 Acta Electrotechnica et Informatica, Vol. 13, No. 2, 2013, 8–12, DOI: 10.2478/aeei-2013-0023

FUNDAMENTAL APPROACH FOR DAY-AHEAD PRICE FORECASTING WITH USING NEURAL NETWORKS

Ján MEZERA*, Zbyněk MARTÍNEK**, Radoslav SOKOL***
*Department of Electrical Power Engineering and Ecology, Faculty of Electrical Engineering, West Bohemia University in Pilsen, Univerzitní 26, 306 14 Plzeň, Czech Republic, tel. +420 724 446 511, e-mail: mezera@kee.zcu.cz
**tel. +420 377 634 347, email: martinek@kee.zcu.cz
***Faculty of Electrical Engineering, Czech Technical University, Technická 2, 166 27 Prague 6 – Dejvice, Czech Republic, tel. +420 725 628 093, e-mail: radoslav.sokol@gmail.com

ABSTRACT

This paper provides approaches for day-ahead electricity price forecasting together with problems existing in this field mainly with nonlinear character of modelation. The fundamental model by using neural networks is shown and output results are presented, for example, failure of the model. Comparison with already existed models and other approaches for prediction of electricity prices are mentioned and carried out in this article. As evidence of the correct function of this method difference between real results of the spot market and output of the model is presented.

Keywords: *Neural network, Backpropagation, Feed-forward net*

1. INTRODUCTION

Nowadays, world energy sector is impacted by economic crisis as reaction on the problem of the EU and its members. During this time world leaders of the energy sector concentrate on the improvement of their own internal company´s processes and cost-effectiveness. More than ever before energy leaders are focused on the maximalization of their benefits and try to avoid further market volatilities. They are not interested only in conventional margin benefits, from the sale of the own generation but they want to find a new market opportunity and improve its own optimization.

As a tool, which can help a company to save money and bring benefit to their budgets is creating new prediction models for better expectation of the wholesale market prices as a place where the big energy leaders sale their own production. The market participant can use the model not only for exact price prediction but it can bring other benefits for a bidding purposes, market expectations and scale down financially risky decisions [12].

We can separate price forecasting into the several categories according to their specific features and delivery/receipt time – intraday (trading date same like delivery/receipt date), short-term (week and day-ahead trading), midterm (months trading) and long term (calendars trading). This scientific work is focused on electricity price prediction of the day-ahead market. There are several possible methods for the day-ahead electricity price forecasting with different mathematical approach. The first group of methods is based on the calculation of the marginal generation costs. New rules (REMIT) intend to make the EU's wholesale gas and power markets more transparent and secure. Therefore, this approach could be more significant. This principal has entered into force on the end of the last year and can partly help with troubles in mentioned method, which requires really accurate data for correct prediction. Second group of methods is based on working with aggregated supply and demand curve. The third approach uses simple statistical calculations – regression, which is used in combination with the others influences on the resulting price forecast like historical similarities among days. All above mentioned approaches are not that accurate for a wider use in practise. The reason is simple, they does not consider nonlinear problem, which occurs in these cases and try to solve this problem by linear models.

In this article, we focus on the prediction model based on the fundamental approach. The neural networks are used for limiting nonlinear problems of the classic models. The model is proposed for conditions of the European Energy Exchange (EEX) and fully uses data, which are available on the webpage of the EEX (published bids and offers).

2. BASIC DESCRIPTION OF THE MODEL AND VARIABLES FORMULATION

We have to mention basic assumptions for model proposal. The model is composed of three separated parts illustrated on the Fig.1. The core of the model has fundamental character based on the four selected fundamentals - solar radiation, wind production, consumption and source availability. These fundamentals are transferred on the one same power unit [MW/h]. Data are published directly on EEX webpages. Furthermore, we consider that market price on day+1 corresponds with bid and offer curves´ shapes of the previous or other similar day (different scenarios for weekdays, workdays, peekload, offpeak). It can be said, that day+1 price is changed proportionately to fundamentals´ change calculated according Eq.1 (expressed in [MW/h]). New price is obtained from subsequent application of the resulted ΔP_i on similar curve (Fig.2).

The most tricky matter is calculation of variables c_x, which are used in Eq.1. We can imagine these variables also as weights for all fundamentals, which express fundamental influence on the resulted power deltas. This is the most difficult part of whole modelation regarding to nonlinear character of the problem and dynamic change of the production from the renewable sources. For a c_x calculation we can use either clearly statistical approach or approach that uses neural networks, which is also the main topic of this scientific work.

