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DECISION-MAKING SUPPORT METHODS, ALGORITHMS AND TOOLS FOR ELECTRICITY MARKET PARTICIPANTS

Doctoral Thesis

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ABSTRACT

Electricity markets are an important tool in ensuring efficient operation of the modern power systems. They enable market participants to maximize the benefits they can receive from trading, at the same time bringing welfare improvements to the market as a whole. However, the participants need to optimize their processes to avoid being outcompeted by other traders. Furthermore, the efficient operation of the market also depends on bodies organizing and regulating it, i.e. market operators, system operators and policy-makers. Often there are multiple objectives that the actors involved in electricity market operation have to pursue.

In this Thesis, the topic of participation in the electricity market and its operation is viewed from multiple sides, i.e. decision-making support methods, algorithms and tools are proposed for both electricity market participants and policy-makers. The subject matters covered are motivated by academic interest, as well as practical necessities expressed by actors within the power industry in Latvia.

Consequently, decision-making methods, algorithms and tools related to large-scale energy storage technologies (scheduling, sizing) and cascaded hydropower plants (scheduling, hydroelectric set selection), as well as heating demand forecasting, which is a prerequisite for efficient combined heat and power plant participation in an electricity market, are developed in this Thesis. On the other hand, for the sake of policy-makers, decision-support is realized in the form of modelling, assessment and recommendations in regards to the influence of large cogeneration plants on the electricity market and, subsequently, the options to change the support these plants are subjected to. A common feature of these topics is the aim to increase the efficiency of electricity market operation, albeit from different perspectives.

ANOTĀCIJA

Elektroenerģijas tirgi ir nozīmīgs rīks moderno energosistēmu efektīvas darbības nodrošināšanā. Tie ļauj tirgus dalībniekiem maksimizēt ieguvumus no tirdzniecības, tanī pat laikā palielinot arī kopējo labumu. Tomēr tirgus dalībniekiem nepieciešams optimizēt savus procesus, lai nezaudētu konkurences cīņā ar citiem tirgotājiem. Turklāt efektīva tirgus darbība ir atkarīga arī no uzņēmumiem un iestādēm, kas organizē un regulē to, t.i., tirgus operatoriem, energosistēmas operatoriem un politikas veidotājiem. Nereti elektroenerģijas tirgus darbības nodrošināšanā iesaistītajiem ir dažādi mērķi, ko nepieciešams sasniegt.

Šajā disertācijā dalība elektroenerģijas tirgū un tā darbība ir apskatīta no vairākām pusēm, t.i., tiek piedāvātas lēmumu pieņemšanas atbalsta metodes, algoritmi un rīki gan elektroenerģijas tirgus dalībniekiem, gan politikas veidotājiem. Apskatītās tēmas motivē gan akadēmiska interese, gan praktiskās vajadzības, kuras paudušas Latvijas enerģētikas industrijā iesaistītas institūcijas.

Tādēļ darbā izstrādātas lēmumu pieņemšanas atbalsta metodes, algoritmi un rīki saistībā ar liela apjoma enerģijas akumulācijas tehnoloģijām (darbības plānošana, ietilpības izvēle), kaskādē esošām hidroelektrostacijām (darbības plānošana, hidroagregātu izvēle) un ar siltumenerģijas pieprasījuma prognozēšanu, kas ir priekšnosacījums efektīvai koģenerācijas staciju dalībai elektroenerģijas tirgū. No otras puses, politikas veidotāju lēmumu pieņemšanas atbalsts realizēts ar modelēšanu, novērtējumu un rekomendācijām saistībā ar lielo koģenerācijas staciju ietekmi uz elektroenerģijas tirgu un no tā izrietošām iespējām mainīt šīm stacijām piešķirto valsts atbalstu. Šo atšķirīgo jautājumu kopīga pazīme ir mērķis palielināt elektroenerģijas tirgus darbības efektivitāti, taču no dažādām perspektīvām.

CONTENTS

List of Figures 8

List of Tables 10

Introduction 11

1. Large-scale storage modelling 20

 1.1. Motivation for energy storage in Latvia and Lithuania 20

  1.1.1. Renewable energy integration 22

 1.2. Currently available large-scale energy storage options in the region 23

  1.2.1. Pumped storage power plants 23

  1.2.2. Reservoir and poundage hydropower plants 24

 1.3. Prospective alternative large-scale energy storage options 25

  1.3.1. Compressed air energy storage 25

  1.3.2. Hydrogen storage 25

 1.4. Large-scale storage optimization methodology 26

  1.4.1. Storage optimization in scientific literature 26

  1.4.2. Price arbitrage in the day-ahead market 27

  1.4.3. Cooperation with wind farms 29

 1.5. Results and discussion 30

  1.5.1. Case study: pumped hydro scheduling for price arbitrage 30

  1.5.2. Case study: compressed air storage sizing 32

  1.5.3. Case study: comparison of pumped vs hydrogen storage for price arbitrage 32

  1.5.4. Case study: energy storage cooperation with wind farms 34

 1.6. Chapter conclusions 36

2. Hydroelectric power plant modelling 37

 2.1. Motivation for hydroelectric power plant optimization 37

 2.2. HPP optimization model 39

  2.2.1. Main assumptions 39

  2.2.2. Overall algorithm of optimization 40

  2.2.3. Objective function 41

  2.2.4. Forecasting module 43

  2.2.5. Handling of unit and reservoir characteristics in the unit commitment model 44

2.2.6. Solving unit commitment with dynamic programming 45
2.3. Object of optimization 48
2.4. Validation of characteristic approximation 49
2.5. Validation of the dynamic programming approach 52
2.5.1. Power (and by extension – revenue) maximization 52
2.5.2. Discharge minimization 53
2.6. Optimization results 53
2.6.1. Linear optimization 53
2.6.2. Nonlinear optimization 55
2.6.3. Unit commitment and dispatch 56
2.7. Discussion regarding the model 58
2.8. Multi-objective approach 59
2.8.1. Case study: multi-objective optimization 60
2.9. Chapter conclusions 61
3. CHP plant modelling to assess impact on electricity market price 63
3.1. Motivation for CHP and electricity market modelling 63
3.2. Factors influencing the electricity market price 64
3.2.1. Characterization of the Nord Pool market 64
3.2.2. Characterization of the Latvian and Lithuanian power systems 66
3.2.3. Correlation analysis 67
3.2.4. Analysis of hourly prices in the Latvian bidding area 77
3.3. Modelling methodology 79
3.3.1. Modelling approach 79
3.3.2. CHP production model 80
3.3.3. Market clearing price modelling 84
3.3.4. CHP plant operation economic assessment 86
3.3.5. Long-term assumptions and forecasts 87
3.3.6. Analyzed scenarios 88
3.4. Results and discussion 89
3.4.1. Conservative Scenario 89
3.4.2. Development Scenario 92
3.4.3. Discussion 93

3.5. Chapter conclusions 94
4. Heating demand forecasting for CHP plant optimal scheduling 95
4.1. Motivation for research in heating demand forecasting 95
4.2. Methodology 96
4.2.1. The underlying regression model 96
4.2.2. Modifications 97
4.2.3. Setup of the simulations 98
4.2.4. Data set 98
4.3. Results 99
4.3.1. Selection of polynomial order 99
4.3.2. Effect of modifications and look-back horizon 100
4.3.3. Automatic feature selection 101
4.4. Chapter conclusions 102
Conclusions 104
References 106
Annexes 115

LIST OF FIGURES

Fig. 1.1. The Nordic and Baltic bidding areas of Nord Pool 20
Fig. 1.2. Annual percentage of hours with day-ahead price equal to LV bidding area 21
Fig. 1.3. Day-ahead price monthly averages in select bidding areas 21
Fig. 1.4. Electricity produced annually in Daugava HPPs 22
Fig. 1.5. Installed power of renewable energy sources in Latvia and Lithuania 23
Fig. 1.6. Potential underground gas storage sites (in red) in Latvia 26
Fig. 1.7. Optimized Kruonis PSHP operation considering different price scenarios 31
Fig. 1.8. Day-ahead electricity market price (Sept. 21–Oct. 4, 2015) 33
Fig. 1.9. Optimal schedule of the PSHP plant 33
Fig. 1.10. Optimal schedule of the hydrogen (electrolysis/GT) facility 33
Fig. 1.11. Planned and actual wind energy generation (Sept. 21–Oct. 4, 2015) 34
Fig. 1.12. Negative imbalance price set by the Latvian TSO (Sept. 21–Oct. 4, 2015) 34
Fig. 1.13. Storage plant operations caused by wind generation imbalances 35
Fig. 1.14. Storage plant operations in the day-ahead market to maintain charge 35
Fig. 2.1. Structure of the overall optimization tool 41
Fig. 2.2. Example of block characteristics of units 46
Fig. 2.3. Application of dynamic programming in solving the UC problem 47
Fig. 2.4. The cascade of HPPs on the river Daugava 48
Fig. 2.5. Model accuracy test on data from February 25, 2015 for Plavinas HPP 50
Fig. 2.6. Model accuracy test on data from February 25, 2015 for Kegums HPP 50
Fig. 2.7. Model accuracy test on data from February 25, 2015 for Riga HPP 50
Fig. 2.8. Model accuracy test on data from September 25, 2015 for Plavinas HPP 51
Fig. 2.9. Model accuracy test on data from September 25, 2015 for Kegums HPP 51
Fig. 2.10. Model accuracy test on data from September 25, 2015 for Riga HPP 51
Fig. 2.11. Comparison of power generation with and without UC optimization 52
Fig. 2.12. Comparison of water discharge with and without UC optimization 53
Fig. 2.13. Hourly water level in Plavinas HPP upstream reservoir in three price scenarios 54
Fig. 2.14. Hourly water level in Kegums HPP upstream reservoir in three price scenarios 54
Fig. 2.15. Hourly water level in Riga HPP upstream reservoir in three price scenarios 54
Fig. 2.16. Price forecasts and actual price on Sept. 25, 2015, LV price area in Nord Pool 56
Fig. 2.17. The bids and accepted generation schedule 57
Fig. 2.18. Dispatch schedule of the HPP with 1-hour constraint (A) 60
Fig. 2.19. Dispatch schedule of the HPP with 2-hour constraint (B) 60
Fig. 2.20. Dispatch schedule of the HPP with 3-hour constraint (C) 61
Fig. 2.21. Pareto optimal set of solutions for the case study 61
Fig. 3.1. Example of Nord Pool supply and demand curves (27.12.2016 at 10–11 AM CET) 65
Fig. 3.2. SYS and LV day-ahead hourly market price correlation 69
Fig. 3.3. LV and LT consumption and LV day-ahead hourly market price correlation 70
Fig. 3.4. LV and LT generation and LV day-ahead hourly market price correlation 71
Fig. 3.5. Market flow SE4–LT and LV day-ahead hourly market price correlation 74

Fig. 3.6. Market flow FI–EE and LV day-ahead hourly market price correlation 74
Fig. 3.7. Market flow EE–LV and LV day-ahead hourly market price correlation 74
Fig. 3.8. Market flow LV–LT and LV day-ahead hourly market price correlation 75
Fig. 3.9. Natural gas monthly price and LV day-ahead weighted monthly average market price correlation 75
Fig. 3.10. CO_2 emission allowance price and LV day-ahead weighted weekly average market price correlation 76
Fig. 3.11. Histogram of the day-ahead prices (≤ 50 €/MWh) in LV bidding area in 2016 78
Fig. 3.12. Duration curve of the day-ahead prices in LV bidding area in 2016 78
Fig. 3.13. The overall structure of the model 79
Fig. 3.14. Decision logic for power generation mode selection of CHP plants 83
Fig. 3.15. Fuel, emission allowance and electricity price projections used in the modelling .. 88
Fig. 3.16. Annual weighted average electricity price in selected hours based on the availability of NordBalt and Riga CHP plants (*Conservative Scenario*) 90
Fig. 3.17. Weighted average electricity price of the whole year with/without Riga CHP plants and electricity cost rise w/o RCHPs (*Conservative Scenario*) 91
Fig. 3.18. Profit of CHP plants with differing amounts of support (*Conservative Scenario*) .. 91
Fig. 3.19. Annual weighted average electricity price in selected hours based on the availability of NordBalt and Riga CHP plants (*Development Scenario*) 92
Fig. 3.20. Weighted average electricity price of the whole year with/without Riga CHP plants and electricity cost rise w/o RCHPs (*Development Scenario*) 92
Fig. 3.21. Profit of CHP plants with differing amounts of support (*Development Scenario*) .. 93
Fig. 4.1. MAPE per different polynomial orders and look-back horizon 99
Fig. 4.2. MAPE per model modification and training set size (Case Study 1) 100
Fig. 4.3. MAPE per filtering type and training set size (Case Study 1) 100
Fig. 4.4. MAPE per model modification and training set size (Case Study 2) 101
Fig. 4.5. MAPE per filtering type and training set size (Case Study 2) 101
Fig. 4.6. Frequency of look-back horizon used in both case studies 102

LIST OF TABLES

Table 1.1. Proportion of hours with the same day-ahead electricity price as in Latvia 21
Table 1.2. Technical parameters of Kruonis PSHP 31
Table 1.3. Profit obtained by a generic AA-CAES plant in a 168-hour timespan 32
Table 1.4. Parameters of the PSHP and H2 plants 32
Table 2.1. Technical parameters and environmental constraints of the Daugava HPPs 49
Table 2.2. Total produced energy in each HPP in the day-ahead horizon (linear model) 55
Table 2.3. Summary of the results of nonlinear optimization 56
Table 2.4. The hourly schedules of particular hydroelectric sets in the Daugava cascade 57
Table 3.1. Correlation of the day-ahead market price of various Nord Pool bidding areas..... 69
Table 3.2. Correlation of electricity production sources in Latvia with the LV day-ahead hourly market price 72
Table 3.3. Correlation of electricity production sources in Lithuania with the LV day-ahead hourly market price 72
Table 3.4. Correlation of electricity production sources in Estonia with the LV day-ahead hourly market price 72
Table 3.5. Correlation of Nordic electricity consumption and production with Nord Pool SYS price and LV area price 73
Table 3.6. Correlation of electricity market flow with the LV day-ahead hourly market price 73
Table 3.7. Rate of occurrence of various day-ahead prices in LV bidding area (2016) 77
Table 3.8. Fossil power plants modelled in the merit order 86
Table 3.9. Expenditure assumptions for the financial assessment of Riga CHP plant operation 87
Table 4.1. Results of Case Study 1 (MAPEs) 100
Table 4.2. Results of Case Study 2 (MAPEs) 101

INTRODUCTION

Topicality of the research

During the previous decades, power systems all around the world have experienced significant transformations, evolving from centrally coordinated monopolies to deregulated liberalized markets. Competitiveness-driven wholesale electricity spot markets have led to considerable research efforts towards improving the short-term efficiency of individual power generators, which is necessary for them to have an edge over the competitors [1].

However, nowadays another major transformation is taking place, whereby increasingly more renewable energy sources are introduced in the power systems. As many of them (e.g. wind, solar) are intermittent in nature, this creates new issues to be solved both from the power system operators' and the electricity market participants' point of view [2]. On the one hand, the uncertainties related to intermittent generation forecasts have a sizable effect on electricity prices [3], while, on the other hand, development of these sources opens the door for new promising research directions, e.g., in energy storage utilization, generation and demand side flexibility, advanced forecasting techniques and improved energy system modelling [4]–[6].

Nevertheless, ultimately, the purpose of an electricity market is to provide reliable electricity at the least cost to the consumers [7]. To this end, measures can be taken by at least three different groups of actors. Firstly, nowadays electricity consumers themselves have significantly more power to influence their energy costs through informed selection of electricity retailer and tariff plan, energy efficiency measures and even participation in various demand response programs. Secondly, operators of power plants and energy storage facilities can increase the overall power system and market efficiency by striving to optimize their own scheduling techniques. And, finally, even in a deregulated electricity market, power system operators and policy-makers have significant impact on the operation of the electricity market and they can influence how it affects electricity end-consumers.

The research work presented in this Thesis concerns two of the groups of actors mentioned – generation/storage operators and policy makers. For the former, methods, algorithms and tools to optimize their participation in an electricity spot market have been proposed and tested, particularly covering peculiarities related to large-scale energy storage technologies (scheduling, sizing) and cascaded hydropower plants (scheduling, hydroelectric set selection), as well as heating demand forecasting, which is a prerequisite for efficient combined heat and power plant participation in an electricity market. For the latter, i.e., policy-makers, decision-support is realized in the form of modelling, assessment and recommendations in regards to the influence of large cogeneration plants on the electricity market and, subsequently, the options to change the support these plants are subjected to. A common feature of these topics is the aim to increase the efficiency of electricity market operation, albeit from different perspectives.

