculations within the context of solution to this experiment a simplified isotropic model is sufficient and meets this process' application of the distributed power microgrid of the RES.

The direct solar radiation of the horizontal plane is determined from the geometry from relation $G_{\mathrm{b}} = G_{\mathrm{bn}} \cdot \sin h$. The diffuse solar radiation of the horizontal plane is determined from the simplified assumption that one third of the sunlight lost in the atmosphere impinges on horizontal plane $G_{\mathrm{d}} = 0.33 \cdot (G_{\mathrm{on}} - G_{\mathrm{bn}}) \cdot \sin h$.

Now different sources of electricity in the microgrid of the RES of this experiment can be defined.

Biomass is a renewable energy source making up for about 10 % of the electricity produced in this distributed microgrid of the fictitious intelligent area of the building complex. The buildings within the intelligent area are defined as intelligent buildings. Production of electricity and heat from biomass has been increasing in recent years in the Czech Republic. In 2015, 2091 GWh of the electricity from the biomass was produced, which is about 2.5 % of total gross electricity production in the country, according to the statistics of the Ministry of Industry and Trade. Roughly half of this amount, 1062 GWh, was produced by burning wood waste, wood chips, bark etc., 688 GWh of the electricity was produced by burning cellulosic liquors and 341 GWh was produced by incineration of the plant materials. Experts predict that by 2020 from 600 to 900 biogas plants will be operating in the Czech Republic. A crucial advantage of using the biomass is that it serves as an energy accumulator because it can be easily stored for long periods of time. From one hectare of the field mass energy content of 40 MWh to 90 MWh can be gained depending on the type of crop. This was the first and fundamental reason for its application in this microgrid of the RES.

Providing that cogeneration units are installed in this microgrid of the RES, the use of biomass is acceptable. Biogas plants generate electricity in cogeneration units. Most often they are modified piston motors, which drive an asynchronous generator and are able to convert electricity from 30 % to 40 % of the energy contained in biogas and about half of the biogas consumption falls on the heat.

In addition, a purposely grown biomass brings benefits from the perspective of improvement of landscape ecology as well — it allows an efficient use of land. I agree with the importance of biomass as one of the most used renewable energy source in the forthcoming future. The potential of biomass is within the range of 9–12.5 million tons of dry matter per year based on studies. From this amount, from 5.1 to 6.5 million tons of residual biomass is instantly available. At present, the estimation of the Ministry of the Environment claims that about 1.9 million tons of the biomass is used, which represents a third of the potential of the residual biomass and a fifth of the viable biomass potential.

The use of biomass is linked to traditional agricultural production – for instance biogas plants came originally into existence due to a disposal of problematic agricultural waste not because of the profit. That means that in no way the biogas plants do not represent speculative investment and that there is no threat of massive growth due to lower prices of the components or any other factor.The only risk is a wrong setting of the purchase prices that would have a similar impact to end consumers of electricity as photovoltaics had. The development of biomass can be predicted by the analysis of the Action Plan. The action plan applies only to the Czech Republic. The Action Plan foresees 417 MW of installed capacity of biogas plants in 2020, although some studies estimate possible potential of up to 200 MW in 2020–21, i.e. roughly three times more than in the Action Plan. The Action Plan predicts an increase in energy production of a mere 1/25 of purposely grown energy crops of estimated potential by 2020. On the contrary, the woody biomass is expected to increase twice. The potential study anticipates the reverse share of biomass used for energy (roughly 4 to 1 in favor of biomass from agricultural land). The facts mentioned above and evaluation of the effectiveness of the biomass use in electricity and heat production decided that the biomass would be used in this microgrid of the RES with reference to the plan of action it is only valid for the Czech Republic.

From a broader perspective, one can say that central electricity production and district heating is on the wane. A development of new technologies based on Smart Grids – in other words decentralized low power energy sources with high utilization of renewable energy sources and combined heat and power generation – is on the rise. That means that thermal insulation and use of automation and regulation decreases the demand for heat and that the heat consumption of hot water and electricity are stagnate. On the other hand, the demand for possible backup power in the place of consumption increases. These facts lead to an increase in local security of thermal and electrical needs of the buildings and areas in the final form of the Smart Cities.

In the Czech Republic from the perspective of the electricity production from renewable energy sources, biomass contributes with over 80 %. Therefore, this experiment is designed to use the most common way that are specialized biogas plants that produce electricity, heat or biomethane. The biogas plants are based on agricultural products as corn silage, grass silage, or agricultural residues. Biogas contains about 55 % to 70 % of volume percentage of methane; the heating power is somewhere between 19.6 and 25.1 MJ/m^3.

Wind energy is currently at the proportion of less than 6 % of the energy produced from the renewable sources, but on the other hand it also has a promising development potential. *Wind energy* in the Czech Republic currently participates in the production of electricity for less than 6 % of the energy produced from renewable sources but on the other hand it also has a promising potential for development.

A use of wind has sufficient reserves and the prognostic viewpoint states that in 2020 it should be possible to produce 13 % of total electricity consumption from renewable sources. In this case reaching this point would mean meeting the objectives within the European Union (EU), i.e. 2.6 milions MW h of electricity. Providing that wind energy will never be essential in the Czech Republic and that prognostic targets can vary widely, this topic will be therefore considered as closed. Because the wind energy is clean energy, which when applied can lead to a reduction of CO_2 emissions and increasing energy self-sufficiency, this RES will be applied in this microgrid of the RES. This is also a parameter that decided about the deployment of the wind energy in the microgrid of the RES in this experiment.

Primarily, wind energy is the most environmentally friendly and efficient as for the climate protection thanks to the fact that it reduces the production of the greenhouse gases. This method uses inexhaustible wind energy, which is completely for free, and therefore not subjected to inflation. When it comes to the return of investment, in the case of wind power plant (WPP) it is very fast comparing nuclear and coal power plants. The time for which the WPP produces as much energy as was consumed for its production is between 6 to 12 months while the lifespan of the WPP is about 20 years. Due to the reduction of unit costs per kWh from the wind it can be expected that during the forthcoming few years the prices of the electricity produced from wind and coal should align.

This experiment is basically an insular system that is "independent" of the grid. Because the wind power plants installed in the microgrid of the RES do not exceed 500 kW, see Tab. I, then the mast is not higher than 35 m and the ensuring procedure pursuant to the EIA (Environmental Impact Assessment) does not have to be carried out. However, erection of a mast must be carried out in accordance with the assessment of the environmental impact and is usually required for each project. The effect on the landscape, birds and noise is usually assessed.

This microgrid is in accordance with the potential approved by the Government of the Czech Republic. While keeping certain criteria, it is estimated that up to 1200 MW will have been installed by 2020. From my point of view these factors are crucial for construction of WPP and to streamline any further development a good media image of WPP is vital. *In 2020, the action plan envisages the installed capacity of only* 743 MW*. This number should be roughly doubled.*

Hydroelectric power. Hydroelectric power plants in the Czech Republic do not have too much potential for development left but they still have a major share within the renewables. Electricity generated by hydroelectric power stations is about 50 % of the total volume produced from renewable energy sources. Czech streams do not have necessary head of water nor sufficient amount of water therefore the share of electricity production by hydroelectric power stations in the total production in the Czech Republic is relatively low. Performance of a turbine depends on head of water, water flow and turbine efficiency.

$$P = \rho \cdot Q \cdot g \cdot H \cdot \mu \quad [\mathrm{W}],$$

where ρ is the density of water (1000 kg/m^3), Q [l/s] is the flow rate, g is the gravitational constant (9.81 m/s^2), H [m] is the head, and μ is the efficiency of a turbine.

Hydroelectric power plants are divided according to installed capacity into small hydro power plants (SHPP) – up to 10 MW, medium – up to 100 MW, and large – over 100 MW and according to head into low head – to 20 m, medium head – from 20 to 100 meters and high head with height over 100 m. This micro-grid of the RES uses hydroelectric power depending on where it is situated. It is assumed that this experiment will be located approximately at the level of the characteristic head, i.e. up to 10 MW, which means a small hydropower plant (see Tab. I). Basically it is an additional source of electricity. A cross-flow turbine along with a modified single Francis turbine is used in these small hydro power plants with difficulties.

In the Czech Republic, the total of 1614 small hydropower plants (HPP) with a total output of 348 MW is installed. In addition to conventional hydroelectric power plants three pumped storage plants with a total installed capacity of 1175 MW are operated.

Most of small hydroelectric power plants serve as a seasonal source of energy. The flows on which they are set up are volatile and appreciably dependent on weather and season. However, it is possible to predict their production fairly accurately based on a daily or weekly basis. This fact was also crucial to their application in the experiment. The Action Plan envisages the development of these plants because the untapped watercourses are simply too small for large hydroelectric power plants. Finally, I emphasize that the Action Plan envisages a slight increase in installed capacity of small hydroelectric power plants in the performance category of 1 MW (55 MW over the current 140 MW) between 2010 and 2020.

Cogeneration. A combined heat and power generation is called a cogeneration. It is a very efficient way of using heat from a primary source, which would otherwise remain unused. Cogeneration units are installed in biogas plants hence they occur in the micro-grid of the RES.

The selection of cogeneration units in the micro-network of the RES is built on the following conclusion, which summarizes its benefits: Significant savings in primary resources and far lower costs for its purchase; Significant savings in distribution because a cogeneration unit is located close to the place of consumption; Traffic ecology because of a significant primary sources savings – there is significantly less exhaust and thus a smaller environmental harm and finally its application in a program tri-generation (heat, cold and electricity).

