RIGA TECHNICAL UNIVERSITY

Dmitrijs Soboļevskis

FORECASTING OF PROCESSES INFLUENCING THE OPERATION OF THE POWER SYSTEM

Summary of the Doctoral Thesis

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RIGA TECHNICAL UNIVERSITY
Faculty of Electrical and Environmental Engineering
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DOCTORAL THESIS PROPOSED TO RIGA TECHNICAL UNIVERSITY FOR THE PROMOTION TO THE SCIENTIFIC DEGREE OF DOCTOR OF SCIENCES

To be granted the scientific degree of Doctor of Sciences (Ph. D.), the present Doctoral Thesis has been submitted for the defence at the open meeting of RTU Promotion Council "RTU P-05" on 29 June 2020 at 10:00 at the Faculty of Electrical and Environmental Engineering of Riga Technical University, 12 k-1 Azenes Street, Room 306.

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DECLARATION OF ACADEMIC INTEGRITY

I hereby confirm that the Doctoral Thesis submitted for the review to Riga Technical University for the promotion to the scientific degree of Doctor of Sciences (Ph. D.) is my own. I confirm that this Doctoral Thesis has not been submitted to any other university for obtaining a scientific degree.

Dmitrijs Soboļevskis .... (signature)

Date ....

The Doctoral Thesis has been written in Latvian and consists of an introduction; 5 chapters; Conclusions; 9 tables; 110 figures; the total number of pages is 153, including 10 appendices. The Bibliography contains 105 titles.

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INTRODUCTION

The Topicality of the Subject of the Doctoral Thesis

Power systems are among the most complex artificial technical systems created by mankind; they are vitally necessary and their main tasks are as follows:

- efficient supply of energy to the consumers;
- reliable and continuous power supply;
- reduction of the impact on climate change;
- ensuring of sustainability.

The seriousness of the above tasks has led to internationally made decisions regarding the use of renewable energy sources, the limiting of the construction of coal and nuclear power plants, the restructuring of power systems, the diversification of the primary energy resources used and the use of market conditions and its mechanisms in the managing of power system development and operation. Nowadays, power system is divided into many legally independent and often mutually competitive parts. Alongside the legal division of power systems into independent parts, the process of further integration of power systems is taking place; new links emerge between hitherto unconnected power systems. From the engineering point of view, it can be said that the Latvian power system has become part of a huge power system located in the European and Asian continents.

It has to be pointed out that the changes in the power sectors of Europe, the Baltic countries and Latvia in particular have taken place at an especially fast rate during the recent decades.

There have been rapid and significant changes in energy demand, prices and standards. A whole range of new technologies have become available within the fields of energy production and distribution. The Baltic countries have been electrically connected with Scandinavia and Poland. The management of power production and consumption processes takes place by means of the united *Nord Pool* electricity market. It can be said that the operation of the market can be controlled on the basis of the forecasts of many parameters which characterise the state of the future power supply.

In order to announce one's bid − an electricity production plan − to the market operator, it is necessary to know the following future data: the electricity prices, the energy demand, water inflow in the reservoirs of hydropower plants, the amount of energy produced at wind and solar power plants, etc. It has become necessary to change the power system control principle. This problem has been investigated in hundreds of scientific publications, including those in journals and conference proceedings [1].

Issues related to the simulation of stochastic optimisation problems have also received the attention of Latvian scientists: Antans S. Sauhats, Romāns Petričenko, Oļegs Linkevičs, Kārlis Baltputnis, and Renāta Varfolomejeva [2]–[10]. This Doctoral Thesis is, to a considerable extent, a continuation of the studies conducted by the above Latvian scientists. The stochastic formulation of the power system regime optimisation task is used, as well as the optimisation criteria and procedures. The present Thesis, first of all, supplements the above procedures with influencing stochastic processes (ISP), forecasting models, algorithms and software products, which become an important part of a large software complex.

The Hypothesis of the Doctoral Thesis

The accuracy of the models of the future state of power system as well as their capability to reflect the future state of power supply, which have a strong influence on the correctness of the decisions of the electricity market participants and the profit of the energy producers, can be improved.

The Goal of the Doctoral Thesis

The goal of this Doctoral Thesis is to create the algorithmic and informational basis for increasing the efficiency of the regimes of power systems and increasing they profit.

The Tasks of the Doctoral Thesis

To achieve the set goal, the following tasks were solved.

- A review and an analysis have been conducted regarding the organisation principles of electricity market, energy production conditions at Latvian power plants, production management and optimisation models.
- A review and an analysis have been conducted regarding the methods and approaches for forecasting future processes, and approaches have been selected for further development.
- For the synthesis of models, those stochastic processes that have the strongest influence on the regimes of Latvian power plants have been selected.
- For the purposes of forecasting of processes, an algorithm for the optimisation of artificial neural network structure and parameters has been synthesised and proposed and the possibility and effectiveness of its use have been proved.
- Models for power production at Riga combined heat and power plants and Daugava hydropower plants have been synthesised. Approximation of the characteristic curves of the production units by means of polynomials has been used.
- Software products have been synthesised for forecasting the water inflow in the reservoir of Plavinas HPP and the heat demand in Riga. The models used have been verified and the software has been tested. It has been proved that the models can be used together with stochastic optimisation methods and algorithms.
- A statistical data analysis algorithm is proposed to increase the accuracy of forecasting future processes.

The Scientific Novelty of the Doctoral Thesis

The results of the research within this Thesis are as follows.

Detailed mathematical models have been developed for forecasting the processes that influence electricity production in Latvia. In-depth research is devoted to the economic costs of process forecasting inaccuracy. Algorithms and applications have been developed for preventing the erroneousness of statistical data as well as for taking a decision both at the design stage and during operation.

The possibility to use the “Thermoflow” industrial software at the initial stage of combined heat and power plant model creation has been proved. Model verification has been performed and the possibility of using models for regime optimisation has been proved.

Correlation analysis has been conducted regarding the processes that influence the efficiency of the Latvian power system. Processes linked by a strong correlation have been identified.

Algorithms for forecasting the heat demand of large district heating systems have been proposed, substantiated and verified (based on the example of the city of Riga). The algorithms use an artificial neural network (ANN) and polynomial approximation (PA) as well as a combination of the two methods. The substantiated algorithms for selecting the parameters of ANN and PA are aimed at minimising forecasting errors.

Three unsolved problems have been identified in the processes of forecasting the heat demand of district heating systems:

- incompleteness of statistical data;
- errors in the statistical data;
- the need to make the forecast at the beginning of the heating season when there is lack of sufficient amount of statistical data.

Algorithms for solving the above problems have been substantiated.

The influence of day-ahead forecasting errors on the profit of the power system and on the potential deviations of the real capacities of power plants from the planned values has been evaluated.

Algorithms for forecasting the inflow from River Daugava at the reservoir of Plavinas HPP have been proposed, substantiated and verified. The algorithms use an artificial neural network and provide a forecast in stochastic form, issuing the result as the set of possible water inflow realisations.

The Methods and Tools Used

In the Thesis, the following research methods and tools have been used.

1. The *Thermoflow* software complex: for simulating steam-gas technologies.
2. The *OPTIBIDUS HES* and *OPTIBIDUS TEC* software complex: for solving the tasks of the optimisation of efficient use of HPP hydro-resources and hydropower plants and combined heat and power plants.

3. The *MatLab 2013a* interactive environment: for intensive computing, data analysis and visual depiction of data.
4. *Microsoft Excel 2013* software.
5. The Monte-Carlo method: for solving the task of optimising the artificial neural network structure and hyperparameters.
6. An artificial neural network.
7. A database of the River Daugava inflow measurements to the reservoir of Plavinas HPP.
8. A database of temperature measurements in the city of Riga.
9. A database of temperature, wind speed, precipitation, solar radiation measurements of the Latvian Environment, Geology and Meteorology Centre.
10. A database of the capacities of turbine sets at Riga combined heat and power plants.

The Practical Significance of the Doctoral Thesis

The practical significance of the algorithms and methodology proposed in the Thesis is as follows.

1. Using the developed process forecasting mathematical models will make it possible to increase the efficiency of the Latvian heat and electricity generation sources in the electricity market of the Baltic countries.
2. The implementation of the proposed algorithms for forecasting the processes that influence electricity production enables electricity-producing companies to effectively compete in the electricity market.
3. The synthesised process forecasting software products have become the basis for solving the task of creating software for optimising the regimes of the JSC "*Latvenergo*" complex of power plants (an agreement between RTU and JSC "*Latvenergo*" has been fulfilled).

The Author's Personal Contribution

The foundation of the basic concepts to be defended consists of ideas created in close co-operation with Professor Antans S. Sauhats and Senior Reseacher Romāns Petričenko. The Doctoral Thesis to be defended can be regarded as a continuation of the long-term work of the Department of Power System Control and Automation headed by Professor Antans S. Sauhats.

The forecasts of electricity price, inflow and district heating load have been performed by means of specific software developed at the Department of Power System Control and Automation headed by Professor Antans S. Sauhats. The River Daugava inflow and energy price forecasting algorithms discussed and verified in this Thesis, the combination of forecasting methods, the methodology for identifying erroneous statistical data and the economic analysis of the forecasting methods belong personally to the author of the Doctoral Thesis.

Approbation of the Research Results

The research results have been discussed at 6 international conferences.

1. Sauhats, A. S., Soboļevskis, D., Varfolomejeva, R., Kucajevs, J., Power plants feasibility studies supported by stochastic programming software. Riga Technical University 55th International Scientific Conference on Power and Electrical Engineering. Rīga: RTU 2014. SCOPUS.
2. Sauhats, A. S., Petrichenko, R., Broka, Z., Baltputnis, K., Sobolevsky, D., Artificial Neural Network-Based Stochastic Forecasting of Daugava River Water Inflow. Riga Technical University 57th International Scientific Conference on Power and Electrical Engineering. Rīga: RTU 2016. SCOPUS.
3. Petrichenko, R., Baltputnis, K., Sauhats, A. S., Sobolevsky, D., District Heating Demand Short-Term Forecasting. IEEE EEEIC 17th International Conference on Environment and Electrical Engineering, Italy, Milano 2017. IEEE Xplore, SCOPUS, Web of Science.
4. Petrichenko, R., Sobolevsky, D., Sauhats, A. S., Short-term forecasting of district heating demand. IEEE 18th International Conference on Environment and Electrical Engineering and 2nd Industrial and Commercial Power Systems Europe, Italy, Palermo 2018. IEEE Xplore, SCOPUS, Web of Science.
5. Petrichenko, R., Baltputnis, K., Sobolevsky, D., Sauhats, A. S., Estimating the Costs of Operating Reserve Provision by Poundage Hydroelectric Power Plants. 15th International Conference on the European Energy Market (EEM), Poland, Lodz, June 27–29, 2018. IEEE Xplore, SCOPUS, Web of Science.
6. Baltputnis, K., Petrichenko, R., Sobolevsky, D., Heating Demand Forecasting with Multiple Regression: Model Setup and Case Study, 6th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE 2018), Vilnius, Lithuania, November 8–10, 2018. IEEE Xplore.

The research results have been published in 11 international sources.

1. Sļiskis, O., Soboļevskis, D., Ketners, K., Zibens izlādes iedarbība uz gaisvadu līniju metālkonstrukcijām. (The influence of lightning discharge on the metal structures of overhead lines.) Publication in a volume of the Scientific Proceedings of Riga Technical University, 2012.
2. Soboļevskis, A., Soboļevskis, D., Sauhats, A. S., Prospects for wind power generation in Latvia. 17th International Practical Student Conference "Human. Environment. Technologies". Rēzekne Higher School, 2013.
3. Soboļevskis, A., Soboļevskis, D., Sauhats, A. S., Augstsprieguma līniju pārvades spēju limitējošie faktori. (Factors limiting the transmission capacity of high-voltage lines) 54th RTU Student Scientific and Technological Conference. Riga: RTU 2013. SCOPUS.