Admittedly, there is also a significant number of other topical research problems relevant in light of the ongoing changes in power system and market operation which could and should be addressed. Among others, these topics include setting up and optimizing flexibility markets for innovative system services (e.g., congestion management), devising and assessing ways for active involvement of electricity consumers and prosumers in system balance provision, establishing effective and fair incentives to aid in speedier and sustainable transition towards fully renewable energy use etc. Some of these topics have been tackled by the author in other research projects the results of which have not been included in this dissertation. However, the particular objects of study selected and research tasks undertaken for this Thesis and subsequently included in it were motivated by two main factors. Firstly, the author's personal interest in the subject matters, e.g., the work on hydropower plant scheduling is a continuation of research started during the development of the Master's Thesis. Secondly, practical considerations, whereby the topics studied were motivated by research projects and contract work carried out by the Institute of Power Engineering with active involvement of the author. Consequently, the relevance of the tasks undertaken follows from the interest shown by project financing bodies and industry.

This work fits in both the international and national research landscape in terms of the topics covered and contributions offered in the overall field of power engineering. Consequently, it builds on and is influenced by the work of foreign, as well as Latvian researchers, such as B. Zakeri, J. P. S. Catalão, H. Abgottspon, C. Johansson, H. Ferreira, A. Sauhats, O. Linkevics, A. Mahnitko, K. Gerhards, R. Petrichenko, and others.

The hypothesis, objective and tasks of the Thesis

The hypothesis of the Thesis: application of well-functioning decision-making support methods, algorithms and tools by power plant operators and policy-makers can increase the benefits from efficient electricity market operation both to individual electricity wholesale market participants (e.g., storage and generator operators) and to the end-consumers at large.

The objective of the Thesis: development, testing and application of decision-making support methods, algorithms, and tools capable to bring benefits to electricity wholesale market participants and electricity end-consumers.

The tasks of the Thesis:

1) To devise and on the basis of case studies test a method and algorithm for the optimized scheduling of and decision-support for large-scale energy storage plants participating in electricity wholesale market.
2) To improve and subsequently validate an algorithm and tool for cascaded hydropower plant optimized scheduling, including hydroelectric set selection subproblem and multi-objective approach.
3) To devise and apply a method for the assessment of large combined heat and power plant impact on the electricity market price and evaluation of options to reduce state support received by such plants, in order to support policy-makers' decision-making process.
4) To devise and test a computationally inexpensive heating demand forecasting algorithm to aid the scheduling decision-making of combined heat and power plant operators.

Research methods and tools

1. For energy large-scale storage plant modelling and storage optimization, the *MATLAB* scripting environment has been used, in conjunction with its *Global Optimization Toolbox*, and, particularly, the *Pattern Search* algorithm.
2. For cascaded hydropower plant modelling, the software tool *OPTIBIDUS-HES* developed by the Institute of Power Engineering of Riga Technical University (with participation of the author of this Thesis) has been used. As the tool is implemented in the *MATLAB* environment, advantage of its add-ons, such as the *Statistics and Machine Learning Toolbox* (for *artificial neural network* implementation) and the *Optimization Toolbox* (for utilization of its *linear programming* and *Quasi-Newton* methods) was taken. A *Dynamic Programming* method has also been implemented by the author for the last stage of scheduling optimization.
3. Additionally, for combined heat and power plant as well as electricity market modelling purposes, the *Microsoft EXCEL* software has been used. It was also utilized to carry out *Pearson's correlation analysis*.
4. Finally, *multiple linear regression* method was used in devising an algorithm and tool for the forecasting of heating demand.

Scientific novelty

The scientific novelty of the research presented in this Thesis can be summarized by the following points:

1. An energy storage scheduling model suitable for a number of applications has been devised. Case studies based on data from the Latvian bidding area of the Nord Pool market showed that while the price spread there can be efficiently exploited for the profitable operation of existing large-scale storage plants, it is unlikely sufficient for the construction of new plants for price-arbitrage alone, and additional revenue streams would need to be explored (for example, from providing ancillary services to transmission system operators).
2. A multi-stage cascaded hydropower plant scheduling algorithm has been improved with an application of dynamic programming for unit selection and multi-objective considerations. The overall model and its implementing tool are well suited for further research endeavors.
3. The assessment of electricity market price peculiarities and combined heat and power plants' role in it adds to the literature on state support impact on the electricity market, by confirming that, in some instances, such support can be beneficial to electricity consumers, but, nevertheless, it can and should be reassessed.
4. A computationally inexpensive heating demand forecasting algorithm has been proposed, well suited for applications where model running time is of essence. Furthermore, several parameters of the model have been tested and their usefulness assessed.

Practical significance of the research

The work carried out during the development of this Thesis as well as its results have contributed to a number of research projects:

- National research programme project "*Energy efficient and low-carbon solutions for a secure, sustainable and climate variability reducing energy supply (LATENERGI)*" (2014–2017);
- The Latvian Council of Science project "*Management and Operation of an Intelligent Power System (I-POWER)*" (2018–2021);
- National Research Programme "*Energy*" project "*Innovative smart grid technologies and their optimization (INGRIDO)*" (2018–2021);
- National Research Programme "*Energy*" project "*Future-proof development of the Latvian power system in an integrated Europe (FutureProof)*" (2018–2021);
- European Union's Horizon 2020 research and innovation programme project "*TSO-DSO-Consumer INTERFACE aRchitecture to provide innovative grid services for an efficient power system (INTERRFACE)*" (2019–2022).

Furthermore, author's contributions to the hydropower plant scheduling model, especially in terms of the dynamic programming application, have been implemented in the software tool *OPTIBIDUS-HES*, and a version of the heating demand forecasting algorithm has been incorporated in a software tool *OPTIBIDUS-TEC*, meant to aid in the decision-making process of combined heat and power plant operators. These two tools were developed by the Institute of Power Engineering of Riga Technical University (with the author's participation) in a contract work for the electricity generation company Latvenergo AS.

Finally, the results of the electricity market price and cogeneration plant support analysis were incorporated by the Ministry of Economics of Latvia in their "*Conceptual Report on Complex Measures for the Development of the Electricity Market*", whereby the policy-makers offered options for reduction of support payments. Following the conceptual report, significant changes were made to the capacity payment system in Latvia.

Author's personal contribution

The energy storage optimization model was devised, and the subsequent case studies were carried out together with Prof. A. Sauhats, Assoc. Prof. O.Linkevics, R. Petrichenko and Z. Broka. The author contributed to all the stages of this work, but particularly in the conceptualization of the model and its development into a MATLAB-based software tool. The author also interpreted and performed analysis of the case studies' results.

Work on the hydropower plant modelling and optimization tool was carried out by a team from the Institute of Power Engineering of Riga Technical University led by prof. A. Sauhats. The author contributed to the validation of the first stages of the multi-stage approach, as well as conceptualized and implemented in the program the last stage, whereby dynamic programming is used for hydroelectric set selection. Most of the results presented in the respective chapter were obtained and assessed by the author in close collaboration with R. Petrichenko and Z. Broka.

The electricity market and cogeneration plant modelling was carried out together with Z. Broka. The author developed the calculation model in Microsoft EXCEL environment and ran the necessary experiments. He also partially participated in gathering the necessary input data and in the analysis of the simulation results.

Finally, work on the heating demand forecasting technique was carried out together with R. Petrichenko and D. Sobolevsky. The author contributed to all the phases of this research, but particularly to conceptualizing the approach, developing code in the MATLAB scripting environment for running the forecasting experiments and analyzing the results.

Approbation of the results

The research results included in this Doctoral Thesis have been presented in the following international scientific conferences:

1. 56th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), October 14, 2015, Riga, Latvia.
2. 10th International Renewable Energy Storage Conference (IRES), March 15–17, 2016, Düsseldorf, Germany.
3. 16th International Conference on Environment and Electrical Engineering (EEEIC), June 7–10, 2016, Florence, Italy.
4. Power Systems Computation Conference (PSCC), June 20–24, 2016, Genoa, Italy.
5. 15th International Conference on the European Energy Market (EEM), June 27–29, 2018, Lodz, Poland.
6. 6th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), November 8–10, 2018, Vilnius, Lithuania.

Other results related to the Thesis have been presented by the author in the following international scientific conferences:

7. 12th IEEE PES PowerTech Conference, June 18–22, 2017, Manchester, Great Britain.
8. 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), November 12–14, 2018, Riga, Latvia.
9. 13th IEEE PES PowerTech Conference, June 23–27, 2019, Milan, Italy.

The results included in this Thesis have been published in the following peer-reviewed scientific publications (indexing in Scopus/Web of Science (WoS) is indicated in parenthesis):

1. **Baltputnis, K.**, Sauhats, A., Linkevičs, O., Petričenko, R., Varfolomejeva, R., Broka, Z. Modeling of Water Utilization in Hydroelectric Power Plants on the Daugava River. In: *2015 56th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON)*, Latvia, Riga, 14 October, 2015. Riga: Riga Technical University, 2015, pp. 47–52. ISBN 978-1-5090-0334-1. e-ISBN 978-1-4673-9752-0. (*Scopus, WoS*) doi: 10.1109/RTUCON.2015.7343135

2. **Baltputnis, K.**, Sauhats, A., Linkevičs, O. Potential for Energy Storage in Latvian and Lithuanian Price Area in the Nord Pool Spot. In: *IRES 2016: 10th International Renewable Energy Storage Conference: Proceedings*, Germany, Düsseldorf, 15–17 March, 2016. Bonn: EUROSOLAR, 2016, pp. 1–10
3. Sauhats, A., Petričenko, R., **Baltputnis, K.**, Broka, Z., Varfolomejeva, R. A Multi-Objective Stochastic Approach to Hydroelectric Power Generation Scheduling. In: *2016 Power Systems Computation Conference (PSCC 2016)*, Italy, Genoa, 20–24 June, 2016. Piscataway, NJ: IEEE, 2016, pp. 56–62. ISBN 978-1-4673-8151-2. e-ISBN 978-88-941051-2-4. (*Scopus, WoS*) doi: 10.1109/PSCC.2016.7540821
4. **Baltputnis, K.**, Broka, Z., Sauhats, A., Petričenko, R. Short-Term Optimization of Storage Power Plant Operation under Market Conditions. In: *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC 2016)*, Italy, Florence, 7–10 June, 2016. Piscataway, NJ: IEEE, 2016, pp .250–255. ISBN 978-1-5090-2321-9. e-ISBN 978-1-5090-2320-2. (*Scopus, WoS*) doi: 10.1109/EEEIC.2016.7555466
5. **Baltputnis, K.**, Broka, Z., Sauhats, A. Assessing the Value of Subsidizing Large CHP Plants. In: *2018 15th International Conference on the European Energy Market (EEM 2018)*, Poland, Lodz, 27–29 June, 2018. Piscataway: IEEE, 2018, pp. 488-492. ISBN 978-1-5386-1489-1. e-ISBN 978-1-5386-1488-4. e-ISSN 2165-4093. (*Scopus, WoS*) doi: 10.1109/EEM.2018.8469816
6. **Baltputnis, K.**, Petričenko, R., Sobolevskis, D. Heating Demand Forecasting with Multiple Regression: Model Setup and Case Study. In: *2018 IEEE 6th Workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE 2018)*, Lithuania, Vilnius, 8–10 November, 2018. Piscataway, NJ: IEEE, 2018, pp. 91–95. ISBN 978-1-7281-2000-3. e-ISBN 978-1-7281-1999-1. (*Scopus, WoS*) doi: 10.1109/AIEEE.2018.8592144

Other results obtained during the development of the Thesis have been published in the following peer-reviewed scientific publications (indexing in Scopus/Web of Science (WoS) is indicated in parenthesis):

7. Sauhats, A., Petričenko, R., Broka, Z., **Baltputnis, K.**, Soboļevskis, D. ANN-Based Forecasting of Hydropower Reservoir Inflow. In: *2016 57th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON 2016)*: Proceedings, Latvia, Riga, 13–14 October, 2016. Piscataway, NJ: IEEE, 2016, pp. 267–272. ISBN 978-1-5090-3732-2. e-ISBN 978-1-5090-3731-5. (*Scopus, WoS*) doi: 10.1109/RTUCON.2016.7763129
8. Sauhats, A., Coban, H., **Baltputnis, K.**, Broka, Z., Petričenko, R., Varfolomejeva, R. Optimal Investment and Operational Planning of a Storage Power Plant. *International Journal of Hydrogen Energy*, 2016, Vol. 41, Iss. 29, pp. 12443–12453. ISSN 0360-3199. (*Scopus, WoS*) doi: 10.1016/j.ijhydene.2016.03.078
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10. Sauhats, A., Kovaļenko, S., **Baltputnis, K.**, Broka, Z., Zicmane, I. Impact of Smart Electric Thermal Storage on Transmission Grid Limitations. In: *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, Italy, Milan, 6–9 June, 2017. Piscataway, NJ: IEEE, 2017, pp. 258–262. ISBN 978-1-5386-3918-4. e-ISBN 978-1-5386-3917-7. (*Scopus, WoS*) doi: 10.1109/EEEIC.2017.7977438
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14. Broka, Z., **Baltputnis, K.**, Sauhats, A., Junghāns, G., Sadoviča, L., Lavrinovičs, V. Towards Optimal Activation of Balancing Energy to Minimize Regulation from Neighboring Control Areas. In: *2018 15th International Conference on the European Energy Market (EEM 2018)*, Poland, Lodz, 27–29 June, 2018. Piscataway: IEEE, 2018, pp. 1042–1046. ISBN 978-1-5386-1489-1. e-ISBN 978-1-5386-1488-4. e-ISSN 2165-4093. (*Scopus, WoS*) doi: 10.1109/EEM.2018.8469935
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17. Petričenko, Ļ., Petričenko, R., Sauhats, A., **Baltputnis, K.** Avoided Costs-Based Comparison of Consumer-Scale Energy Storage Control Approaches. In: *2019 16th International Conference on the European Energy Market (EEM 2019)*, Slovenia, Ljubljana, 18–20 September, 2019. Piscataway: IEEE, 2019, pp. 1–5. ISBN 978-1-7281-1258-9, e-ISBN 978-1-7281-1257-2, e-ISSN 2165-4093. (*Scopus, WoS*) doi: 10.1109/EEM.2019.8916502
18. **Baltputnis, K.**, Broka, Z., Sauhats, A. Influence of Flexibility Modeling Parameters on Residential-Scale Demand Response Assessment. In: *2019 IEEE Milan PowerTech*, Italy, Milan, 23–27 June, 2019. Piscataway: IEEE, 2019, pp. 2053–2058. ISBN 978-1-5386-4723-3. e-ISBN 978-1-5386-4722-6. (*Scopus*) doi: 10.1109/PTC.2019.8810947
19. Broka, Z., **Baltputnis, K.**, Sauhats, A. Analysis of the Potential Benefits from Participation in Explicit and Implicit Demand Response. In: *2019 54th International Universities Power Engineering Conference (UPEC 2019)*, Romania, Bukareste, 3–6 September, 2019. Piscataway: IEEE, 2019, pp. 72–76. ISBN 978-1-7281-3350-8. e-ISBN 978-1-7281-3349-2. (*Scopus*) doi: 10.1109/UPEC.2019.8893589
20. Broka, Z., **Baltputnis, K.** Handling of the Rebound Effect in Independent Aggregator Framework. In: *17th International Conference on the European Energy Market (EEM 2020)*, Sweden, Stockholm, 16–18 Sept., 2020. Piscataway: IEEE, 2020 (*accepted*)
21. **Baltputnis, K.**, Repo, S., Mutanen, A. The Role of TSO-DSO Coordination in Flexibility Asset Prequalification. In: *17th International Conference on the European Energy Market (EEM 2020)*, Sweden, Stockholm, 16–18 Sept., 2020. Piscataway: IEEE, 2020 (*accepted*)

During the development of this Thesis, a number of popular science articles have also been published:

1. Sauhats, A., Žalostība, D., Broka, Z., **Baltputnis, K.**, Linkevičs, O., Kuņickis, M., Balodis, M., Vesperis, E. RealValue - Smart Electric Heating System. *Enerģija un Pasaule*, 2016, Vol. 1, pp. 54–59. ISSN 1407-5911. (*in Latvian)*
2. Broka, Z., **Baltputnis, K.** The Role of Smart Electric Thermal Storage in Power Engineering. *REA vēstnesis*, 2016, Vol. 31. (*in Latvian*)
3. Kuņickis, M., Balodis, M., Sauhats, A., Žalostība, D., Broka, Z., **Baltputnis, K.**, Kozadajevs, J., Antonovs, D., Linkevičs, O. Demand Response Aggregation in Latvia: Ready, Steady, Go!. *Enerģija un Pasaule*, 2017, Vol. 2, pp. 33–39. ISSN 1407-5911. (*in Latvian*)
4. **Baltputnis, K.** Electrical Energy Storage Technologies in the Context of the Baltic States. *Enerģija un Pasaule*, 2017, Vol. 1, pp. 37–41. ISSN 1407-5911. (*in Latvian)*
5. Sauhats, A., Broka, Z., Zemīte, L., **Baltputnis, K.**, Petričenko, R., Junghāns, G., Linkevičs, O., Zeltiņš, N., Varfolomejeva, R., Petričenko, Ļ., Kozadajevs, J. Achievements in Science 2017. *Enerģija un Pasaule*, 2018, Vol. 2, pp. 1–6. ISSN 1407-5911. (*in Latvian*)
6. **Baltputnis, K.**, Broka, Z., Zemīte, L., Sauhats, A., Dolgicers, A., Zeltiņš, N., Kleperis, J., Dzelzītis, E., Bezrukovs, V. RTU Institute of Power Engineering together with Partners have Begun Carrying out Projects of the New National Research Programme. *Enerģija un Pasaule*, 2019, Vol. 2, pp. 60–62. ISSN 1407-5911. (*in Latvian*)

Finally, part of the results presented in this Thesis are published in the following online material:

- Sauhats, A., **Baltputnis, K.**, Broka, Z. Price of Electricity and Its Influencing Factors [online]. Riga Technical University, 2017.
  Available: https://www.em.gov.lv/files/attachments/Elektroenergijas_cenu_petijuma_nosleguma_zinojums_2017-05-31.pdf. (*in Latvian*)

Volume and structure of the Thesis

The Doctoral Thesis is written in English. It contains four main chapters, 24 second-level subchapters, 44 third-level subchapters, conclusions and a bibliography with 149 references. The Thesis also contains 62 figures and 19 tables. The volume of the Thesis is 117 pages.

