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PHYSICAL AND TECHNICAL ENERGY PROBLEMS

SHORT-TERM FORECASTING OF LOADS AND WIND POWER FOR LATVIAN POWER SYSTEM: ACCURACY AND CAPACITY OF THE DEVELOPED TOOLS

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The paper analyses the performance results of the recently developed short-term forecasting suit for the Latvian power system. The system load and wind power are forecasted using ANN and ARIMA models, respectively, and the forecasting accuracy is evaluated in terms of errors, mean absolute errors and mean absolute percentage errors. The investigation of influence of additional input variables on load forecasting errors is performed. The interplay of hourly loads and wind power forecasting errors is also evaluated for the Latvian power system with historical loads (the year 2011) and planned wind power capacities (the year 2023).

Keywords: *forecasting error, short-term forecasting, system load, wind power, wind speed.*

1. INTRODUCTION

The ongoing large-scale integration of wind power plants into EU countries and extended cross-border transfers of load flows bring challenges to transmission system operators (TSOs) as how to schedule and control the intermittent loads, generation and transit in a transparent, secure and optimal way [1]–[3]. It leads to the increased need for short-term forecasts enabling TSOs to better match generation and loads and reduce the transboundary propagation of related imbalances [1]–[3].

The need for a good short-term forecasting practice is arising in Latvia as well where (1) the adequacy of system loads and generation is highly dependent on availability of hydro resources; (2) the high transit across Baltic power system (PS) are expected with implementation of the Baltic Energy Market Interconnection Plan (BEMIP); and (3) large wind power capacities (in respect of system load) will be connected to: up to 500 MW in Latvian PS by 2023 and 800 MW and 1000 MW in neighbouring Lithuanian and Estonian PSs, respectively [4]–[6].

In response to the situation as such, a new short-term forecasting suit was developed consisting of 3 tools (computer programs). *LOADS-LV* and *WIND-LV* tools serve for system load and wind power forecasting, respectively, and are based on the well-known forecasting models: ANN (Artificial Neural Network) – for loads and ARIMA (Autoregressive Integrated Moving Average) – for wind power. *JOINT-LV*, the 3rd tool, serves for the combined forecast. In general, both ANN and ARIMA models are problem dependent and their customisation to the problem is often conditioned on input data. The tools are customised to Latvian weather and load profile situation. The current paper aims at the evaluation of operability and effectiveness of these tools.

The early application of ANN model for short-term load forecasting refers to 1992 [7] and first comprehensive review of models application seems to be published in 2001 [8]. Although a number of authors point to the good forecasting results, it can hardly be generalised as a rule. Specifically, when dealing with the complete set of all the days in the year, which present dissimilar profiles, the ANN model cannot offer good forecasts [9].

The forecasting for wind power gained momentum in the early 1990s when the increase of the installed wind energy capacity all over the world attracted the attention of electricity companies, wind energy promoters and researchers towards the short-term prediction, mainly motivated by the necessity of integration into the grid of an increasing "unknown" (fluctuating) amount of wind power. The comprehensive review of the forecasting methods over the 30-year period can be found in [10]. ARIMA and other time series models were addressed to significant extent and some authors point to a good performance of ARIMA model [11], [12]. Nevertheless, since acceptable forecasting time horizon of ARIMA is 6–10 h, the strengthening of ARIMA capacity is achieved by means of its modification, e.g. fractional-ARIMA [13] or hybrid applications (combined with other models) [14], [15].

In addition to the evaluation of performance of the developed forecasting tools, the current paper sets the goals to investigate:

1) How influential may additional input variables (weather temperature, wind speed, weekday index) be on the accuracy of load forecasting?

2) Presuming that forecasting errors of load and wind power should be compensated by Latvian TSO, what decrease of load-frequency regulation reserves could be gained due to the self-cancellation of positive and negative errors?

2. INPUT TO FORECASTING TOOLS

The following input variables have been applied to the forecasting models:

- *for load forecasting (LOADS-LV* tool*):*

(1) Historical power system loads [16];

(2) Weekday index (workday, weekend) of a load;

(3) Past and future (next-day) weather temperatures (both historical);

(4) Past and future (next-day) wind speeds at 10-m height (both historical);

- *for wind speed forecasting (WIND-LV* tool*):*

(5) Historical wind speeds at 10-m height.