4. Soboļevskis, A., Soboļevskis, D., Linkevičs, O., Sauhats, A. S., Vēja elektrostaciju pieslēgšana pie elektrotīkla reģionos ar ierobežoto elektroapgādes spēju. (Connection of wind power plants to the power grid in regions with a limited power supply capacity.) 54th RTU Student Scientific and Technological Conference. Riga: RTU 2013. SCOPUS.
5. Sauhats, A. S., Soboļevskis, D., Varfolomejeva, R., Kucajevs, J., Power plants feasibility studies supported by stochastic programming software. Riga Technical University 55th International Scientific Conference on Power and Electrical Engineering. Riga: RTU 2014. SCOPUS.
6. Sļiskis, O., Dvornikovs, I., Ketners, K., Soboļevskis, D., Specification of Transmission Tower Structure for Following Surge Protection Simulation. 16th International Scientific Conference on Electric Power Engineering (EPE 2015), Czech Republic, Kouty nad Desnou, 2015. May 20–22. Ostrava: Technical University of Ostrava, 2015. SCOPUS.
7. Sauhats, A. S., Petrichenko, R., Broka, Z., Baltputnis, K., Sobolevsky, D., Artificial Neural Network-Based Stochastic Forecasting of Daugava River Water Inflow. Riga Technical University 57th International Scientific Conference on Power and Electrical Engineering. Riga: RTU 2016. SCOPUS.
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11. Baltputnis, K., Petrichenko, R., Sobolevsky, D. Heating Demand Forecasting with Multiple Regression: Model Setup and Case Study, 6th IEEE Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE 2018), Vilnus, Lithuania, November 8–10, 2018. IEEE Xplore.

The Structure and Contents of the Doctoral Thesis

The Thesis has been written in Latvian. It consists of an introduction, 5 chapters, conclusions and recommendations, appendices and a bibliography. The Thesis contains 110 figures, 9 tables, 164 pages all in all. The bibliography lists 105 sources.

Chapter 1 is dedicated to the peculiarities of power company regime control at the conditions of an electricity market. The organisational principles of an exchange have been reviewed, along with the formulation of an energy supply/demand optimisation task at the conditions of uncertainty. A number of methods have been described for addressing the task of energy company regime control. The market-limiting factors that are characteristic of the Baltic countries have been reviewed.

Chapter 2 is dedicated to the role and methods of forecasting of the processes that influence the power system. The criteria for computing the inaccuracy of the forecasting procedure have been analysed; much attention has been paid to interrelations of processes and correlation analysis.

Chapter 3 contains correlation analysis of the possible input data and the set of input data for further exchange price forecasting has been selected. The author proposes three realisations of the algorithm with artificial neural networks for forecasting energy prices. The chapter forecasts one of the parameters that influence the Latvian power system, namely, the water inflow in the Daugava.

Investigation of district heating load forecasting has received detailed and all-round description in **Chapter 4**. The forecasting of the discussed parameters has been implemented both by ANNs and polynomial models. The problem of input data incompleteness or distortion has been fundamentally investigated. Economic analysis makes it possible to show the costs of district heating load forecasting inaccuracy.

Chapter 5 contains optimisation by using the operating regimes of combined heat and power plants and the Daugava hydropower plants. The influence of district heating load, energy price and inflow forecasting on the Latvian power system is illustrated. The chapter contains investigation regarding the operating regimes of the Daugava cascade and the possibilities to maintain a capacity reserve. The costs of maintaining the reserve have been calculated.

1. THE LATVIAN POWER SYSTEM AND FORECASTING OF PROCESSES AS THE BASIS FOR SOLVING PLANNING TASKS

Society's striving to increase power supply efficiency and reliability and to decrease the impact on climate change has led to significant changes in energy production [11].

1. The number of renewable energy sources (RES), their capacity and their share in the amount of energy produced are growing rapidly [11].
2. The role of combined heat and power plants has increased [12], [13].

In many countries, the power system is divided into a number of mutually independent parts, which, on the one hand, compete with one another, and, on the other hand, ensure the exchange of reserves and provide assistance to partners in case of need. In order to ensure coordination between the independent energy producers, various types of energy markets have been created by means of which a certain order is brought to the overall activity. At the same time, varying energy prices are formed at market conditions. In this way, the producers are compelled to accommodate their energy production to varying prices [14].

Summing up the above peculiarities of a modern power system, the following can be stated that the operation of power companies and the factors characterising it, such as the amount of energy produced and fuel consumed, profit, production costs and others, are variable and depend on natural factors.

In addition, the old problem has to be taken into account: the amount of energy produced has to be equal to a varying demand. This problem can only be solved by planning energy production for a future time period. The length of the planning period depending on the formulation of the task may be a matter of seconds, minutes, hours or even ten years − when planning the control and regimes of power companies.

When planning the regimes of a future power system, many influencing factors and processes need to be taken into account. The next step is the choice of the process forecasting method, which is closely related to the particular character of the power system, its structure, internal and external processes, and energy market organisation principles.

In order to perform the analysis of power-generating entities, mathematical models of influencing processes are needed. It is to the synthesis of such models that this Thesis is dedicated. A united algorithm will be used the general structure of which is shown in Figure 1.1.

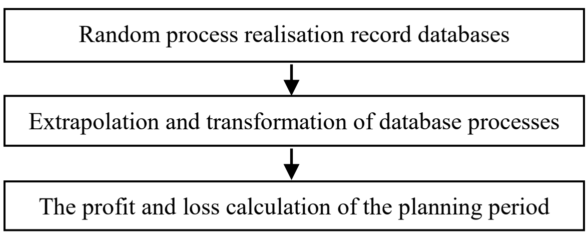
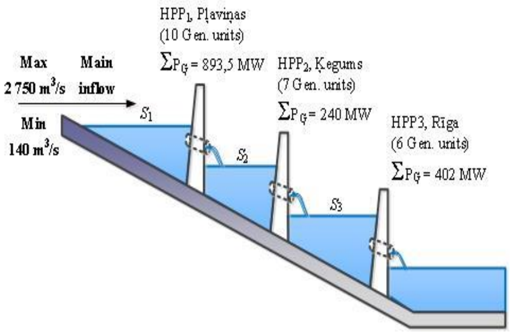


Fig. 1.1. A generalised structure of the algorithm used.

1.1. The Structure and the Links of the Latvian Power System

The energy production portfolio of the Latvian power system is mainly made up of hydropower plants (Plavinas HPP, Kegums HPP, and Riga HPP) and highly-efficient thermal power plants (Riga CHPP No.1 and Riga CHPP No. 2). According to the data provided by the leading producer of electricity and heat (Latvenergo Group [15],[16]), the total electrical capacity of power plants at the end of 2016 was 2569 MW and their total heat capacity was 1842 MW.

The potential of the Daugava HPPs (Fig. 1.2 (a)) to produce electricity is closely, almost proportionally dependent on the water inflow in the Daugava. The Daugava HPPs can operate at full capacity during the spring floods, which last for approximately one to two months a year. During the spring floods, the water inflow exceeds the low-water-period inflow more than ten times; this makes it possible to meet the electricity demand of all the customers of the Latvenergo Group and sell the surplus.



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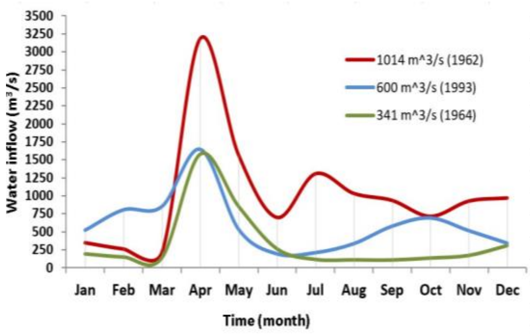

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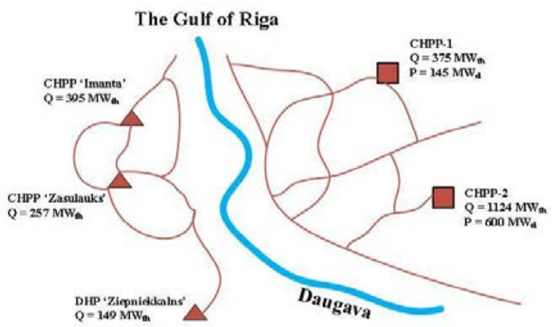


c

Fig. 1.2. A simplified structure of the Daugava HPP cascade (a). Water inflow in the reservoir of Plavinas HPP (b). A simplified structural layout of Riga district heating (c).

The operation of hydropower plants, their profit and operating schedule are largely dependent on the water inflow, which is variable and depends on the season and on the weather conditions. Figure 1.2 (b) shows the value of the maximum water inflow over a set of three different years.

The Daugava HPPs are equipped with relatively small reservoirs with quite a limited permissible water level. As a result, the regime planning is done by taking into account the water inflow forecast and the level limitations of the reservoirs and, as far as possible, striving to produce energy at high-price hours.

The city of Riga consumes 52 % of the whole amount of heat supplied within district heating in Latvia. In Riga, district heating is the main type of heating, which ensures about 76 % of the whole heat amount consumed. Approximately 69 % of the required heat is produced at two large modernised state-owned CHP plants − Riga CHPP No. 1 (37.63 %) and Riga CHPP No. 2 (60.15 %). A simplified layout of heat supply in Riga is shown in Figure 1.2 (c).

1.2. The Peculiarities of the Regime Control of Power-Generating Companies at the Conditions of an Electricity Market

The organisational principles of the market can be classified according to different features, for example, according to the planning period: the day-ahead market, the hour-ahead market; the market of ancillary services.

The day-ahead electricity trading deals are organised in the form of auctions. Every day, the participants of the exchange have to submit trading bids for each hour of the following 24-hour period. As a result of the auction, each participant receives a notification regarding the amount and price of the energy to be bought and sold. After that, the participant has to choose the capacities of their generators. An example of the problem-solving result is shown in Figure 1.3, which depicts the generation plan of the Latvian HPPs for the following days, in accordance with the forecast energy price and inflow values. Upon analysing Figure 1.3, it can be seen that the HPPs only operate for a few hours per day, when the electricity price is sufficiently high.

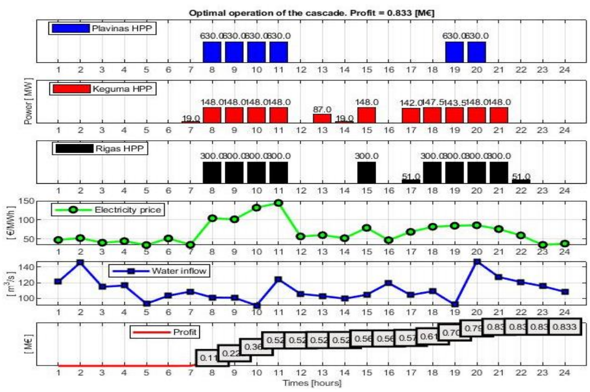


Fig. 1.3. The profile of generated capacity and load for a 24-hour period.