Chapter 1 is dedicated to large-scale storage modelling. It lays out the case for energy storage in Latvia and Lithuania, also describing the currently available large-scale storage facilities as well as giving attention to prospective future options. The crux of the chapter describes an approach to energy storage plant modelling and assesses the application of energy storage in various conditions on case studies basis.

Chapter 2 deals with hydroelectric power plant modelling. It describes the multi-stage scheduling optimization algorithm, its validation and the addition of a dynamic programming-based unit commitment module. The chapter also contains a case study with a further advanced model, whereby multi-objective capability has been implemented.

Chapter 3 describes CHP plant modelling to assess impact on electricity market prices. It contains a thorough discussion and analysis of the factors influencing electricity market price. However, the main part of the chapter is devoted to an explanation of the methodology used and the results of scenario-based analysis.

Chapter 4 is dedicated to heating demand forecasting. It contains both the model description and the results of various forecasting tests carried out.

Finally, the overall results of the Thesis are summarized in **Conclusions**.

1. LARGE-SCALE STORAGE MODELLING

1.1. Motivation for energy storage in Latvia and Lithuania

Most of the electrical energy produced in Latvia and Lithuania is traded in the Nord Pool power market. The latter joined the exchange in 2012, whereas the former – in 2013. Nord Pool is the largest electrical energy market in Europe bringing together the producers, traders and consumers of the Nordic and Baltic countries [8].

In order to account for congestion in the transmission network, the market is separated into several bidding areas, each country being its own area. Norway, Denmark and Sweden is an exception to this, however, as due to their low population density and large geographic scope congestion can happen within the country and thereby they are each divided further into multiple bidding areas, as displayed in Fig. 1.1.

Fig. 1.1. The Nordic and Baltic bidding areas of Nord Pool.

While most of the areas in Nord Pool are well integrated and high price differences caused by insufficient transmission capacities are rather the exception than the norm [9], the situation in the Latvian and Lithuanian power systems has proven to be different. In Table 1.1, the proportion of hours annually when the day-ahead (Elspot) electricity market price in the Latvian bidding area equals that of a neighboring bidding area is shown. It can be noticed that only in the last four years the differences with the SE4 (South of Sweden) and FI (Finland) areas have decreased and the prices have become more often equal than different. Indeed, if, in 2014, only for 11.14% of hours the price in LV was equal to the price in SE4, in 2019 it is already 59.19%. In fact, the situation was even better in 2017, when for 66.28% of hours the price was the same. Similarly, in regards to Finland, the proportion of hours with the same price as in LV has risen from 23.70% in 2014 to 82.52% in 2019. The same is true for the EE (Estonia) area – from 30.39% to 94.21%. The main reason for the increase of price similarity across the areas is primarily better network integration. Especially noted should be the commissioning of the

NordBalt cable linking LT and SE4 at the end of 2015. Nevertheless, Table 1.1 and Fig. 1.2 also clearly show that Latvian and Lithuanian price areas have always been very well integrated and, within the six years compared, there has never been different price for more than 5.87% of hours annually.

Table 1.1. Proportion of hours with the same day-ahead electricity price as in Latvia

Year / Area	2014	2015	2016	2017	2018	2019
SE4	11.14%	10.88%	43.69%	66.28%	64.29%	59.19%
FI	23.70%	26.62%	62.67%	80.90%	69.00%	82.52%
EE	30.39%	33.95%	70.80%	82.04%	74.01%	94.21%
LT	99.67%	99.17%	96.51%	94.13%	97.60%	97.10%

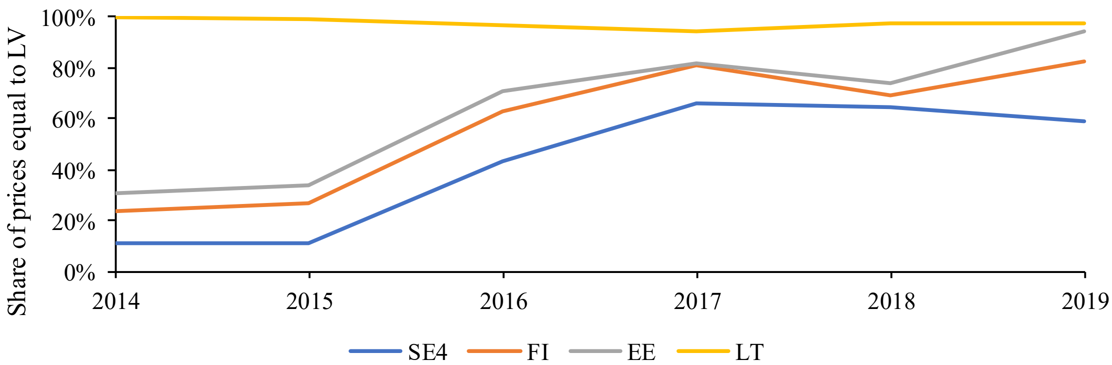


Fig. 1.2. Annual percentage of hours with day-ahead price equal to LV bidding area.

In essence, we can conclude that the Latvian and Lithuanian areas have been somewhat isolated from the rest of the Nord Pool, but the situation has notably improved with increased interconnector development. The same conclusion can be drawn from Fig. 1.3 which is also constructed from Nord Pool historical data [9][1].

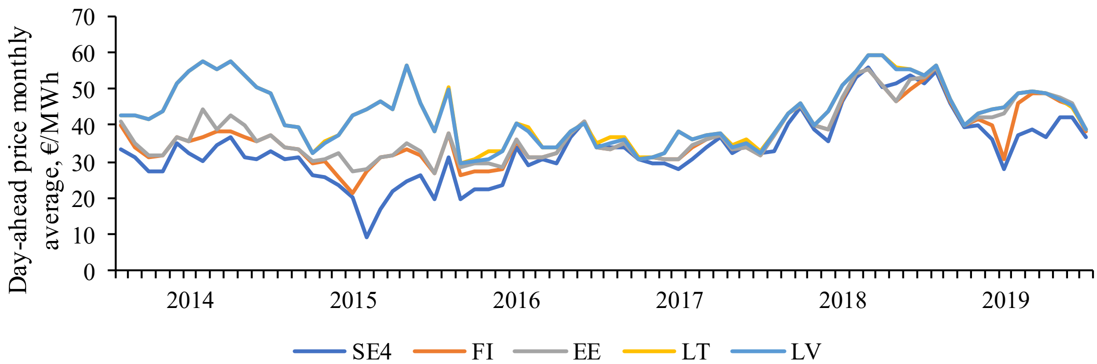


Fig. 1.3. Day-ahead price monthly averages in select bidding areas.

Additionally, it shows that the limited access to the Scandinavian markets rich in cheap hydropower resources results in the electricity price consistently being higher in Latvia and Lithuania than in the other bidding areas. Both countries are net importers of electrical energy, especially since the closure of Ignalina nuclear power plant in 2009. Latvia does occasionally

[1] Price data was extracted from the corresponding *Elspot Prices* annual files with hourly resolution.

have power to export, but only during the spring flood season or in exceptionally wet years, such as 2017, when it was possible to cover 101% of the national demand with local generation mainly thanks to the cascaded hydropower plants (HPPs) on the Daugava river [10]. Overall, there is a lot of variability in annual production in the hydroelectric plants in Latvia as can be seen in Fig. 1.4 [11][2]. This can at least partially be explained by the size of the reservoirs of the Daugava HPPs because of which they are essentially poundage HPPs, i.e., the storage capacity is insufficient for seasonal regulation and is more suitable for one or two week-ahead planning.

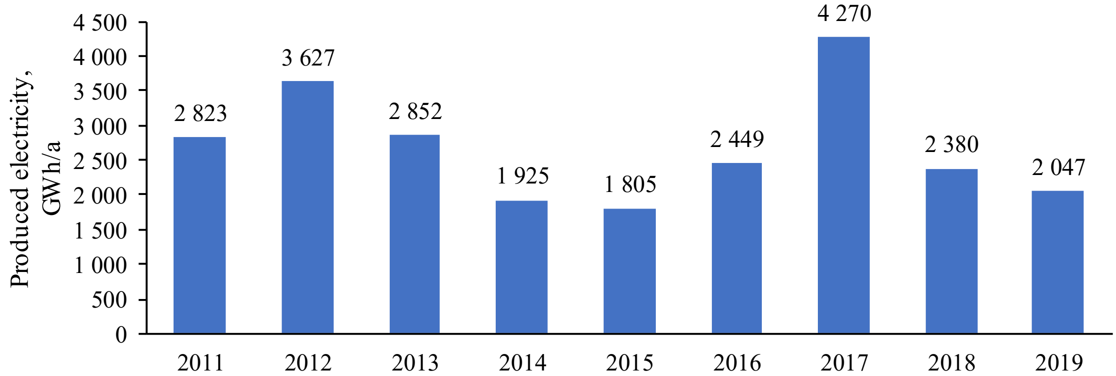


Fig. 1.4. Electricity produced annually in Daugava HPPs.

Furthermore, while the differences between day-ahead prices among various bidding areas have notably decreased over the years, this effect relies strongly on the available interconnection capacities between bidding areas. When interconnectors are out of service or operate at reduced capacity, electricity market prices reflect this in sharp price peaks at times of high demand. This is analyzed in detail in Chapter 3.2.

1.1.1. Renewable energy integration

The above mentioned reasons illustrate the potential necessity for developing electrical energy storage options in the region. While the limited interconnectivity problem might be at least partially mitigated as further inclusion of the Baltic power systems into the European grid is realized (synchronization with the grid of Continental Europe is planned by 2025 [12]), these developments are likely to only increase the value of storage options, especially since the European Union is moving towards decarbonizing its economy and significantly increasing the share of renewable sources in its energy balance. The previous target of at least 27% share of renewable energy in final energy consumption by 2030 was revised to an even more ambitious 32% target in the revised Renewable Energy directive in 2018 [13].

This, however, introduces new issues for power system operators and market participants as a significant portion of the renewable energy sources are intermittent in nature, e.g. wind, solar and to some extent also run-of-the-river hydropower. Even though the current penetration of wind and solar energy in Latvia is small, it has rapidly grown in Lithuania (2.49% of total electricity production in 2019 in the former [10] and 42.23% in the latter [14]). There is a trend

[2] Fig. 1.4 is constructed using data from the Unaudited Condensed Financial Statements of AS Latvenergo available in reference [11].

for the deployment of intermittent renewable energy technologies to increase in the region. Fig. 1.5 [15], [16] shows how the installed capacity of wind and solar has grown fivefold from 127 MW to 695 MW within the last ten years in Latvia and Lithuania.

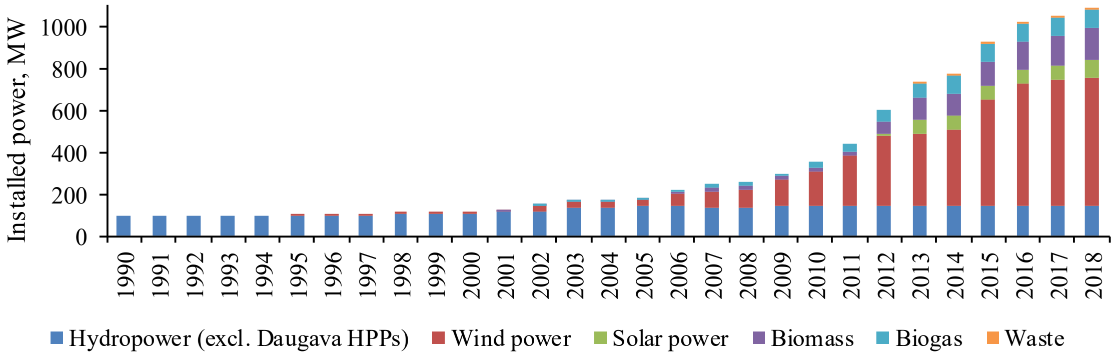


Fig. 1.5. Installed power of renewable energy sources in Latvia and Lithuania[3].

Nevertheless, there is still a lot of untapped potential. For instance, Wind Europe projects in their Central Scenario the installed wind power capacity to reach 0.5 GW in Latvia and 1.1 GW in Lithuania by 2030 [17]. Furthermore, the theoretically possible wind power capacities are even more significantly higher. In a recent, comprehensive study, where Enevoldsen *et al*. [18] examined the wind power potential in Europe based on available landmass, they estimated the maximum potential installed onshore capacity to be 288 GW and 196 GW in Latvia and Lithuania respectively.

Energy storage technologies have a significant role to play to accommodate and better integrate such rapidly developing intermittent energy sources like wind and solar in the power system.

1.2. Currently available large-scale energy storage options in the region

1.2.1. Pumped storage power plants

Pumped storage hydroelectric power (PSHP) plants are the oldest and most widely used electrical energy storage technology. More than 99% of the storage capacity in the world can be attributed to PSHP plants [19]. Their high popularity can be explained by the maturity and relative simplicity of the technology – in accumulation mode water is pumped from the lower to the upper reservoir, whereas in generation mode it is released and discharged through turbines. The most important requirement for pumped storage is the availability of locations where sufficiently high elevation between the upper and lower reservoirs can be achieved, which is needed for effective water head. PSHP plants can be built as standalone facilities (pure pumping) or some pumping capacity can be installed in conventional reservoir hydroelectric plants.

[3] The data is presented by type of source and the numbers are combined for Latvia and Lithuania. Daugava HPPs are excluded from the chart as their sum capacity (1536 MW) far exceed the other sources combined. The data for Latvia is extracted from statistical table *ENG090. Electrical capacity and produced electricity from renewables*, but for Lithuania – from *Electrical capacity*.

Currently the only pure pumping plant in the Baltics is located in Lithuania – the Kruonis PSHP. It has four reversible pump/turbine units and their total installed capacity constitutes 900 MW in both pumping and generation mode [20]. Commissioning of a fifth unit is under consideration [21]. When the upper reservoir has been filled, the Kruonis PSHP can discharge at rated power for about 12 hours.