Statistical approaches calculate c_x by solving linear regression according to Eq 2, 3, 4, 5, where the right side of each equation is sum of the fundamental changes against previous or other similar day (wind, solar, availability, consumption) multiply by associated coefficient and left sides are resulted deltas between two neighboring days expressed in power unit [MW/h].

Other possible statistical approaches are different only in the formulation of the right side of the Eq.1. Increase in production from the renewable sources encourages to take this fact into account and modify Eq.1 into new exponential form, which considers only two fundamentals (wind and solar production) as main parts for power delta calculation (Eq.6).

As it has been said, the main goal of this scientific paper is using the neural network as forecasting tool..

$$\Delta P_i = \Delta W_i \cdot c_{W_i} + \Delta S_i \cdot c_{S_i} + \Delta A_i \cdot c_{A_i} + \Delta C_i \cdot c_{C_i} \qquad (1)$$

$$\Delta f = \left[\begin{pmatrix} f_1(x_1) & \cdots & f_k(x_1) \\ \vdots & \ddots & \vdots \\ f_1(x_n) & \cdots & f_k(x_n) \end{pmatrix}\right] = \begin{bmatrix} \Delta f_{1,1} & \cdots & \Delta f_{1,k} \\ \vdots & \ddots & \vdots \\ \Delta f_{n,1} & \cdots & \Delta f_{n,k} \end{bmatrix} \qquad (2)$$

$$\{\Delta p\} = \{\Delta P_1 \ \ \Delta P_2 \ \ \ldots \ \ \Delta P_n\}^T \qquad (3)$$

$$\{C\} = \{c_1 \ \ c_2 \ \ \ldots \ \ c_k\}^T \qquad (4)$$

$$C = \Delta f \ \setminus \ \Delta p \quad \left(\frac{MW}{h}; -, \frac{MW}{h}\right) \qquad k < n \qquad (5)$$

Letter *k* presents number of fundamentals (*k*=4) and letter *n* is number of samples.

$$\Delta P_i = \Delta W_i \cdot c_{W_i} + \Delta W_i^2 \cdot c_{W2_i} + \Delta S_i \cdot c_{S2_i} + \\ + \Delta S_i^2 \cdot c_{S_i} + c_{0_i} \qquad (6)$$

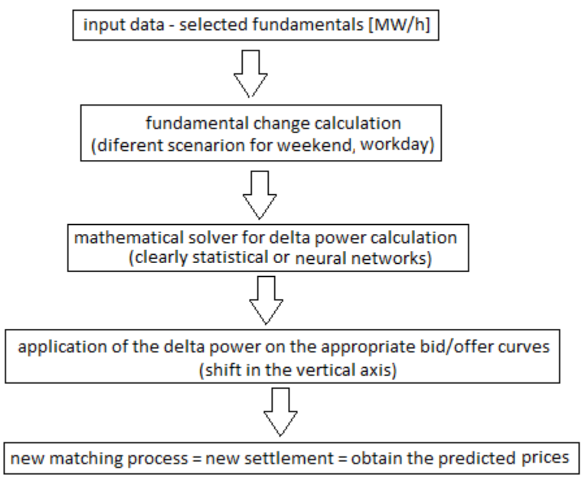

Fig. 1 Basic concept of the prediction model

3. FEED-FORWARD NEURAL NETWORK

Neural network (NN) is applied for calculation of vector Δp. Therefore, it is necessary to choose a correct type of the NN. Moreover, the architecture, topology, inputs, propagation function and way for learning have to be determined. According to the literature [1] and [2], where the individual types of NN are explained and demonstrated, the feed-forward NN with back-propagation learning was chosen. This network type is characterised by interconnection strengths known as synaptic weights, which are used to store the knowledge and integration of the multilayer composition. The structure of the back-propagation NN is shown on (Fig. 3) together with an example of weights calculation inside the net.

In general, two types of the learning principles of NN are known. The first type (with “teacher”) is characterised by existence of the input and output (= targets) set. The output of the output layer is compared with the target output values (target values are these that we attempt to teach our network). The error between actual output values and target is calculated and propagated back toward hidden layer. This is called the back-propagation pass of the back propagation algorithm. The error is used to update the connection strengths between nodes (weight matrices are updated as well). The second type requires only input samples set, where, in general, the structure of all variables and characteristic measurements is contained (variables in bar and measurements or samples in the rows). Both of them are used for different application, the learning with teacher is used for prediction purposes, learning without teacher mainly for sorting of unknown input data set.