1.3. The Physical Formulation of the Power System Control Regime Optimisation Procedure

The fundamentals of the power plant regime optimisation tasks discussed in the Thesis can be regarded as rather complicated ones, since a task of this type, depending on the needs of the solution, can be characterised as a dynamic, multi-parametric, non-linear and stochastic task with continuous or discrete optimisation parameters. The previous studies of the Institute of Power Engineering of Riga Technical University assumed that the influencing stochastic processes are ergodic [2]–[10]. In this case, the optimum operating regime of the power system can be described as follows:

$$\bar{M}\left[R\right]=\lim_{T_{\mathrm{p}}\to\infty}\left(\frac{1}{2T_{\mathrm{p}}}\int_{-T_{\mathrm{p}}}^{+T_{\mathrm{p}}}R\left(X\left(t\right),\Pi\left(t\right)\right)\mathrm{d}t\right), \tag{1.1}$$

where $\Pi(t)$ − the changes of the optimisation parameters over time; T_{p} − the duration of the planning period; X − the set of random and uncertain factors (expected price and load, water inflow, outdoor air temperature, etc.); R − the profit of the power company; $\bar{M}$ [..] − the end result of the power system optimisation.

The physical essence of using Eq. (1.1) is the replacement of a set of scenarios with one sufficiently long realisation of a random process. As a result, the optimisation task becomes many times simpler (Fig. 1.4). The set of scenarios is thus replaced with one sufficiently long realisation of a random process. In the general case, this process can be multi-dimensional.

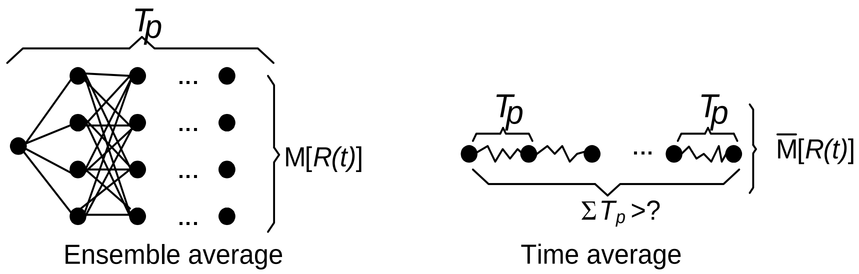


Fig. 1.4. Transformation of the optimisation task.

2. THE ROLE AND METHODS OF FORECASTING THE PROCESSES THAT INFLUENCE THE POWER SYSTEM

The need to solve a forecasting task arises when planning operation in any industry since forecasts provide information about the future, about the influence of expected and possible factors and processes on the planned activities. The correctness and accuracy of the forecasting method and the forecast itself determine the development of industrial or other enterprises, their competitiveness and even their viability.

2.1. The Methodology for Selecting the Forecasting Algorithm

There is no one generally accepted method for selecting and substantiating the process forecasting algorithm. The algorithms are selected by means of numerical eksperiments, by checking the approaches and methods for solving the task in hand and choosing the best one, which is capable of ensuring the solution of the task [17], [18].

A generalised structure of the selection of the forecasting algorithm used is shown in Figure 2.1.

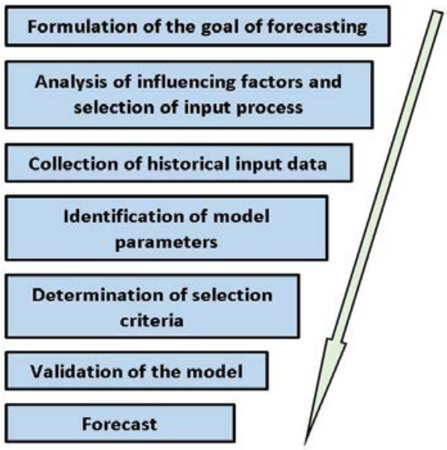


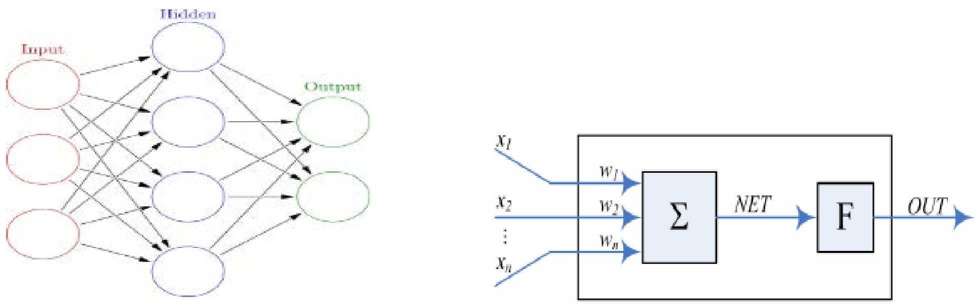
Fig. 2.1. Forecasting approaches and their classification.

The methods published in scientific journals can be divided as follows.

1. Depending on the end goal.
2. Depending on the length of the forecasting period.
3. Depending on the degree of detailing used.
4. Depending on the models used.
5. Depending on the mathematical approach used for forecasting.
6. Depending on the mathematical approach used for solving the planning, development or optimisation task.
7. Depending on the output and input data description.

2.2. Artificial Neural Networks

In the recent years, the forecasting of influencing processes has been done in many cases by means of artificial neural networks [18]–[23]. An artificial neural network (ANN) is a mathematical model which comprises parallel computing equipment, which make up a system of simple processors that are mutually connected and co-operate with one another. Each processor uses only the signals that it periodically receives and periodically sends to the other processors. Connected into a sufficiently large network with controllable interaction, such local procesors are capable of jointly performing complicated tasks (Fig. 2.2 (a)).



a b

Fig. 2.2. A model of an artificial neural network (‘Input’ − input layer; ‘Hidden’ − hidden layer; ‘Output’ − output layer).

A set of signals (x_1, x_2, ..., x_n) is fed to the inputs of the neuron, each signal being the output signal of a different neuron. The value of each input signal is multiplied by the corresponding coefficient [weight (w_1, w_2, ..., w_n)] and all the products are added together (the ‘NET’ value), in this way determining the level of neuron activation, obtaining the output value (‘OUT’) (Fig. 2.2 (b)) [24].

2.3. Forecasts that Use the Laws of Physics. Forecasting of Weather Conditions

The operation of many power-generating entities depends on weather conditions. It can be said that the development of weather forecasting methods has been taking place for thousands of years already and has reached a very high level [25], [26]. Irrespective of the powerfulness of methods, measurements and computers used, the forecasts inevitably contain errors and inaccuracies. Figure 2.3 shows the forecast and actual temperatures in Riga over a time period. This Thesis uses weather forecasts as input data for making other forecasts.

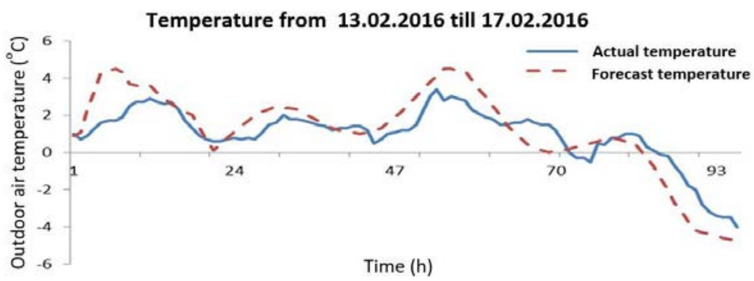


Fig. 2.3. The difference of outdoor air temperature forecasting data from actual data.

2.4. Evaluating the Accuracy of the Forecasting Result

At different conditions, forecasting methods are characterised by unstable accuracy, and no method can be singled out as a universal one. In order to compare the forecasting results after using different methods as well as to be able to further use the dominant forecasting method, a number of ways for evaluating the accuracy of the forecasting result are used (*MAPE, MAE, MSE, RMSE, ME, SD*) [27]. In this Thesis, the mean absolute percentage error (*MAPE*) was used as the main criterion for evaluating the accuracy of forecasting time series processes:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{\left|R(t)-P(t)\right|}{R(t)}\cdot 100,\ \%, \tag{2.1}$$

where N is the number of points of the time series; t is the instantaneous value of the point of the time series; R is the actual value of the point of the time series; and P is the forecast of the value.

2.5. Analysis of the Factors Influencing the Forecasting Procedure

Pre-processing of historical data makes it possible to considerably increase the accuracy of the forecast. One of the ways of pre-processing of data is finding the linear regularities between the forecast process and other processes or parameters influencing it, in other words − correlation analysis. Correlation analysis of statistical data clearly shows the existence or non-existence of a regularity between two or more parameters. The degree to which the values of one parameter change depending on changes in the values of another parameter is the result of such evaluation. Table 2.1 shows the interpretation of the values of the correlation coefficient.

Table 2.1

The Meaning of the Value of Correlation Coefficient

Values of correlation coefficient	
Correlation coefficient value *r*	**Interpretation**
$0.0 < r \leq 0.2$	Very weak correlation
$0.2 < r \leq 0.5$	Weak correlation
$0.5 < r \leq 0.7$	Medium correlation
$0.7 < r \leq 0.9$	Strong correlation
$0.9 < r \leq 1.0$	Very strong correlation

3. INPUT PROCESSES FOR THE CONTROL OF THE DAUGAVA HPPS

Assuming that the energy produced in the Daugava HPP cascade was sold at the average market price, it is easy to calculate the annual income, which is approx. 60 million EUR. Still, in 2017, when the water inflow was considerably larger, the income doubled. Such relatively large sums of money are important for the national economy of Latvia. It is important to point out that the reservoir levels of the cascade power plants are strongly regulated − only limited changes of the reservoir level are allowed during every day and every hour. It can be established that the primary task of the HPP cascade operator is to avoid exceeding the allowed limits. The water level fluctuations in an HPP reservoir are strongly influenced by the water inflow and the capacity of the equipment sets that are active. Thus, the second task is to ensure larger income as far as possible. In order to sell electricity to the operator during the high-price period, it is necessary to use the forecast of two processes for the day ahead: that of the electricity market price and of the water inflow.

3.1. Input Process Registration Databases and the Methodology of Forecasting

In the Thesis, the stochastic formulation of the power plant control task has been chosen, which determines the need for depicting the results of forecasts. Forecasts of two types will be performed, which are depicted as follows:

- in the form of one realisation over the length of the planning period;
- in the form of a realisation, the length of which is chosen in such way as to ensure accuracy of calculations, based on the hypothesis about the ergodic nature of the random processes.

In order to perform a forecast of the second type, a modified naïve approach is used and artificial neural networks have been taken as the basis of the forecasting algorithm [28].

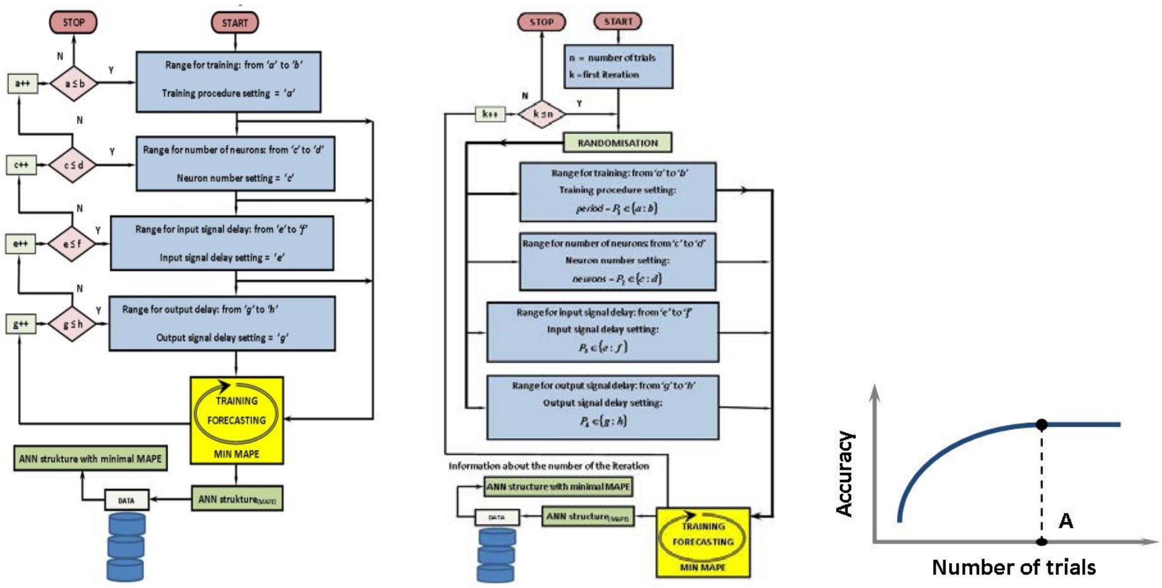
3.2. The Methodology for the Automatic Selection of the Artificial Neural Network Structure and Parameters

There are many types of ANNs but no methodology has been developed yet for selecting the appropriate network type [20], [23], [29]–[31]. Taking into account recommendations from earlier researchers and the existing possibilities to use available software (the *MATLAB 2013a* ANN package), an ANN for forecasting time series was chosen − *narxnet* − a non-linear autoregressive neural network with an external input. After choosing the network type, a number of additional complicated tasks need to be solved: choosing the training algorithm [32], [33]; more precisely defining the input-output processes; performing the pre-processing of the historical data, which, with a high degree of probability, contain erroneous data;

choosing the ANN parameters; testing the selected ANN with certain parameters, forecasting, analysing the results obtained afterwards and possibly correcting them [19], [34]–[36].