All variables are presented as hourly data. The data arrays elapse over 4 months, from 1 Nov 2011 to 29 Feb 2012, which constitute an investigation period. Data (3)–(5) are records of meteorological data for Riga site (Central Latvia) [17]. They can be *a priori* thought of as all-Latvian averages.

The input data (1)–(4) are employed for model identification, training, validation, testing and forecasting purposes, while the input data (5) – for model identification and forecasting purposes.

Since Ref. [17] presents the wind speeds as whole numbers (e.g. 5 m/s), these should be considered very rough values for forecasting purposes. We derived the "rounded out" values from these whole numbers by adding a random fraction (-0.4, -0.3,…,0.5). Thus, the "rounded out" speeds contain one decimal number after the decimal point (e.g. 5.4 m/s).

The load profile over the investigation period seems to be rather variable with mean load 890 MW, maximum load 1320 MW and, respectively, the load factor 0.67. Separated by weekday type, mean workday load accounts for 925 MW vs mean weekend load 815 MW. The minimum load in the investigation period is recorded 510 MW. The temperatures range from -30 °C to 10 °C. The maximum hourly wind speed (10-m height) was 11 m/s and the number of calm hours (at a wind speed < 2m/s) was 255 h from a total of 2904 h.

The wind power capacity was simulated to be connected in amount of 500 MW.

3. FORECASTING PROCEDURE

3.1. Load Forecasting Procedure

As known, ANNs are trained by adapting a network and comparing the output obtained with the input training and target data. The training is carried out until the network output matches the target data. Feed forward neural networks permit the signals to travel from an input layer to an output layer in only one way, which means that the output of any layer does not affect the same layer. The layer in between these two layers is the hidden layer. The neural networks use weights for each input variable and a bias that acts as a threshold to produce outputs. They further use learning algorithms to fine tune the weights and biases of a network such that the output can be obtained from the weights and biases. The learning algorithm is effective if a small change in the weights and biases leads to a small change in the output [18].

The load forecasting was performed in the sequence of steps corresponding to algorithms implemented in the *LOADS-LV* tool.

1) *Network Identifier*

The algorithm works within the MATLAB toolbox ANN. It sets up (identifies) the structure and characteristics of the neural network so as to fit a specific problem. Like in usual practices, a network is identified by experimentation. Identification period for the considered problem was chosen 3 months back from the start of the forecasting period (1 Feb 2012). Four network models were identified (and subsequently trained, see an algorithm below) using 4 different identification data sets (Table 1):

Table 1

Identification Results of ANN for Latvian Short-term Load Forecasts

Identification characteristic	Identification data set			
	workday loads only	weekend loads only	workday loads, temperatures, wind speeds	weekend loads, temperatures, wind speeds
Network type/paradigm	feed forward	feed forward	feed forward	feed forward
Number of hidden layers	2	2	2	2
Number of hidden neurons	1st layer – 3 2nd – 4	1st layer – 6 2nd – 4	1st layer – 6 2nd – 7	1st layer – 7 2nd – 7
Transfer function	linear	linear	linear	Linear

2) *Network Trainer/ Retrainer*

This algorithm works mostly concurrently with *Network Identifier*. It trains the identified network to find the implicit relations between the input variables and outputs. The outputs are next day hourly loads (forecasts). The training period coincides with the identification period (1 Nov 2011 – 31 Jan 2012) and is split to 70 % of hours for training, 15 % for validation and 15 % for testing. The supervised training was exercised when the weekday index was pointed to.

The separate training sets were applied for workdays and weekend days as well as for baseline input (loads) and extended input (loads, temperatures, wind speeds).

3) *Load Forecaster*

This algorithm produces 24-hour load forecasts for the next day imitating the forecasting time at 24:00 of the previous day and using the input of historical data from the 3 preceding months. The input period is moved consecutively by one day for each new day. In the end, the last new day of the forecasting period was 29 Feb, with the preceding input period from 29 Nov to 28 Feb. During the process, the retraining was not addressed.

4) *Accuracy Evaluator*: Load power forecasts are compared with actual wind powers and the relevant forecasting errors are calculated: errors, absolute errors (AE), mean absolute errors (MAE), absolute percentage errors (APE), mean absolute percentage errors (MAPE), etc.