Another contestable advantage of cogeneration units in the micro-grid of the RES is a benefit for the environment. The cogeneration reduces the production of SO_2, NO_x, CO, CO_2 due to the savings in losses of primary sources. From the relation:

$$\frac{M_x}{Q_s} = \left(\frac{m_x^{\text{výt}}}{\eta_{\text{výt}}} - \frac{m_x^{\text{tep}}}{\eta_{\text{tep}}}\right) + e\left(\frac{m_x^{\text{el}}}{\eta_{\text{el}}\eta_{\text{re}}} - \frac{m_x^{\text{tep}}}{\eta_{\text{tep}}}\right),$$

where M [kg] is the reduction of the emissions of the substance, m is the size of the emissions produced by combustion of fuel, indexes 'výt', 'kj', 'el' express the relationship with the heating plant, a cogeneration unit and a condensing power plant; the index 'x' indicates the type of emitting substances [11]. Furthermore $\eta_{\text{výt}}$ is the efficiency of the heating plants, η_{tep} is the efficiency of the heating plant, η_{re} is the efficiency of the electricity distribution from the remote micro-grid of the RES to the consumption place, η_{el} is the efficiency of the power plant and $e = E_{\text{tep}}/Q_{\text{s}}$, where E_{tep} [GJ] is the amount of electricity that is delivered from the heating plant to the consumer and Q_{s} [GJ] is the amount of heat that is delivered from the heating station to the consumer.

Sustainable development of human society which depends on energy resources logically requires a focus on the RES. To what extent will the RES be implemented into the process of existence of human society and its continued growth and identification with sustainable development depends on the erudition of the humanity. One of the major ideas is the relationship with the environment and efficient energy management. Minimization of costs of energy consumption is the alpha and omega of sustainable development. An intelligent building and its integration into Smart Cities represent room that is suitable for application of these ideas. The effective process of energy production and consumption is key issue that this article deals with.

2. Unit Commitment

The task of unit commitment is an optimization problem with a goal of minimization of total costs of production of energy given by the prediction of its consumption for the considered period, sampled e.g. by hours. In other words, this constitutes a plan for sorting sources and their generated outputs covering the predicted consumption in each hour of the given period.

The task of sorting sources of electrical energy produced in the system of RES distributed in microgrid is defined by the optimization procedure to minimize total cost of production of desired amount of energy. The volume of produced electricity is determined by the prediction of its consumption within the considered period sampled by hours. In other words, this constitutes a plan for the sorting sources and their generated outputs covering the predicted consumption in each hour of the given period.

The optimization problem can be in general formally expressed as follows [12]:

$$f : \mathbb{R}^n \to \mathbb{R}, \quad \Omega \subset \mathbb{R}^n, \quad f(\mathbf{x}_0) = \min_{\mathbf{x}\in\Omega} f(\mathbf{x}), \tag{1}$$

$f(\mathbf{x}_0) = \min_{\mathbf{x}\in} f(\mathbf{x})$ – functional regulation (how the function is supposed to work), where for function f there is a functional value $[\min_{\mathbf{x}\in\Omega} f(\mathbf{x})]$ in a point $\mathbf{x}_0$; where $\mathbf{x}_0$ is an argument of the function, i.e. a chain of "*independent variables*" and $[\min_{\mathbf{x}\in} f(\mathbf{x})\ ]$ is functional value.

Here:

$\mathbb{R}$	–	set of real numbers,
$\mathbb{R}^n$	–	set of the order tuple of the real numbers: $n = 10$ (n-various outputs),
$f(\mathbf{x}_0)$	–	for a function f there is a point $\mathbf{x}_0$ with a function value $[\min_{\mathbf{x}\in\Omega} f(\mathbf{x})]$,
$\mathbf{x}_0$	–	it is a functional value $[\min_{\mathbf{x}\in\Omega} f(\mathbf{x})]$ where $\mathbf{x}_0$ is an argument of the function, i.e. the string of "independent variables" and $[\min_{\mathbf{x}\in\Omega} f(\mathbf{x})]$ is a functional value, i.e. "dependent variable"),
Ω	–	specifies the area of admissible solutions containing the optimum as given by operating-technical parameters of sources,
f	–	represents the cost function given by a sum of operating and start-up costs (see Fig. 1) for sources integrated in the given period (Fig. 1 a, b), and mathematically expressed by Eqns. (2) and (3).

$$f(P(t),\mathbf{x}(t)) = \sum_t \sum_i \left(A_i + B_i P_i(t) + C_i P_i^2(t) + D_i \left(1 - \mathrm{e}^{-\frac{\Delta T_i(t)}{\tau_i}} \right) \right) x_i(t), \quad (2)$$

$$f(\mathbf{x}(t)) = \sum_t \sum_i (A_i P_i(t) + B_i P_i^2(t))\, x_i(t) + C_i x_i(t)(1 - x_i(t-1)). \quad (3)$$

where

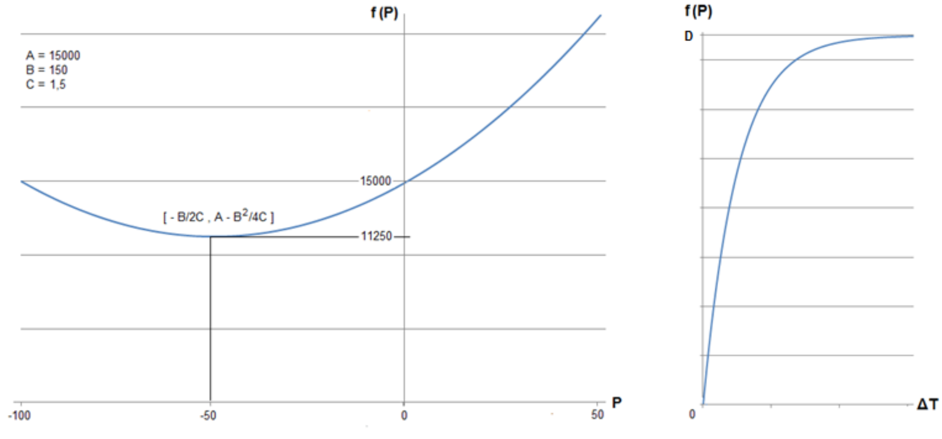
i	–	index of the source (in this experiment there is N-sources of electrical energy from the renewable energies, $i \in \{1, 2, \ldots, N\}$),
t	–	it is a time, in this case it is a time of a scheduled mode of sorting sources which is $T = 24$ hours (time mode is scheduled hour after hour, $t \in \{1, 2, \ldots, T\}$),
$P_i(t)$	–	it is a power of i-th source in time t,
P_i	–	it is a power rating of i-th source, i.e. same for the entire observed time (time is set for 24 hours)],
$x_i(t)$	–	a state of i-th source in time t (in this case it is running – that means a state "1" or it is shut off, i.e. a state "0"),
A_i	–	cost coefficient,
B_i	–	cost coefficient,
C_i	–	cost coefficient,
$\Delta T_i(t), \tau_i$	–	time of a downtime and a constant of time of an exponential increase of increasing costs of i-th source in time t); they occur only in Eq. (2),
N, T	–	number of sources in the network and number of time sectional views considered in the period of running of the sources.

This computational experiment is in general mathematically expressed by Eq. (1) and the objective function (objective function also called a cost function) is suggested by *the solution of optimization* by Eq. (3). The reason for this is that power generators (power sources) only work on rated power, there are no requirements for their power options within a defined power range (then it would be based on relationship given by Eq. (3) – in this case, other cost functions are accepted). From the perspective of mathematics this experiment is a task of programming with integers, especially bivalent. That is why its solution is going to be focused on heuristic probability method – *simulated annealing.* The principle of simulated annealing will be described in Sec. 3.

Independent variables of objective functions are $(x_1, x_2, \ldots, x_n)$, where n is the number of generators in this experiment. The status of each generator is either "0" – the generator is off or "1" – the generator is turned on.

Note: The purposeful (cost and consumption characteristics) function is given by the "mathematical approximation" of economic indicators obtained empirically (empiricism). The cost characteristics are expressed either graphically or with a help of algebraic relations – from measurements or statistically processed data. The cost characteristics can also be constructed from consumer characteristics.

Now the mathematical expression $x_i(t)(1 - x_i(t-1))$ will be explained.



a) *b)*

Fig. 1 *Dependence of the operating costs on the electricity production [12]. a) Dependence of operating costs on fuels for the production of electricity, b) Dependence of startup costs for downtime (graphical representation of function* $(1 - \exp((\Delta T_i(t))/\tau_i))$*. $f(P)$ – Start-up costs; ΔT – Downtime; D – Operating costs.*

A part of the mathematical expression $x_i(t)\,(1 - x_i(t-1))$ from Eq. (3) can be explained using Fig. 2, that shows the time of receiving an order for running or shutting off the sources of electrical energy.

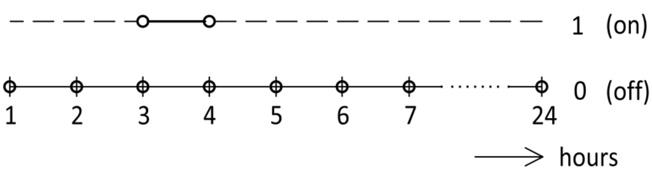


Fig. 2 *Start-up of the sources.*

The cost function is divided into:

(a) $(A_iP_i + B_iP_i^2) \cdot x_i(t)$ – operating costs,

(b) $C_ix_i(t)(1 - x_i(t-1))$ – running costs,

where

i	–	resource index (in this experiment there is a total of N sources of electricity from RES, $i \in \{1, 2, \ldots, N\}$),
t	–	is time, in this case, the time of planned resource sorting mode, which is $T = 24\,\mathrm{h}$ (time mode is scheduled after hours, $t \in \{1, 2, \ldots, T\}$),
$P_i(t)$	–	is the power of the i-th source at time t,
P_i	–	is the nominal power of the i-th source at time t; in this case it is the rated power of the source, that means that it is the same for the entire monitored time (the time in this case is set to 24 hours),
$x_i(t)$	–	is the state of the i-th source at time t (here it is operating so "1" is assigned, otherwise "0" would be assigned),

A_i, B_i, C_i, D_i	–	are the cost coefficients (because this purpose – cost function is given by Eq. (5), the coefficient D_i is not considered). Cost coefficients are in CZK,
A_i	–	cost factor [CZK],
B_i	–	cost factor [CZK/MW],
C_i	–	cost factor [CZK/MW^2].