The optimal ANN parameters are specific to the task in hand and can be only determined experimentally [17]. The Thesis proposes two methods for automated searching for the optimal structure of the ANN (the ANNOSS procedure, ANN optimal structure search).

1. The explicit complete enumeration method (ECEM) − enumerating all the possible combinations of ANN internal parameters (Fig. 3.1 (a)).
2. The implicit complete enumeration method (ICEM) [37]) − using a randomly chosen subset of the possible combinations of ANN internal parameters (Fig. 3.1 (b)).



a b c

Fig. 3.1. Structural diagram of ANNOSS by using ECEM and ICEM. The hypothetical dependence of forecast accuracy on the number of cycles.

The explicit complete enumeration method is characterised by a considerable amount of computational effort. The ANNOSS procedure was implemented with the second, less time-consuming algorithm (ICEM) (Fig. 3.1 (b)). Generating random numbers within the set ranges a selection of certain ANN parameters is done. After a period of ANN training and testing, the *MAPE* (mean absolute percentage error) is determined and the ANN structure corresponding to it is stored in a database. After the end of each iteration, an ANN structure is singled out, which corresponds to the minimal *MAPE* value. In this way, the result of the last iteration consists in information that is exhaustive for the needs of ANN development and that corresponds to the minimum value of the mean absolute percentage error set.

The question arises as to the number of iterations of the ANNOSS procedure which is necessary to ensure an acceptable degree of forecasting accuracy. In the case of a small number of iterations, the accuracy of the ANN forecast is low; however, after reaching a certain value (point A in the graph), the increase in the number of iterations fails to yield a considerable improvement in forecast accuracy (Fig. 3.1 (c)). One of the many goals and tasks of this Thesis is investigation of the above issue.

3.3. Pre-Processing of Data − Data Clustering

One of the ways of pre-processing of historical data is detecting of the possible errors. Besides, the data can be divided into clusters on the basis of additional features, for example, sorting the historical data according to the following criteria:

- lack of any changes in the time series of the historical data;
- the division of the historical days into weekdays and holidays;
- the ordinal number of the forecast day within each week.

After the sorting, or clustering, of the data, further forecasting of energy market price and water inflow is done by means of an algorithm the block diagram of which is shown in Figure 3.2. This algorithm makes it possible to determine the input data clustering method according to the highest forecasting accuracy level. As has been already mentioned, the performed forecast can be adjusted; in our case, we will apply filtering of the output data by means of a smoothing filter.

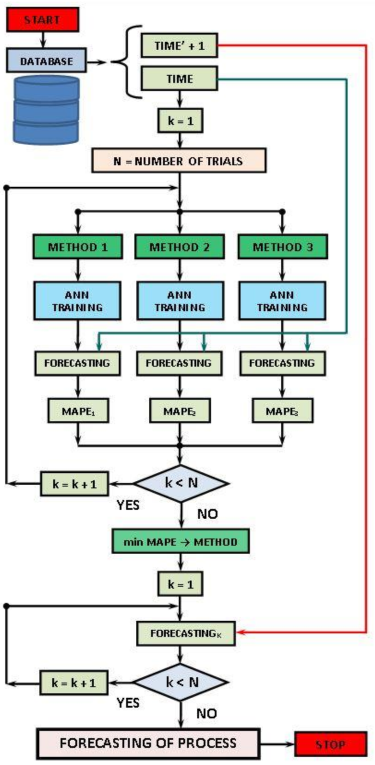


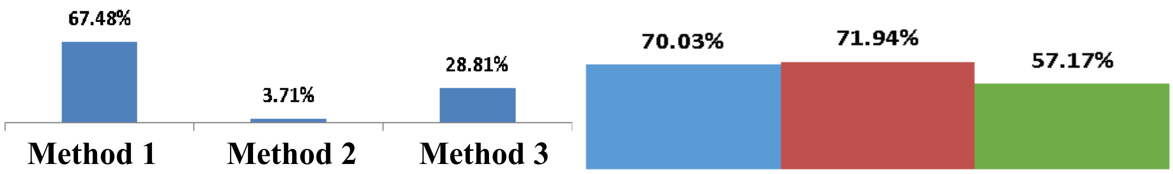
Fig. 3.2. A structural diagram for selecting the process forecasting algorithm.

3.4. Forecasting of Energy Price With an Artificial Neural Network Model

The electricity price forecasting procedure was investigated for the time period from 1 February 2014, till 31 December 2017. For the accuracy of the forecast to be better seen, we have used a value that characterises the accuracy of the forecast:

$$Ac = 100\ \% - MAPE. \tag{3.1}$$

Histogram in Figure 3.3 (a) shows the probability of an event in case of which the set type of input data clustering with subsequent forecasting will prove better than two others. The results of the analysis conducted show that in 96.29 per cent (67.48 % + 28.81 %) of the considered electricity price forecasting cases, the lowest errors were yielded by the 1st and the 3rd of the energy price forecasting methods. Histogram in Figure 3.3 (b) shows the dominant methods of electricity price forecasting, namely: the blue column corresponds to the 1st energy price forecasting method (without any clustering of historical data); the second column − the brick-red one − illustrates the degree of accuracy of filtered data obtained by the first method; the last column − the green one − corresponds to the third method of energy exchange price forecasting.



a b

Fig. 3.3. The probability of electricity price forecasting methods having the highest accuracy. The accuracy of electricity price forecasting by the first method (blue) and after filtering (red) as well as with the third method, for the time period from 01.02.2014 till 31.12.2017.

The first of the three discussed electricity exchange price forecasting methods showed the highest results as to the level of accuracy. Figure 3.4 shows the distribution density of the accuracy of the energy price forecast by the above method. Approximately one third (37.69 %) of the electricity exchange price forecasts that have been implemented by means of the first method with subsequent filtering, are in the accuracy range from 80 % to 90 %. Approximately one fifth, or 22.45 %, of the performed forecasts lie in the accuracy range from 70 % to 80 %.

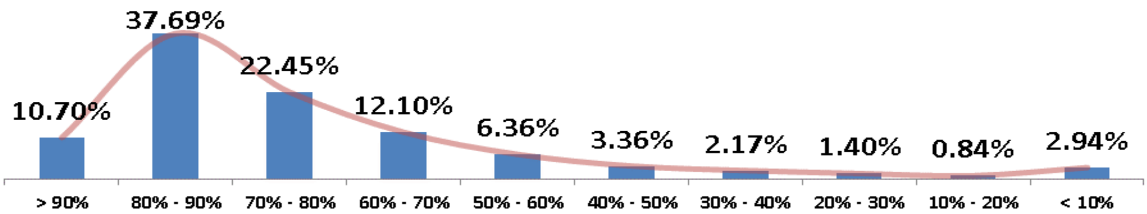


Fig. 3.4. The distribution of the forecasting accuracy, using the first method with subsequent filtering.

Let us illustrate some electricity price forecasting examples and the influence of the filtering procedure on the accuracy of the forecast. Figure 3.5 shows the hourly values of the electricity price forecast on 10 March 2017.

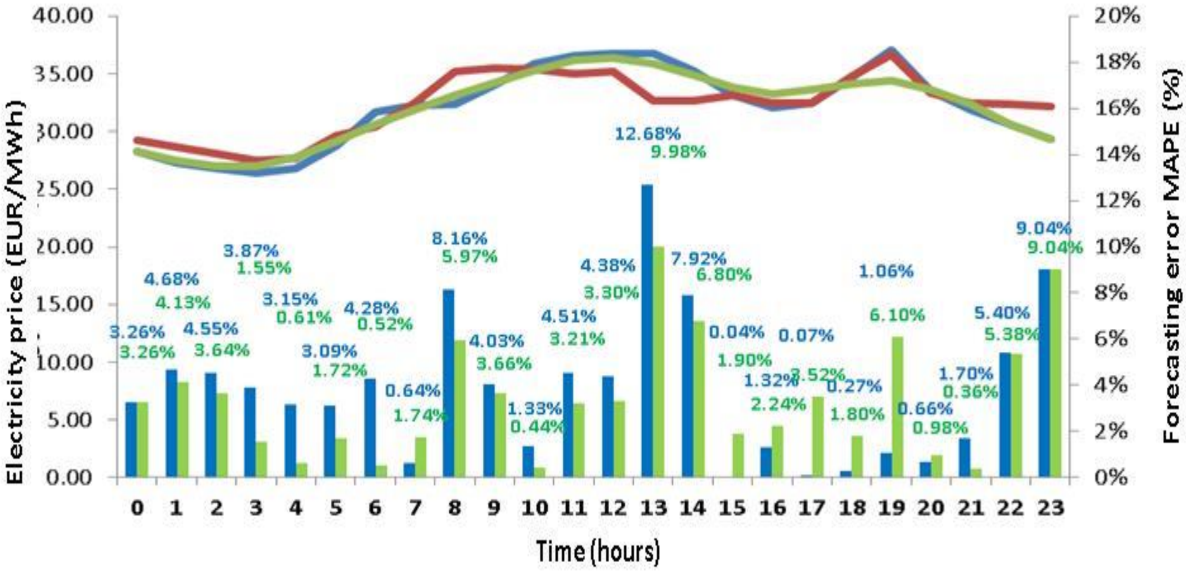


Fig. 3.5. The actual price of electricity and its forecasts, 10 March 2017.

The colour legend for graph 3.5 is as follows:

- – the actual value of electricity price, EUR/MWh;
- – the electricity price forecast, EUR/MWh;
- – the electricity price forecast with subsequent filtering, EUR/MWh;

■ – the hourly forecasting errors MAPE, %;

■ – the hourly forecasting errors with subsequent filtering, %.

The average inaccuracy of the forecast and its filtered result is 3.75 % and 3.41 %. The results of the electricity price forecast have a high degree of accuracy: 100 % – 3.41 % = 96.59 %.

3.5. Forecasting of the Inflow of the Daugava

In order to find the parameter that provides the most accurate inflow forecasting result, four types of calculations were produced, which differ by the type of initial, or input, data:

- temperature data regarding the year 2015 [37];
- precipitation data regarding the year 2015 [37];
- the inflow forecast of the weather forecast service for the year 2015 [37];
- the water inflow forecast that is based on the temperature data of the year 2015 (the water resource forecast based on the forecast data of water inflow).