From countries participating in the Nord Pool, only Norway, Sweden and Lithuania have pumped storage capability [22]. Besides, in Norway, pumps are installed as addition to their large conventional reservoir hydroelectric power plants (HPPs) and the pumping/discharging cycle is seasonal in nature. However, the Kruonis PSHP in Lithuania is pure pumping type and schedules its operation on daily and weekly cycles.

1.2.2. Reservoir and poundage hydropower plants

In Latvia, on the other hand, there is significant conventional poundage hydroelectric power capacity. The scheme of three hydroelectric power plants on the Daugava River (total capacity above 1500 MW) comprises approximately 30 to 50% of the total annual electrical energy production in the country, but the exact amount differs each year depending on its wetness (as explained in Fig. 1.4). It should be noted that one of the cascaded plants (Plavinas HPP) is one of the largest in the European Union by installed capacity [23].

While not a storage option in the most traditional sense, reservoir and poundage HPPs without pumping capacity can still provide similar services to conventional storage plants by increasing or decreasing their production, as when generation is halted, water is accumulated in the reservoirs. Granted, there are several constraints that limit the flexibility of poundage HPPs compared to reservoir HPPs, namely, the risk of overflowing when inflow is large and, conversely, limited production capabilities when inflow is low. This is due to the fact that the reservoir size for poundage HPPs only allows regulation and planning with a scope of one to several weeks, while large reservoir HPPs have storage capabilities enabling even seasonal planning. There have been a number of studies on construction of pumping station in Plavinas HPP or building new PSHP on Daugava river [24].

There are no other large or medium scale electrical energy storage facilities in either Latvia or Lithuania. However, there are some notable options of storing energy in different mediums, particularly, underground gas storage (UGS). Currently there is one active UGS site in Latvia – Inčukalns UGS which stores natural gas imported from Russia. Thanks to unique geological formations – porous sandstone layers – there exist several other sites in Latvia where underground storage might prove to be technologically feasible. This is potentially interesting not only in terms of natural gas storage, but also in developing power to gas conversion to prevent intermittent renewable generation curtailment or investing in compressed air energy storage (CAES).

1.3. Prospective alternative large-scale energy storage options

1.3.1. Compressed air energy storage

The operation of a CAES plant has certain similarities to a conventional gas turbine based power plant, the difference being that CAES decouples the compression and expansion cycles of a gas turbine into separate processes that occur at different time [25]. Cheap electricity is used to compress ambient air. It is then cooled via intercoolers and stored in underground caverns. In the generation phase the compressed air is preheated and mixed with natural gas, burned in combustion chamber and expanded through a multistage turbine-generator. This setup allows a CAES plant to generate three times more electricity than a simple cycle natural gas power plant using the same amount of fuel. Until recently, there were only two large-scale CAES plants in the world – Huntorf, Germany (290 MW) and McIntosh, USA (110 MW) [26], however, since then several other projects have received funding or government approval.

The necessity to burn fuel in the generation phase is the most obvious deficiency in the conventional CAES technology, as this fuel is most often natural gas. There are, however, plans to solve this issue by introducing advanced adiabatic compressed air energy storage (AA-CAES) which strives to eliminate the need for a combustor. This is achieved by storing the heat from the compression and using it during the expansion process. The main technical challenges in AA-CAES development are designing cost-effective thermal energy storage and high-pressure compressors capable of handling increased compression temperatures [26]. Nevertheless, if the need for fossil fuel combustion is eliminated AA-CAES can be viewed as a near closed-loop storage and thus the modeling of its operation becomes similar to other storage technologies, especially, pumped storage.

1.3.2. Hydrogen storage

The idea of using hydrogen gas as a storage medium has gained a lot of attention lately in context of accommodating renewable energy. Hydrogen can be produced in the electrolysis process using either cheap off-peak electricity or excess power produced by intermittent sources.

Hydrogen can afterwards be stored in various forms, e.g., as a gas, liquid or within metal hydrides. It can be injected into the natural gas grid or contained in tanks for small- and medium-scale and underground for large-scale storage. The latter is especially interesting for the Latvian case as there exist several unique geological locations (Fig. 1.6 [27]) where gas storage might be possible in porous sandstone layers. One of these sites, Incukalns UGS, is currently being used for natural gas storage while other sites have been or are being investigated for the same purpose.

Stored hydrogen can later be used in industry, transport or converted back to electricity employing either fuel cells or gas turbines. In this study, we consider a hypothetical power-to-gas-to-power plant which uses electrolysis for hydrogen production and gas turbines for re-electrification.

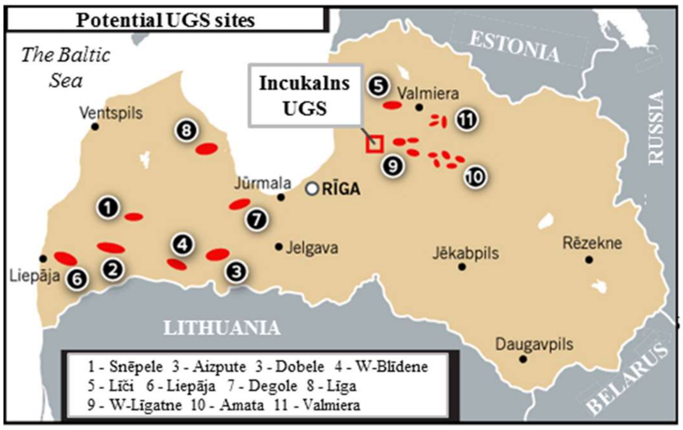


Fig. 1.6. Potential underground gas storage sites (in red) in Latvia.

1.4. Large-scale storage optimization methodology

1.4.1. Storage optimization in scientific literature

One of the most important input parameters when estimating the feasibility of a storage plant is its ability to provide positive cash flow when operating in electricity market. In this study we assume that the owners of storage plants strive to increase their profit and thereby try to optimize their operation. There are several approaches in scientific literature to solving the task of storage plant scheduling optimization.

For instance, the authors of [28] deal with the problem of devising optimal bidding strategy for a multi-unit pumped storage plant. They propose a solution employing evolutionary tristate particle swarm optimization. The same authors have also proposed a multi-looping sequential optimization approach using mixed integer programming [29].

The participation of battery energy storage in day-ahead electricity market is studied in [30]. The task is divided in two subtasks where the first finds optimum bidding/offering schedule using stochastic mixed integer linear programming while the second simulates market clearing procedures.

Another model similarly employing stochastic mixed integer linear programming is proposed in [31]. The electricity market price is forecasted using ARMA and ARIMA time series models.

Ref. [32] introduces biogas plants as energy storage options that are capable to provide demand-based renewable energy. The authors found that by utilizing a market-based optimization model a biogas power plant is capable of achieving more profit when operating on direct marketing (optimization based on price signals) as opposed to relaying on feed-in tariffs (optimization to maintain high efficiency).

In this study, we consider two storage power plant operational strategies – firstly, a stand-alone storage plant benefiting solely from price differences in the day-ahead market (arbitrage) and, secondly, cooperation between intermittent energy producers (particularly, wind farms) and storage in order to balance discrepancies between the planned and actual generation from renewable energy.

1.4.2. Price arbitrage in the day-ahead market

The feasibility of exploiting price differences to gain profit in day-ahead markets largely depends on price dynamics in the particular market. For instance, researchers in [33] found that although a hypothetical PSHP could generate positive operational profits in all regions of Italy (MGP market), the net present value (NPV) of the future cash flows at the end of the project's lifetime was nevertheless negative in all cases. The authors explained it by the fact that even though peak prices in the MGP market are high compared to other European markets, the off-peak prices are comparatively high as well, resulting in an insufficient price spread.

The day-ahead market in the Netherlands (APX) is analyzed in [34]. The authors there have devised a strategy of using two different time horizons in storage self-scheduling – 24 hours for weekdays and 72 hours for weekends to account for the possibility of severely decreased prices during weekends. In the study the results of which are presented in the subsequent subchapters, the potential effect of weekends is also covered by extending the scheduling horizon to two weeks (336 hours) and using the results from the first 24 hours to submit bids to the market.

In [6], storage operation in price arbitrage mode is found to be profitable. The authors have also found a noteworthy peculiarity – the profits increase in correspondence to increased storage size (discharge duration), however, this effect stabilizes and eventually stops for discharge durations of about 24–26 hours. This conclusion holds true for all storage technologies (described by round-trip efficiencies) the authors considered.

The authors of [35] have assessed two different potential value streams for storage plants in Finland – price arbitrage in the Nord Pool Elspot market and participation in the balancing market. The authors identified that the electricity price was more volatile in the Finnish bidding area than in other Nordic countries sans Denmark. Nevertheless, [35] found the balancing market to be 3–6 times more profitable than the day-ahead market, depending on the storage technology.

In most of the studies, self-scheduling is implemented by means of linear programming (e.g., CPLEX linear solver [33]). In [29], [30] bilevel mixed integer linear programming models are devised. One drawback of the mixed integer approach is that charging and discharging at each hour has to be done either at full power or not at all, which does not allow for variability and thus limits the flexibility of operation.

Some other notable optimization methods used for storage power plant scheduling are dynamic programming [36] and evolutionary tristate particle swarm optimization [28].

A factor commonly found important is the effect stochastic parameters have on the optimal operation of storage plants, e.g., electricity market price when planning the day-ahead operation of a plant that aims to benefit from price arbitrage. In [31], AR, MA and ARIMA models are used for price forecasting and scenario generation. In [34], artificial neural networks (ANN) are used for this purpose.

In the large-scale energy storage optimization study presented here, the optimization problem of a closed-loop storage plant operating on price arbitrage is described by a nonlinear objective function (1.1)–(1.2) and constraints (1.3)–(1.6). The studied power producer is assumed to be a price-taker and the price is exogenous to the optimization model, meaning that, in general, it can be provided by either of the previously mentioned forecasting tools or even from the actual price statistics, depending on the purpose of optimization.

The objective function is formulated as profit maximization as follows:

$$f\left(\Delta L, c\right) = \frac{1}{M}\sum_{m=1}^{M}\sum_{t=1}^{T}\left(P_t \cdot c_{m,t} - \left|P_t\right| \cdot om_{\text{var.}}\right) \to \max, \tag{1.1}$$

where ΔL – change in the amount of stored energy (MWh);

P_t – power at hour t (MW);

$c_{m,t}$ – electricity market price at hour t for forecast realization m (€/MWh);

M – number of forecast realizations;

T – length of the optimization horizon in hours;

$om_{\text{var.}}$ – variable operation and maintenance (O&M) costs;

for

$$\begin{cases} P_t = -f\left(\Delta L_t\right)/\eta_{\text{acc}}, & \text{if} \quad \Delta L_t > 0 \\ P_t = -f\left(\Delta L_t\right)\cdot\eta_{\text{gen}}, & \text{if} \quad \Delta L_t \le 0 \end{cases} \quad \forall t \in T, \tag{1.2}$$

where $f\left(\Delta L_t\right)$ – a function that links the power generation and changes in the volume of storage medium (it depends on the technology being studied and can introduce nonlinearity);

η_{acc} – accumulation efficiency;

η_{gen} – generation efficiency;

subject to

$$\sum_{t=1}^{T}\Delta L_t = L_T - L_0 \tag{1.3}$$

$$-\sum_{t=1}^{S}\Delta L_t \le L_0 - \underline{L} \tag{1.4}$$

$$\sum_{t=1}^{S}\Delta L_t \le \overline{L} - L_0 \tag{1.5}$$

$$P_t \in \left[\underline{P}_{\text{charg.}}, \overline{P}_{\text{charg.}}\right] \cup \left[\underline{P}_{\text{disch.}}, \overline{P}_{\text{disch.}}\right] \quad \forall t \in T \tag{1.6}$$

where L_0, L_T – initial and final storage level;

$\underline{L}$, $\overline{L}$ – bounds on storage capacity;

$S \in T$ – variable to enforce storage capacity bounds;

$\underline{P}_{\text{disch.}}$, $\overline{P}_{\text{disch.}}$ – lower and upper limit on power in discharging mode;

$\underline{P}_{\text{charg.}}$, $\overline{P}_{\text{charg.}}$ – lower and upper limit on power in charging mode (negative);

The equality constraint defined in Eq. (1.3) ensures that the model reaches a certain previously set level of its storage medium at the end of the optimization horizon. On the other hand, constraints (1.4) and (1.5) ensure that at no point in the horizon the bounds on the storage level are violated.

The model is implemented in MATLAB scripting environment which provides useful tools for solving various types of optimization problems. As Eq. (1.2) introduces non-smoothness in the objective function, gradient methods would not guarantee a correct solution. So instead the pattern search algorithm [37] from Global Optimization Toolbox, which is able to handle non-smooth and discontinuous functions, is used.

1.4.3. Cooperation with wind farms

Some previous notable studies in the field of co-optimized wind and storage scheduling are found in [38]–[40]. Ref. [38] offers methodology to determine the optimal storage capacity to be added to wind farms. They conclude that the storage system rated power should be at least 20% of the wind farm power and the optimal charge/discharge duration for a 100 MW farm constitutes 4 hours.

In [39], particular focus is given to various hydrogen storage technologies that could be integrated with wind power in micro-grid applications. Methodologies to optimize the sizing, design and operation of storage to accommodate intermittent wind power are devised in both [39] and [40].

In the work presented here, the potential benefits of a storage plant operation based on balancing the discrepancies of the power sold in the day-ahead market and the actual wind power generation are assessed here.

In Latvia, support for renewable generation sources is implemented through mandatory procurement, which means that all the wind power produced in plants that receive support is procured by a specially-created company (public trader), which in turn sells this energy in the day-ahead market. In practice, it means that any deviations from the energy offered in the day-ahead market are handled not by the owners or operators of the wind farms but by the public trader instead.

Let us assume that the hourly income the public trader receives from selling the wind power can be expressed as follows:

$$R_t = \begin{cases} wp_{\text{real}.t} \cdot c_t, & \text{if} \quad \Delta wp_t = 0 \\ wp_{\text{pred}.t} \cdot c_t - \Delta wp_t \cdot cb_t^+, & \text{if} \quad \Delta wp_t > 0 \\ wp_{\text{pred}.t} \cdot c_t - \Delta wp_t \cdot cb_t^-, & \text{if} \quad \Delta wp_t < 0 \end{cases} \quad \forall t \in [1, 24], \tag{1.7}$$

$$\Delta wp_t = wp_{\text{pred}.t} - wp_{\text{real}.t} \quad \forall t \in [1, 24], \tag{1.8}$$

where $wp_{\text{real}.t}$ – actual produced wind power (MWh);

$wp_{\text{pred}.t}$ – forecasted wind power (MWh) that was offered in the day-ahead market;

Δwp_t – difference between the forecasted and actual wind power (MWh);

cb_t^+ – negative imbalance price (€/MWh);

cb_t^- – positive imbalance price (€/MWh).

Essentially, this means that in the case when the actual generation is lower than the planned generation, the trader receives less revenue than planned and additionally has to purchase the balancing power from the TSO (i.e., perform imbalance settlement). In the reverse scenario, the trader sells its overproduction to the TSO at a price which is usually lower than the day-ahead market price.

If, however, the trader also has energy storage options, these negative effects can be alleviated:

$$P_t = \Delta wp_t \pm \Delta p_t \quad \forall t \in [1, 24], \tag{1.9}$$

subject to constraints (1.3)–(1.6), where Δp_t are the final deviations from the day-ahead generation plan that emerge if the storage constraints would otherwise be violated.

In this operational strategy, the storage plant does not aim to exploit the day-ahead price arbitrage; it does, however, have to periodically purchase or sell energy in the market when the wind power forecasting errors have been largely one-sided in order to restore the state of storage to approximately 50%. This ought to be done each day (*d*) by registering the offset in storage level by the end of the previous day (*d* – 1) and bidding this amount in the next day (*d* + 1) market.

1.5. Results and discussion

The results described in this subchapter where originally presented in the 10th International Renewable Energy Storage Conference (IRES 2016) and the 16th IEEE International Conference on Environment and Electrical Engineering, both in 2016. The corresponding publications can be found in [41] and [42].