(that means $\Delta T_i(t)$ and τ_i is the downtime and time constant of the exponential increase in the cost of the i-th resource at time t).

N and T is the number of network resources and the number of time slots in the considered resource deployment period respectively.

If we break the load function into a form so that we could describe the significance of individual coefficients:

Thus, the operating cost of the output producing power can be expressed by the relation

$$P = A + B \cdot P + C \cdot P^2 \quad [\mathrm{CZK}].$$

This relation is written without expressing running costs D. In other words, relation (3) is simplified because the generators (sources) are always in the state $x_i(t) = 1$.

Then, the individual cost items mean:

A	–	cost independent of an output (power source e.g. some photovoltaic systems) [CZK],
B	–	costs dependent on an output (e.g. fuel quantity dependent on the higher output) – [CZK/MW]; example: $B_i \cdot P_i =$ [CZK],
C	–	costs dependent on the second power of output power [e.g. Loss Joule's heat]. Q arises in a conductor (winding generator) through which the electric current flows for a period of time t that is under voltage. The losses are the greater the larger the current passing through the conductor (the winding of the generator). Joule's heat is then: $Q = RI^2t$ [J]. Those could be further losses in iron, losses due to the friction etc.[CZK/MW^2]
P	–	output power [MW].

For acceptable or tolerable solution to the cost function (the objective function) (3) a mathematical expression is utilized with the following inequalities possibly equalities:

$$P_i^{\min} \le P_i \le P_i^{\max}, \tag{4}$$

$$\sum_i P_i(t)\, x_i(t) = C(t). \tag{5}$$

Inequalities and equalities (4) and (5) are the conditions laid down for solving the cost function (2). For this experiment the cost function (3) is used and it is determined by the condition

$$\sum_i P_i x_i(t) = C(t), \tag{6}$$

where $C(t)$ indicates the expression of the predicted consumption in a specific hour of a defined period, $\sum_i P_i x_i(t)$ – a total production of electrical energy (the sum of all the outputs over all generators) at time t.

Then it is possible to write an equation that expresses the goal. Modification of Eq. (6) gets a relation for a limiting condition of the cost function

$$g\left(\mathbf{x}(t)\right) = \sum_i P_i x_i(t) - C(t) = 0. \tag{7}$$

Limiting condition (6) can be received for direct integration into the objective function f_g, for instance the following ways (8) or (9) – the conditions (4) and (5) are not applicable in this experiment, they would be applicable in the case of application of objective (cost) function (2):

$$f_g(\mathbf{x}) = f(\mathbf{x}) + w\, g^2(\mathbf{x}) \approx \min, \tag{8}$$

$$f_g(\mathbf{x}) = f(\mathbf{x}) - w\, \mu(g(\mathbf{x})), \tag{9}$$

where

$f(\mathbf{x})$	–	objective (cost) function,
$wg^2(\mathbf{x})$	–	penalties for unsolicited supplies,
w	–	value of function $g^2(\mathbf{x})$ (defines the conditions of the cost function, i.e. puts into numerical proportions the costs and the balance deviation, which is a parameter that is set programmatically),
μ	–	fuzzy number zero.

If function $f_g(\mathbf{x})$ in Eq. (8) approaches the minimum, which is also of our interest and it is a task of the optimization, then we are dealing with a *balanced power balance*:

1. If it is strictly insisted that production equals consumption (state level) $\rightarrow$ there will be a feasible solution.

2. Proceeded to a temporary extension of the set of admissible solutions, followed by a solution according to step c).

3. It is permitted to have a little tolerance between the consumption and the production because from all the connected sources such a performance cannot be gained at the time of need. For this reason, there is a possibility of composing individual power sources, so that the performance required at any given time approaches as much as possible the fuel consumption.

4. The solution that little tolerance ΔP between the consumption and the production was admitted.

3. Simulated annealing

According to the results in [6] simulated annealing is one of the most successful traditional stochastic optimization algorithms. Each function call is used for searching for state space; which means that there is no need for an unnecessary call of the objective function. In principle it works like this: During the simulated annealing global state space is searched for at first, because later on (at a lower temperature there is a lower probability of accepting a worse result) the simulated annealing becomes more of a local character.

Simulated annealing is algorithm [7] that uses *sequential random searching*. The principle of the method is following: A randomly acceptable result $\mathbf{x} \in \mathbb{R}^n$ is picked and then sets the initial temperature to $T = 1$, see Algorithm 1.

Algorithm 1 The principle of simulated annealing – its algorithm written as a function of C++.

```
double MetropolisAlgorithm(double xini, double kmax, double t)
{
    double k = 0;
    double x = xini;
    double pr;

    while (k < kmax)
    {
        k++;
        xt = Opert(x);
        pr = min (1, exp(-(f(xt)-f(x))/t));
        if (rand() < pr) x = xt;
    }
    return x;
}

double SimulatedAnnealing(double tmin, double tmax, int kmax, double alfa)
{
    double x = RandomlyGeneratedState();
    double t = tmax;

    while (t > tmin)
    {
        x = MetropolisAlgorithm(x, kmax, t);
        t = alfa * t;
    }
    return x;
}
```

Let us think of a hypothetical system described with n-dimensional state $\mathbf{x} = (x_1, x_2, \ldots, x_n)$, where x_i belongs to an interval. The states of this system are valued with function f that assigns the value $y = f(\mathbf{x})$. The task is to find such a state $\mathbf{x}_{\min}$, in which the function f takes the value of the global minimum.

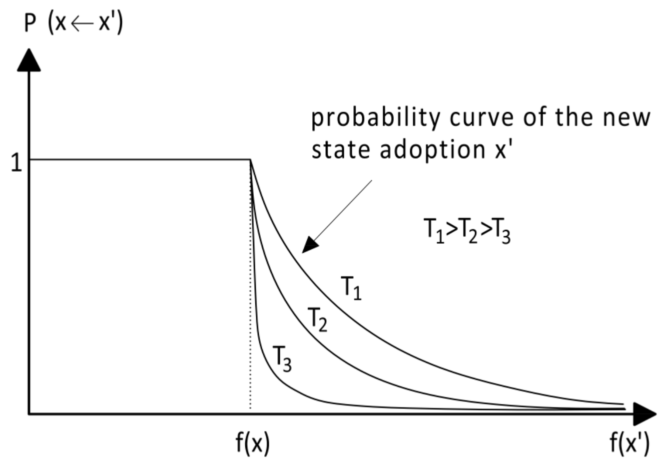


Fig. 3 *Metropolis scatter.*

Let $\mathbf{x}$ be an acceptable state of the system that enters a new state $\mathbf{x}'$, formally $\mathbf{x}' = O_{\text{pert}}(x)$, where O_{pert} is "the operator" of a fault – perturbation. The question whether a new state is going to be accepted into the new process is solved by the "Metropolis criterion" see Fig. 3, the Metropolis algorithm [5] respectively, that sets the probability of a substitution of the old state by a new one. The relation is as follows:

$$P\left(\mathbf{x} \to \mathbf{x}'\right) = \begin{cases} 1 & \text{for } f(\mathbf{x}') \leq f(\mathbf{x}) \\ \exp\left(-\frac{|f(\mathbf{x}')-f(\mathbf{x})|}{T}\right) & \text{for } f(\mathbf{x}') > f(\mathbf{x}) \end{cases}, \tag{10}$$

where T is a parameter interpreted as a "temperature".

In case of new state $\mathbf{x}'$ of a smaller or the same function value as initial state $\mathbf{x}$, the substitution of state $\mathbf{x}$ by state $\mathbf{x}'$ occurs. Otherwise new state $\mathbf{x}'$ is accepted with a probability of $0 < P(\mathbf{x} \to \mathbf{x}') < 1$. If r is a random number from the interval $(0, 1)$, then the new state is accepted only if $r < P(\mathbf{x} \to \mathbf{x}')$, otherwise the process repeats itself with initial state x.

The value of parameter T substantially affects the value of probability $P(\mathbf{x} \to \mathbf{x}')$ for the case $f(\mathbf{x}') > f(\mathbf{x})$. For higher values of T the probability is close to one (almost all new states will be accepted) but in case that value T approaches zero, the probability of receiving becomes very low, almost zero.

This probability is affected by both the quality of the previous solution and the temperature. This can be demonstrated in a graph, see Fig. 3.

This probability is a function of a difference of functional values, actual temperature and also of functional value at point $\mathbf{x}$. There are several ways to calculate this probability; it depends entirely on us, which one we decide to choose. After each step (in fact each worsening step) the temperature is to be lowered according to the cooling plan. The simplest cooling plan is the multiplication of the temperature by coefficient α. Based on experience it is advised that α should be chosen between 0.8 and 0.99. Other option is to use simulated cooling according to the equation

$$T' = \frac{T}{(1+\beta T)}.$$

Coefficient β is a small nonnegative constant, $\beta < 1$. If the temperature falls under a certain limit (freezing of the crystal), $T = 1$ is to be set again.