The investigation data for the time period from 1 January 2015 till 1 November 2015 are shown in histogram 3.6. The lowest average error of unfiltered forecasting is shown by the method that is based on an inflow value forecast at an earlier time, this value being dependent on outdoor air temperature.

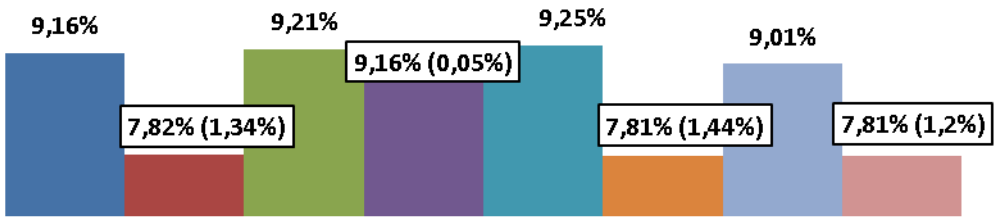


Fig. 3.6. The average value of the 24-hour forecast error for the time period from 01.01.2015 till 01.11.2015.

The colour legend:

■,■ – forecasting of water inflow based on the forecasting of precipitation and the filtered precipitation forecast values;

■,■ – forecasting of water inflow based on the forecasting of water inflow according to the weather service and the filtered values of this forecast;

■,■ – forecasting of water inflow based on the forecasting of outdoor air temperature and the filtered values of this forecast;

■,■ – forecasting of water inflow based on the forecasting of water inflow depending on outdoor air temperature.

As a result of the filtering of the inflow forecasts, the degree of accuracy increases for all types of input data. Figure 3.7 shows the actual water inflow values on 21 April 2015 and the considered types of forecasts. The accuracy results for the water inflow forecasts obtained according to the considered methods enable the statement that these methods are equally valid.

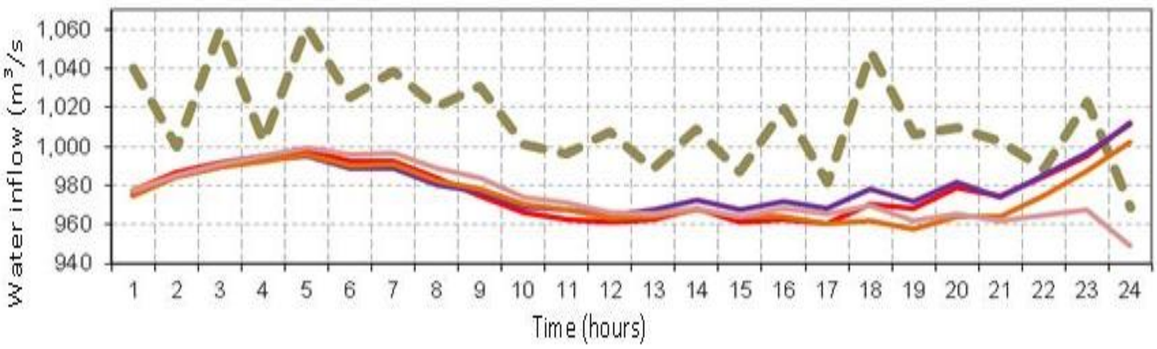


Fig. 3.7. The actual value of water inflow and its forecasts, 21.04.2015.

The color legend:

-- Actual inflow, m^3/s.

-- Inflow forecast (precipitation), m^3/s. *MAPE* = 3.77 %.

-- Inflow forecast (water inflow forecast of the weather service), m^3/s. *MAPE* = 3.59 %.

-- Inflow forecast (outdoor air temperature), m^3/s. *MAPE* = 3.97 %.

-- Inflow forecast (RTU's inflow forecast and outdoor air temperature), m^3/s. *MAPE* = 3.76 %.

3.6. Realisation Set of Modelling of the Water Inflow Forecast

Naïve methods are based on the assumption that the future is best characterised by the most recent changes [3], [5], [7], [8], [38]–[41]. The advantages of the naïve methods lie in their being easy to use and able to generate forecasts based on short-term preliminary observations in cases when longer series of historical data are not available. In our case, we assume that in the future, forecasting errors persist that are determined by the past. As a result, a very simple algorithm emerges (Fig. 3.8): using the recorded actually observed water inflow from the past and the past forecast of this inflow the errors of the past are calculated. After that, we naïvely assume that the errors will persist the next day. If we use a number of past days, then also a number of forecasts can be made for the following day adding the past errors to the only performed realisation of the forecast process. Further follow examples of the realisation of the above algorithm (Fig. 3.9).

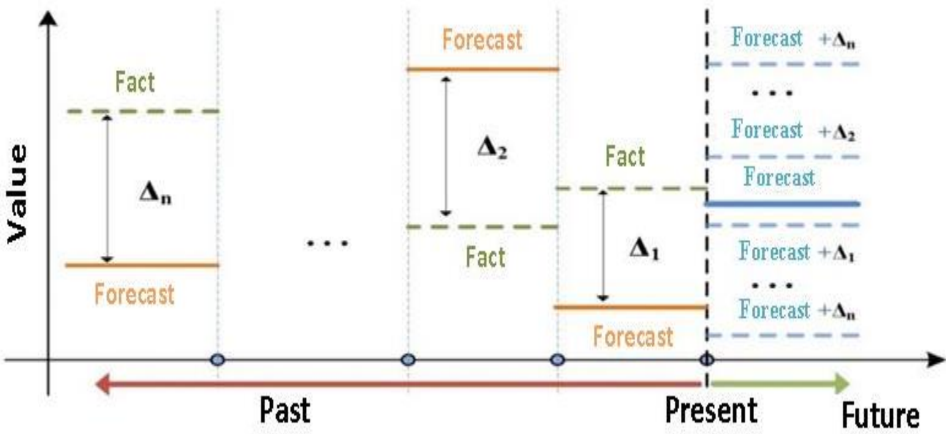


Fig. 3.8. A description of the essence of the naïve algorithm.

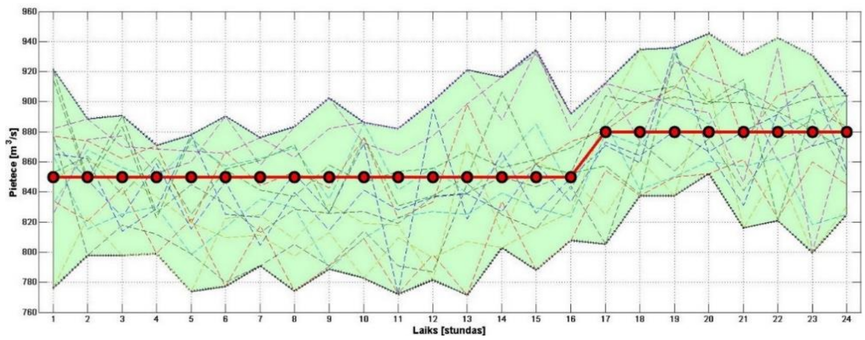


Fig. 3.9. An example of modelling the water inflow forecast realisations set for 6 April 2015. Red curve − the next day's forecast; dashed line curves − addition of errors of the past forecast.

The power plant operator has to take into account the varied nature of the forecast realisations depicted in Figure 3.9 and to choose the operating regimes of the power plants accordingly, without violating a whole range of environmental, technological and legal limitations. This can be done by using special software, whose one important part is constituted by the forecasting tools and techniques discussed in this Thesis.

4. FORECASTING OF HEAT CONSUMPTION PROCESSES

4.1. Input Data. Factors That Influence District Heating Load

After the reviewed correlation analysis results regarding correlations between external environment factors and district heating load, it can be seen that one parameter that is in strong correlation with district heating load is outdoor air temperature. The historical records of outdoor air temperature are used for heat and electricity generation planning (Fig. 4.1).

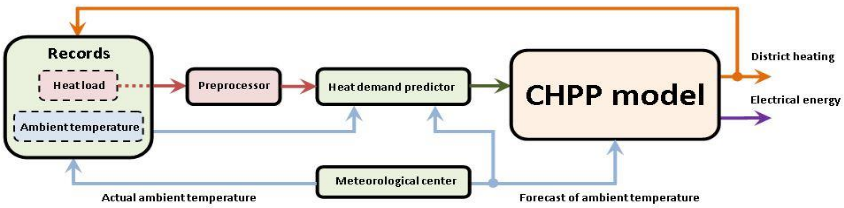


Fig. 4.1. Simplified block diagram of a thermal power plant planning model.

4.2. Forecasting of District Heating Load by Means of the ANN and Polynomial Models

4.2.1. The Polynomial Model of Forecasting

The task to forecast the operating regimes of Riga combined heat and power plants has been in existence for many years already. To solve this task, the operators of Riga power plants use a third-degree polynomial model whose coefficients are selected by using the previous year's district heating load measurement data.

To evaluate the degree of the polynomial and the coefficients, it is necessary to choose the length of the experimental data collecting period. One of the possible approaches is to use all the data of the previous year. Another approach is to use the presence of daily data renewal and a limited period for adjusting and fine-tuning the polynomial.

In this case, there is a need for specialised software, which renews the choice of the polynomial degree and coefficients every day. It is this approach that is used in this study. Polynomials of various degrees were checked (with a degree of up to 20) and the best results were yielded by first- and third-degree polynomials (Table 4.1). The value of the degree depends on the existence of outdoor air temperature 'experience' for the forecast day in the historical data. In this way, the developed polynomial model adapts itself to the present situation. Table 4.1 compares two models for forecasting district heating load: the model developed by Riga Technical University (RTU polynomial) and the one used by JSC *"Latvenergo"* (LE polynomial).

Table 4.1

A Comparison of the Accuracy of District Heating Load Forecasts

Date	Polynomial (RTU)		Polynomial (LE)									
	MAPE (%)	Degree	MAPE (%) / degree (1–10)									
31.12.2016	4.80	3	7.58	8.39	8.81	7.65	9.51	9.90	8.71	8.66	8.72	8.47
01.01.2017	5.52	3	13.82	10.50	11.16	14.09	12.02	8.18	9.83	9.75	9.95	8.20
02.01.2017	3.21	1	6.06	5.05	4.93	5.07	4.77	4.83	5.15	5.20	5.64	6.16
03.01.2017	3.60	1	4.50	4.97	4.93	4.94	5.37	5.50	5.79	5.86	5.94	5.93
04.01.2017	8.47	1	12.24	15.18	12.94	13.65	13.43	13.55	13.11	13.18	13.33	13.43

4.2.2. Pre-Processing of Data

Before the implementation of district heating load forecasting, it is necessary to choose the data to be used and check them as to correctness and sufficiency, i.e. data pre-processing [33], [42]–[44]. Discovering erroneous data in the historical records of district heating loads and their correction can considerably improve the degree of forecasting accuracy. Figure 4.2 shows a situation when anomal behaviour of district heating load in relation to the outdoor air temperature is found. To discover illogical behaviour of district heating load, the present Thesis used Eqs. (4.1) and (4.2).