3.2. Wind Power Forecasting Procedure

The indirect forecasting of wind power is implemented by the forecasting tool *WIND-LV*, i.e. wind power forecasts are not derived from historical wind power time series but calculated from the wind speed forecasts.

The ARIMA model was taken as a basis for *WIND-LV* as most promising for purpose of this investigation after preliminary revision of parametric models ARMA, ARX, ARMAX, ARIMAX, etc. The ARIMA model is expressed as follows:

$$A(q)y(t) = \frac{C(q)}{(1-q^{-1})}e(t), \tag{1}$$

where $y(t)$ – direct system output at time moment t;
q – time delay operator, i.e. $q^{-1}u(t)=u(t-1)$;
$u(t-1)$ – input signal;
A, C – polynomials;
$e(t)$ – white noise.

WIND-LV consists of the following algorithms:

1) *Height Calculator*: Time series of historical wind speeds at 10-m height is upscaled to the time series for the selected hub heights. For the problem in question, the "rounded-out" wind speeds were converted to those at 80-m height using classical Hellman exponential law formula [19]:

$$\frac{v}{v_0} = \left(\frac{H}{H_0}\right)^{\alpha}, \tag{2}$$

where v – speed to the height H;
v_0 – speed to the height H_0;
α – friction coefficient or Hellman exponent. Assuming that the Latvian wind farms would be constructed in open landscape, α value was taken to be 0.14 [19].

2) *ARIMA Identificator*: Structure of ARIMA model is identified using MATLAB ARIMA toolbox.

In the considered problem, Latvian wind speed data of Jan 2012 were used for model identification. The procedure was done by experimentation in the same way as in [20]. Identification resulted in parameter values p=3, d=1 and q=4.

3) *Speed Forecaster*: The ARIMA model produces the short-term forecasts of wind speeds at the chosen hub height. The forecasts are derived from the 3-day past data input.

4) *Power Converter*: Wind speed forecasts are converted to wind power using the power curve of country-specific wind turbine. The curve of Enercon turbine E-82 was assumed to be a typical one for the planned Latvian wind parks [21].

The option for geographically differentiated wind speed forecasting is also implemented in the *WIND-LV* tool. As seen from Fig. 1, the total wind power capacity can be broken down up to the level of individual or aggregated wind parks.

5) *Accuracy Evaluator*: Wind power forecasts are compared with actual wind power and the relevant forecasting errors are evaluated.

Verification of the *WIND-LV* tool included the search of tool maximum forecasting time horizon and investigation of forecasting errors for a total of 500 MW.

3.3. Consolidation of System Load and Wind Power Forecasts

The hourly forecasts from the *LOADS-LV* and *WIND-LV* tools are supplied as inputs to the *JOINT-LV* tool, which integrates them into one consolidated load (see

Fig. 1).

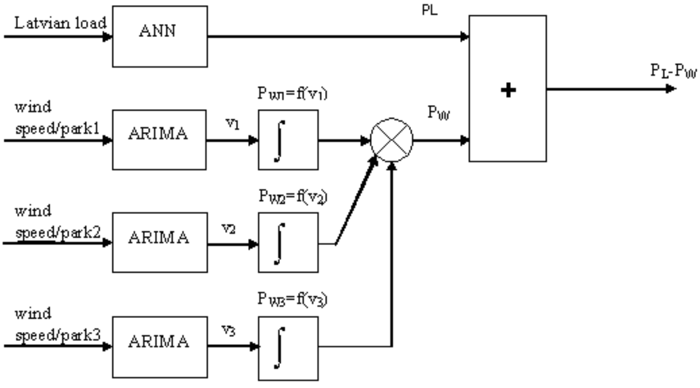

Fig. 1. Structure of the forecasting suit for Latvian power system: P_L – load, P_W – wind power, v – speed.

Here, the investigation was focused on the interplay of forecast errors in order to identify the extent to which they cancel each other. For each pair of hourly load and wind power, the errors are calculated (3) and combined (4) as:

$$E_{Li} = L_i^{act} - L_i^f$$
$$E_{Wi} = G_{Wi}^{act} - G_{Wi}^f, \tag{3}$$

where E_{Li} and E_{Wi} – load and wind power forecasting errors for *i-th* hour;
L_i^{act} L_i^f – actual and forecasted loads for *i-th* hour;
G_{Wi}^{act} G_{Wi}^f – actual and forecasted wind power for *i-th* hour.

$$E_{\Sigma i} = E_{Li} + E_{Wi}, \tag{4}$$

where $E_{\Sigma i}$ – joint forecasting error for *i-th* hour. The joint error effect is achieved when

$$\left|E_{\Sigma i}\right| < \left|E_{Li}\right| + \left|E_{Wi}\right|. \tag{5}$$

The investigation covered 1 month of Latvian PS operation in hypothetical situation with loads from Feb 2012 and planned wind power 500 MW in 2023.