If the initial "temperature" $T_{\max}$ (greater value) is set properly, firstly, the method of simulated annealing scans the space of solutions $\mathcal{D}$ (which is strongly stochastic) and then it also accepts the states with a worse solution than the current one. This feature is a very important trait of the simulated annealing, because it enables us to avoid searching just locally and allows us to search for other possible solutions. Next, this possibility gradually decreases in proportion with the decreasing values of T. As far as low T is concerned, the Metropolis criterion accepts only a better solution than the current one.

It can be proved (e.g. [9]) that if the cooling plan is slow enough and simultaneously the method of generating new allowable solutions covers the entire state space then the simulated annealing converges with a probability to an optimum.

The possibility of realization of the energetically unfavorable transitions decreases gradually and proportionally to decreasing values of T. For low values of T the Metropolis criterion accepts only a better solution than the current one.

According to the results [18] the *simulated annealing is one of the most successful traditional stochastic optimization algorithms.* For this reason it could be faster, more exact and precise than genetic algorithms. Based on the evidence given by the results supported by testing (partial sample), see Sec. 3.1. (testing function approximation), we can say that SH is fully possible for the experiment.

Simulated annealing can be implemented as a parallel algorithm, see Algorithm 2. That means, that it will search for as many independent routes of each step, in relation to many possibilities of parallelization of the problem (algorithm is to be run multiple times independently). As for the best running solution, the best solution from all of the searched routs is taken into account.

Algorithm 2 Parallel simulated annealing.

Require: Function $f(x) : \mathbb{R} \to \mathbb{R}$, P the possibility of parallelization of the problem
Ensure: $\min_x f(x)$
  {Initialization}
  Generating random initial acceptable solutions $x^{(0)}_{(1)}, \ldots, x^{(0)}_{(P)}$.
  {Each solution $x^{(0)}_{(i)}$ corresponds to the i-th independent rout.}
  For each rout temperature $T_{(i)} = 1$, $i = 1, \ldots, P$ is set. {Iteration}
  for $i = 1$ **to** N **do**
    One step of unparalleled version of simulated annealing is made.
  end for
  The result is the best solution of all of the routs.

Comment: The modification of this algorithm can be achieved in many various ways: there is the possibility to achieve the calculation of the probability by accepting worse solutions and then to modify a cooling plan to suit the particular situation Moreover, we may choose a method of generating neighboring solutions, for instance when deciding for $x^{(k+1)}$ we are allowed to choose from all of the components and not only the initially chosen one. There is also a possibility to use a general random transformation.

A significant improvement (but at the cost of slowing down the algorithm) is to run a fast local (e.g., rock-climbing) algorithm from point $x^{(k+1)}$ and the use of this improved point as a reference for comparison with $x^{(k)}$. This reduces the likelihood of overpassing the state space global optimum when searching. The details of possible modifications can be found in [4].

Algorithm 3 Randomly generating one point x from the neighborhood of points $\mathbf{x}^{(0)}$.

Randomly choosing a direction based on an even distribution.
Moving in j-th component:

$$\widetilde{x}_j = \begin{cases} u_j^{(0)} + u\left(1 - x_j^{(0)}\right) & \text{for } u \in [0,1), \\ x_j^{(0)} + u x_j^{(0)} & \text{for } u \in (-1,0) \end{cases} \tag{11}$$
$$\widetilde{x}_i = x_i^{(0)} \qquad \text{for } i \neq j$$

where $u \sim \mathcal{U}(-1,1)$
Computing the original sum of the vector components $\mathbf{x}^{(0)}$:

$$S^{(0)} = \sum_{i=1}^{n} x_i^{(0)} \tag{12}$$

And computing a new sum S analogically to b) first row:

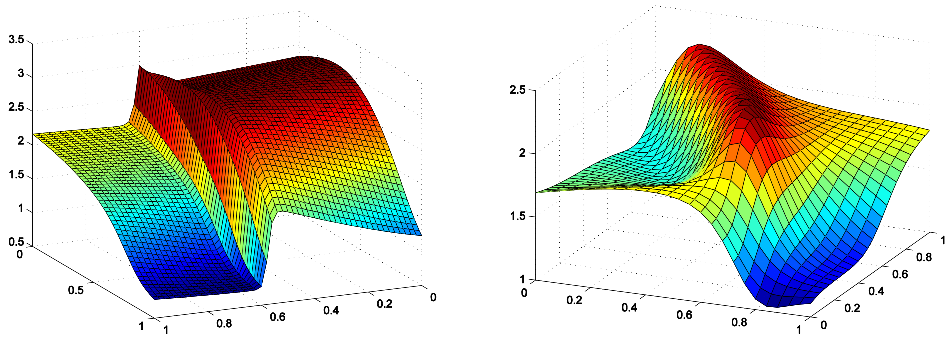
$$S = \begin{cases} S^{(0)} + v\left(1 - S^{(0)}\right) & \text{for } v \in [0,1), \\ S^{(0)} + vS^{(0)} & \text{for } v \in (-1,0), \end{cases} \tag{13}$$

where $v \sim \mathcal{U}(-1,1)$.
Normalizing the vector components $\tilde{\mathbf{x}}$ in the way that $\sum_{i=1}^{n} x_i = S$:

$$\forall j \in \hat{n} \;\; x_j = \widetilde{x}_j \frac{S}{\sum_{i=1}^{n} \widetilde{x}_i}. \tag{14}$$

3.1 Testing of the approximations of the functions for technical optimization

Before it is proceeded to the point of this chapter, we can mention that from the tests on analytical functions that are not mentioned in this article, the simulated annealing is slow. It converges slowly and seems as a global rather than a local extreme. For high values of N, however, simulated annealing and stochastic climbing algorithm show steady improvement in functional values, where N is the number



a) MLP1 b) MLP2

Fig. 4 *Sectional view of the function MLP1 and MLP2 around local maxima.*

of steps in which the state space is scanned in the analysis process in excess of the objective function call.

Now let us follow the partial results of the comparison of the stochastic algorithms for the functions represented by use of the artificial neural networks, which were obtained as an approximation of the data from practice. As the parallelization option 8 was chosen. Each algorithm was independently launched 50 times; every time 500 iterations were performed (i.e., 500 associated calls of cost function, except for the RBF1, in which it only made 300 iterations). The mean values of functional values for each algorithm, a standard deviation, and percentiles were all measured. The x-axis is only logarithmic in the graphs of individual variables; axis of function values is linear. For all functions the maximum was searched for.

Generating the neighboring points for the stochastic climbing algorithm and for the simulated annealing is described in Algorithm 3.

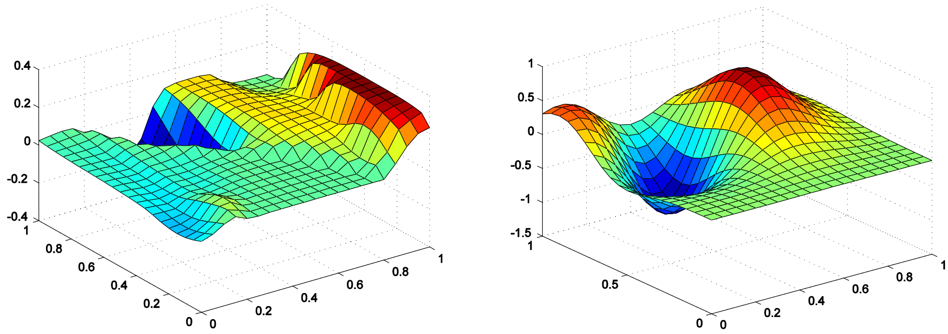
Analogically to this the method for generating feasible solutions for a random searching and the operators of a genetic algorithms was modified.

This chapter describes the implementation and testing of the selected algorithms for the artificial neural network functions that have been learned on the dates from practice and are therefore intended to simulate real problems in practice. Selected algorithms have been implemented in MATLAB [20]. The individual functions are referred to as MLP1, MLP2, MLP33 and RBF1 because they are considered unknown "purpose" functions.

A function called for instance MLP1 is presented by artificial neural network that was taught based on real data used in practice. It is therefore an approximation of an unknown function. The dimension of a state space is $n = 5$. The sectional view of the function around one of the local maxima is in, see Fig. 4 (the zooming was picked so that the local maxima was in a coordinate $(0.5, 0.5)$).

Function MLP3 is again an approximation of a function acquired by neural that was taught based on the data from the real world. The dimension of the state space is in this case $n = 13$. There is a sectional view in, see Fig. 5 this time around the area of feasible solutions, not only around any local maxima.

RBF1 is a 5-D function mediated by artificial neural networks using radial basis functions. All the views of this function look similar to those in, see Fig. 5. At



a) MLP3 b) RBF1

Fig. 5 *Sectional view of MLP3 and RBF1 around approximation of maxima.*

this function all the algorithms behave the same way and they can be compared with a random search. That is why the optimization was only limited to the area of the approximation of optimum, which was obtained by using MATLAB function `fmincon()`. Around this area the condition was compiled and during the generation of the neighboring solutions the normalization to a specific sum was not carried out.

The test results and the analysis of optimization prove that the simulated annealing is the most suitable algorithm for a technical optimization. From the tests carried out on function MLP1 it is evident that the algorithms achieve high levels of variance and also at 0.1 quantile they are approximately of the same value for all algorithms. It can be said that it is very important to monitor the median and 0.9 quantile.

Simulated annealing for this function achieves very good results even for low values N and therefore it is the most suitable algorithm for this function. Also the simulated annealing is the most appropriate algorithm for function MLP2 although the results are not as clear as for functions MLP1 and MLP3. For low values of Nthese algorithms behave very similarly, therefore it cannot be unambiguously said, which algorithm is better. In this case the best algorithm seems to be the stochastic climbing algorithm. For high values Ndominates the simulated annealing because it achieves high average value of the objective function but also the variance is lower than climbing stochastic algorithm and genetic algorithm.