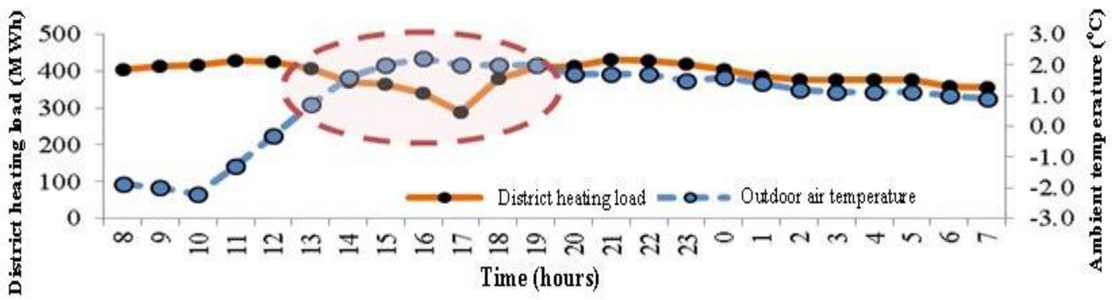


Fig. 4.2. Historical district heating load and outdoor air temperature data for the period 27.02.2015–28.02.2015.

$$MAPE_1 = \frac{1}{N}\sum_{t=1}^{N}\frac{\left|Q_i^{\mathrm{F}} - Q_i^{\mathrm{P}}\right|}{Q_i^{\mathrm{F}}}\cdot 100, \%, \tag{4.1}$$

$$MAPE_2 = \frac{1}{N}\sum_{t=1}^{N}\frac{\left|Q_i^{\mathrm{F}} - Q_{i-1}^{\mathrm{F}}\right|}{Q_i^{\mathrm{F}}}\cdot 100, \%, \tag{4.2}$$

where N stands for the number of iterations (24 hours); Q_i^{F} is the actual value of heat consumption; and Q_i^{P} is the forecast value of heat consumption.

To remedy the anomalies found, the following measures are proposed:

- ignoring the warnings;
- manual correction;
- application of filtration, combining the simple and weighted sliding average over a range of 24 hours;

- o application of filtration, combining the simple and weighted sliding average over a range that corresponds to the time range of the comparison criterion (in our case, 60 days);
- o automatic correction of the expected district heating load value anomaly.

4.2.3. Forecasting of District Heating Load With the Polynomial Model

The investigated time period for district heating load comprised two heating seasons (15.10.2015–20.04.2016 and 15.10.2016–21.04.2017). The mean average percentage error (MAPE) for these time ranges is 5.19 % and 5.60 %, respectively. Figure 4.3 shows the actual heat consumption values from 05.01.2016, 8 a.m. till 06.01.2016, 7 a.m. as well as the forecast for this time period. The daily average error (MAPE) of the district heating load forecast in Figure 4.3 is 2.01 %.

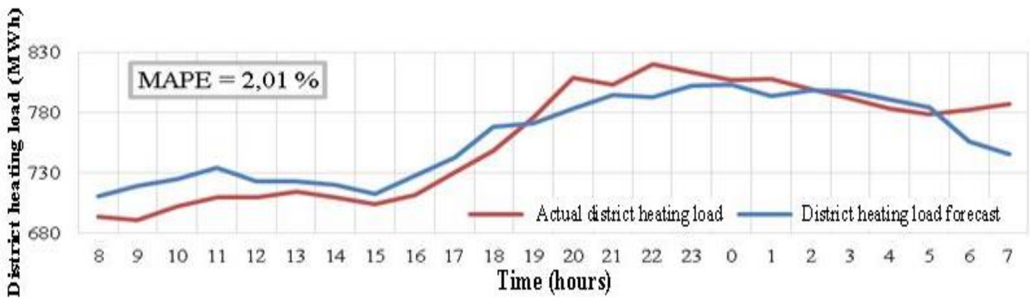


Fig. 4.3. The actual district heating load values and their forecasts for the time period of 05.01.2016, 8 a.m. to 06.01.2016, 7 a.m.

4.2.4. Forecasting of District Heating Load With the ANN Model

Before the implementation of district heating load forecasting by an ANN model, it is necessary to determine the optimal structure parameters. The district heating load forecasting is done by means of the second algorithm − the above-described algorithm, which uses the Monte-Carlo method. The optimal parameters of the ANN structure found (let us call it the 'optimal' one) are provided in Table 4.2. Also, for comparison purposes, Table 4.2 provides the structure of the ANN the parameters of which have been found by way of many non-automated experiments. Figure 4.4 forecasts the district heating load from 31 December 2015 till 1 January 2016. The forecasting inaccuracy of the 'optimal' ANN is practically two times less than in the 'traditional' ANN.

Table 4.2

Traditional and Optimal Structure of ANN

ANN structure parameter	'Traditional' ANN structure	'Optimal' ANN structure
Training period (hours)	8760	2030
Input data delay (hours)	1 : 24	1 : 19
Feedback delay (hours)	1 : 24	17 : 17
Number of neurons	20	10
Goal of training	0.01	0.213
Gradient	0.01	0.877
Training speed	0.01	0.035

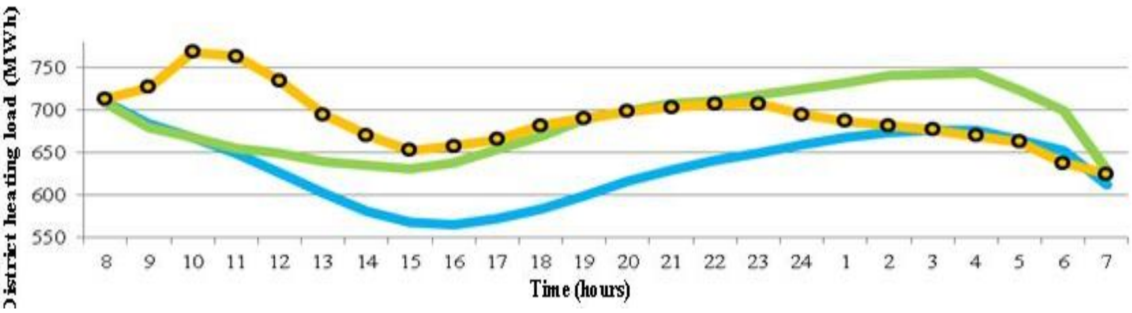


Fig. 4.4. Actual district heating load and its forecasts from 31.12.2015 till 01.01.2016.

- Actual district heating load.
- The "traditional" ANN (outdoor air temperature forecast). *MAPE* = 8.31 %.
- The "optimal" ANN (outdoor air temperature forecast). *MAPE* = 5.51 %.

4.2.5. Temperature Forecasting Accuracy and Its Influence on District Heating Load Forecasting

As the input data for the heat consumption forecast, the outdoor air temperature forecast is used. The error of the input data considerably influences the degree of accuracy of district heating load forecasting. The average value of the outdoor air temperature forecast accuracy is 84.47 % (Fig. 4.5). The daily maximum value of the forecast accuracy is 99.05 % and the minimum value is 65.43 %.

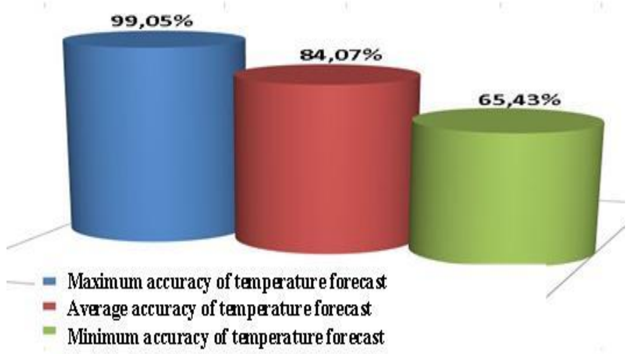


Fig. 4.5. Temperature forecasting accuracy from 31.12.2015 till 01.01.2016.

Figure 4.6 shows the evaluation results for those forecasts which used as the input data the actual and forecast outdoor air temperature values from 31.12.2015 till 01.01.2016. Thus, for the 'traditional' and 'optimal' structure of ANN, for artificial neural networks that use as the input data the temperature forecast and its actual values, the drop in the heat consumption forecasting error (MAPE) is 1.68 % and 1.33 %, respectively. By using the 'optimal' ANN structure, in the case when the forecast outdoor air temperature data are used, the accuracy of the forecast increases by 2.80 % as compared with the 'traditional' ANN structure.

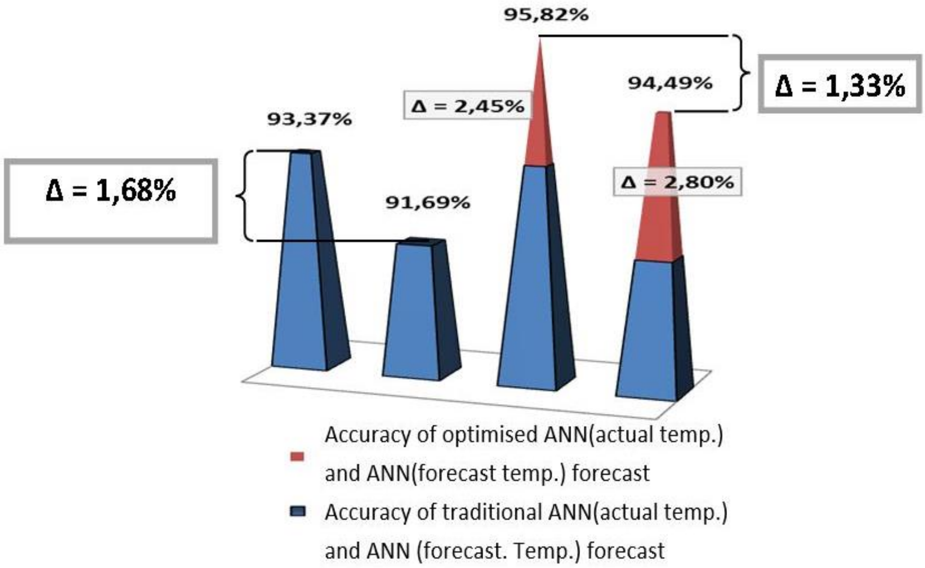


Fig. 4.6. District heating load forecasting accuracy with the 'traditional' ANN structure and the 'optimal' one, using the outdoor air temperature forecast and the actual values.

4.2.6. Modelling With Combined Method

Both of the above-discussed different district heating load forecasting approaches give results that are close. This fact makes it possible to create one more approach, which combines the polynomial model and the ANN. Figure 4.7 shows the absolute values of the deviations of forecast district heating load values from the actual data. The results of the graph as well as certain assumptions (that are discussed in detail in the Thesis) make it possible to determine the value of the accuracy of the heat consumption forecast in economic terms (Table 4.3). The combination of the ANN and polynomial models at the conditions of cold weather yielded savings in the amount of more than 1000.00 EUR, thus diminishing the balancing costs.

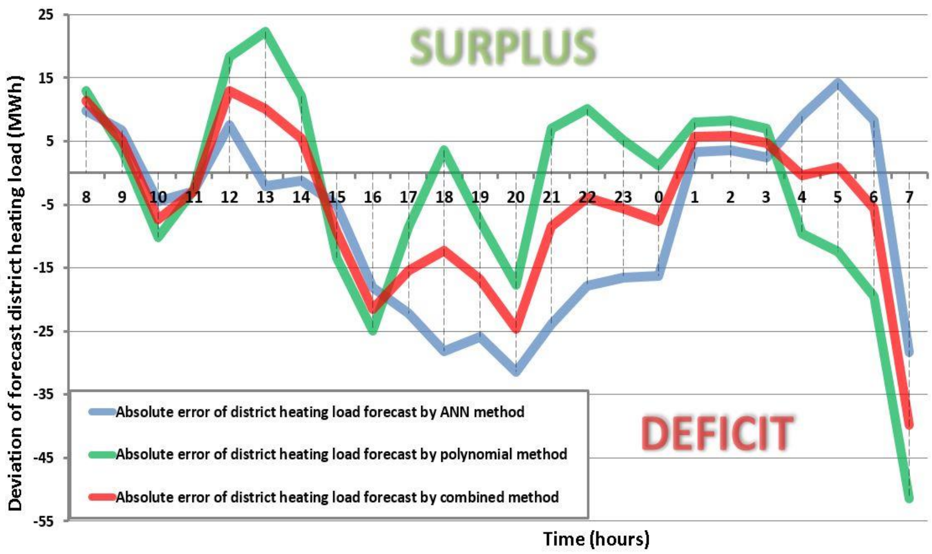


Fig. 4.7. The absolute values of the deviations of forecast district heating load values from the actual data, 8−9 December 2016.