The back-propagation learning, which was selected as teaching tool of our NN, is separated into three characteristic periods – initialize the weights and biases, train and validate the NN. After completion of these three procedures the proposed NN is prepared.

3.1. Price curves

Furthermore, the above mentioned delta vector {Δp} is applied to the price curves of the appropriate (= „similar“) day. In order to get the price curves, the own

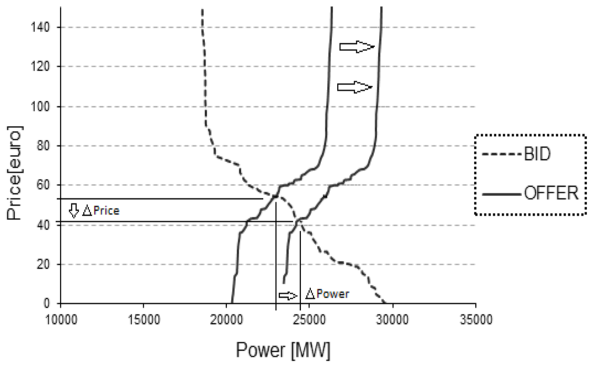

Fig. 2 Daily Bid&Offer curves shifting (price forecast)

ISSN 1335-8243 (print) © 2013 FEI TUKE
www.aei.tuke.sk

ISSN 1338-3957 (online)
www.versita.com/aei

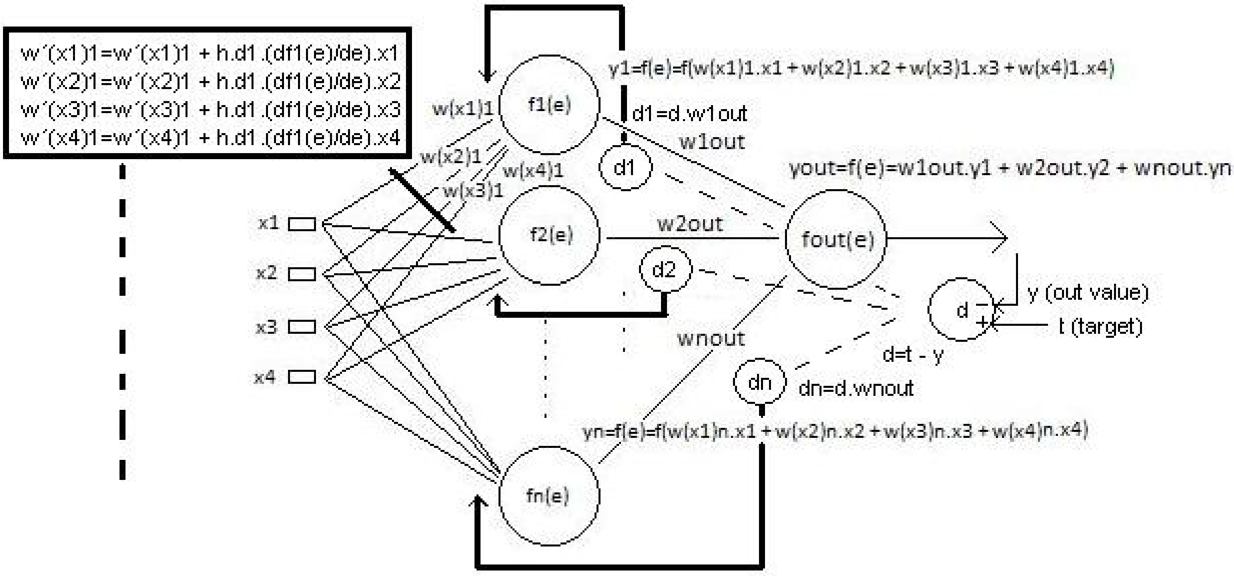

Fig. 3 Back-propagation

matching process of EEX is necessary to simulate the establishment of the clearing price and power. The chart of the single demand and supply curves, where intersection of both curves shows clearing price and amount, is presented on Fig. 2.

The interconnection points of the bid and offer curve are found gradually by calculating the difference between bid and offer curves for associated price. The procedure starts from the lowest price of the bid curve, where volume difference is bigger, then the price increases in each iterration and new differences are calculated. The end of whole calculation is just when difference between bid and ask curve for chosen price is equal to zero or approximately zero. Then we can say that the clearing price and volume were found.