4. RESULTS AND DISCUSSION

The results of load forecasting are presented in Figs. 2–4, wind power forecasting – in Figs. 5 and 6 and combined forecasting results – in Fig. 7.

Figure 2 shows the general view on the accuracy of hourly load forecasts by comparison of forecast and actual load curves. The accuracy can easily be seen to be good, with small errors, without domination of negative or positive forecasts. Figure 3 quantifies the accuracy in terms of mean absolute percentage error (MAPE). The least error appeared in the 24th hour of day cycle with the values of 2.6 % and 2.8 %, while the largest values 5.4 % and 4.5 % were reached in the 6th hour.

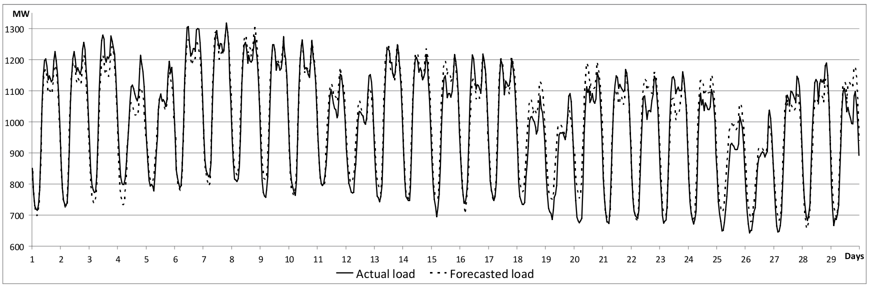

Fig. 2. Latvian hourly load forecasts versus actual loads under next day forecast lead time, Feb 2012.

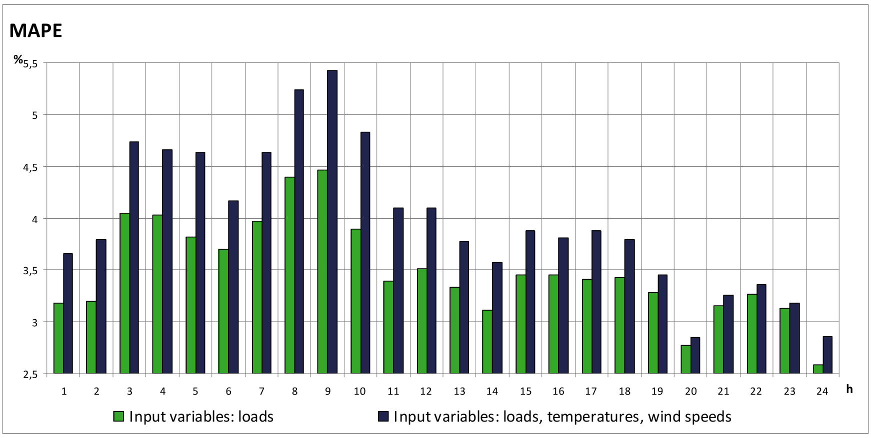

Fig. 3. Latvian load forecasting MAPE as monthly means for each hour of a day cycle under next day forecast lead time, Feb 2012.

Figure 3 also points to an unexpected finding that an increase in the input variable number adversely affects forecasting accuracy. This finding is confirmed in terms of daily MAPE by comparison of forecasts under baseline input (loads only) and extended input (loads, temperatures, wind speeds) in Fig. 3. Such a deterioration can be explained by a negligible or weak correlation:

- 0.04 between loads and temperatures,
- 0.27 between loads and wind speeds,
- 0.35 between wind speeds and temperatures

in the investigation period (4 months).