Table 4.3

Forecasting Errors and Their Respective Values for the Three Discussed Methodologies

Date	ANN	Polynomial	Combined
8−9 Dec. 2016	MAPE (%)	MAPE (%)	MAPE (%)
	3.88	3.63	2.99
	FIC (EUR)	FIC (EUR)	FIC (EUR)
	29 102.35	24 309.35	23 164.68

FIC − forecast inaccuracy costs.

5. EXAMPLES OF AND TOOLS FOR USING THE RESULTS OF INFLUENCING PROCESS FORECASTS

5.1. Estimating the Costs of Operating Reserve Provision by a Pondage Hydroelectric Power Plant

Operating reserves constitute an essential tool in the hands of transmission system operators (TSOs) who are entrusted with the task of ensuring stable and reliable functioning of power system. In a modern power system, there are three distinct groups of market actors who can be called upon by TSOs to aid in power system operation management: controllable generation, energy storage, and controllable load.

The Thesis is focused on the opportunity costs that reserve provision incurs on pondage hydroelectric power plants (HPPs), which is an imortant step towards formulating fair and justified bids in reserve markets. During HPP profit maximisation it is paramount to consider the volatility of energy prices [13], water inflow as well as a multitude of environmental restrictions.

The estimation of the opportunity costs of operating reserve provision is the main task of the Thesis. For this purpose, the day-ahead scheduling optimisation is carried out three times with distinct operational modes (OM) in mind − participation in the day-ahead electricity wholesale market:

- without additional constraints imposed by operating reserve provision (let us call this OM reserve-free (RF);
- with additional constraints imposed by spinning reserve provision (RR);
- with additional constraints imposed by non-spinning reserve provision (NSR).

Comparing the revenue in EF mode to the revenue in SR or NSR modes (Fig. 5.1), the minimal compensation required for spinning reserve can be established. Such evaluation of maintaining reserves can be used by the owners of HPPs when preparing a proposal for the operator's intra-day and balancing market bids, and managers of numerous small energy sources, either operational or merely in the design stage, when deciding on participation in the balancing of the power system. In a competitive electricity market, the main goal of the market player is profit maximisation [Eq. (5.1)]. The problem [Eq. (5.1)] has to be solved by taking into account a number of technical and environmental constraints [1]–[10].

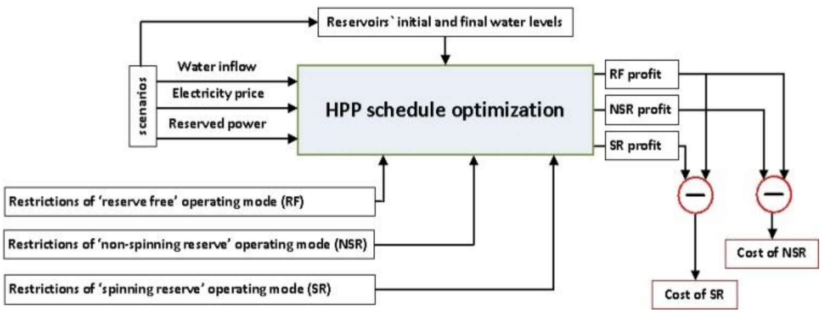


Fig. 5.1. Flowchart of operational reserve provision cost estimation.

The aim of the producer for the day-ahead market could be presented as follows:

$$\sum_{t=1}^{N}\left(\sum\nolimits_{k\in\{1,2,3\}} P_t^k\right)C_t \to \max, \tag{5.1}$$

where N is number of hours; k is a variable of set {1, 2, 3}, which marks a specific HPP in the cascade; P_t^k is generated power of a specific HPP k at hour t, MW; and C_t is electricity price at hour t.

In turn, the power production at an HPP depends on several parameters:

$$P_t^k = f_{\text{p}}\left(\eta_t^k, \Delta h_t^k, Q_t^k\right), \tag{5.2}$$

where η_t^k is the efficiency of HPP k at hour t, %; Δh_t^k is water discharge (change in reservoir level) at HPP k at hour t, m; and Q_t^k is water inflow at HPP k at hour t, m^3/s.

In general, a stochastic nonlinear optimisation problem [Eq. (5.1)] can be divided into three interconnected parts:

1) forecast of future processes (C_t, Q_t^k);
2) formulation of the objective function;
3) solution of the maximisation problem.

At the second operation mode (SR), the problem [Eq. (5.1)] must be solved, taking into account additional conditions:

$$P_{\text{res}_t}^k \le P_t^k \le P_{\max_t}^k, \tag{5.3}$$

where $P_{\text{res}_t}^k$ is the minimum power reserve of HPP k at hour t, MW; $P_{\max_t}^k$ is the maximum capacity of HPP k at hour t, MW; and P_t^k is the active power generation of HPP k at hour t, MW.

In the third operation mode (NSR), we solve the problem [Eq. (5.1)], assuming that the reserves will not be used, but we need the constraints to be respected also in the opposite case, when they are fully activated. Thus, the solution of the optimisation problem [Eq. (5.1)] for the NSR mode is subject to:

- the upper bounds of generated power;
- limitation of maximum water discharge permissible to not hinder activation of reserves, which can be expressed by substituting the required reserve power in Eq. (5.2) with the water used for reserve activation $\Delta h_{\text{res}_t}^k$:

$$\begin{cases} \Delta h_t^k \le \Delta h_{\max_t}^k - \Delta h_{\text{res}_t}^k; \\ h_{\max_t}^k = f_{\Delta h_t^k}\left(\eta_t^k, P_t^k, Q_t^k\right); \\ \Delta h_{\text{res}_t}^k = f_{\Delta h_t^k}\left(\eta_t^k, P_{\text{res}}^k, Q_t^k\right). \end{cases} \tag{5.4}$$

5.1.1. Case Study

The proposed cost assessment algorithm for operating reserve provision allows us to consider a relatively wide range of power producer behaviours depending on the volatility of external (water inflow, energy price, etc.) and internal processes (efficiency, technical and ecological restrictions, etc.). Figure 5.2 (a) shows three actual values of water inflow. The curve is based on real-life data of 11.04.2015 and the series differ only by amplitude. The used electricity prices are shown in Figure 5.2 (b). As in the previous case, they differ only by absolute values. Such an assumption allows us to retain the character of the curves.

The radar chart in Figure 5.2 (c). illustrates different reserve provision cases studied. In most of the scenarios (A, A1, B, C, D, E), the required reserves differ in amount but not in their time of readiness. A subcase of scenario A is also considered, A1, where the reserves have to be maintained at hours of relatively cheap electricity instead.

The results of the cost estimation of spinning and non-spinning reserve provision using the proposed methodology are shown in Figures 5.3 (a, b) and 5.5 (a, b). The costs of non-spinning reserve provision of 4500 MWh (Scenario A) at variations of energy price and main inflow are depicted in Figure 5.3 (a).

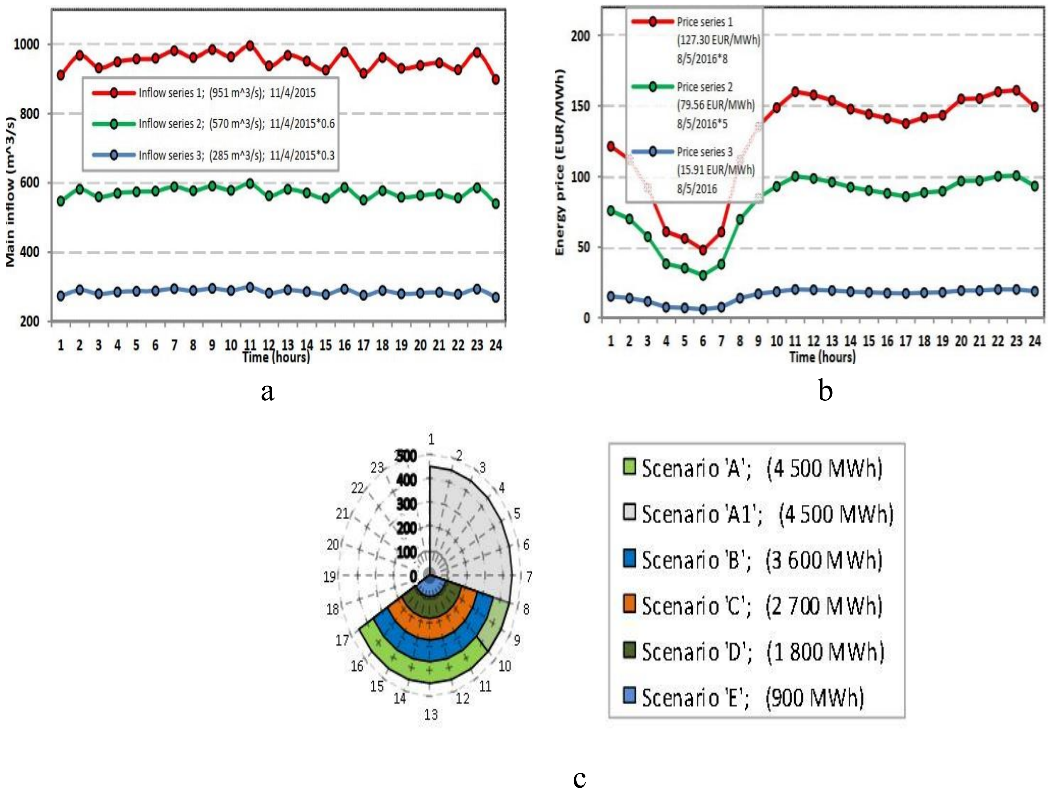
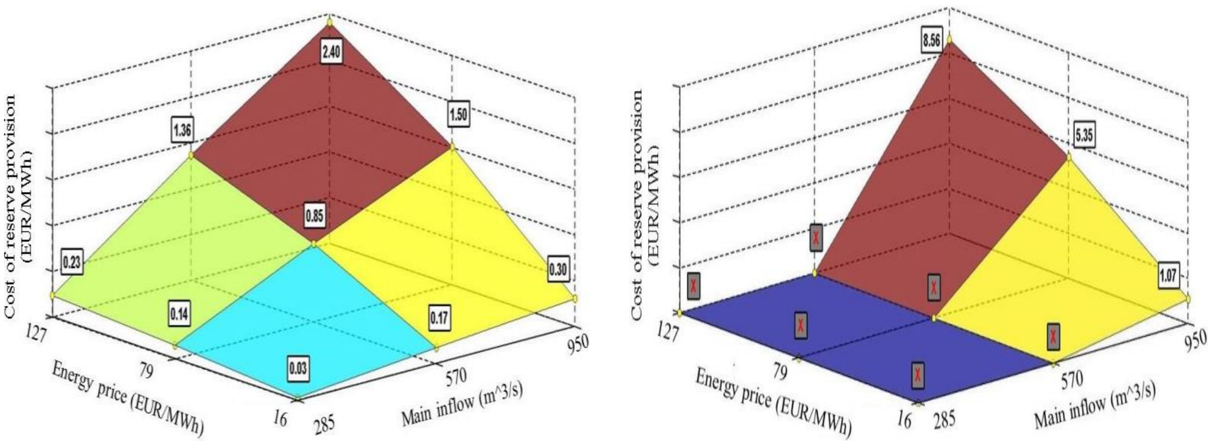


Fig. 5.2. Actual water inflow on 11.04.2015 and its two variants and the electricity price of the observed day. Reserve provision scenarios (MWh/h).