For a function of MLP3 the simulated annealing shows steady growth in the functional value and also achieves relatively low level of variance for all values of parallelization tasks. For high values of parallelization task $(32, 128)$ low N (tens) it is obviously preferable to use stochastic climbing algorithm (this was not put up to the test). A distinct character of simulated annealing and the remaining algorithms is clearly visible at function RBF1.

For all the functions the most suitable algorithm seems to be the simulated annealing (except for low values N of RBF1).

4. Experiment 1

A part of this experiment is to create a class of typical daily diagrams of supplies and thus the power consumption for a given group of customers with a defined characteristics of consumption. By the term the daily type chart we mean relative values characterizing the consumption of electricity of customers, in this case represented by a complex of intelligent buildings integrated into the electrical microgrid of the RES. The daily type charts are to be evaluated for a working day in the middle of a week, i.e. Wednesday, and for non-working day, i.e. Saturday.

In terms of evaluating the effectiveness of data analysis from the classes of daily type diagrams for the purpose of gaining knowledge from these databases the cluster analysis method is used. For this purpose, the annual history of hourly electricity consumption was simulated. Then it was possible to proceed to comparison of the identified daily type chart of hourly consumption of the selected standard.

As the basic standards of daily diagrams hourly consumption characteristic curves hourly of the electricity consumption of two selected days of the week, i.e. Wednesday and Saturday were used. Each hourly consumption of each of mentioned days of the week was randomly modified by a random number generator with a normal probability distribution. This was done several times in order to meet year history of hourly consumption, i.e. Wednesday and Saturday.

Looking at the waveforms of daily diagrams year history, see Fig. 7 and see Fig. 9, these differ from each other, however, the resulting waveform daily diagrams are quite similar to the waveforms shown in, see Fig. 8 and Fig. 10. This is documented by the fact that the method of analysis of data clustering is very effective. The experiment was processed in the computer program C++, see Fig. 6.

A demonstration of the source code, in C++, of the used computer program is shown below:

```
double mvalue; // mean value
double sdev; // standard deviation

double random (double ix, double x)
{
    double mvalue = x;
    double sdev = 0.01 * mvalue;
    double a = 0;
    for ( int i=1; i<12; i++ )
    {
        iy = ix * 65539;
        if ( iy < 0 )
            iy = iy + 2147483648;
        else
            y = iy;
        y = y * 4.656613E-10;
        ix = iy;
        a = a + y;
    }
    return (a - 6) * sdev + mvalue;
}

```

```
int nhours; // number of hours (24 hours per day)
int ndays; // number of days 312 (260 working days and 52 Saturdays)
int diagrams[nhours][ndays]; // diagrams of days in year history

for ( int j=1; j<nhours; j++ )
{
    x = hload(j); // hourly load
    for ( int i=1; i<ndays; i++ )
        diagrams[i][j] = random(seed, x);
}
```

There are four examples of randomly modeled daytime diagrams of Wednesdays (Fig. 6) and of Saturdays (Fig. 7) in the images.

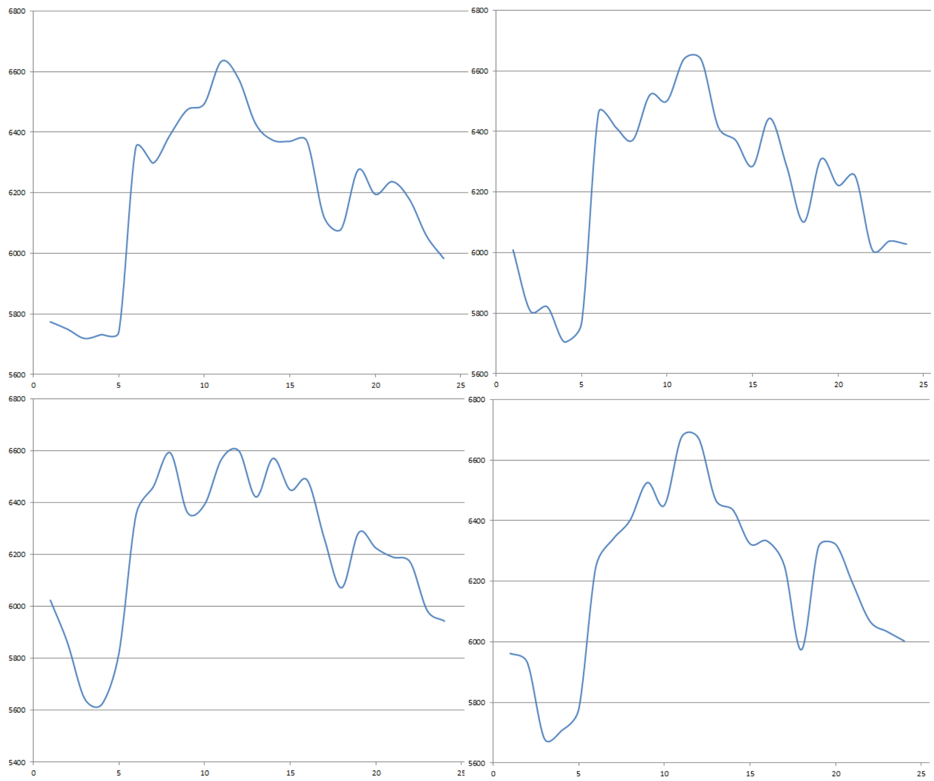


Fig. 6 *The consumption of electricity of randomly modeled Wednesday.*

The presented yearly history of hourly energy consumption can be arranged into a rectangular array of 24 columns and 312 lines representing multidimensional data. This multi-dimensional data matrix forms a training set of patterns (1 through 312) within learning or *adaptation*. These patterns are presented to the Competence Model of the Artificial Neural Network by each day, i.e. the inputs of the network, determined by 24 attributes. During the learning, the weigh vectors sketch the clusters of the training patterns of the annual history. The weight vectors are

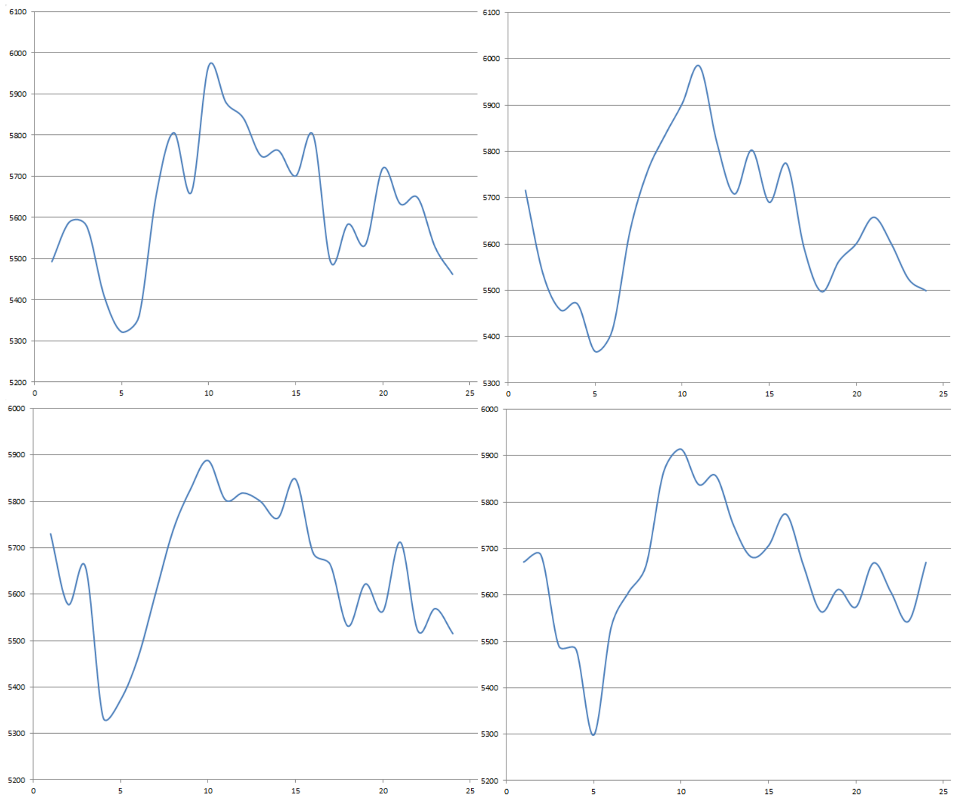


Fig. 7 *The consumption of electricity of randomly modeled Saturday.*

deployed similarly to the training patterns during the neural network learning.

After learning in *active mode*, the training patterns are re-submitted to the neural network input [10]. Nothing happens with the weight vectors in the Kohonen map [8, 12], the output layer neurons gradually turn on. The number of neuron lights gives information about the deployment of training patterns. How to read the Kohonen's 15-by-18 map is the number given in the square, which corresponds to the fictitious altitude of the top. Then we find the prototypes corresponding to the weight vectors, which neuron (gain) lights up most of the time. The number of clusters is equal to the number of prototypes, which is the type of a daily diagram of the corresponding seasonal period.

The plasticity rate during network adaptation exponentially decreased from default value of 1 to final value of 0.005. The order of the gain neuron exponentially decreased from default value 7 to final value of 0 during the network adaptation. Gain neuron surrounds the entire mesh of the output layer of the network, and at the end of the network adaptation it only degenerates to the gain neuron.

After the network adaptation has ended, i.e. after learning the neural network, the weight vectors are distributed as well as the patterns (objects). The trained networks re-submit the whole set of objects (sequentially), drawing the Kohonen's map, see Fig. 8 from which two well separable clusters can be read. One cluster is less massive, probably corresponding to Saturday, and one cluster is more massive, probably corresponding to Wednesday.