3.2. Delta application

For the final estimation of the day-ahead price forecast the vector $\{\Delta p\}$ has to be applied on the simulated price curves. The bid curve is shifted about associated delta. In the intersection of the shifted bid curve and old offer curve the new predicted price lies. In general, we assume that the price curves between two subsequent days are similar and that volume deltas (increase or decline) can be expressed by deltas fundamental. In addition, we can calculate sensitivity of the predicted price on the inserted bid volume. In other words, we can artificially increase bid volume (± 1000MW) and then simulate new matching process with an old offer curve. These two displayed

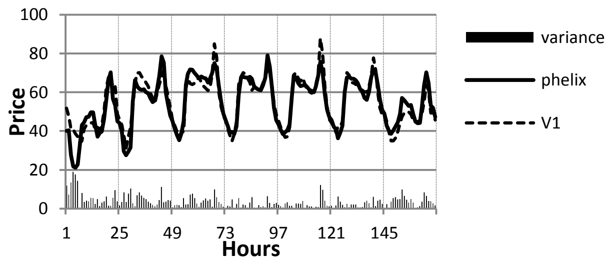

Fig. 4 Mean absolute average error (MAPE)

curves are significantly useful from the trading view and express how reliable our forecast is. When the spread between curves ± 1000MW is tight, there is probability that predicted forecast is very reliable, however wider spread between ± 1000MW curves marks unlikely and unreliable price prediction (usually during morning off-peak hours).

4. SELF-ORGANIZING MAPS (SOM)

In classic feed-forward model the neural network is trained on the variable data set, where variance of input data is wide. The first idea was to separate one big training set into more smaller sets, where samples would be more similar to each other and value variance would be lower. Therefore, the SOM was chosen as a way for future development of designed model.

The self-organizing map is really useful tool for data clustering and its advantage is simplicity. The SOM consists of the individual neurons, which are deployed into topology (one, two or more dimensional grid).

Training of this type of the neural network is realized according to the following procedure. Firstly, the input patterns are entered, then the calculation of the distance between every neuron in topology and entered pattern is made (Eg.7). One neuron becomes active, namely neuron *i* with the shortest calculated distance (Eg.8). The neuron centers are moved within the input space according to the rule in Eg.9,

$$\|input - c_k\| = \Delta_k \ , \ \ k = 1 \div n \tag{7}$$

$$\|input - c_i\| \leq \|input - c_k\| \ \forall \ k \neq i \tag{8}$$

$$\Delta_{c_k} = \eta(t).\, h(i,k,t).\, (input - c_k) \tag{9}$$

where the values Δ_{c_k} are simply added to the existing centers. The last factor $(input - c_k)$ shows that the change in position of the neuron k is proportional to the distance to the input pattern and the timely dependent learning rate $\eta(t)$. The topology function $h(i,k,t)$

describes the neighbourhood relationships in the topology. It can be any unimodal function reached maximum, when $k = i$. This procedure repeats for all patterns in the trading set.

The proposed model uses SOM for separation the big trading set for learning the feed-forward network into smaller groups. All of these groups occur new smaller traning set for new more accurate feed-forward neural networks. Pattern for SOM is input vector consisting of 48 hourly values of the renewable sources production per day (24 hours solar and 24 hours wind production).

5. RESULTS

Results of the EEX day-ahead market were used to examine the accuracy of the forecast. The mean absolute percentage error (MAPE) is considered here to evaluate the performance of the forecast results. MAPE represents the average prediction error between prediction P_f and actual targets P_r (Eq.10).

$$MAPE = \left(\frac{1}{T}\sum_{t=1}^{T}\frac{|P_f - P_r|}{P_f}\right).100\% \qquad (10)$$

Table 1 Comparison of the daily MAPE

TESTED WEEK (25.9. - 1.10.2012)				
DATE	DAILY MAPE	MAX. MAPE	MIN. MAPE	ERROR
25.9.2012	20,3%	87,38%	1,32%	6,56 €
26.9.2012	10,0%	32,81%	1,90%	4,75 €
27.9.2012	5,7%	13,19%	1,31%	3,55 €
28.9.2012	3,6%	12,05%	0,03%	2,06 €
29.9.2012	4,2%	16,03%	0,15%	2,47 €
30.9.2012	4,4%	17,08%	0,14%	2,34 €
1.10.2012	7,4%	17,16%	0,13%	3,84 €
WEEKLY AVG	***7,9%***	***27,96%***	***0,71%***	***3,65 €***