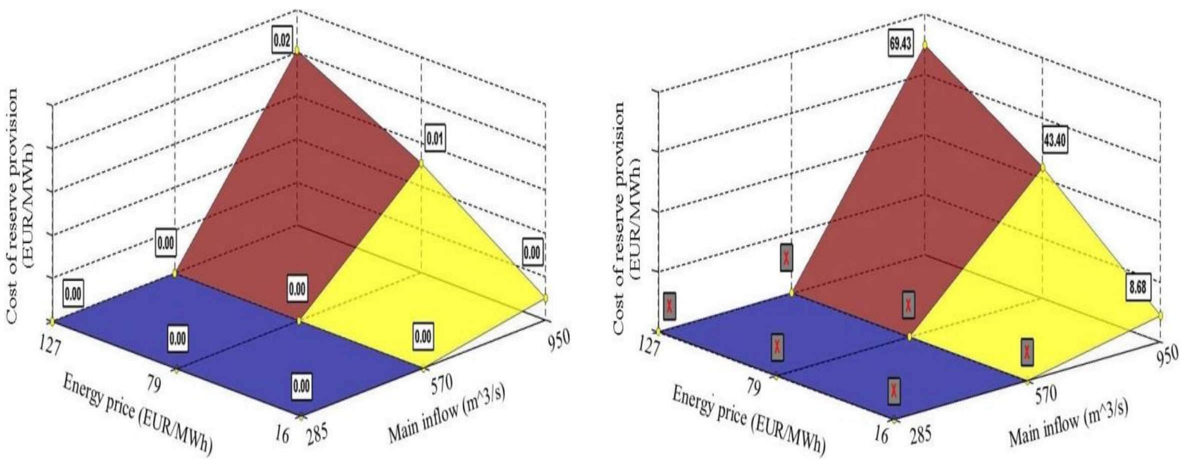
At the highest energy price and water inflow values, the generating units have to work in suboptimal conditions to provide the SR mode (Fig. 5.3 (b)). In some cases, it is impossible to satisfy the constraints (5.4) or environmental or technical restrictions and these situations are marked with a red cross in a grey box. In Scenario A1 the amount of reserved power is the same, but the hours when it is necessary are shifted. Figures 5.4 (a) and 5.4 (b) show the reserve provision costs for the NSR and SR modes respectively: higher inflow and electricity day-ahead price values result in higher reserve provision costs.

Scenario C is indeed somewhat peculiar in that for the medium inflow case the cost is almost as large as in the high inflow case for the NSR mode (Fig. 5.5 (a)) and even higher in the SR mode (Fig. 5.5 (b)). Furthermore, in the low inflow case the desired reserve power could not be provided.



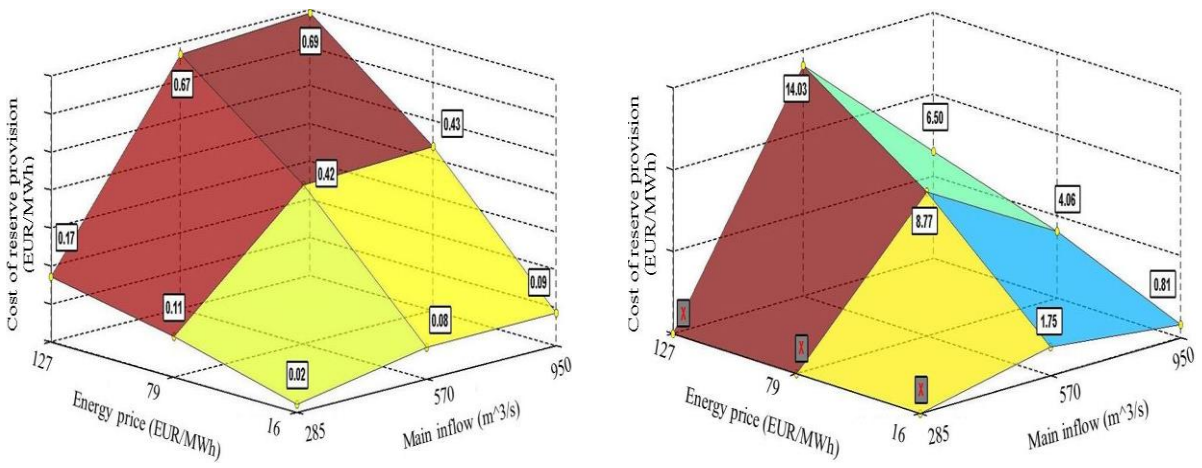
a b

Fig. 5.3. Costs due to non-spinning and spinning reserve provision at Scenario A with varying average energy prices and water inflow.



a b

Fig. 5.4. Costs due to non-spinning and spinning reserve provision at Scenario A1 with varying average energy prices and water inflow.



a b

Fig. 5.5. Costs due to non-spinning and spinning reserve provision at scenario C with varying average energy prices and water inflow.

The discussed scenarios and the results shown in the diagrams enable the conclusion that the costs of maintaining reserves are strongly dependent on the prices, the water inflow and the condition of the reservoirs. This means that the discussed problem needs to be solved every day after receiving new information and making new forecasts. Only then can the power plant operator evaluate the reserve maintaining costs and successfully operate in the balancing market.

OVERALL CONCLUSIONS

1. The bulk of energy produced in Latvia is generated at the Daugava hydropower plants and at the thermal power plants of Riga. The Riga thermal power plants, in most cases, operate in the cogeneration mode, which is strongly influenced by the heat demand of the Riga right bank area. The Latvian power network is connected to those of Lithuania and Estonia and via these to the Scandinavian countries and Poland, which ensures wide export and import possibilities and operation in the electricity market with a high degree of freedom. In order to successfully operate in the market, it is necessary to conduct optimisation of the operation of power plants by choosing the hourly operating regimes of the plants.
2. The regimes are managed by observing input and output processes, simulating the possible changes, applying one of the optimisation procedures, which in fact operates on the basis of model experiments. The main peculiarity of the plant operation optimisation problem arises out of the problem formulation: the regimes need to be chosen for the future (for a day, week, year and more ahead). At these conditions, the input and output processes are only observed partly.
3. Energy production is strongly influenced by weather conditions − outdoor air temperature, precipitation, humidity, water inflow in the Daugava, wind speed and direction, solar irradiation. The electricity production amount of Riga CHPPs is strongly dependent on the heat demand in Riga. The changeability of the energy production amount determines the necessity and importance of forecasting tasks.
4. When planning the construction of new entities or the reconstruction of existing ones, an optimisation problem arises, which has to be solved by taking into account operating conditions for many years ahead; as a result, it is necessary to perform an hourly forecast of entity operating conditions for many years ahead. It is necessary to solve the forecasting problem when planning operation in any industry, since forecasts provide information about the future and about the influence of expected and possible factors and processes on the operation of the planned entity or system.
5. The selection and substantiation of the process forecasting algorithm is done by means of numerical experiments, by testing the solving approaches and methods for the problem in question and choosing the best one that can ensure the solution of the problem.
6. Often, forecasts are made on the basis of an analysis of the changes in historical quantities over time and of registration data. To detect permanent regularities, time series of various kinds are used.
7. Abundance of statistical data makes forecasting more difficult. There is a need for a filter that could allow discarding the statistical data that influence the forecast most of all.
8. The operation of the Daugava HPP cascade is planned by forecasting the *Nord Pool* electricity prices and the water inflows in the Daugava. At market conditions, making use of the flexibility of plants, the operator tries to sell energy at the high-price period. The forecast of processes is used to solve three important tasks:
   - for making bids to the electricity market operator;

- for preparing reconstruction design sketches;
- for preparing construction designs for new power plants.

9. In the forecasting of processes, artificial neural networks can be applied. The suitable type of network is chosen on the basis of recommendations from earlier researchers and the possibility to use the available software products. Taking into account the availability of the *Matlab* package, an artificial neural network for forecasting time series was chosen, namely, a *narxnet* type network − a non-linear autoregressive neural network with an external input, which is offered in the neural networks package of the technical computing language *Matlab 2013a*.
10. After selecting the network type, in striving to increase the accuracy of the forecasts, a number of complicated tasks need to be solved:
    - To concretise the input/output processes. In the forecasting of water inflow and market prices, the historical data of hourly measurements of prices and water inflow are used.
    - To perform pre-processing of historical data.
    - To perform the selection of ANN parameters: a) the time period of the registered data used in the training process; b) the number of neurons in the hidden layer; c) the direct communication delay; d) the feedback delay ('Fd').
11. For the selection of the network type and network parameters, it is possible to use a forecasting error minimisation algorithm and software that enumerates the possible network type and parameter combinations.
12. The checking of the synthesised forecasting software products by using the real market price and Daugava River water inflow measurements has proved the possibility of making and using a forecast.
13. Heat demand is influenced by many factors, some of them are of stochastic nature. Part of the factors can be, and are, controllable. A complex control system has been implemented, with the participation of energy producers, heating networks, operators of heating units and thousands of end consumers.
14. In order to ensure continuous, reliable and economically substantiated supply of heat to the consumers, it is very important to precisely forecast the district heating load and set the correct heating network regimes and parameters. Simultaneously with heat, combined heat and power plants produce electricity, which is sold in accordance with the market conditions. Deviations from the plan result in significant economic losses. Thus, exact forecasting of district heating load is important both for the heat supplier and the energy producer.
15. For the forecasting of Riga district heating, hourly measurement results of district heating load are available as well as measurements of temperature and other parameters characterising weather conditions. These measurements are used as the basis when planning the generation of heat and electricity.
16. Heat demand is strongly related to outdoor air temperature, which makes it possible to use weather forecasts for regime planning.
17. To solve the Riga power plant regime planning problem, it is possible to use the polynomial model or the ANN model, with the ratios and structure selected by using last

year's district heating load and temperature measurement data, temperature forecasts and numerical experiments to select the best parameters.

18. Forecasting errors create the need to buy or sell electricity at balancing (increased) prices, which, even within one 24-hour period, may result in economic losses amounting to tens of thousands of euros. Pre-processing of the input data can considerably increase the accuracy of the forecasts.
19. The accuracy of a model that uses an ANN can be considerably improved by performing optimisation with the Monte-Carlo method.
20. Using the ANN and polynomial models in combination yields an increase in accuracy as compared with the separate models.
21. The developed reserve cost estimation software provides wide opportunities to consider additional scenarios and take into account new information.
22. If a power producer cannot fully participate in an energy wholesale market due to constraints imposed by a necessity to provide reserves, the power production schedule is inevitably suboptimal. By comparing the potential day-ahead profit in an unconstrained operatioal mode to profit attainable if some capacity is reserved, one can estimate the minimum remuneration necessary to make reserve provision an attractive business opportunity for the owners of a power production company.
23. It was found that water inflow volatility has a very notable effect on the opportunity costs of reserve provision. For a relatively high amount of reserved energy, a higher inflow resulted in larger reserve provision costs than in cases with smaller inflow. However, if the amount of reserve energy is relatively smaller, this characteristic flips and reserves become more costly in the cases with small inflow. This effect can be explained by the twofold way in which reserve provision hinders effective participation in the day-ahead market for an HPP. The larger non-spinning reserves are required, the lesser is the HPP's ability to exploit its notable water resources lucratively. On the other hand, when the inflow is small, spinning reserves which act as a must-run capacity cause more hindrance than during large inflows, since in the latter case a pondage hydroelectric plant would likely run at the hours with the highest prices anyway, but if the water resources are very limited, more freedom in their use is needed to achieve a profitability that is close to the optimum.
24. The reserve maintenance costs are strongly dependent on the prices, the water inflow and the condition of the power plant reservoirs. This means that the cost estimation problem needs to be solved every day after receiving new information and making new forecasts. Only in such a case can the power plant operator evaluate the reserve maintenance costs and confidently operate in the energy balancing market.

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