Neurons with zero excitation frequency during adaptive dynamics are not close enough to clusters of the training patterns. During the dynamics of the learned network configuration, the necessary weight vectors can be extracted, i.e. the type of day diagrams, shown in Figs. 9 and 10, see also in [6], for comparison always presented with the appropriate standard.

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
0	0	0	0	0	0	0	4	6	6	5	6	3	0	0
0	0	0	0	2	2	3	3	4	5	3	5	3	1	0
0	0	0	5	5	5	2	4	1	4	1	3	1	2	0
0	0	0	5	8	3	1	3	4	3	4	3	3	1	0
0	0	0	1	1	4	0	9	2	2	11	1	7	1	0
0	0	0	3	5	3	5	4	9	0	8	3	1	0	0
0	0	0	6	5	6	8	5	2	10	3	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	3	4	5	1	0	0	0	0	0	0
0	0	0	0	0	0	4	0	3	2	4	0	0	0	0
0	3	2	1	0	0	0	6	8	6	2	1	0	0	0
0	3	3	1	1	0	0	2	1	0	0	0	0	0	0
0	7	6	3	2	0	0	0	0	0	0	0	0	0	0
0	3	5	12	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 8 *Example from Kohonen's map from the program C++.*

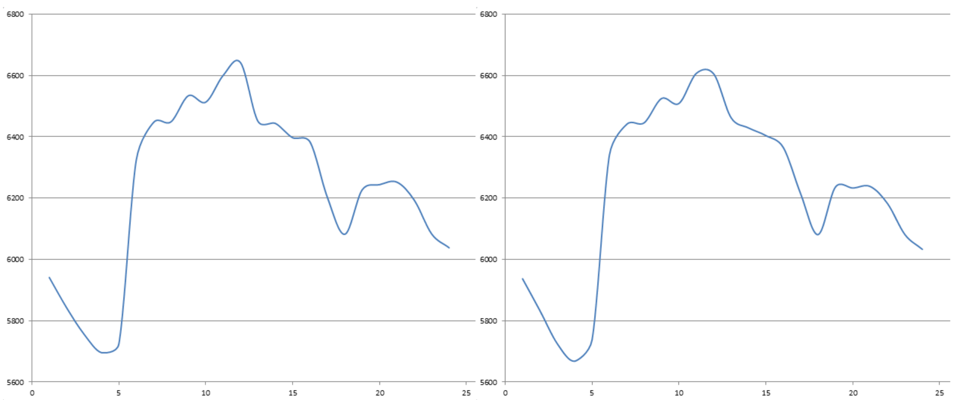


Fig. 9 *The consumption of electric energy of standard Wednesday.*

Although the individual daily diagrams of the annual history, see Figs. 6 and 7, are relatively different, the typical daily diagrams are quite similar to relevant standards, see Figs. 9 and 10, which shows very good efficiency of the method of

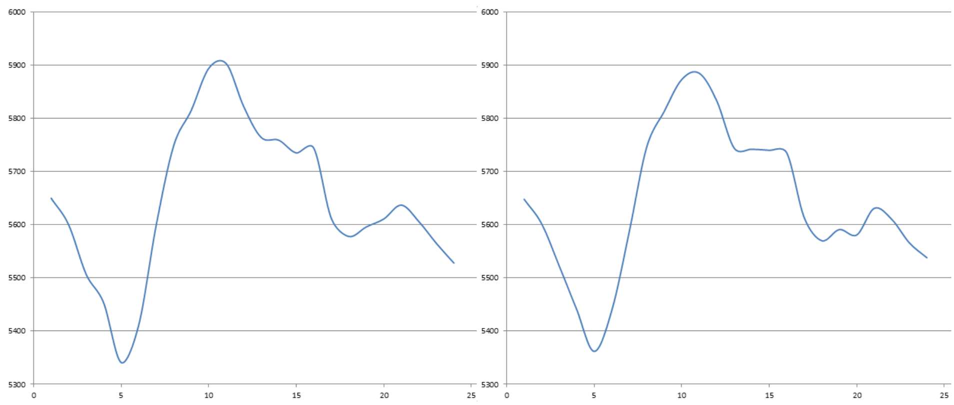


Fig. 10 *The consumption of electric energy of standard Saturday.*

cluster analysis. Tab. I see also in [6], contains a numerical comparison of the type of daily diagrams with relevant standards, their average, and the maximum deviations are about 0.2 % and 0.56 % respectively.

4.1 Final evaluation and discussion of the experiment results

After processing the analytical part of the experiment, see Sec. 2, the optimization project was created. We proposed to minimize the total cost of generating electricity supplied by the RES system. The volume of the produced electricity is based on the prediction (estimation) of the consumption of the intelligent buildings complex within the considered period, sampled by hours. The goal is to create a plan for sorting resources and their generated outputs that cover predicted consumption at each hour of the given period. By mathematical analysis with an optimization stochastic method (simulated annealing, see Sec. 3) an assessment and design of input parameters for the purpose of designing the program module – the software for applications of C++ programming language were attained.

The input parameters for the optimization program are:

1. Prediction of hourly load (obtained from the history of experimental scientific observation) – what will be the electricity consumption at a given time.

2. The number of power sources.

3. The number of hours we process the plan.

4. The cost coefficients of resources.

5. Technical restrictions on resources.

6. Predicted consumption of each hour of the given period.

7. Maximum allowable deviation of the well-balanced output balance.

	Saturday			Wednesday	
TDD [kW]	standard [kW]	difference [%]	TDD [kW]	standard [kW]	difference [%]
5650	5648	0.04	5941	5937	0.07
5600	5602	0.04	5842	5833	0.15
5507	5523	0.29	5756	5725	0.54
5453	5441	0.22	5696	5668	0.49
5341	5362	0.39	5724	5738	0.24
5411	5438	0.50	6323	6341	0.28
5599	5586	0.23	6447	6441	0.09
5749	5746	0.05	6449	6446	0.05
5815	5813	0.03	6534	6525	0.14
5894	5873	0.36	6513	6509	0.06
5903	5885	0.31	6600	6607	0.11
5822	5833	0.19	6642	6605	0.56
5764	5744	0.35	6451	6462	0.17
5759	5742	0.30	6444	6429	0.23
5735	5740	0.09	6397	6404	0.11
5744	5735	0.16	6383	6365	0.28
5612	5613	0.02	6202	6214	0.19
5578	5570	0.14	6082	6081	0.02
5596	5591	0.09	6227	6236	0.14
5611	5581	0.54	6244	6233	0.18
5637	5631	0.11	6252	6238	0.22
5606	5610	0.07	6193	6182	0.18
5565	5566	0.02	6083	6081	0.03
5528	5538	0.18	6038	6033	0.08
	MEAN =	0.20		MEAN =	0.19
	MAX =	0.54		MAX =	0.56

Tab. I *Type a daily chart vs. standard.*

Note: To evaluate this data, a neural network was used to transmit and process the information (data). Furthermore, mathematical and informatics-oriented clustering method was used throughout the data analysis - aggregate data analysis. Several types of daytime diagrams were created as objects that were then grouped into "clusters" so that two objects of the same cluster were similar to two objects of different clusters. The result of individual clusters was the so-called prototype. The prototypes, cost coefficients and constraints were inputs into the neural network.

The conclusion from this analytical description and experiment is that it is suitable to use the principle of cluster analyzes. The cluster analysis is a method of teaching without a teacher.

The task can be in general formulated as follows: There are n objects and p are the characters that each object is characterized by $= \{1, 2, \ldots, n\}$. is the set of all objects, $\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{ip})^{\mathrm{T}}$ are observations of the p-section vectors and

$\mathbf{X} = (\mathbf{x_1}, \mathbf{x}_2, \ldots, \mathbf{x}_n)$ is the n-dimensional object vector (array). The goal is to create a disjoint decomposition into individual clusters so that objects within a group were as similar as possible and objects that belong to different groups are similar as little as possible. Thus, the clusters $\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_k$ are created so that $\forall i \in \{1, 2, \ldots, k\} : \mathcal{C}_i \subseteq \mathcal{C}, \mathcal{C}_i \neq \emptyset$ (clusters $\mathcal{C}_i$ are non-empty subsets of $\mathcal{C}$), $\forall i, j \in \{1, 2, \ldots, k\}, i \neq j : \mathcal{C}_i \cap \mathcal{C}_j = \emptyset$ (clusters do not intersect), and $\mathcal{C}_1 \cup \mathcal{C}_2 \cup \cdots \cup \mathcal{C}_k = \mathcal{C}$. Theoretically it is possible for the number of clusters k to reach the number of objects n, however a practical significance will only have the number of clusters that is significantly lower than the theoretical maximum.

Basically, this is an information-based knowledge discovery in data-based mining, see [1] for example. In terms of the data analysis, the matrix input is a data matrix representing multidimensional data, and the output is an identification of clusters that may be of different types. It is based on an input data matrix, in which rows represent the vectors of the data on the individual objects. The data vector of the individual object is the hourly electricity consumption of the relevant day for fulfillment of the annual history. The cluster analysis examines the similarity of the objects. This type of analysis does not use a dependent variable (learning without a teacher), the goal is to detect non-trivial clusters in data. We will use the artificial neural network in the form of the so called Kohonen maps [11]. The Kohonen's maps have very good results and are very well suited to solution to this problem. The problem, however, is that it is necessary to determine a suitable model for a given task, which means certain time losses.

The only input are the values of independent variables. The Kohonen's map is understood as a kind of cluster analysis (vector quantization) [19]. The creation of a hierarchy of clusters of objects can also be read from the Kohonen's map, because within each cluster the map is obviously visible also in the sub-holes contained therein, shown in Fig. 8.