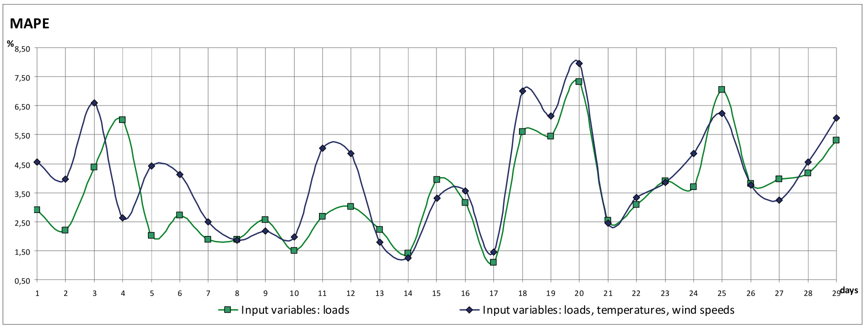

Fig. 4. Daily MAPE of Latvian load forecasting under next day forecast lead time, Feb 2012: 1 – hourly loads as a single input variable; 2 – hourly loads, day type attribute, outdoor temperatures and wind speeds as multiple input variables.

The investigation for maximum forecasting horizon for wind speeds yielded the trend of consistent degradation of accuracy with the increase in forecast lead time. Figure 5 presents the results of this search where forecasting is imitated to be performed each day from 00:00 and 12:00 for 1–12 hours ahead, from 1 Feb to 29 Feb. Thus, every monthly MAE is derived from 58 AE values. Figure 5 demonstrates rather mediocre forecasting capability of ARIMA model, mainly due to the MAE values exceeding 1 m/s for 1–2 h lead time. The acceptable maximum time horizon could be set to no more than 6 h with 1.8 m/s MAE value.

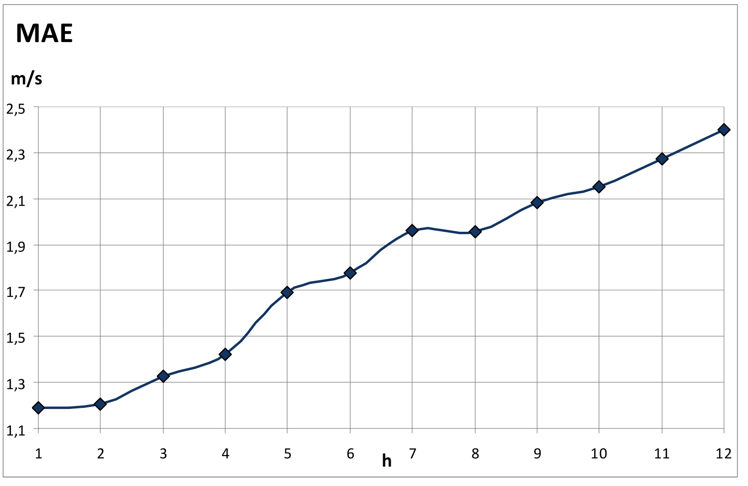

Fig. 5. Monthly MAE of hourly wind speed forecasts under lead time 1–12 h for Riga site, 80-m height, Feb 2012.

Further wind speeds were forecasted with 6-h lead time. Both these forecasts and actual wind speeds (Feb 2012) were converted to hourly wind power values using the aforementioned E-82 power curve for 500 MW capacity rating. The forecasting errors in terms of daily MAPE are presented in Fig. 6. After filtering out 4 values above 20 % as unacceptable from a total of 29 ones, the forecasting accuracy can be considered mediocre but acceptable, with 10–12 % monthly average of remaining 25 daily MAPE.

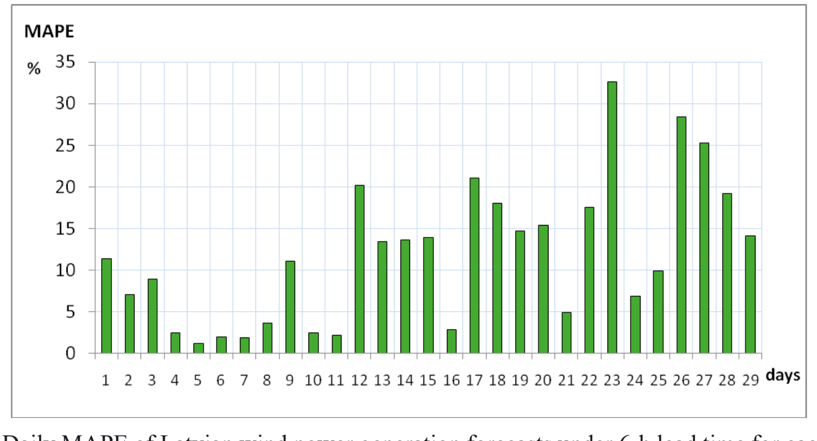

Fig. 6. Daily MAPE of Latvian wind power generation forecasts under 6-h lead time for each hour, Feb 2012 (wind speeds) and 500 MW of planned wind power.

