THE USE OF EVOLUTIONARY ALGORITHMS TO OPTIMIZE INTELLIGENT BUILDINGS ELECTRICITY SUPPLY

Bohumír Garlík,* *Miloš Křivan*†

Abstract: This paper formulates a unit commitment optimization problem for renewable energy sources distributed in a micro-grid formed by a complex of intelligent buildings of both office and residential characters, including a wide range of amenities. We present a general description of the solution of this task using the simulated annealing heuristic optimization technique. The experiment was processed in the specialized computer program. For comparison, Appendix A of the article describes the Lagrange multipliers optimization method as the conventional alternative to the used heuristic technique. A description of the concept of intelligent buildings is provided in Appendix B.

Key words: *Simulated annealing, unit commitment, intelligent building, micro grid*

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1. Introduction

In the context of sustainable development of human society, which depends on the planet's energy sources, covering the needs of the society requires a focus on renewable energy sources such as geothermal energy, atmospheric currents, hydrogeological cycles, solar radiation or biomass, due to their relative inexhaustibility and the minimization of the impacts of human activities on the environment related to their conversion to energy.

Biomass is a renewable energy source meeting the requirements to stabilize the amount of carbon dioxide in the atmosphere, i.e. the amount of carbon dioxide absorbed during the growth of the organic matter is equal to the amount of carbon

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dioxide emitted into the atmosphere during the combustion process. In connection to the decrease of fossil fuels and the deterioration of the global climate, the use of biomass energy accumulated from the sun appears to be desirable. Photovoltaic power plants are based on the direct conversion of sunlight into electrical energy in photovoltaic panels generating direct current, and so they must be equipped with a solid-state voltage invertor for their connection to the grid.

Atmospheric circulations as well as the hydrological cycle are powered by thermal energy from sunlight. Uneven heating of the planet's surface and adjacent air layers leads to differences in air pressure in the atmosphere and the result of the balancing of these pressure differences is the atmospheric flow, the kinetic energy of which is converted into electrical energy in wind power stations.

The kinetic energy of the water flow, caused by an altitude difference between two positions of the flow (the slope), is converted into electrical energy in water or pump storage units. Pump storage power plants, unlike standard power plants, operate as follows: when there is a shortage of energy, it operates as a generator, and during periods with excess energy, it operates as a motor which pumps water from a lower to a higher altitude, thereby storing electrical energy generated by other sources in the network in the form of potential energy of the transferred water.

Geothermal energy is available everywhere, is stable and can be easily regulated. Current technologies for using geothermal energy are relatively expensive from an investment standpoint, but have a quick economic return and have no negative impacts on the environment. The issue of geothermal energy is complicated and its proper utilization requires the connection of different results from many disciplines, and so now geothermal energy is becoming a new scientific field of its own.

Cogeneration units are another convenient addition to the range of renewable energy sources. These typically operate by burning fossil fuels to produce electricity while at the same time delivering the residual heat of the Carnot cycle for further use instead of letting it escape into the atmosphere through cooling towers, as is the case in conventional power plants. By the construction of cogeneration units, we could gain the advantage of self-sufficient energy units, such as in the case of complex intelligent buildings or even individual intelligent buildings. This saves energy costs and also protects the environment by eliminating the need for a separate heat source.

When connecting the above mentioned energy sources to the grid via transformers, the surplus can be sold off to the respective distribution companies. The implementation rate of the above proposition depends on the cost of the chain of production, transmission and consumption of energy. In relation to electricity, we are therefore minimizing production costs through the optimal operation of the electrical transmission network, i.e. a suitable choice for the connection and size of the injection active or reactive power in the network nodes, and finally by minimizing the consumption side.

Minimizing the above costs, due to the complexity of the problem as a whole, is usually realized more or less separately on three separate planes (generation, transmission and consumption), i.e. instead of one optimum we only obtain three sub-optima. In connection with the second or third plane, we speak of smart networks [2] or intelligent buildings [3], however the subject of this paper is the solution of this problem on the first level, i.e. unit commitment optimization problem.

2. Unit Commitment

The task of unit commitment is an optimization problem with a goal of minimizing the total costs of producing the volume 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 the sorting of sources and their generated outputs covering the predicted consumption in each hour of the given period.

The optimization problem may in general formally be expressed as follows:

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

where $\vec{x}_0$ is the optimum, whereas Ω specifies the area of admissible solutions containing the optimum as given by operating-technical parameters of sources, and whereas f represents the cost function given by a sum of operating and start-up costs (Fig. 1) for sources integrated in the given period:

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

where $i \in \{1, -, N\}, t \in \{1, -, T\}$ and $P_i(t)$ resp. $x_i(t)$ are the output resp. state of the i-th source in time t, and where A_i, B_i, C_i, D_i resp. $\Delta T_i(t)$ and τ_i are the appropriate cost coefficients resp. downtime and the time constant of the exponential growth of start-up costs for the i-th source in time t, and furthermore N resp. T is the number of sources in the network resp. the number of time snaps of the considered period.