In order to measure the effectiveness of the used cluster analysis method, the annual history of the hourly electricity consumption was artificially modeled to allow the identified daytime diagram to be compared to a standard. Hourly consumption patterns were used as default hourly consumption patterns for two days (Wednesday, Saturday), where each hourly consumption of both of them was randomly modified by using a random number generator with a normal probability distribution.

For the experiment, cluster analysis meets the conditions for its fulfillment. At the same time, the attributes of ideal methods of searching for the information in large databases or pattern recognition are also met. However, some authors, see [9], use cluster analysis for a wider range of methods than the traditional methods.

From the results obtained by the experiment it can be concluded:

The goals of the cluster analysis cannot be separated from searching and selecting appropriate characters to characterize the clustered objects. The found clusters capture the data structure only with respect to the selected characters. The character selection must be based on theoretical, conceptual and practical considerations. Custom cluster analysis does not include a technique how to distinguish significant and insignificant characters. It only performs the cluster differentiation. Incorrect character grading leads to the inclusion of outlying objects that may interfere with the results of the analysis. Only features that distinguish sufficiently between objects should be used.

Based on the experimental findings, it can be concluded that the used clustering method meets the generally formulated attributes of an ideal method:

- The method does not require a user to have any a priori information (e.g. the number of clusters).
- The method recognizes clusters of general shapes in any quantity and density of contained objects.
- The method does not impose specific requirements on the order of submitted object observations.
- The method is robust to remote object observation, robustness of the Kohonen's maps, resistance to weight vector damage. At 25 % network failure, the average model success rate dropped to 6.9 %. [15]
- The method does not have any problem of analyzing a set of large numbers of observations even in the case of a large number of variables during one submission.
- The method is hierarchical, as can be seen from the Kohonen's map, as the clusters contained in the cluster are clearly visible on the map.

The most commonly used methods of cluster analysis are the non-hierarchical method of k-means (clustering by the method of the nearest centers), which is offered by all virtually statistical programs. This method is most useful when creating a small number of clusters from a large number of objects.

This method uses the center of clusters as sample points. At the beginning, it is still necessary to select the k of the initial sample points. The points can be selected randomly from the input set of objects. Subsequently, the individual objects are taken and assigned to the nearest sample points. After each assignment, the center of gravity of the enlarged clusters is recalculated. After assigning all the points, the resulting center points are the resultant pattern points, and the assignment and recalibration of the center of gravity is performed again [16]. Individual steps of the algorithm are shown in Algorithm 4.

The advantage is a simplicity and speed, it can be used for a large amount of data. In the final set of steps, it converges to a solution, but there may be more of them. The disadvantage is that the results are again influenced by the selection of initial clusters, and since the assignment of the point results in an instant recalculation of the center of gravity, the result is also affected by the original order of the objects. The function of the squared error count is again minimized only locally. k-means is not useful if overlapping clusters are to be expected. The presence of isolated objects lying outside has a great negative effect on the result. [14]

This method does not completely meet any of the attributes of the ideal method, it is suitable for the analysis of sufficiently distant homogeneous clusters of approximately spherical shape, thereby reducing its utility value. The k-means method is the only one among the non-hierarchical methods. Another problem with this method lies in the necessity to choose the resulting number of clusters at

Algorithm 4 k-means algorithm [14].

Require: Number of clusters to generate k, list of object to cluster
Ensure: Assignment of objects to k clusters
  Specify the k centres of gravity.
  repeat
    for all objects o **do**
      Select a cluster κ whose center of gravity is the closest to o
      if κ not equal to the original cluster **then**
        Move o into κ
      end if
    end for
    Calculate new centres of gravity
  until no cluster changes

the beginning of the algorithm, which can affect the success of the method. And last but not least, another disadvantage is that after the point is assigned to the cluster, the center of gravity is immediately recalculated. The result is therefore affected by the original order of the objects.

Therefore, the cluster analysis of the neural network is completely versatile in terms of the spatial distribution of objects in an investigated set (it is also able to identify the even distribution of the objects in the n-dimensional space), but the interpretation of its results is partly dependent on the subjective reading from the Kohonen's map.

5. Experiment 2

This experiment will introduce the calculation and design of sorting sources of electricity centered in the microgrid of RES within a reasonable distance from the imaginary field of intelligent buildings. The types of microgrids of RES were described in the introduction of this article, with the due respect for the different sources (bio-energy, wind energy, water energy and cogeneration) to meet the conditions of installation, both technically and in terms of efficiency and performance difficulty. Photovoltaic power plant was avoided, because local conditions for the installation are not acceptable to the wind conditions and also in terms of spatial development.

To achieve the required reliability of electricity supply, high voltage transformers are connected to the microgrid of RES after the approval from the distributor in the transmission system. The aim of this experiment is to design sorting resources of a typical weekdays – Saturday and Wednesday in the month of November, for which there are hourly consumption forecasts. The experiment assignment is the supply of electrical energy to be conveyed from thirty-two rotating synchronous generators and the eight transformers, i.e. a total of forty resources and their cost characteristics and technical limitations are given in Tab. II, see also in [7]. In Tab. II there are header codes in the columns, where $\mathrm{HC} = \mathrm{HC1} \cdot \mathrm{HC2} \cdot P$ is the consumption of the resource. The experiment was processed in a computer program UniCom, see Fig. 11.

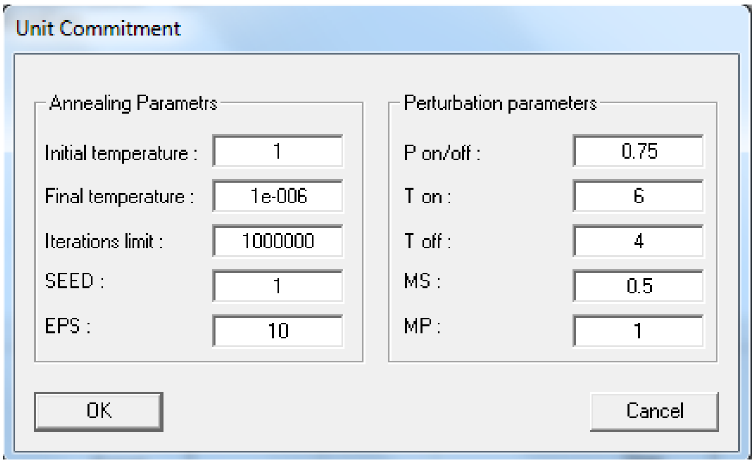


Fig. 11 *An input form for analysis by Unicom [3].*

6. Conclusion

By comparing, see Fig. 9 to Tab. III (see also in [7]) it is clear that the Wednesday's consumption is covered in a similar way but due to the increased volumes, i.e. a larger area below its progression, the cluster of outputs supplied by the first and second biomass power plants covering the mid-day and evening peaks is larger. Three transformers of one of the distribution companies, specifically the one with lower price of energy, were turned on during the midday peak – one of which was turned off temporarily between the peak hours. The third biomass power plant was not used at all, due to its higher start-up costs and relatively high operating costs.

Comparing the graphs in one graph instead of comparing Fig. 9 with the values in Tab. III, as mentioned above, we can conclude: when comparing the patterns of power consumption through a typical day diagram for Wednesday, see Fig. 9 (standard) and Fig. 6 (model) is as follows – if it is based on the tip of the sampling, i.e. at 12.00 pm, then the sampling is predominantly the same with a difference of maximum 2 %, which corresponds to the type of the daily diagram expressed in Tab. I. From this simple comparison it can be concluded that the clustering method meets the demanding requirements of this experiment. A more detailed assessment was made in this article.

Referential or optimal costs for the coverage of the Wednesday energy consumption amount to 69 220 or 45 000 CZK then.

By comparing Fig. 10 to Tab. IV (see also in [7]), it is clear that the power consumption on Saturday is primarily covered by the sources with more or lower production costs, such as both hydroelectric plants and the first wind-power park together with cogeneration units, which contribute by supplying the town with heat. The mid-day consumption peak corresponds well with the cluster of outputs supplied by the biomass power plant and the start-up of one transformer, which together with one source of the specified cluster also covers the evening consump-

UNIT	NR	P_{min} [kW]	P_{max} [kW]	HC1 [kW]	HC2 [-]	A [CZK]	B [CZK/MW^2]	C [CZK/MW]
Water1	1	600	980	5	0.065	12 046	142.0	0.029
Water1	2	600	980	5	0.065	12 046	142.0	0.029
Water2	1	390	440	5	0.065	14 667	161.2	0.030
Water2	2	390	440	5	0.65	14 667	160.7	0.030
Water2	3	390	440	5	0.067	14 667	161.4	0.030
Water2	4	390	440	5	0.068	14 667	162.4	0.030
Wind1	1	120	200	10	0.078	15 104	170.7	0.383
Wind1	2	120	200	10	0.078	15 104	170.7	0.380
Wind1	3	120	200	10	0.078	15 104	170.07	0.387
Wind1	4	120	200	10	0.078	15 104	170.07	0.390
Wind1	5	120	200	10	0.078	15 104	170.07	0.393
Wind2	1	140	210	10	0.114	16 480	188.3	0.448
Wind2	2	140	210	10	0.114	16 659	188.3	0.459
Wind2	3	140	210	10	0.114	16 480	188.3	0.451
Wind2	4	140	210	10	0.114	16 659	188.3	0.469
Wind2	5	140	210	10	0.114	16 480	188.3	0.455
Cogener1	1	300	500	15	0.054	15 902	198.8	0.152
Cogener2	1	130	200	15	0.088	15 815	176.8	0.437
Cogener2	2	130	200	15	0.088	15 815	176.8	0.431
Cogener2	3	130	200	15	0.088	15 815	176.8	0.434
Cogener2	4	130	200	15	0.088	15 815	176.8	0.427
Biomasa1	1	100	150	5	0.131	8483	199.5	0.884
Biomasa1	2	100	150	5	0.131	8534	200.7	0.853
Biomasa1	3	100	150	5	0.120	9273	224.0	0.701
Biomasa2	1	100	150	5	0.132	7948	204.4	0.939
Biomasa2	2	100	150	5	0.132	7948	204.4	0.943
Biomasa2	3	100	150	5	0.132	7948	204.4	0.947
Biomasa2	4	100	150	5	0.132	7948	204.0	0.950
Biomasa3	1	100	150	5	0.173	10 505	282.3	1.101
Biomasa3	2	100	150	5	0.173	10 505	282.3	1.051
Biomasa3	3	100	150	5	0.173	10 505	282.3	1.001
Biomasa3	4	100	150	5	0.173	10 505	282.3	0.951
Network2	1	100	200	1	0.084	20 903	338.8	1.554
Network2	2	100	200	1	0.084	20 903	338.8	1.550
Network2	3	100	200	1	0.084	20 903	338.8	1.545
Network2	4	100	200	1	0.084	20 903	338.8	1.541
Network2	1	100	200	1	0.071	24 409	387.2	1.574
Network2	2	100	200	1	0.071	24 409	387.2	1.569
Network2	3	100	200	1	0.071	24 409	387.2	1.563
Network2	4	100	200	1	0.071	24 409	387.2	1.580