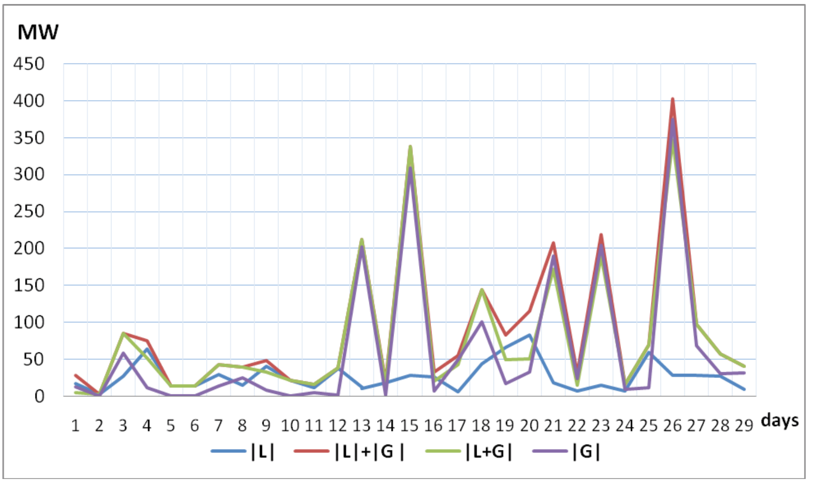

Fig. 7. Combinations of forecasting absolute errors for the 6th hour under weather conditions of Feb 2012 for Latvian maximum load of 825 MW and wind power capacity of 500 MW: L – load, G – wind power.

Results of investigation of forecasting error interplay is presented in Fig. 7. It refers to the 6th hour of each February day when forecasts were made as next-day forecast for load and 6-h lead time forecast for wind power. The contraction of joint error due to the different signs of single errors (for load and wind power) can be observed in certain days but it never falls below any of its single errors. After summarising all 29 days, the contraction of joint error was evaluated to be 13 % as seen from the following:

- 88.6 MW – monthly mean joint error for non-cancelling single errors summed up as |L| +|G|;
- 77.4 MW – monthly mean joint error for cancelling single errors |L + G|:
- 11.2 MW (13 %) – contraction rate.

5. CONCLUSIONS

A new short-term forecasting suit developed for the Latvian power system consisting of *LOADS-LV*, *WIND-LV* and *JOINT-LV* tools for system load, wind power and combined forecasts, respectively, demonstrated acceptable suitability for power system needs, with good performance for load forecasting (ANN model) and mediocre performance for wind speed forecasting (ARIMA model).

Extended input to load forecasting ANN model may lead to less accuracy than baseline input (historical loads only). The reason lies in the weak load correlation with weather temperatures and wind speeds, which hinders the model to capture the true relations between input and output variables.

The combined short-term forecasting of load and wind power brings down the joint forecasting error to appreciable extent.

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SLODZES UN VĒJA JAUDAS ĪSTERMIŅA PROGNOZĒŠANA LATVIJAS ENERGOSISTĒMAI: IZSTRĀDĀTĀS METODIKAS PRECIZITĀTE UN VEIKTSPĒJA

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K o p s a v i l k u m s

Rakstā veikta Latvijas energosistēmas slodzes un vēja jaudas īstermiņa prognozēšana. Analizēti iegūtie rezultāti. Energosistēmas slodzi un vēja jaudu var prognozēt, izmantojot ANN un ARIMA modeļus. Prognozēšanas precizitāti var novērtēt ar vidējo absolūto kļūdu un vidējo absolūto kļūdu procentos. Tika pētīts kā slodzes prognozēšanas kļūdu ietekmē dažādi energosistēmas parametri. Izmantojot Latvijas energosistēmas vēsturiskos parametrus (2011.g.), tika noteiktas ikstundas slodzes un vēja jaudas prognozēšanas kļūdas, kā arī prognozēta plānota vēja jauda 2023. gadam.

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