Admissible solutions are in general specified by the following inequalities resp. equality:

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{3}$$

$$\sum_i P_i(t) x_i(t) = C(t) \tag{4}$$

where $C(t)$ represents a prediction of the consumption in the appropriate hour of the considered period.

3. Simulated Annealing

Evolutionary algorithms are used to find a solution with sufficient quality for large-scale general optimization tasks in a sufficiently short time. Evolutionary algorithms inspired by nature include a whole spectrum of optimization heuristic techniques, e.g. Particle swarm resp. Ant Colony optimization, genetic algorithms or simulated annealing. Heuristics may be described as a procedure for searching the solution space via shortcuts, which are not guaranteed to find the correct solution but do not suffer from a range of problems of conventional optimization methods such as e.g. the requirement of connectivity or differentiability of the criterion or link function, the problem of respecting constraints, being stuck in a shallow local minimum or divergence. However, their application requires the configuration of

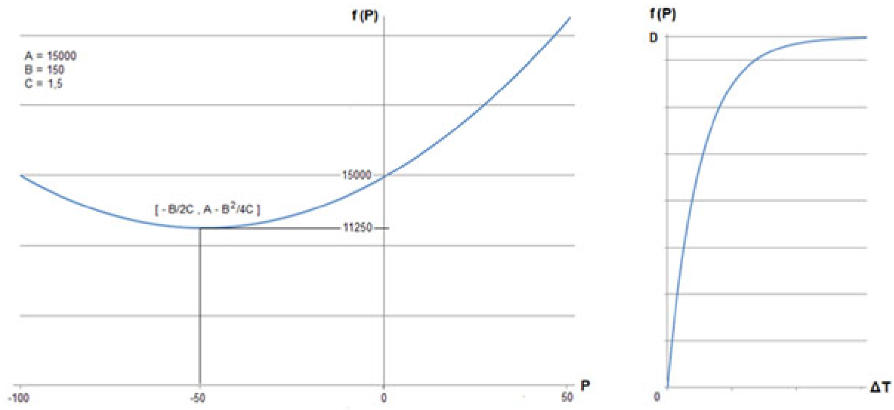

Fig. 1 *Dependence of operating costs on power and start-up costs on downtime.*

certain free parameters, which need to be setup based on the specific optimization task – these may e.g. include the starting or final temperature and the number of iterations of the simulated annealing algorithm described below and based on the evolution of thermodynamic systems. In physics, annealing is a process where an object, heated up to a certain high temperature, is being gradually cooled down to remove internal defects in the object. The high temperature causes the particles in the object to rearrange randomly, which destroys defects in the crystal lattice, and the gradual cooling then allows the particles to stabilize in equilibrium points with a lower probability of the creation of new defects.

Consider the case that the cost function argument (2) unambiguously specifies the macroscopic state of a certain thermodynamic system with energy equal to the function value. Then we can express its thermodynamic probability:

$$P(E_i) = |\{\vec{x} \in \mathbb{R}^n | f(\vec{x}) = E_i\}| \tag{5}$$

as the number of micro-states corresponding to it.

If we immerse this system with various macro-states with energies E_i in a thermal reservoir, then the Boltzmann equation for the unit size of the Boltzmann constant together with the Taylor expansion of a differentiable function, allows us to express the entropy of the reservoir after the temperatures equilibration for $E = E_0 + E_i = const$ and $E \gg E_i$ as follows:

$$S(E_i) = S(E) - \frac{dS(E)}{dE_i} E_i = \ln P(E - E_i) \tag{6}$$

and then, by using the definition of temperature *dS(E)/dE=1/T* ($T > 0$), we can express the thermodynamic probability of a macro-state of the thermal reservoir as a function of the energy of the macro-state of the inserted system, i.e. by the following Boltzmann factor:

$$P(E - E_i) = ce^{-\frac{E_i}{T}} \tag{7}$$

The simulated annealing algorithm is based on the perturbation of an optimum candidate and a following decision on its replacement by a perturbation in each iteration of the algorithm based on the Metropolis criterion [1]:

$$p(\vec{x}_i \to \vec{x}_j) = \frac{P(E_j)}{P(E_i)} = e^{-\frac{\Delta E}{T}} \qquad \Delta E > 0 \tag{8}$$

$$p(\vec{x}_i \to \vec{x}_j) = 1 \qquad \Delta E \leq 0 \tag{9}$$

which expresses the probability of the system transferring from one macro-state to another, where $\Delta E = E_j - E_i$ and $\Delta E/T$ expresses the increase of entropy, i.e. in accordance with the second law of thermodynamics an impossible event is artificially redefined as a certain event in the specified criterion.

The sequence of accepted perturbations, i.e. acceptable solutions to the optimization task, forms a Markov chain with memory of order one, i.e. the occurrence of the given solution is only conditioned by the occurrence of the previous solution. The perturbations which lie outside of the area of admissible solutions are automatically rejected.