Tab. II *Parameters of sources.*

Supply	Nr.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Water1	1	979	979	980	980	970	978	976	980	970	978	969	980	960	980	979	976	975	979	979	978	956	959	974	969
Water1	2	980	980	979	978	976	976	978	980	979	978	975	976	973	972	969	979	976	975	979	974	974	966	964	975
Water2	1	438	438	438	438	438	438	440	438	438	438	438	440	438	438	436	437	438	438	435	436	437	438	438	440
Water2	2	438	438	438	438	438	440	440	437	438	438	438	437	437	438	438	436	438	438	438	440	436	436	438	435
Water2	3	440	440	440	440	439	439	439	440	439	440	437	438	440	438	435	440	440	440	439	440	439	439	437	440
Water2	4	440	439	440	440	440	439	440	438	440	437	439	433	440	439	439	437	438	439	437	437	440	432	439	438
Wind1	1	198	195	197	196	194	198	197	197	198	200	192	195	197	196	194	196	195	198	196	198	197	195	194	198
Wind1	2	198	196	196	198	191	198	196	196	196	197	198	195	198	192	197	198	192	197	196	198	196	198	198	198
Wind1	3	196	197	196	197	196	197	197	198	198	198	195	198	198	198	194	196	195	185	194	197	198	200	198	197
Wind1	4	200	196	197	196	198	198	198	197	197	200	196	197	197	196	198	191	198	198	192	194	185	193	198	191
Wind1	5	197	195	200	198	198	198	196	198	198	198	195	197	198	198	198	193	191	193	194	195	196	196	196	198
Wind2	1	178	170	175	166	158	206	205	206	208	210	204	199	182	205	205	206	188	167	191	194	200	185	175	197
Wind2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wind2	3	170	153	153	151	166	210	205	203	204	205	210	205	199	206	205	205	205	161	187	184	206	179	201	183
Wind2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wind2	5	171	153	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cogener1	1	488	484	487	486	487	498	499	498	496	499	498	499	488	487	498	490	497	496	497	496	492	497	488	487
Cogener2	1	197	173	175	197	195	198	198	198	198	195	198	186	197	200	186	191	174	195	176	197	196	197	187	194
Cogener2	2	198	176	187	198	194	197	197	200	198	197	198	193	196	198	194	195	187	200	195	183	190	186	185	187
Cogener2	3	196	186	187	187	192	198	198	196	197	198	198	190	198	198	176	197	198	178	198	196	194	194	174	194
Cogener2	4	197	198	186	196	197	198	197	198	198	197	198	196	196	198	195	189	192	198	195	183	173	193	175	184
Biomass1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass1	2	102	100	102	0	101	141	148	133	143	137	141	136	102	141	146	133	108	101	115	118	114	106	100	102
Biomass1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass2	1	0	0	0	0	0	127	139	149	130	140	139	139	114	115	117	121	100	100	108	102	122	101	101	0
Biomass2	2	0	0	0	0	0	145	132	140	132	123	143	145	122	116	130	101	102	102	102	108	104	100	109	102
Biomass2	3	0	0	0	0	0	145	136	134	144	132	128	109	117	114	107	131	102	100	106	105	107	102	105	104
Biomass2	4	0	0	0	0	0	117	139	140	140	129	146	137	117	106	109	126	102	107	109	102	109	101	0	0
Biomass3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network1	2	0	0	0	0	0	0	100	103	103	100	157	118	101	0	0	0	0	0	101	100	103	105	103	101
Network1	3	0	0	0	0	0	0	0	0	0	0	0	106	101	100	100	141	100	0	0	0	0	0	0	0
Network1	4	0	0	0	0	0	0	0	0	101	101	143	128	100	104	101	0	0	0	0	0	0	0	0	0
Network2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	[kW]:	6601	6486	6353	6280	6368	7079	7190	7197	7283	7265	7373	7372	7206	7173	7146	7105	6931	6785	6959	6955	6964	6898	6777	6714
Load	[kW]:	5937	5833	5725	5668	5738	6341	6441	6446	6525	6509	6607	6605	6462	6429	6404	6365	6214	6081	6236	6233	6238	6182	6081	6033
Consum	[kW]:	674	663	638	622	640	748	759	761	768	766	776	777	754	754	752	750	727	714	733	732	736	726	706	691

Tab. III *Unit Commitment of Wednesday.*

tion peak. Referential or optimal costs for the coverage of the Saturday energy consumption amount to 65 345 CZK 38 442 CZK then.

In practice, the unit commitment optimization problem is usually solved by the Lagrange multipliers method, but it does not work correctly with bivalent independent variables from objective function, i.e. with the state of source. Therefore, heuristic methods seem more appropriate to solve this optimization problem and are a demonstrably suitable method that can be applied to the Smart Cities.

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Supply	Nr.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Water1	1	979	979	980	976	978	976	974	978	970	976	961	970	971	975	963	974	963	972	976	965	959	974	975	952
Water1	2	979	976	980	976	976	976	976	979	980	979	975	979	975	980	978	978	975	975	978	970	973	976	967	980
Water2	1	440	440	438	438	438	440	438	440	438	438	438	438	440	438	437	437	437	438	438	438	437	440	438	434
Water2	2	438	438	438	438	438	438	438	438	438	438	440	438	437	440	438	436	429	438	440	438	438	438	433	435
Water2	3	440	440	440	440	440	440	440	439	439	438	440	438	439	438	439	436	439	437	437	437	439	438	439	438
Water2	4	440	440	440	439	440	439	439	439	439	440	440	440	439	438	439	433	433	439	440	438	438	433	437	437
Wind1	1	196	196	197	197	196	181	194	198	196	180	198	198	195	185	189	189	183	191	197	183	175	184	198	185
Wind1	2	198	197	198	196	184	184	197	193	193	198	192	198	197	183	184	198	195	192	183	173	198	198	173	181
Wind1	3	195	194	195	198	194	197	180	185	198	198	185	194	185	192	196	198	196	198	198	191	183	195	198	184
Wind1	4	198	193	196	198	193	193	195	180	197	196	196	198	198	183	198	198	192	178	196	197	197	198	170	194
Wind1	5	198	194	192	198	198	180	195	197	193	198	197	197	180	196	187	198	187	173	173	182	200	192	193	175
Wind2	1	162	162	144	151	153	144	142	173	185	162	159	159	153	177	173	206	196	160	153	141	179	171	184	171
Wind2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wind2	3	170	152	152	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wind2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wind2	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cogener1	1	472	482	444	483	442	453	471	490	482	500	497	488	489	484	481	485	490	472	489	498	492	486	490	482
Cogener2	1	184	175	174	164	171	175	169	185	185	151	187	176	176	186	198	173	179	158	163	195	176	149	162	172
Cogener2	2	187	186	169	186	176	161	173	175	164	180	167	174	140	186	195	174	163	176	173	175	192	185	185	174
Cogener2	3	197	183	176	160	163	183	176	196	159	176	176	186	167	198	184	163	176	174	175	172	164	170	174	172
Cogener2	4	186	182	170	176	151	164	196	192	198	175	183	190	191	186	181	179	176	195	181	185	187	183	147	169
Biomass1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass2	1	0	0	0	0	0	100	102	100	101	100	102	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass2	2	0	0	0	0	0	0	100	106	107	102	100	101	106	0	0	0	0	0	0	0	0	0	0	0
Biomass2	3	0	0	0	0	0	0	0	101	100	101	102	109	100	101	101	102	109	104	100	102	108	101	101	101
Biomass2	4	0	0	0	0	0	0	0	0	105	102	101	106	102	101	107	100	0	0	0	0	0	0	0	0
Biomass3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Biomass3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network1	3	0	0	0	0	0	0	0	0	0	101	108	100	100	101	101	104	100	100	101	101	103	101	101	101
Network1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network2	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Network2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	[kW]:	6259	6209	6123	6014	5931	6024	6195	6384	6467	6529	6544	6477	6380	6368	6369	6361	6218	6170	6191	6181	6238	6212	6165	6137
Load	[kW]:	5648	5602	5523	5441	5362	5438	5586	5746	5813	5873	5885	5833	5744	5742	5740	5735	5613	5570	5591	5581	5631	5610	5566	5538
Consum	[kW]:	621	617	610	583	579	596	619	648	664	666	669	654	646	636	639	636	615	610	610	610	617	612	609	609

Tab. IV *Unit Commitment of Saturday.*

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