1.5.1. Case study: pumped hydro scheduling for price arbitrage

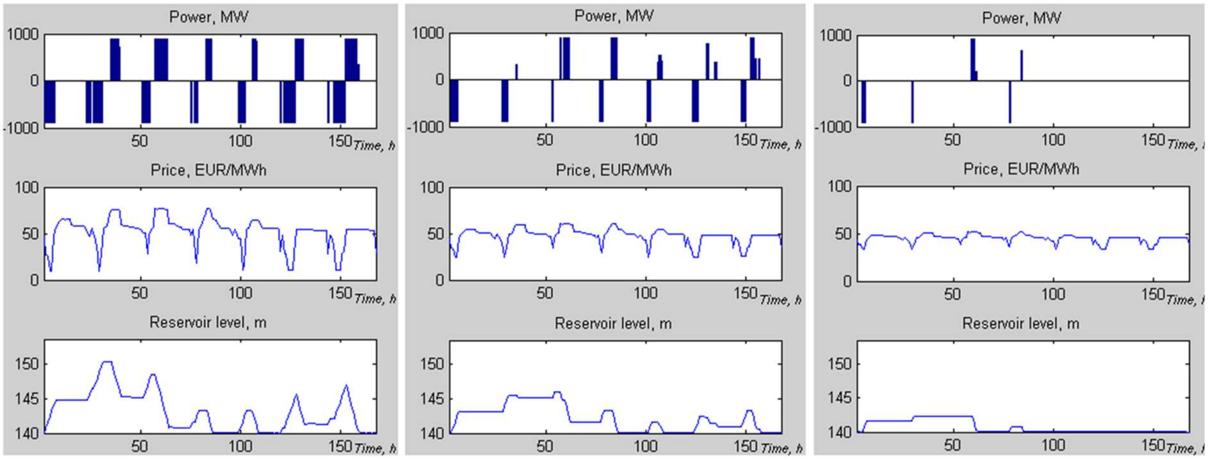
The model described in Section 1.4 is applied to Kruonis PSHP in Lithuania (Table 1.2). Several assumptions have been made: the storage plant aims to operate on price arbitrage, price is exogenous and the duration of charging/discharging cycles is only constrained by upper reservoir capacity. Operating costs are assumed to be 1 €/MWh.

Table 1.2. Technical parameters of Kruonis PSHP

	Pump mode	**Turbine mode**
Capacity	900 MW	900 MW
Efficiency	0.8	0.9
Discharge (one unit)	226 m^3/s	189 m^3/s
Life storage	41 million m^3	
Maximum water level	153.5 m	
Minimum water level	140 m	

The price profile for one week (Nord Pool statistics in the Latvian/Lithuanian price areas from August 10 to 16, 2015 [9][4]) is used to carry out the optimization of Kruonis PSHP scheduling. During this week, the ratio between minimum and maximum price was 0.117. It proved to be sufficient for feasible operation resulting in 696 119 € profit (Fig. 1.7).

In order to assess the effect price spread can have on PSHP scheduling, the optimization procedure was repeated using price curves that have been smoothened to achieve 0.4 and 0.65 ratio between minimum and maximum prices. Decreasing the price spread significantly reduced the number of hours of PSHP operation. For instance, in the last case the plant would only work for 7 hours in the 168-hour period (one week). Furthermore, as can be assessed from the data in Fig. 1.7, the reduced price spread notably diminishes the operational profit obtainable.



Min. price	**Max. price**	**Price ratio**
9.06 €/MWh	77.14 €/MWh	**0.117**
Consumption	**Production**	
34.2 GWh	25.3 GWh	
Expenditure	**Revenue**	**Profit**
988 281 €	1 684 400 €	**696 119 €**

Min. price	**Max. price**	**Price ratio**
24.39 €/MWh	60.96 €/MWh	**0.4**
Consumption	**Production**	
16.2 GWh	11.69 GWh	
Expenditure	**Revenue**	**Profit**
461 710 €	654 900 €	**193 190 €**

Min. price	**Max. price**	**Price ratio**
33.43 €/MWh	51.41 €/MWh	**0.65**
Consumption	**Production**	
3.6 GWh	2.66 GWh	
Expenditure	**Revenue**	**Profit**
122 620 €	136 610 €	**13 990 €**

Fig. 1.7. Optimized Kruonis PSHP operation considering different price scenarios.

The results from performing Kruonis PSHP scheduling optimization show that price profiles in the Latvian and Lithuanian price areas in the Nord Pool can have sufficient spread to motivate active storage plant operation. The model developed during this study should be expanded to include additional value streams a storage plant can access, for instance, providing reserves and various grid services.

[4] Data extracted from file *elspot-prices_2015_hourly_eur.xls*.

1.5.2. Case study: compressed air storage sizing

As described in Section 1.3, there are geographical sites in Latvia where compressed air storage might be technologically feasible. In order to estimate the potential economic performance of an AA-CAES plant, the same model is applied, but with varied input parameters like efficiency and storage capacity. Nominal power of 200 MW is assumed. The results are summarized in Table 1.3.

Table 1.3. Profit obtained by a generic AA-CAES plant in a 168-hour timespan

		Discharge duration		
		4 h	8 h	12 h
Full cycle efficiency	0.65	106 550 €	111 790 €	111 790 €
	0.70	123 080 €	134 170 €	134 730 €
	0.75	141 270 €	157 090 €	159 870 €

If the efficiency is lower (0.65), increasing the storage capacity has little effect on the schedule and by extension – on the profit. Doubling the storage capacity from 4 to 8 hours only increased profit by 4.92%. Further increases in the storage size had no impact as already in the 8 hour discharge duration scenario the storage site did not reach full capacity within the week.

In case the full cycle efficiency is higher, the benefit from increasing storage size also becomes more evident. If we increase the capacity from 4 to 8 hours then profit increases by 9.01% for a 0.70 round trip efficiency plant and by 11.20% for a 0.75 efficiency plant. Again, however, further increases had little effect, i.e. 0.42% and 1.77%.

1.5.3. Case study: comparison of pumped vs hydrogen storage for price arbitrage

The model presented in Eq. (1.1)–(1.6) is used once more. This time, to optimize the operation of storage plants of two different technologies (Table 1.4) – pumped storage again modeled using the characteristics of Kruonis PSHP plant and a hypothetical power-to-gas-to-power scheme that uses underground hydrogen storage as means of energy accumulation and realizes re-electrification with gas turbines (GT). The parameters of the second plant are assumptions based on general characteristics of polymer electrolyte membrane (PEM) electrolysis and GT equipment.

Table 1.4. Parameters of the PSHP and H2 plants

Technology / Parameters	PSHP (large-scale storage)	Hydrogen (medium-scale storage)
Nominal input and output power (MW)	900	25
Accumulation/ generation efficiency	0.8 (pump)/ 0.9 (turbine)	0.7 (PEM electrolysis)/ 0.6 (GT)
Storage capacity	10800 MWh	600 MWh
Variable O&M costs	0.22 €/MWh [43]	1.7 €/MWh

The day-ahead electricity market price for the case study (Fig. 1.8) is taken from the Nord Pool statistics for the Latvian bidding area, particularly, two weeks from September 21 to October 4, 2015 [9]. The results of the simulations are illustrated in Fig. 1.9 and Fig. 1.10.

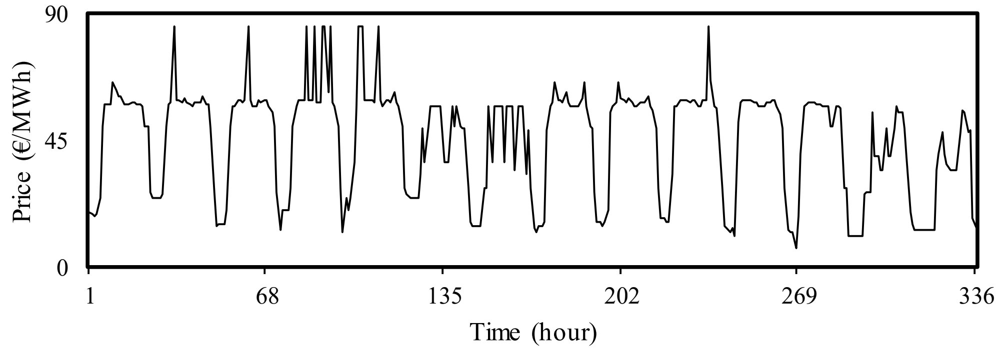


Fig. 1.8. Day-ahead electricity market price (Sept. 21–Oct. 4, 2015)[5].

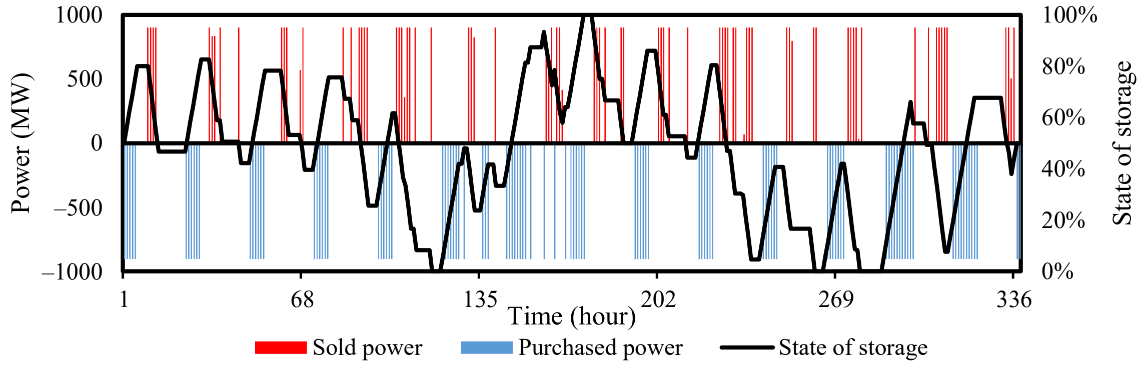


Fig. 1.9. Optimal schedule of the PSHP plant.

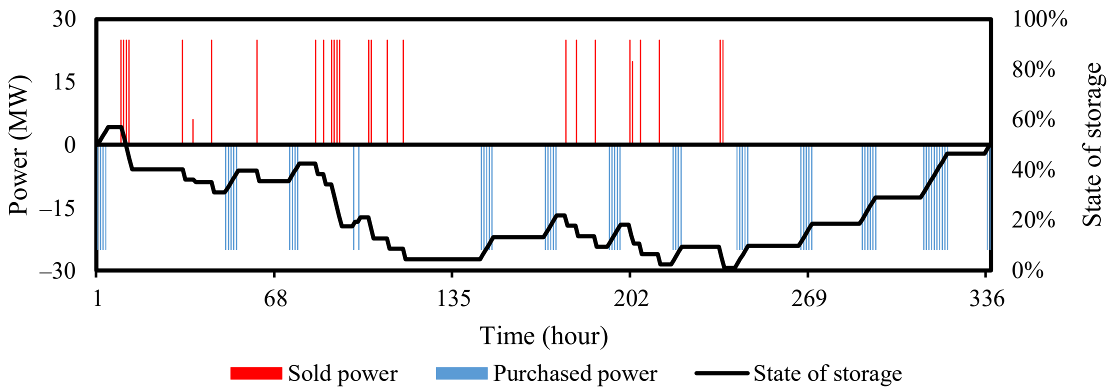


Fig. 1.10. Optimal schedule of the hydrogen (electrolysis/GT) facility.

During the selected time horizon both stations manage to operate profitably. For the large-scale PSHP, the income from the sold electricity exceeds expenditure for the purchased power and variable O&M costs by 2.281 million €, whereas for the medium-scale hydrogen scheme this difference constitutes 20 869 €. The revenue is understandably smaller due to the smaller size of the proposed GT facility.

[5] Data extracted from file *elspot-prices_2015_hourly_eur.xls*.

From Fig. 1.10 it can be concluded that the selected storage capacity of the hydrogen scheme is larger than necessary, as during the optimization horizon the volume of the stored energy never exceeds even 60% of the total capacity. Thus, the proposed model is indeed useful in assessing the feasibility of various storage sizes for a storage plant. Such application of the model was tested in the previous case study on compressed air energy storage sizing.

1.5.4. Case study: energy storage cooperation with wind farms

In order to assess the coordinated wind farm and storage operation scheme described in Section 1.4, we use statistics (Fig. 1.11 [9][6], Fig. 1.12 [44][7]) from the same time period as in the previous example.

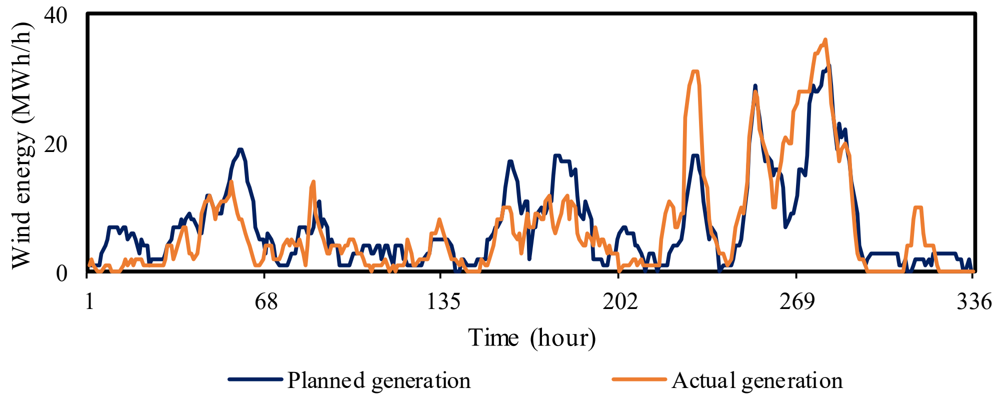


Fig. 1.11. Planned and actual wind energy generation (Sept. 21–Oct. 4, 2015).

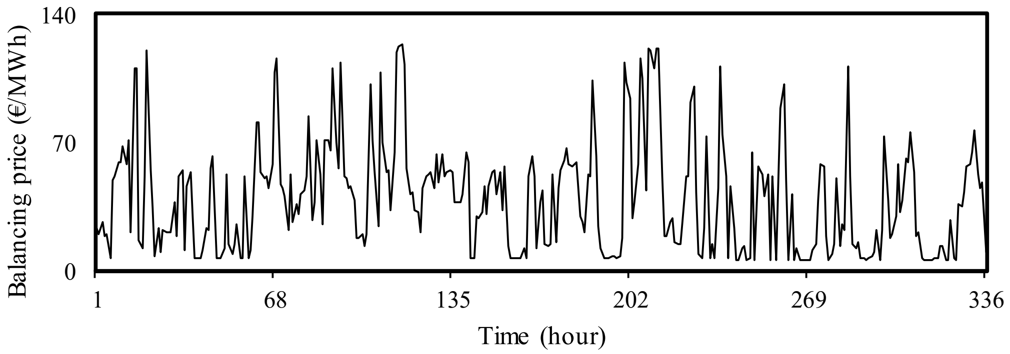


Fig. 1.12. Negative imbalance[8] price set by the Latvian TSO (Sept. 21–Oct. 4, 2015).

If the forecasted wind energy production (blue line in Fig. 1.11) were accurate, the trader would receive 123 825 € revenue from the day-ahead market during the two-week period under study. However, due to inaccurate forecasts, the trader receives 89 183 € and has to pay 29 419 € for up-regulation, but it also earns 10 840 € for overproduced power netting 70 604 € in total revenue.

[6] Data extracted from files *wind-power-lv_2015_hourly.xls* and *wind-power-lv-prognosis_2015_hourly.xls*.

[7] Data extracted from files *Balans_Cenas_2015_09_LAT.xlsx* and *Balans_Cenas_2015_10_LAT.xlsx*

[8] The positive imbalance (when the TSO buys the excess energy from a BRP) price is not displayed in this figure, but, in this time period, it consistently was at about 94.1–94.2% of the negative imbalance (when a BRP buys lacking energy from the TSO) price [44].

Now, let us consider a hydrogen storage plant as described in Table 1.4 operating in coordination with the wind farm. Fig. 1.13 illustrates the amount of energy the storage plant stores from excess wind generation and supplies to the market to balance insufficient wind generation, whereas Fig. 1.14 shows the additional activities in the day-ahead market to maintain the state of charge at about 50%.