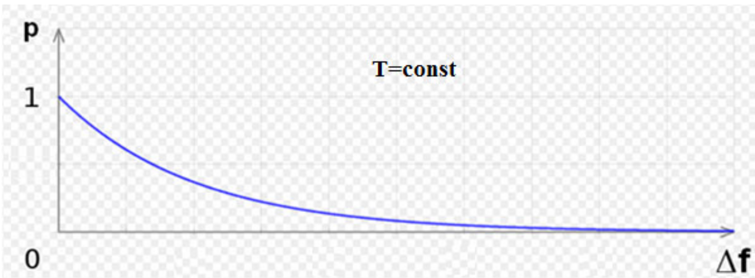

Fig. 2 *Dependence of probability on increase of energy.*

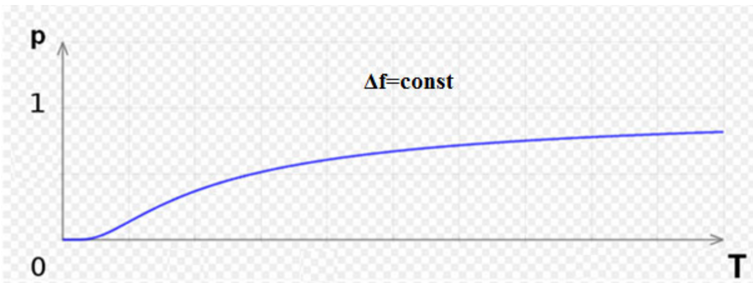

Fig. 3 *Dependence of probability on temperature.*

From $p(\Delta f)$ (Fig. 2), it is clear that a significantly "worse" solution is accepted with respect to the previous solution at a much lower probability than a slightly "worse" solution. $p(T)$ (Fig. 3) may be used to control the probability of the acceptance of the solution during the iteration cycle. We initiate the iteration cycle with a sufficiently high temperature to ensure that almost every proposed solution is accepted for a certain period of time, which will allow an initial approximation of the solution to "escape" areas with shallow local minima. Later on, we reduce the temperature so that almost no "worse" solution is accepted, i.e. during the iteration cycle we cool down the system representing the optimization task from a sufficiently high temperature to a sufficiently low temperature until a solution is "frozen" in a sufficiently deep local minimum (Fig. 4). The temperature drop may be modeled e.g. as an exponentially decreasing function:

$$T = T_0 e^{-\frac{iter}{\tau}} \qquad \tau = -\frac{N}{\ln(T_\infty/T_0)} \qquad T_\infty \approx \lim_{iter\to\infty} T_0 e^{-\frac{iter}{\tau}} = 0$$

where T_0 resp. T_∞ are the initial resp. final temperatures and N is the number of iterations of the algorithm (Fig. 5).

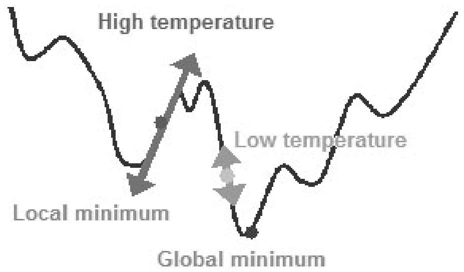

Fig. 4 *Freezing of solution (adapted from [5]).*

4. Experiment

The scenario of the following computational experiment is as follows: Let us assume a fictitious town formed by a complex of intelligent residential and office buildings and with a wide spectrum of associated amenities. The town, located near the foothills of a mountain range, is near a small river flowing from a lake, with a sufficient slant to build two hydro-electric plants. The vicinity of the mountains provides stable winds which are of sufficient power to build a park with wind power plants. Next to the town, there is a cogeneration plant which supplies the town with heat and power. Due to the highly developed agricultural production in the inland areas nearby, a biomass power plant has been built near the town. Due to the dominant cloudy weather in the considered period, the photovoltaic power cells located in the town do not provide sufficient output, and so these will not be included in the experiment. To retain the reliability of the delivery of power, the town is connected to two high-voltage power lines from different power suppliers.

The objective of the experiment is a proposal for an ordering of sources for a typical Saturday resp. Wednesday in November, for which predictions of the hourly consumptions are available [4], see (Fig. 6) resp. (Fig. 7).

The cost function (2) is a function with mixed independent variables, i.e. with continuous independent variables (outputs produced by individual sources) resp.

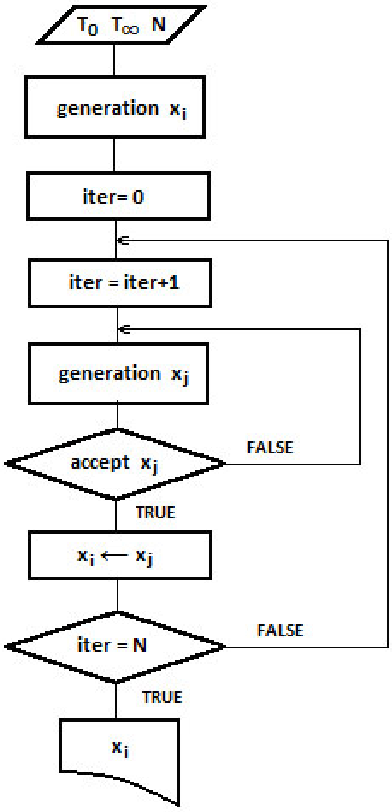

Fig. 5 *Simulated Annealing Algorithm.*

with discrete independent variables (states of individual sources). The specified continuous variables are transferred to discrete independent variables via sufficiently fine graining (by MW units) of the interval between the minimal and maximal output of each source.