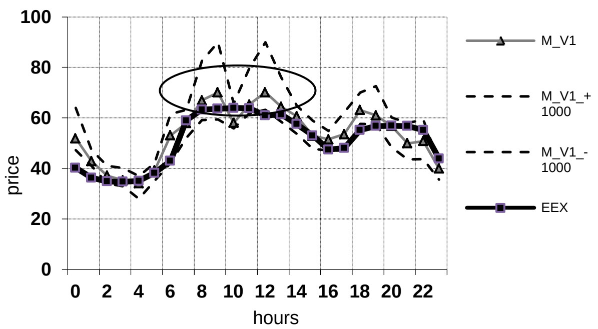

Fig. 5 Confident interval around prediction

Fig. 4 shows comparison between model forecast and real prices published by EEX. After the trial operation of the model we can claim that price forecast is relatively reliable (MAPE lies in interval 0÷10%) for days with lower fundamental change of renewable sources. We tried to separate this problem by using SOM neural network. It helped us to cluster data into more similar groups. But we had not enough samples for correct training of all groups. This method is still under development. Despite the lower amount of the samples the new method had already shown better results, when dynamic fundamental changes had occurred.

Next, using the confident interval, which we got by increasing a decreasing the bid volume about ± 1000MW, is really useful. Back-testing showed that real price lies within this interval with 95% probability. Width of this interval represents the price sensitivity. On the Fig.5 is showed day forecast with ± 1000MW border together with sensitivity corridor around the forecast curve. We can observe that change of the confidence interval is huge and it is associated with market liquidity (Tab.2).

Table 2 Price forecast with confident interval

24.4.2012				
HOURS	M_V1	+1000	-1000	CONFIDENT
1	51,92	47,26	63,99	16,73
2	42,90	41,05	47,35	6,30
3	37,14	34,04	41,05	7,01
4	35,30	32,90	40,20	7,30
5	34,13	28,00	36,95	8,95
6	39,17	35,04	42,07	7,03
7	53,07	42,17	61,60	19,43
8	57,94	52,10	63,22	11,12
9	67,00	59,11	82,55	23,44
10	70,06	59,43	89,90	30,47
11	58,07	55,82	65,72	9,90
12	65,31	61,81	79,68	17,87
13	70,17	63,14	89,96	26,82
14	64,46	58,52	76,08	17,56
15	60,61	53,66	64,85	11,19
16	52,93	47,69	58,87	11,18
17	51,54	47,05	54,78	7,73
18	53,51	47,17	62,13	14,96
19	63,08	57,68	70,07	12,39
20	61,01	57,56	72,63	15,07
21	56,79	48,37	60,10	11,73
22	49,90	43,59	57,95	14,36
23	50,80	43,74	59,26	15,52
24	39,95	35,57	42,02	6,45

6. CONCLUSIONS

Four different scenarios (weekend, workday, holidays, Monday) can occur in accordance to the similarities among daily price curves. These scenarios were discovered by back-testing of the proposed model. Aggregated curves are considered as price curves of all bids and offers on the EEX, which are published every day on the webpage of this institution. Whole curve is shifted according to calculated power deltas for selected day and discovers new clearing price. This is performed for every hour of the day by using calculated delta, which respects the fundamental change. The entire price curves of the day can be subsequently plotted by simple connection of these prices. Feed-forward NN allows to predict with very high reliability but its net using is restricted by boundary condition. It means high fundamental deltas, which NN could not learn by training period or simply these deltas have never happened before.

ACKNOWLEDGMENTS

This paper was supported by science project SGS-2012-047.

REFERENCES

[1] KISEL, D.: A Brief Introduction to Neural Networks, EPSILON-EN, 2010.

[2] HAGAN, T. – DCMUTH, B. – BEALE, M.: Neural Network Design, Publishing Company 1996, ISBN 7-111-10841-8/TP.

[3] TŮMA, J. – RUSEK, S. – MARTÍNEK, Z. – CHEMIŠINEC, I. – GOŇO, R.: Spolehlivost v elektroenergetice (monografie), CONTE spol. s r. o., ČVUT Praha 2006, ISBN 80-239-6483-6.

[4] RUSNÁK, J. – BEŇA, Ľ. – KOLCUN, M.: Experiences with examination of dispersed sources impact on distribution power system. 2010, In: Electric Power Engineering 2010: Proceedings of the 11th international scientific conference: 4.-6. 5. 2010, Hotel Santon, Brno, Czech Republic, Brno: University of Technology, 2010 P. 219-222, ISBN 978-80-214-4094-4.