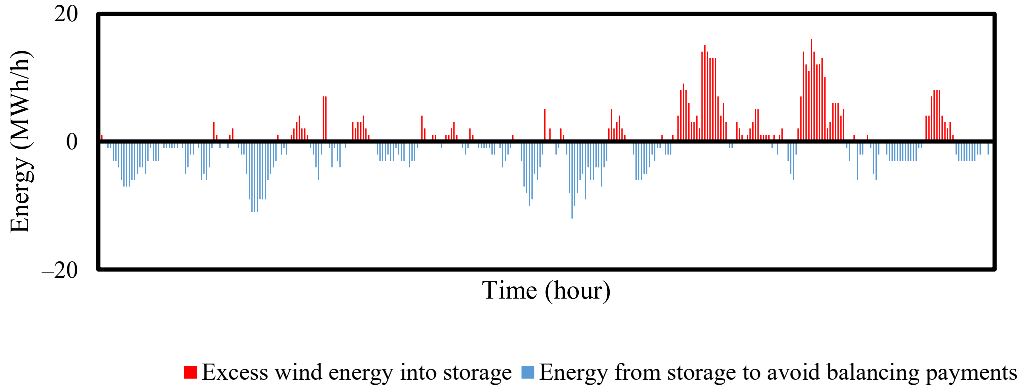


Fig. 1.13. Storage plant operations caused by wind generation imbalances.

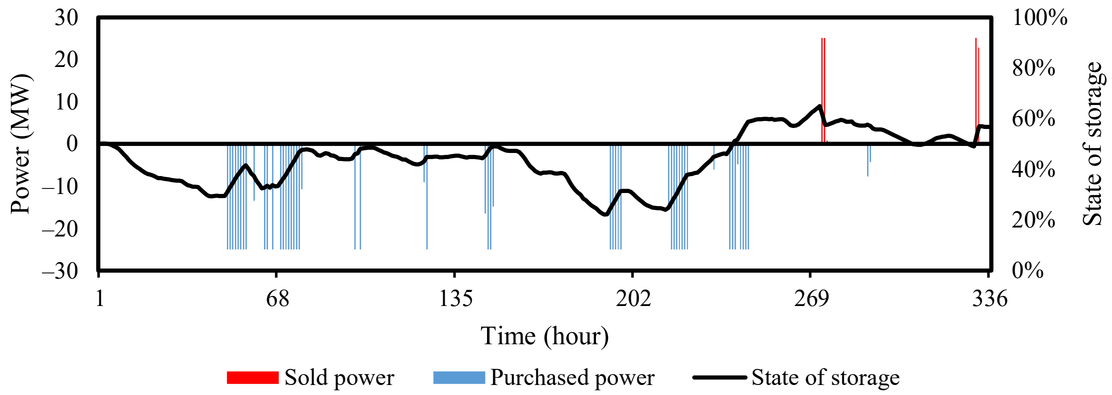


Fig. 1.14. Storage plant operations in the day-ahead market to maintain charge.

As a result of coordination, the wind and storage operation receives 122 630 € from bidding the forecasted wind generation in the day-ahead market; however, 27 750 € are spent to maintain adequate energy levels in the storage, additional 216 € are necessary to provide some minor imbalance settlement at times when the storage was insufficient and 2 262 € are received for selling unaccommodated wind energy production with the imbalance settlement mechanism, finally, 4 197 € are costs associated with storage O&M. In total, the net revenue constitutes 92 729 €. Compared to the wind farm operation without storage, this results in an income increase of 22 125 €.

As established in the previous subsection, the opportunity cost of the hydrogen storage plant operating independently based on the day-ahead price arbitrage was 20 869 €, meaning that cooperation with wind farms might be capable of providing a slightly better value. However, further studies should be conducted incorporating larger time frames to establish the potential benefits of such synergy throughout the lifetime of the power plants. Another area of future research is incorporating other generation sources in the coordinated dispatch.

1.6. Chapter conclusions

While electrical energy storage options already established in the Latvian and Lithuanian region, particularly, Kruonis PSHP, can effectively exploit the price spread observable in the corresponding Nord Pool price area, the construction of new large-scale projects is hindered by high capital costs, specific location requirements and historically limited share of intermittent renewable generation sources. The deployment of wind generation, however, is projected to increase steadily, amplifying volatility in the electricity markets. This factor in combination with better access to Nordic power systems signifies renewed interest in the development of electrical energy storage in the region.

Advanced adiabatic compressed air energy storage is particularly interesting in the Latvian case, as among all the unconventional storage technologies AA-CAES has the best efficiency and its technological and economic parameters are similar to PSHP plants. The presence of several locations in Latvia suited for underground gas storage opens the possibility of utilizing these sites for CAES, but further research in this direction is necessary to quantify the storage potential this technology might bring to the Latvian and Lithuanian power systems.

The simulations carried out using the proposed optimization model did confirm that the day-ahead price profile in Latvia is sufficient for price arbitrage to provide a positive operational cash flow (i.e., excluding capital expenditure). This holds true for all the considered technologies, including hydrogen storage. The results this model provides could potentially be used as input data when evaluating the feasibility of a current storage project's future operations or when assessing capital expenditure ceiling to achieve break-even for a prospective new storage project. An evolved version of this approach has been applied by the author in the optimal investment and operational planning methodology devised by Sauhats *et al.* in [45].

In terms of the hydrogen storage modelling results presented in Section 1.5, the initially assumed hydrogen storage size corresponding to a 24-hour discharge duration proved to be unnecessarily large for operation in the day-ahead price arbitrage mode as within the studied time period the state of charge did not exceed even 60% of the available storage capacity.

Finally, the coordinated participation of the wind power and storage plants in the day-ahead market was found to be beneficial for both the wind power traders and storage operators. In the time period considered this cooperation proved to provide slightly better net revenue than if the storage plant had operated independently. Furthermore, it offers additional environmental and societal benefits by avoiding wind power curtailment and making a maximum use of the available renewable energy.

2. HYDROELECTRIC POWER PLANT MODELLING

2.1. Motivation for hydroelectric power plant optimization

Nowadays, the power systems of most countries have moved away from vertical integration and regulation. Instead, they rely on market forces to achieve improved operational efficiency, cost-effective resource allocation and, ultimately, more transparent prices and reliable services for the consumers brought by enhanced competition. The latter has an effect on the overall performance of the national economy by easing the cost burden on energy-intensive enterprises. However, achieving these benefits is not as straightforward as it may initially seem since it requires market participants to adapt to the new conditions, act rationally and make the best decisions under imperfect information.

Decision making problems and optimization tasks in power system operation range from power flow analysis and reconfiguration of electric distribution networks to unit commitment and scheduling [46]. Solving power system optimization problems is an important issue for various stakeholders, i.e., system operators, wholesalers and power generating companies (GENCO). Depending on the specifics of the interested party, it may have different objectives such as maximization of reliability or social welfare; minimization of production cost, emissions etc.

This chapter is focused particularly on hydropower scheduling in the short-term. It is a large, time-coupled, stochastic, space-coupled and nonlinear optimization problem [47]. While in the previous structure of power system asset ownership, a vertically integrated utility managed all the main supply-side components of the power system – transmission network, distribution network and generating units – then under the conditions of deregulation these entities are legally separated. That is, the transmission system operators (TSO) and distribution system operators (DSO) must be independent from power producers, who, in turn, have to compete against one another in electricity markets. This change is of particular importance in regards to hydropower scheduling optimization. Previously it was performed by the TSO with the goal mostly being provision of peaking power, but now this task falls on the owners of hydropower plants themselves. Furthermore, the objective function has changed to profit maximization [48].

The scheduling of an HPP production while participating in an electricity market is a complex task due to the many uncertainties involved, especially water inflow and electricity price. Recent challenges have caused a lot of new research aimed at improving unit commitment (UC) algorithms and tools and tackle the uncertainties by implementing stochastic methods. While there are well-developed traditional applications of stochastic programming in power systems applications, they are mostly used for long-term planning. The most promising directions of current studies are focused on the implementation of stochastic approaches for short-term planning within the new environment of decentralized operation, deregulated markets, and competition [49].

This chapter lays out the development of a mathematical model which would allow the owner of several hydraulically linked HPPs to optimize their operation and subsequently achieve increased profitability from the participation in day-ahead electricity markets. While there are several vastly different mathematical models of HPP operation offered in literature, a sizeable portion of them do not yet follow the observed switch to profit-based scheduling. Some notable exceptions, however, are [50] where the authors perform self-scheduling of HPPs by nonlinear complementarity method; [51] where the authors additionally consider head-dependency of the power produced and solve their model by a mixed integer quadratic programming approach; and [52] which considers a multi-criterial problem statement by co-optimizing HPPs and thermal power plants with the additional objective of emission minimization.

A crucial factor that must not be forgotten when developing mathematical optimization models, however, is their ease of implementation and peculiarities caused by application to a particular HPP system. In other words, to have a practical purpose the mathematical model has to be implemented in an actual software tool which can be deployed on an operator's workstation and would allow the GENCO to utilize it. However, the complexity of this task increases furthermore when the requirement to abide by environmental constraints is prescribed. These limitations cannot be relaxed, thereby some other assumptions have to be made for the optimization procedure to be computationally feasible and efficient for daily application in the GENCO scheduling efforts.

The most suitable mathematical description of the optimization problem and the procedure of finding its solution ought to best be selected based on the distinctive features of the HPP system where the tool is meant to be utilized. The case study in this chapter is devised in accordance to the parameters of the three HPPs on the river Daugava, Latvia. The following assumptions are made accordingly.

Firstly, it is presumed that the power system where the plants operate is well interconnected to its neighbors and the producer under consideration provides relatively minor part of the total energy traded in the market exchange. Consequently, it does not have significant impact on the market clearing price and the GENCO is a price-taker. As the GENCO likely operates not only hydroelectric power plants, but thermoelectric plants as well, normally it would have been required to optimize their hydro-thermal dispatch. The previous decision to assume electricity market prices as exogenous variables, however, allows hydroelectric power cascade to be optimized independently from other types of generation.

Another step to simplify the optimization procedure is the decomposition of the task. There have been many methodologies proposed on how to decompose the problem of water utilization optimization in hydroelectric power plants. For instance, [53] studies the use of search procedures like progressive optimality algorithm to decompose the problem into multiple two stage decision tasks. References [54] and [55] offer techniques on how to separate the complex task into parts where the master problem can be solved using linear programming, but the secondary tasks – dynamic programming (DP).

The proposal laid out in this chapter is specifically aimed at cascaded hydropower plants with medium-sized reservoirs (also often called poundage HPPs), i.e., they are not large enough for seasonal planning, causing the necessity for weekly scheduling. The task originally was motivated by interest of the owners and operators of the Daugava HPPs to better optimize the market-based scheduling of these particular power plants, but has since evolved further fueled by purely academic research interests as well. Work on the cascaded HPP optimization model and software was performed by a research team led by Professor A. Sauhats. Parts of the model itself and experimental results obtained by it have been presented in a number of scientific articles. However, this chapter only includes results with the most direct contributions by the author, including some that have been presented in the 56th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON) in 2015 [56] and the Power Systems Computation Conference (PSCC) in 2016 [57], as well as some yet unpublished results.

The main idea of the model proposed is to solve the scheduling problem in three stages, the first two of which are performed before submitting bids to the exchange. Firstly, a simplified linear deterministic water utilization problem is solved for the medium-term (two weeks) to find the optimum reservoir level at the end of the first day. Secondly, the result from the simplified optimization is introduced as a constraint in the more detailed stochastic nonlinear model which determines the optimum hourly power generation schedule for the day-ahead horizon. Finally, after market clearing when the prices are known, dynamic programming is performed to allocate the sold power between the generating units of the hydropower cascade. The software solution carrying out the model is comprised of the multi-stage optimization program as well as an artificial neural network based forecasting model for the day-ahead electricity prices and river inflow.

2.2. HPP optimization model

2.2.1. Main assumptions

The electricity market where the model is used is assumed to be organized according to the day-ahead trading rules as they are implemented in the Elspot market of the Nord Pool (NP) power exchange, which is one of the largest electrical power exchanges in Europe. As the purpose of the study is to present a model to build and execute the generation bids of medium-sized cascaded HPPs, the profit maximization problem is formulated from a price-taker's perspective, e.g., market price is an exogenous variable that has to be forecasted and is not dependent of the GENCO's price and volume bids. This assumption is justified when the producer under consideration indeed operates only a small part of the pool capacity.

The peculiarity of medium-sized reservoirs causes an important distinction to large HPPs the models of which traditionally do not consider the constraints of maximum and minimum water levels in the short-term planning. Moreover, these constraints cannot be violated as it would result in environmental damage and subsequent penalties to the GENCO. In this case, both upstream and downstream limits have to be taken into account. Consequently, in a general case, the fluctuations of water level affect the effective head available for power production.

The hydraulically linked HPPs are assumed to be connected in one series with no off-branches. Furthermore, only the most upstream reservoir receives sizable natural inflow; the lateral inflows in the downstream reservoirs are assumed to be constant in time and miniscule compared to the main flow.

Another point that should be brought up when describing power plant modeling is the approach taken to variable operation and maintenance (O&M) cost modelling. Generally, the profit of a GENCO operating more than one HPP unit can be expressed as:

$$PF = \sum_{t=1}^{T} \sum_{i=1}^{I} (c_t - om_i) \cdot p_{i,t} \tag{2.1}$$

where t, T – time step index and set (hour);

i, I – generation unit (hydroelectric set) index and set;

c_t – electricity market price (€/MWh);

$p_{i,t}$ – energy generated by unit i at time step t (MWh)[9];

om_i – operation and maintenance cost of unit i (€/MWh).

The last component is the variable expense caused by the operation of a generating unit, i.e., the more energy the GENCO generates the larger is this expense position. However, the comparatively negligible size of the variable O&M cost of HPPs [58] allows it to be disregarded without significantly affecting the optimality of the solutions found.

2.2.2. Overall algorithm of optimization

The HPP scheduling problem is decomposed into several sub-problems. In the first stage, a simplified deterministic linear optimization is carried out for dispatch of the water resources over a 14-day long planning horizon. This step is needed to obtain the water reservoir level at the end of the first day, which is then used as input in the second stage – a stochastic nonlinear optimization based on Equations (2.2)–(2.6). The Quasi-Newton method of solving nonlinear programming problems is selected to handle nonlinearities. The result is the GENCO's bidding strategy for the next day. The bids would normally be submitted to the market operator, but, for the purposes of this study, the market clearing is simulated so that the third and final optimization stage can be validated as well. The overall algorithm is illustrated in Fig. 2.1.

For the purposes of this study, it is assumed that the GENCO will submit its bid with three price steps. Subsequently, the first two steps of the decomposed optimization problem are repeated three times for three different price scenarios – normal (forecasted) price, low price and high price. The last two scenarios have the same price profile as the normal price, but are additionally rescaled according to user input. Here the low price scenario is selected to be 75% and the high price – 125% of the initially forecasted 'normal' price. Once the three-level bids are submitted, the market clears and returns the hourly schedule the GENCO has to follow.

Consequently, the company can decide on its UC schedule after the market has cleared and the amount of power to be sold at each hour is known. Optimal UC and dispatch schedule comprises the last step of the optimization procedure for which deterministic dynamic programming (DP) is employed.

[9] The resolution (time step) of the model is one hour. Thereby, for practical purposes, it can be assumed that each unit runs at constant power throughout any particular hour.

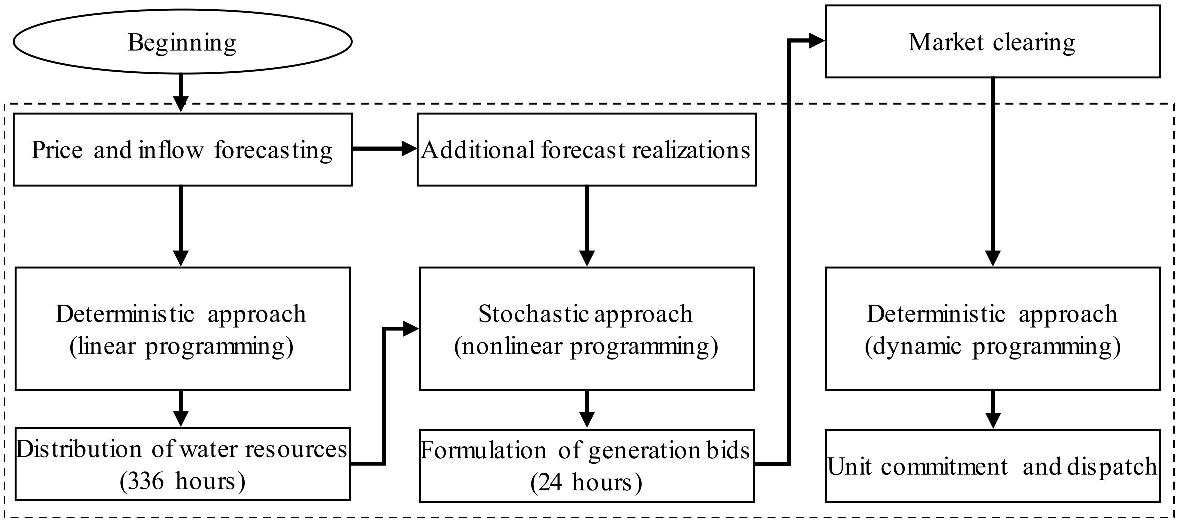


Fig. 2.1. Structure of the overall optimization tool.