The final set of admissible solutions of the task specified by the technical limits of the output of each source at the given hour of the considered period then has a cardinality given by the following combinatorial product: $50^{15} \times 70^{9} \times 80^{5} \times 100^{8} \times 200^{1} \times 380^{2} \cong 10^{75}$.

The costs of a trivial solution, where all the sources operated during the whole considered period at medium capacity (see 2.), were set as the reference costs for the production of energy for the prediction consumption during the given period:

$$P_i(t) = C(t)\frac{P_i^C}{\sum_i P_i^C} \qquad P_i^C = \frac{1}{2}(P_i^{\max} - P_i^{\min}) \tag{10}$$

The parameters of the optimization algorithm T_0 resp. T_∞ resp. N were set to the values 10^0 resp. 10^{-6} resp. 10^6 for the experiment. The mechanism for setting the initial temperature was based on its default estimate and subsequent increase up to a value where during the first circa ten percent of iterations almost all perturbations are accepted, which is an analogue to the heating up of the object during annealing. Similarly, the mechanism for setting the final temperature was based on its default estimate and subsequent decrease up to a value where during the circa last ten percent of iterations almost no perturbations which increase the value of the cost function are accepted. The mechanism for setting the number of iterations was based on their default estimate and subsequent gradual increase up to a value such that its further increase did not result in a significant reduction of the final production costs for the required volume of energy.

In the specified experiment, the town is supplied by electrical power from thirty two rotary (synchronous generator) and eight non-rotary (transformer) machines, i.e. a total of forty sources and its cost characteristics and technical limitations are specified in Tab. I, where $HC = HC1 + HC2 * P$ is the consumption of the source itself based on the produced output.

UNIT	NR	Pmin	Pmax	HC1	HC2	A	B	C	D	TAU
		[kW]	[kW]	[kW]	[-]	[CZK]	[CZK/MW]	[CZK/MW²]	[CZK]	[-]
Water1	1	600	980	5	0,065	12046	142,0	0,029	48429	6,257
Water1	2	600	980	5	0,065	12046	142,0	0,029	48429	6,257
Water2	1	390	440	5	0,065	14667	161,2	0,030	53826	5,948
Water2	2	390	440	5	0,065	14667	160,7	0,030	53826	5,948
Water2	3	390	440	5	0,067	14667	161,4	0,030	53826	5,948
Water2	4	390	440	5	0,068	14667	162,4	0,030	53826	5,948
Wind1	1	120	200	10	0,078	15104	170,7	0,383	220797	6,633
Wind1	2	120	200	10	0,078	15104	170,7	0,380	220797	6,633
Wind1	3	120	200	10	0,078	15104	170,7	0,387	220797	6,633
Wind1	4	120	200	10	0,078	15104	170,7	0,390	220797	6,633
Wind1	5	120	200	10	0,078	15104	170,7	0,393	220797	6,633
Wind2	1	140	210	10	0,114	16480	188,3	0,448	352258	7,164
Wind2	2	140	210	10	0,114	16659	188,3	0,459	352258	7,164
Wind2	3	140	210	10	0,114	16480	188,3	0,451	352258	7,164
Wind2	4	140	210	10	0,114	16659	188,3	0,462	352258	7,164
Wind2	5	140	210	10	0,114	16480	188,3	0,455	352258	7,164
Cogener1	1	300	500	15	0,054	15902	198,8	0,152	278466	5,788
Cogener2	1	130	200	15	0,088	15815	176,8	0,437	230474	7,948
Cogener2	2	130	200	15	0,088	15815	176,8	0,431	230474	7,948
Cogener2	3	130	200	15	0,088	15815	176,8	0,434	230474	7,948
Cogener2	4	130	200	15	0,088	15815	176,8	0,427	230474	7,948
Biomass1	1	100	150	5	0,131	8483	199,5	0,884	167598	9,224
Biomass1	2	100	150	5	0,131	8534	200,7	0,853	155921	9,076
Biomass1	3	100	150	5	0,120	9273	224,0	0,701	153513	9,044
Biomass2	1	100	150	5	0,132	7948	204,4	0,939	72779	7,447
Biomass2	2	100	150	5	0,132	7948	204,4	0,943	72779	7,447
Biomass2	3	100	150	5	0,132	7948	204,4	0,947	72779	7,447
Biomass2	4	100	150	5	0,132	7948	204,4	0,950	72779	7,447
Biomass3	1	100	150	5	0,173	10505	282,3	1,101	128197	8,669
Biomass3	2	100	150	5	0,173	10505	282,3	1,051	128197	8,669
Biomass3	3	100	150	5	0,173	10505	282,3	1,001	128197	8,669
Biomass3	4	100	150	5	0,173	10505	282,3	0,951	128197	8,669
Network1	1	100	200	1	0,084	20903	338,8	1,554	50000	5
Network1	2	100	200	1	0,084	20903	338,8	1,550	50000	5
Network1	3	100	200	1	0,084	20903	338,8	1,545	50000	5
Network1	4	100	200	1	0,084	20903	338,8	1,541	50000	5
Network2	1	100	200	1	0,071	24409	387,2	1,574	50000	5
Network2	2	100	200	1	0,071	24409	387,2	1,569	50000	5
Network2	3	100	200	1	0,071	24409	387,2	1,563	50000	5
Network2	4	100	200	1	0,071	24409	387,2	1,580	50000	5