[5] MINARČÍK, M. – OTČENÁŠOVÁ, A.: Practical measurement of power quality and the possibility of its improvement, 12-th International Scientific Conference Electric Power Engineering 2011, Kouty nad Desnou, Czech Republic, 2011, 05, 17.-19., str.: 478-481, ISBN 978-80-248-2393-5.

[6] ALTUS, J. – OTČENÁŠOVÁ, A.: Connection of photovoltaic power plants into the electricity system in the SR, Przeglad elektrotechnniczny (Electrical Review), Varšava, Poľsko, 2010, str.: 159 - 163, ISSN 0033-2097.

[7] GOŇO, R. – GOŇO, M. – KYNCL, M.: Využití bioplynu z čistíren odpadních vod jako zdroje elektrické energie. In Sborník konference EPE 2009, Ostrava : VŠB-TU, 2009, 404-408, 5, ISBN 978-80-248-1947.

[8] SKALA, P. – DĚTŘICH, V.: Modelling of the reliability of MV lines and its utilization in real distribution network. In Reliability of Transmission and Distribution Networks RTDN 2011 [CD-ROM]. London, 22.-24.11.2011. ISBN 978-1-84919-557-7.

[9] MEZERA, J. – MARTÍNEK, Z.: Continuous supply of electricity from biogas and wind power plant - proposal of the system components, system dynamic and economic. In Sborník konference EPE 2011, Ostrava : VŠB-TU, 2011, ISBN 978-80-248-2393-5.

[10] MEZERA, J. – MARTÍNEK, Z.: Continuous supply of electricity from biogas and wind power plant - economical calculation. In Sborník konference EPE 2011, Ostrava : VŠB-TU, 2011, ISBN 978-80-248-2393-5.

[11] MEZERA, J. – MARTÍNEK, Z. – KŮS, D. – ZBORNÍK, J.: Continuous supply of electricity from biogas and wind power plant - basic formulation. In Sborník konference EPE 2011, Ostrava : VŠB-TU, 2011, ISBN 978-80-248-2393-5.

[12] LEI, W. – SHAHIDEHPOUR, M.: A hybrid model for day-ahead price forecastin. Manuscript in Chicago, IL 60616 USA, Illinois institut of Technology 2008.

[13] CIMBALA, R. – KOLCUNOVÁ, I.: Určenie polarizačného spektra izolačného materiálu na báze sľuda epoxid / - 2011. – electronic optical disk (CD-ROM). In: Electric Power Engineering 2011 : proceedings of the 12th international scientific conference : May 17-19 2011, Kouty nad Desnou, Czech Republic. - Ostrava : VŠB-TU, 2011 P. 1-4. - ISBN 978-80-248-2393-5.

[14] KUŠNÍR, S. – KRIŠTOF, V. – BEŇA, L. –, KOLCUN, M.: Regulácia tokov výkonov na profile medzi Slovenskou republikou a Maďarskom. In: Electric Power Engineering 2011 : proceedings of the 12th international scientific conference : May 17-19 2011, Kouty nad Desnou, Czech Republic. - Ostrava : VŠB-TU, 2011 P. 1-4. - ISBN 978-80-248-2393-5.

Received October 28, 2012, accepted April 5, 2013

BIOGRAPHIES

Ján Mezera was born on 4.4.1986. In 2010 he graduated (MSc) at the Department of Electrical Power Engineering and Ecology of the Faculty of Electrical Engineering at University of West Bohemia in Pilsen. He studies PhD in the field of renewable sources and its integration into electricity markets. His scientific research is focusing on prediction models and its application on the energetic environment.

Zbyněk Martínek was born on 22.4.1955. In 1983 he graduated (MSc) with distinction at the Department of Power Engineering of the Faculty of Electrical Engineering at University of West Bohemia in Pilsen. He defended his PhD in the field of Reliability of Power grid in 1990; his habilitation title was “Synthesis of reliability of power plant unit in the Czech Republic“. Since 1990 he is working as a tutor with the Department of Computers and Informatics. His scientific research is focusing on reliability of power grid and devices in power engineering, heating industry and electrical installation design. Since the year 1990 he is regularly named a member of the commission at final exams. These commissions are at the Department of Electric Power Engineering and Ecology and he is also a chairman of bachelor commission since the year 2005.

Radoslav Sokol born August 17, 1982. Graduated (MSc) at the Faculty of Electrical Engineering, Czech Technical University, Prague in 2007. Thesis awarded in a competition “Cena ČEZ”. Representative and member of SG Balancing & Intra-day markets, Eurelectric for the Czech Republic. His PhD study focuses on new approaches to cross-border capacity allocation in electricity trading context.