The optimization problem is subject to several technical, environmental and safety constraints, such as the minimum and maximum power generation and ramping rate of the hydro units, minimum and maximum water head of the plant, water level of reservoirs and permissible rate of water level changes. Besides that, the allowable operation zones and efficiency curves of the hydro units, which are subject to the previously mentioned variables – power generated, water head and water discharge through the turbines – need to be considered in the calculations.

There is a nonlinear dependency between the power generated by the HPP and several uncertain random variables (e.g., inflow) and, additionally, the profit of GENCO is subject to the market price of electricity having a stochastic nature. The formulation of the optimization problem (2.2)–(2.6) and uncertainty tackling approach described in the next sections allows consideration of the random nature of the problem with an acceptable computation time.

2.2.3. Objective function

For the medium-sized multi-reservoir cascaded HPPs operation, the objective function for stochastic nonlinear optimization of daily bidding strategy is the daily profit expectation expressed as

$$E\left(PF\right)=\sum_{n=1}^{N}\frac{f_n}{R}\rightarrow \max, \tag{2.2}$$

where

$$f_n=\sum_{r=1}^{\mathrm{R}}\sum_{t=1}^{\mathrm{T}}\mathrm{g}\cdot\eta_{\mathrm{turb}.n}\cdot\eta_{\mathrm{gen}.n}\cdot H_{n,r,t}\cdot v_{n,t}\cdot c_{r,t}, \tag{2.3}$$

$$v_{n,t}=\mathrm{S}_n\cdot\frac{\Delta L_{n,t}}{\tau_n}. \tag{2.4}$$

For $n = 1$:

$$H_{n,r,t} = L^{\text{up}}_{n,r,t} - L^{\text{down}}_{n,r,t} - \Delta L_{n,t} + \mathrm{k}_n \cdot w_{n,r,t}\,. \tag{2.5}$$

For $n = \{2, \mathrm{N}\}$:

$$H_{n,r,t} = L^{\text{up}}_{n,r,t} - L^{\text{down}}_{n,r,t} - \Delta L_{n,t} + \mathrm{k}_n \cdot \mathrm{w}^{\text{lateral}}_n + \mathrm{b}_n \cdot \Delta L_{n-1,t-1}\,. \tag{2.6}$$

Subject to

$$\overline{L^{\text{up}}_n} \le L^{\text{up}}_{n,r,t} \le \underline{L^{\text{up}}_n}\,, \tag{2.7}$$

$$\overline{L^{\text{down}}_n} \le L^{\text{down}}_{n,r,t} \le \underline{L^{\text{down}}_n}\,, \tag{2.8}$$

$$\Delta L_{n,t} \le \overline{\Delta L_n}\,, \tag{2.9}$$

$$\sum_{t=1}^{s} \Delta L_{n,t} \le \Delta L_{n,\text{24-h max}}, \qquad \forall s \in [1, t]. \tag{2.10}$$

where n, N – index of HPP in the cascade;

r, R – price or water discharge forecast realization;

g – gravitational acceleration (9.81 m/s^2);

$\eta_{\text{turb.}n}$ – mechanical efficiency;

$\eta_{\text{gen.}n}$ – electrical efficiency;

S_n – surface area of the reservoir of the n HPP (m^2);

τ_n – experimental constant linking water discharge and reservoir level (1/s);

$\mathrm{w}^{\text{lateral}}_n$ – lateral inflow in downstream reservoirs[10] (m^3/h);

k_n – coefficient linking water inflow and reservoir level (s/m^2);

b_n – coefficient linking discharge in upstream and water level in downstream reservoirs;

$H_{n,r,t}$ – water head (m);

$v_{n,t}$ – water discharge (m^3/s);

$w_{n,r,t}$ – water inflow in the most upstream reservoir (m^3/s);

$L^{\text{up}}_{n,r,t}$, $L^{\text{down}}_{n,r,t}$ – water levels in upstream/ downstream reservoirs at beginning of hour (m);

$\overline{L^{\text{up}}_n}$, $\underline{L^{\text{up}}_n}$, $\overline{L^{\text{down}}_n}$, $\underline{L^{\text{down}}_n}$ – upper and lower limits of water level in upstream and downstream reservoirs (m);

$\Delta L_{n,t}$ – change in upstream reservoir due to power generation (m);

ΔL_n – the maximum decrease of water level within one hour (m);

$\Delta L_{n,\text{24-h max}}$ – the maximum decrease of water level within 24 hours.

[10] Assumed to be miniscule and constant.

The nonlinearity here is introduced in order to account for head-dependency of the power output of an HPP unit, expressed by the term $H_{n,r,t}$. The reservoirs at this stage, however, are modelled linearly as in Eq. (2.4). A more accurate representation of the reservoirs is used in the final modelling stage.

Equations (2.7) and (2.8) represent the upper and lower constraints on reservoir water level that are usually determined in the environmental permits issued to a particular HPP operator. Eq. (2.9) signifies the maximum permissible change in water level within one hour and (10) – the maximum permissible change in water level within 24 hours.

The term f_n in (2.2) and (2.3) denotes the sum of the profit obtained in HPP *n* in all the price forecast realizations. To find the mathematical expectation, this variable is divided by the total number of realizations R.

The optimization variable is the change of water level in each reservoir, $\Delta L_{n,t}$. The output of the optimization procedure provides the GENCO with the day-ahead bidding strategy which includes the total hourly power generation for a certain bidding price for the HPP cascade to maximize its profit.

2.2.4. Forecasting module

This section describes the forecasting of electricity market price and water inflow and the subsequent sampling of numerous forecast realizations $c_{r,t}$ and $w_{n,r,t}$ which are used as input data for the optimization procedure.

Ref. [59] indicates that the approaches most often used for electricity spot price modeling are statistical time series and computational intelligence models (e.g., artificial neural networks (ANN)) . The same study also concludes that statistical methods for market price forecasting perform poorly in the presence of spikes, whereas computational intelligence models are flexible and can handle complexity and non-linearity which makes them promising for short-term forecasts. However, the ability to adapt to non-linear, spiky behaviors may not necessarily result in better point projections. ANNs are also the method of choice for electricity spot price forecasting in [60], [61] and more recently – [62].

Various models of water inflow projection are compared in [63] where it is concluded that a dynamic autoregressive ANN model with sigmoid activity function is superior to the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models, especially at peak points.

We have incorporated in our software tool a three-layer ANN which is being trained on historical data of market prices, water inflow and ambient temperature. Furthermore, selection of the most suitable ANN parameters for a particular task is an endeavor on its own and the state of the art in this field suggests employing an experimental approach in obtaining them [62], [64]. Among the design parameters of an ANN's structure is the number of neurons in the hidden layer, size of the training data set, input and feedback delays. In our implementation, these properties are adjusted each day anew to suit the best forecast performance in the previous forecasting horizon. The adaptation procedure is described in more detail in our paper [65]. The output of the ANN is smoothed in order to filter out unreasonable outliers in the forecasted series [66]. Let us assume that $\hat{y}_t$ is an element of the forecasted time series, then

$$
\begin{aligned}
\hat{y}_{t,smoothed} &= \hat{y}_{t,} && \text{for } t \in \{1, T\} \\
\hat{y}_{t,smoothed} &= \frac{\hat{y}_{t-1,} + \hat{y}_{t,} + \hat{y}_{t+1,}}{3} && \text{for } t \in \{2, T-1\} \\
\hat{y}_{t,smoothed} &= \frac{0.5 \cdot \left(\hat{y}_{t-2} + \hat{y}_{t+2,}\right) + 0.7 \cdot \left(\hat{y}_{t-1} + \hat{y}_{t+1,}\right) + \hat{y}_{t,}}{3.4} && \text{for } t \in [3, T-2]
\end{aligned}
\tag{2.11}
$$

The output of the ANN module provides point forecasts of the hourly day-ahead electricity price and water inflow. To consider uncertainties, historical residuals are used to generate additional realizations of the forecast. By assuming that the errors retain generally the same characteristics in the medium-term, the forecasting module uses the hourly relative errors from the forecasts of the previous 10 days. Each new realization is obtained by adding or subtracting the historical error to the new forecast at the respective hour. In such a way, the 10-day old historical data provides 20 new time series in addition to the one initial forecast. It is then assumed that all the forecasts have equal realization probabilities. Consequently, for the optimization, 21 electricity market price time series, $c_{r,t}$, and water inflow time series, $w_{n,r,t}$, are used as input data.

By this simplified approach, we can consider the uncertainty of electricity prices and water inflow while not increasing computational burden too much for a practical application in GENCO's daily operation optimization.

2.2.5. Handling of unit and reservoir characteristics in the unit commitment model

After the market is cleared and the hourly amount of power generation for the next day has been determined, it is necessary to establish the optimal dispatch schedule of the HPPs' generating units.

At this stage, the characteristic of each hydro unit has to be modelled. These characteristics illustrate the relationship between effective water head, power and water discharge through the hydro unit.

To enable using these relationship curves in calculations, they have to be described mathematically. In general, the water discharge through a particular hydroelectric set is a function of its power and effective water head:

$$v_i = f\left(p_i, H_n\right), \tag{2.12}$$

$$v_i = a_1 \cdot p_i + a_2 \cdot H_n + a_3 \cdot p_i \cdot H_n + a_4 \cdot p_i^2 + a_5 \cdot H_n^2 + a_0. \tag{2.13}$$

where v_i – water discharge rate of unit i (m^3/s);

p_i – power of unit i (MW);

a_0, a_1, a_2, a_3 – polynomial coefficients.

In this study, the characteristics are approximated by a third-order polynomial such that, for every value of water head (H_n) of HPP *n*, the water discharge through a particular hydroelectric set *i* can be expressed as:

$$v_i = a_1 \cdot p_i^3 + a_2 \cdot p_i^2 + a_3 \cdot p_i + a_0. \tag{2.14}$$

For instance, if the characteristic is defined by water head values in the interval from 33 to 40 meters and the chosen step is 0.1 meters, then we have to interpolate 71 functions. This can be easily done by creating a looping script in any scripting environment.

By increasing the rank of the polynomial (2.14), we could achieve greater precision of interpolation. Precision can be evaluated by comparing the curves obtained in the interpolation to the source data. However, the third-order expressions used in this study were deemed sufficiently accurate as the largest error value calculated among the points of the characteristics was 3.59%.

On the other hand, the effective water head at each time step of this optimization stage is found as the difference between the upstream and downstream reservoir levels:

$$H_{n,t} = L_{n,t}^{\text{up}} - L_{n,t}^{\text{down}}, \tag{2.15}$$

where the upstream and downstream water levels can be calculated utilizing the relationship curves of water storage versus forebay elevation for the first and tailwater elevation versus outflow release for the second.

Thus it can be concluded that change in upstream level is a function of inflow and outflow (2.16)–(2.17), whereas downstream level is a function of outflow (2.18).

$$\Delta L_{n,t}^{\text{up}} = f\left(q_{n,t} - v_{n,t}\right), \tag{2.16}$$

$$L_{n,t}^{\text{up}} = L_{n,t-1}^{\text{up}} + \Delta L_{n,t}^{\text{up}}, \tag{2.17}$$

$$L_{n,t}^{\text{down}} = f\left(v_{n,t}\right), \tag{2.18}$$

where $q_{n,t}$ is the sum rate of inflow in the upper reservoir (m^3/s), this includes the time-delayed discharge from the upstream HPP, the natural main and/or lateral inflow (or whichever of these are applicable for a particular HPP).

These functions are nonlinear because of the relatively small size and irregular form of the reservoirs, but they provide better reservoir level accuracy compared to the linearized reservoir models used in the first two stages of the overall optimization process (expressed by Equations (2.4)–(2.6)).

2.2.6. Solving unit commitment with dynamic programming

Evidently, the objective function (2.19) of the UC sub-task is additive in nature. It provides the option to solve the problem by using DP as opposed to performing full exhaustive enumeration.

Traditionally, when DP is applied for optimization of HPP operation, it is done for longer planning horizons and decisions are made at different time stages as, for instance, in [67] and [68]. Here, however, it is employed within each hour solving a UC problem static in time. Solution is obtained by choosing the optimal outflow through each hydroelectric unit in regards to other units as well as deciding on whether a certain unit should be connected at all.

Fig. 2.2 explains the application of the DP approach to the selection of hydroelectric units. In the example, each blue line corresponds to a different combination of units (block), whereby each block essentially has its own efficiency curve. It is evident from the figure that to generate the same sum amount of power in an HPP it can take varying amounts of water discharge, depending on what combination of units has been selected.

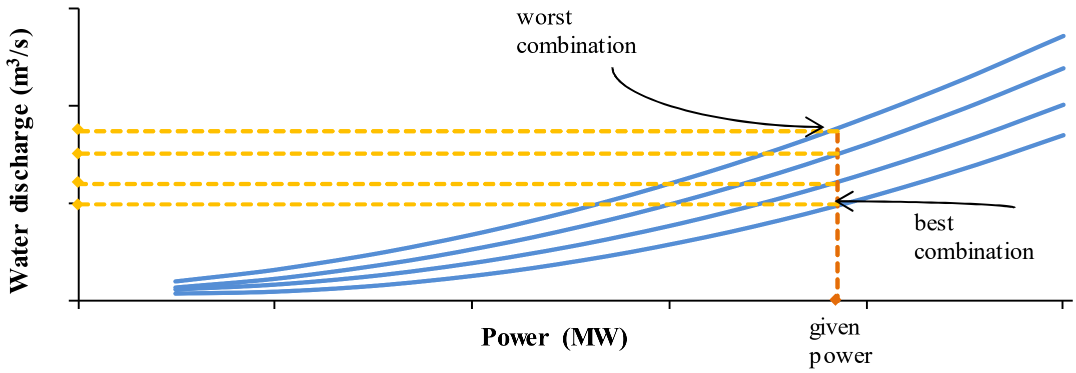


Fig. 2.2. Example of block characteristics of units.

However, there are two ways how to employ DP to find the optimal HPP unit dispatch schedule. If the input variable for each hour is the total amount of water to be discharged through the particular HPP, then DP solves the problem of power generation maximization. On the other hand, if the input variable for each hour is the total power generated by the HPP, water discharge minimization is performed instead. Both approaches essentially strive to increase the efficiency of operation and, consequently, higher water value, but the hourly water discharge minimization is selected as the objective function of DP:

$$v_{t\Sigma} = \sum_{i=1}^{I} v_{i,t} \;\rightarrow\; \min \qquad (2.19)$$

subject to

$$\sum_{i=1}^{I} p_{i,t} \leq p_{t\Sigma} \qquad (2.20)$$

$$p_{i,t} \in [0] \cup \left[\underline{p}_i, \overline{p}_i\right] \quad \forall t \in T \qquad (2.21)$$

where $v_{t\Sigma}$ – the sum discharge rate of all the hydroelectric units (m^3/s) during time step t;

$p_{t\Sigma}$ – the sum power of all the hydroelectric units (MW) during time step t;

$\underline{p}_i$, $\overline{p}_i$ – the lower and upper bounds on the power of hydroelectric unit i (MW).

Eq. (2.20) is not an equality because of the fact that at this stage the hydroelectric units are modelled with greater accuracy and the result of the previous stage might not be feasible in terms of the operational zones of the individual units. Thereby, the sum power to be produced in a particular HPP can be decreased to respect all power constraints.

Eq. (2.21) shows that the power of each particular hydroelectric unit has to either fall within its operational zone defined by an upper and lower constraint, or the unit should not be in operation at all, i.e., have power equal to zero.

Furthermore, at the last stage of optimization, previously described constraints (2.7)–(2.10) also must be respected to follow the environmental limitations of each HPP and their reservoirs.