Tab. I *Parameters of sources.*

During the optimization algorithm, the state and output will be set randomly for a randomly selected unit, namely for each hour of the considered period and for each iteration of simulated annealing. The randomness will be obtained by the use of a random number generator with a parameterizable initiation of a sequence of pseudo-randomly generated numbers, see the SEED variable in the fragment of the source code presented in Fortran:

```
C
C     S T A R T - H O U R   C Y C L E
C
      DO J=2,NT+1
C
C     S T A R T - I T E R A T I O N   C Y C L E
C
      DO ITER=1,N
C
C     STATE RANDOM GENERATION
C
C RANDOM CHOICE OF SOURCE
      I=RAN(SEED)*(NG-1)+1
      IJ=(I-1)*(NT+1)+J
C RANDOM CHANGE OF STATE
      IF(X(IJ).EQ.0)THEN
            IF(RAN(SEED).LE.Ponoff)X(IJ)=1
      ELSE
            IF(RAN(SEED).LE.Ponoff)X(IJ)=0
      ENDIF
C
C     POWER RANDOM GENERATION
C
C RANDOM CHOICE OF SOURCE
      I=RAN(SEED)*(NG-1)+1
      IJ=(I-1)*(NT+1)+J
C RANDOM SET OF POWER
      P(IJ)=RAN(SEED)*(Pmax(I)-Pmin(I))+Pmin(I)
C
C     S T O P - I T E R A T I O N   C Y C L E
C
      ENDDO

C
C     S T O P - H O U R   C Y C L E
C
      ENDDO
```

where NT resp. NG is the number of hours resp. of available source, P(IJ) resp. X(IJ) is the output resp. state of the I-th source in the J-th hour, Pmin(I) resp. Pmax(I) are the output limits of the I-th source, Ponoff is the parameterizable probability of a change of the state of the source and the function RAN is a random number generator whose outputs form an uniform distribution of numbers in the interval (0,1).

The resulting ordering of sources for Saturday resp. Wednesday is provided in Tab. II resp. Tab. III. The time of the computation, carried out on a notebook with a 2 GHz processor, was two minutes and thirty seconds.

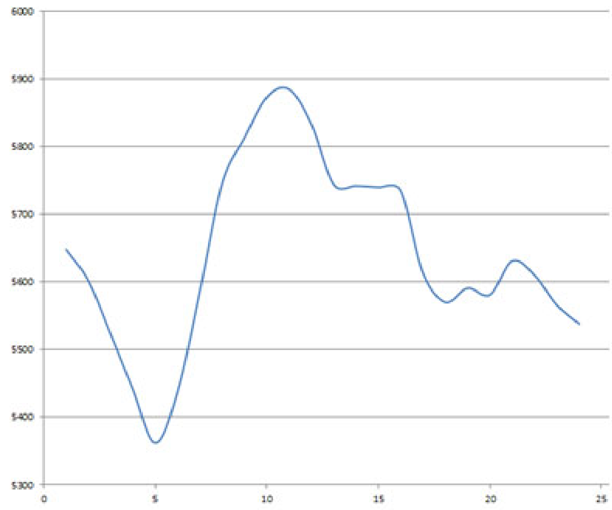

Fig. 6 *Predicted Daily Diagram of Saturday.*

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. II *Unit Commitment of Saturday.*

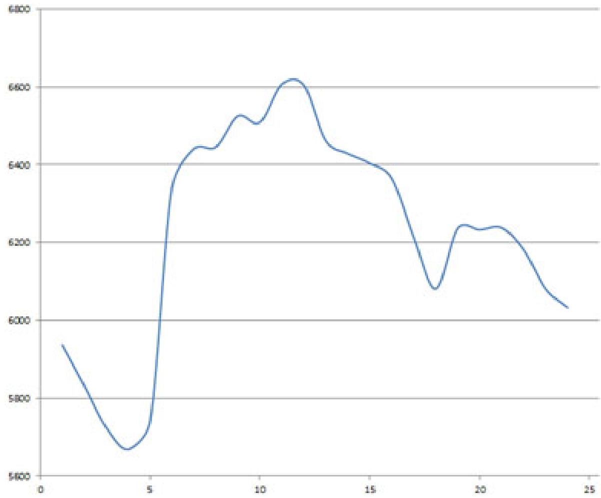

Fig. 7 *Predicted Daily Diagram of Wednesday.*

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.*

5. Conclusion

By comparing Fig. 6 to Tab. II, it is clear that the power consumption on Saturday is primarily covered by sources with more or less lower production costs, such as both hydro-electric 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 startup of one transformer, which together with one source of the specified cluster also covers the evening consumption peak. Referential resp. optimal costs for the coverage of the Saturday energy consumption then amount to 65 254 resp. 38 446 CZK, i.e. the optimization has led to savings amounting to 26 809 CZK.

By comparing Fig. 7 to Tab. III, it is clear that the Wednesday consumption is covered in a similar fashion, 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 the 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 startup costs and relatively high operating costs. Referential resp. optimal costs for the coverage of the Wednesday energy consumption then amount to 69 216 resp. 45 006 CZK, i.e. the optimization has led to savings amounting to 24 210 CZK.

The proposed sorting of the sources in general implies that sources with the highest production costs, i.e. transformers supplying energy from distribution companies, are only used during peak hours, which is in compliance with the accentuation on the energy self-sustainability of the town in our example.

The description of the computational experiment implies a high efficiency of the optimization algorithm of simulated annealing when searching the admissible solution space, given by the ratio of the total number of admissible solutions to the number of simulated admissible solutions in each hour of the considered period, i.e. $10^{75} : 10^{6}$.

Appendix A

When solving optimization problems, it is possible to choose from a wide range of optimization methods, and specifically from two categories depending on the method of solution of the optimization task: conventional or heuristic methods. Conventional methods, for instance mathematic programming methods, precisely specify a free or constrained local extreme in a relatively short time, while heuristic methods only specify one approximately and in a relatively long time. The task of sorting sources is conventionally solved by the method of Lagrange multipliers. As an alternative to the presented simulated annealing method, we briefly describe the method of Lagrange multipliers below.

Consider an optimization task (1) with the following area of admissible solutions:

$$\vec{g}:\mathbb{R}^n \to \mathbb{R}^m \quad \Omega = \{\vec{x} \in \mathbb{R}^n | \vec{g}(\vec{x}) = \vec{0}\} \quad m < n \qquad (A.1)$$

where f, g_j are continuously differentiable functions and additionally let us introduce the following so-called Lagrange function:

$$F:\mathbb{R}^{n+m} \to \mathbb{R} \quad F(\vec{z}) = f(\vec{x}) + \vec{\alpha}.\vec{g}(\vec{x}) \quad \vec{z} = [\vec{x}, \vec{\alpha}] \qquad (A.2)$$

where the components of vector $\vec{\alpha}$ are the so-called "Lagrange multipliers", then assuming the linear independence of vectors $\nabla g_1(\vec{x}), \ldots, \nabla g_m(\vec{x})$ is the necessary condition for the existence of a local extreme of the function (A.2) at point $\vec{z}_0$ in the shape $\nabla F(\vec{z}_0) = \vec{0}$, i.e.:

$$\frac{\partial F}{\partial x_i} = \frac{\partial f}{\partial x_i} + \sum_j \alpha_j \frac{\partial g_j}{\partial x_i} = 0$$

$$\frac{\partial F}{\partial \alpha_j} = g_j = 0$$

$i \in \{1, -, n\}, j \in \{1, -, m\}$.

If, in the area of admissible solutions (A.1), we replace the equality for an inequality, then we can return to a constraint in the shape of an equality by an equivalent representation of the following constraints and a Lagrange function with an auxiliary variable $\vec{y}$:

$$\Omega = \{\vec{x} \in \mathbb{R}^n | \vec{g}(\vec{x}) + \vec{y} = \vec{0}\} \qquad (A.3)$$

$$F(\vec{z}) = f(\vec{x}) + \vec{\alpha}.(\vec{g}(\vec{x}) + \vec{y}) \quad \vec{z} = [\vec{x}, \vec{y}, \vec{\alpha}] \qquad (A.4)$$

together with equivalent necessary conditions for the existence of a local extreme of the function at $\vec{z}_0$:

$$\frac{\partial F}{\partial x_i} = \frac{\partial f}{\partial x_i} + \sum_j \alpha_j \frac{\partial g_j}{\partial x_i} = 0$$

$$\frac{\partial F}{\partial y_j} = \alpha_j = 0$$

$$\frac{\partial F}{\partial \alpha_j} = g_j + y_j = 0$$

Let us consider in general the restriction of task (1) in the shape: $\Omega = \{\vec{x} \in \mathbb{R}^n | \vec{x} \geq \vec{0}\}$, then the following holds for the optimal internal resp. border point of Ω:

$$\forall_i \quad x_{0i} > 0 \to \frac{\partial f}{\partial x_{0i}} = 0$$

resp.

$$\exists_j \quad x_{0j} = 0 \to \frac{\partial f}{\partial x_{0j}} \geq 0$$

$i, j \in \{1, -, n\}$, so obviously the following holds for any optimal point from Ω:

$$\forall_i \quad x_{0i} \frac{\partial f}{\partial x_{0i}} = 0 \tag{A.5}$$

and then we can express the necessary condition for the existence of a local extreme of function (1) at $\vec{x}_0$ by using (A.5) as follows:

$$\nabla f(\vec{x}_0) \geq \vec{0} \quad \vec{x}_0 . \nabla f(\vec{x}_0) = 0 \tag{A.6}$$

Subsequently, for $\vec{x} \geq \vec{0}$ and $\vec{y} \geq \vec{0}$ we obtain the following set of necessary conditions for the existence of a local extreme of function (A.4) analogously to (A.6) at $\vec{z}_0$:

$$\frac{\partial F}{\partial \vec{x}} \geq \vec{0} \quad \vec{x}_0 . \frac{\partial F}{\partial \vec{x}} = 0$$

$$\frac{\partial F}{\partial \vec{y}} \geq \vec{0} \quad \vec{y}_0 . \frac{\partial F}{\partial \vec{y}} = 0$$

$$\frac{\partial F}{\partial \vec{\alpha}} = \vec{g}(\vec{x}_0) + \vec{y}_0 = \vec{0}$$

and by adjusting these conditions we may then, by omitting the auxiliary variable $\vec{y}$, express the necessary conditions for the existence of a local extreme of the function (A.2) at $\vec{z}_0$ in the are delimited by the inequalities in the so-called "Kuhn-Tucker" compact symmetrical shape:

$$\frac{\partial F}{\partial \vec{x}} \geq \vec{0} \quad \vec{x}_0 \geq \vec{0} \quad \vec{x}_0 . \frac{\partial F}{\partial \vec{x}} = 0 \tag{A.7}$$

$$\vec{g}(\vec{x}_0) \leq \vec{0} \quad \vec{\alpha}_0 \geq \vec{0} \quad \vec{\alpha}_0 . \vec{g}(\vec{x}_0) = 0 \tag{A.8}$$

and point $\vec{z}_0$ is the so-called "saddle" point of function (A.2), i.e. the Lagrange function reaches at this point its minimum resp. maximum with respect to variables $\vec{x}$ resp. $\vec{\alpha}$ and based on (A.8) it holds that $F(\vec{z}_0) = f(\vec{x}_0)$, and so $\vec{x}_0$ is obviously the sought optimum of the criterion function f in the area delimited by the constraints in the inequalities.

The saddle point of function (A.2) can then be obtained by solving a set of $n + m$ non-linear equations with $n + m$ variables specified by the scalar products (A.7), (A.8) with the following Jacobian matrix:

$$\mathbf{J} = \begin{bmatrix} \mathbf{H} & \mathbf{E} \\ \mathbf{F} & \mathbf{G} \end{bmatrix} \tag{A.9}$$

$$\mathbf{H} = \begin{bmatrix} \frac{\partial F}{\partial x_1} + x_1 \frac{\partial^2 F}{\partial x_1^2} & \cdots & x_1 \frac{\partial^2 F}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ x_n \frac{\partial^2 F}{\partial x_n \partial x_1} & \cdots & \frac{\partial F}{\partial x_n} + x_n \frac{\partial^2 F}{\partial x_n^2} \end{bmatrix}$$

$$\mathbf{E} = \begin{bmatrix} x_1 \dfrac{\partial g^1}{\partial x_1} & \dots & x_1 \dfrac{\partial g_m}{\partial x_1} \\ \vdots & \ddots & \vdots \\ x_n \dfrac{\partial g_1}{\partial x_n} & \dots & x_n \dfrac{\partial g_m}{\partial x_n} \end{bmatrix}$$

$$\mathbf{F} = \begin{bmatrix} \alpha_1 \dfrac{\partial g_1}{\partial x_1} & \dots & \alpha_1 \dfrac{\partial g_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \alpha_m \dfrac{\partial g_m}{\partial x_1} & \dots & \alpha_m \dfrac{\partial g_m}{\partial x_n} \end{bmatrix}$$

$$\mathbf{G} = \begin{bmatrix} g_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & g_m \end{bmatrix}$$

For $\frac{\partial F}{\partial x_i} \neq 0$ and $g_j \neq 0$ the Jacobian matrix is clearly regular, and so there exists an unambiguous solution to the set of equalities based on the fixed point theorem.

Appendix B

Fig. 8 displays the content of individual sub-dimensions of intelligent buildings (and files of intelligent buildings), reflecting the theoretical and practical perspectives of the composition and expressing its significance. Our contribution focused on the solution of the "intelligence" of the outer building – a smart micro-network, as the basic premise of sustainable energy solutions with maximum efficiency of constructing the intelligent buildings complex in the selected metropolitan area.

In connection with the integration of energy in the building at the level of intelligent buildings, there exists a control center in the context of the third level of integration links. This control center then performs monitoring and energy management as well as prediction and optimization with databases of planned consumption of commodities used in confrontation with the state and later its adjustments so that everything integrates towards strict efficiency and proposals for possible diagram revisions. Sustained and sustainable construction in the context of sustainable energy integrates towards energy quality, which is one of the fundamental factors in the design of intelligent buildings. The standard of a passive or low-energy house is universal thanks to focusing on purely functional requirements, which can be reached everywhere in a natural way through a high potential for energy savings. This is a condition defining sustainable energy. Buildings account for roughly half of the total energy consumption, i.e. about a half share in causing the greenhouse effect due to nitrogen oxide emissions. Therefore projects, construction work and operation of buildings for people is vital now as well as in the future. This of course applies to all, both old and new, buildings. A shared feature should be the general compliance with the formulated sustainability requirements, which in addition to the IAQ and low production of pollutants of all kinds and power

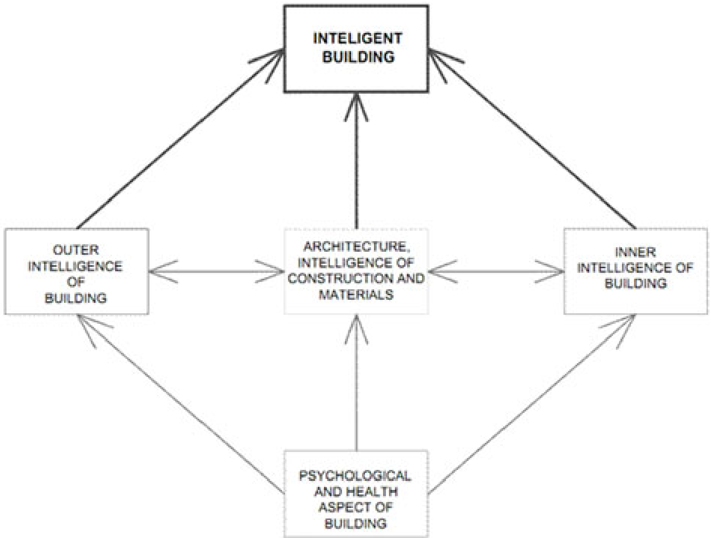

Fig. 8 *Expression of the process model and intelligent building structures (Adapted from [3]).*

relations may also include social and economic factors. Sustainability in construction is a solution that meets the needs of the present without compromising the ability of future generations to meet their needs, and this also applies to energy.

The basic condition for sustainable energy is the application of new sources of renewable energy. The problem of energy efficiency, which takes into account the massive deployment of information technologies in the transmission and distribution of energy with its own power generation, energy storage, energy consumption and interaction with intelligent micro-networks, is to dynamically manage energy demand and/or production. This problem may be addressed by including it into the process of an intelligent building or a complex of intelligent buildings, in other words, we are talking about intelligent solutions outside of buildings. This represents broad multidisciplinary process which addresses the issues of life and human habitation and not only the solution of the specific energy problems - i.e. a process which seeks to deal with these issues in a broad context.

The complex of intelligent buildings is an example of smart grids in the process of electricity demand in the micro-network of an experiment with several intelligent buildings. Management of renewable energy in the distribution of intelligent micro-networks and accumulators in real time, including the optimization of energy management systems such as HEMS, BEMS, etc., are the basic characteristics of the problem that we solve in our experiment.

Efficient use of electricity on the demand-side, efficiency of its use and its diversification in the application of energy management is a prerequisite for reducing the cost characteristics. One problem in the implementation of decentralized accumulation of resources is the matter of their instability and the complexity of management of the electricity from the grid.

The basic characteristic of intelligent micro-networks is the use of nuclear energy, as well as solar, wind and geothermal energy. Another condition is the highly efficient transfer of energy (UHV, superconducting lines), and electricity transmission on demand instead of eccentrically localized renewable sources. Harmonized management of intelligent micro-networks with smart distribution grids (Smart Grids) is an environment in the near future which is both logical and targeted. The reason for such a complex solution is to reduce the consumption in kWh, resulting in a reduction in consumption and peak demand. Savings can vary from 20% to 40%. Furthermore, this includes network balancing, i.e. diverting, shaping and shifting of demand. This allows additional potential savings of 10 to 20% of production costs.

The driving forces of "smart" power are optimization and network balancing. Besides tariff flexibility, we can achieve network balancing and so reduce costly investments in new power plants, increase the quality of energy and efficiently utilize renewable energy sources. We estimate, based on our experiment, that for instance a 5% reduction in peak power consumption during a crisis period may reduce the maximum wholesale price by almost 50%.

Through our experiment, the importance of optimization and the optimization task of reducing the cost of supply of electricity algorithms are underlined. This will enable the construction of intelligent building environments at the level of Smart grids and Smart micro-grids.

Currently, for instance in Europe there is a large amount of unusable opportunities to achieve energy savings. This is another problem, which is discussed and resolved by this submission at the level of the mentioned external intelligent building, as shown in Fig. 8.

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[5] URL: `http://www.fit.vutbr.cz/~jarosjir/groups/eva/sa.html.cs` © FIT VUT Brno (translated)