For the DP, a recursive equation is formulated to describe the total discharge of the HPP depending on the power of unit i and the units optimized before it:

$$rec_k(p) = \max\left\{rec_{k-1}\left(p - p_{ik}\right) + v_k\left(p_{ik}\right)\right\} \tag{2.22}$$

Recursion is used to obtain intermediate results which are stored in an array with dimensions $k \times I$, where k is the number of steps (value of the constraint (2.20) divided by the increment between the steps)[11]. Once the array is filled, trace-back procedure is initialized starting from the last entry (Fig. 2.3). The optimal trajectory is thereby acquired, which, in this instance, is a vector containing the water discharge through each hydroelectric unit and, consequently, the power generated by it.

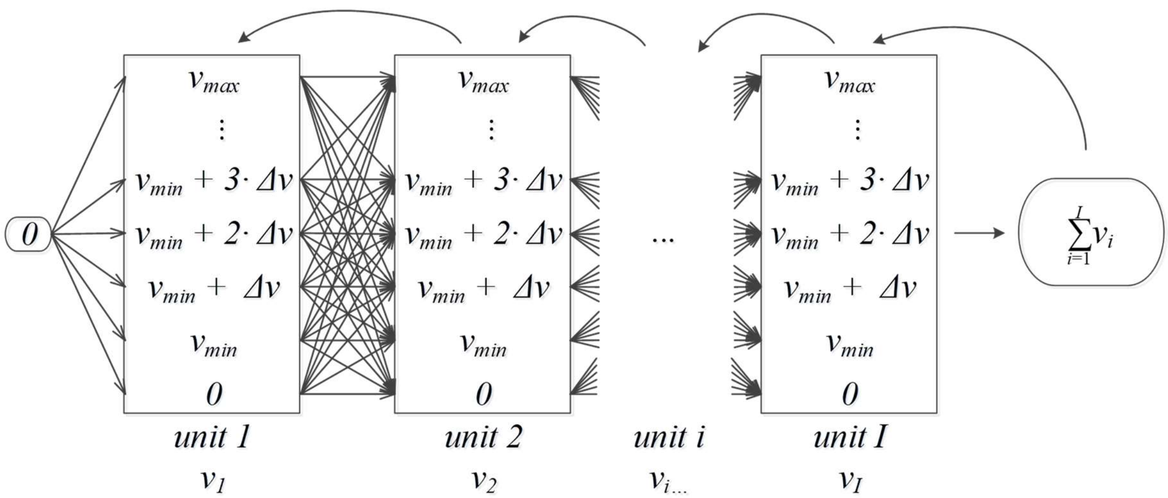


Fig. 2.3. Application of dynamic programming in solving the UC problem.

[11] Given that there are 23 units in the Daugava river HPP cascade, the total amount of information that needs to be stored during calculations can be quite taxing. For instance, if in a given hour Kegums HPP is supposed to have a discharge of 1000 m3/s and the calculations are done in increments of 5 m^3/s, then the array where intermediate results are written will have dimensions of 200x7. Though still time consuming, this approach, however, is more effective than evaluating every possible combination.

Along with the hourly power schedule of each of the hydroelectric units in the cascade, the DP module also outputs refined values of changes in the level of all the water reservoirs during the day. This is thanks to the fact that, at this stage, a more accurate mathematical representation is used for both the hydroelectric units and reservoirs – the actual water head, discharge and power characteristics of the former and level versus discharge relationship curves for the latter. This crucial input data has to be prepared by the HPP operators, but normally it can be ascertained from their statistical databases.

The DP approach described in this section, however, does not address issues of uniform and even operations. This is rectified by introducing a priority list for each hour. If there are several units with the same or very similar characteristics in an HPP and either of them is chosen to be operational by DP, then it can be replaced according to this preset list. If a turbine's id is omitted from the list, it is not considered in the calculations. That allows to set the state of a certain hydroelectric unit as unavailable for production because of maintenance or any other reasons.

Alternatively, decision on which turbines from a set of equal units should be generating can ultimately be made by the operators. For this purpose they must be presented with all the viable combinations of generator loading that offer maximum value of the target function.

2.3. Object of optimization

The proposed model has been thoroughly tested and validated on the parameters of a real HPP cascade operating in a liberalized electricity market. Thereby the model is adjusted according to the parameters of the cascade of HPPs on the river Daugava, Latvia.

As explained before, the studied power plants are Plavinas HPP, Kegums HPP and Riga HPP (Fig. 2.4 [57]). Their installed active power is 893.5 MW, 264 MW and 402 MW respectively. Due to the limited natural inflow, these power plants can utilize their full capacity only during the spring flood season which is rarely longer than a month. For the rest of the year water resources are scarce and the necessity to manage them becomes evident. Indeed, unlike in [54], the comparatively smaller reservoir volumes create circumstances where changes in water level are more immediate and have bigger effect on efficiency of water turbines. Therefore, if the goal is HPP short-term operation planning to build hourly generation bids for day-ahead trading, it is crucial to calculate water head changes within the planning interval for each power plant. The most important parameters and constraints are summarized in Table 2.1.

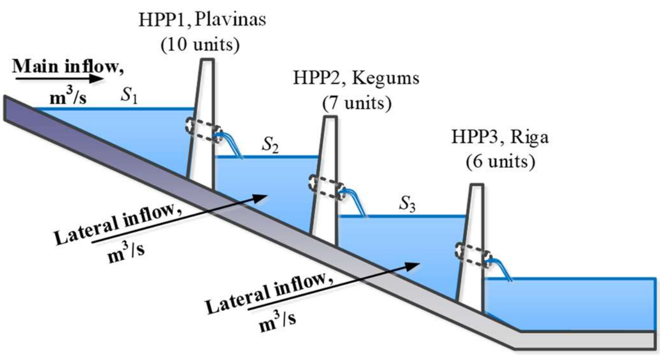


Fig. 2.4. The cascade of HPPs on the river Daugava.

Table 2.1. Technical parameters and environmental constraints of the Daugava HPPs

Type of Constraint / Power plant	**Plavinas HPP** [69]	**Kegums HPP** [70]	**Riga HPP** [71]
Installed capacity (MW)	893.5	266	402
Surface area of the reservoir (km^2)	35.0	24.9	35.8
Useful volume of the reservoir (mill. m^3)	143	37.5	34.6
Permissible upstream level (m)	69–72	30.4–32.0	17.0–18.0
Permissible downstream level (m)	30.5–35.9	17–18.5	–1.5–3.9
Permissible hourly decrease in reservoir level (m/h)	0.30	0.30	0.20–0.30
Permissible daily decrease in reservoir level (m/day), depends on the season	0.75–1.5	0.75–1.60	0.75–1.00

Furthermore, only Plavinas reservoir is filled by natural inflow in Daugava, the lateral inflow in the other two stations is negligible. This means that water level in Kegums and Riga reservoirs rises only when the water discharged by upstream HPP reaches them. Techniques on how to calculate the time it takes for discharged water to travel to and have an impact on a downstream reservoir are offered in [55]. In order to simplify the mathematical model, it is assumed in this study that the travel time of water between two Daugava HPPs is equal to 1 hour and is not dependent on any other variables, such as elevation of tailwater or volume of discharge.

2.4. Validation of characteristic approximation

The hydroelectric set and reservoir characteristics normally are defined as data tables, obtained either during routine operation of the power plants or in specially organized experiments by the HPP operators. The most appropriate form in which to express them afterwards depends on the intended application. For the purposes of developing this water resource management and schedule optimization tool, they were expressed as a series of 3rd order polynomials. By comparing values obtained by the polynomials (2.14) to the original data tables, it was found that the maximum error value for a single discharge curve data point reached 3.59% [56], which is deemed acceptable.

On the other hand, there is no direct way to validate the performance of approximated reservoir curves. Instead we can try and verify the hydraulic model as a whole. To achieve this, the historical data on the power production in each of the HPPs and the registered natural inflow at the most upstream point in the cascade is used as input. The model is then used to calculate the corresponding water level in each reservoir with hourly resolution, which can then be compared to the actual registered level[12].

The resulting comparisons are summarized in Figures 2.5–2.10.

[12] Data of the actual produced energy in each HPP, the inflow in the most upstream reservoir and the actual registered water levels in each reservoir – courtesy of the plant operator Latvenergo AS.

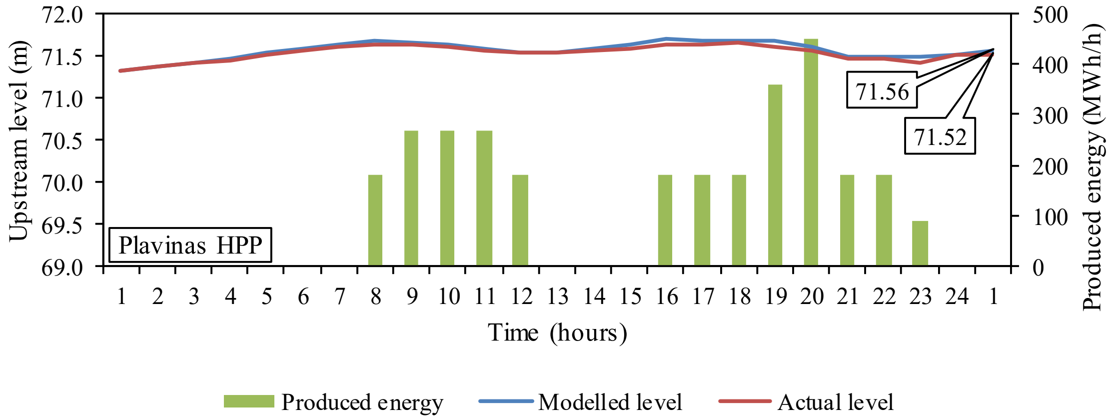


Fig. 2.5. Model accuracy test on data from February 25, 2015 for Plavinas HPP.

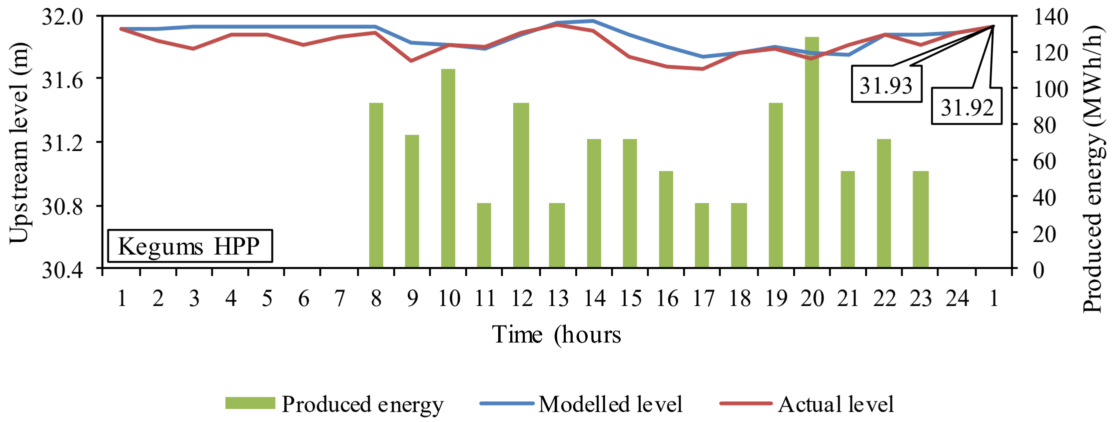


Fig. 2.6. Model accuracy test on data from February 25, 2015 for Kegums HPP.

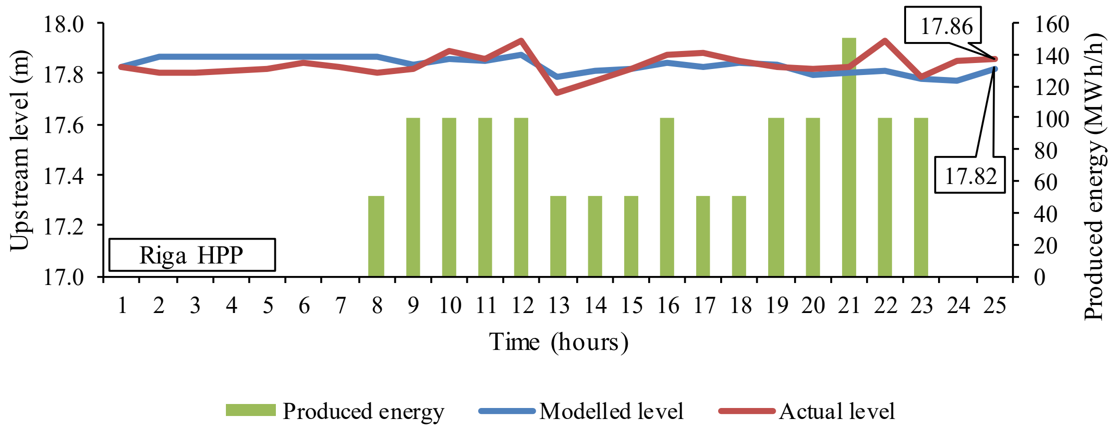


Fig. 2.7. Model accuracy test on data from February 25, 2015 for Riga HPP.

Model performance tests were carried out on data from two seasonally distinct days – February 25, 2015 (average inflow 428 m^3/s) and September 25, 2015 (average inflow 105 m^3/s). In the first case the deviation of the modelled water level from the actual historical one was –0.04 m, 0.01 m and 0.04 m at the end of the day in each of the reservoirs. In the second case, they were –0.04 m, –0.01 m and 0.02 m. These errors are a compound of the initial accuracy and reliability of the relationship curves and their approximation and implementation in the software.

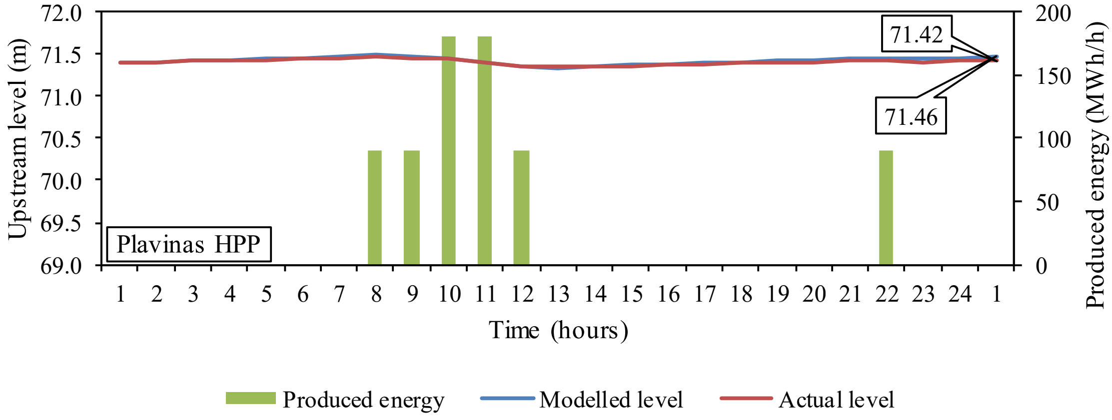


Fig. 2.8. Model accuracy test on data from September 25, 2015 for Plavinas HPP.

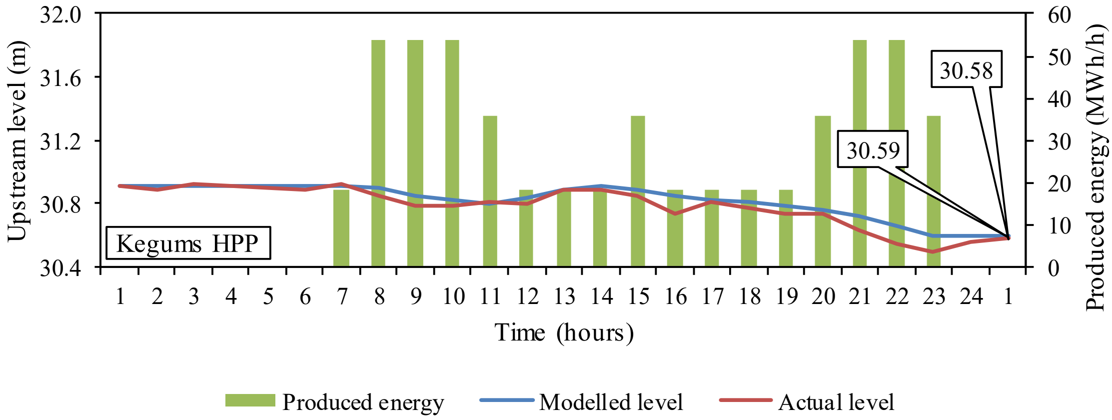


Fig. 2.9. Model accuracy test on data from September 25, 2015 for Kegums HPP.

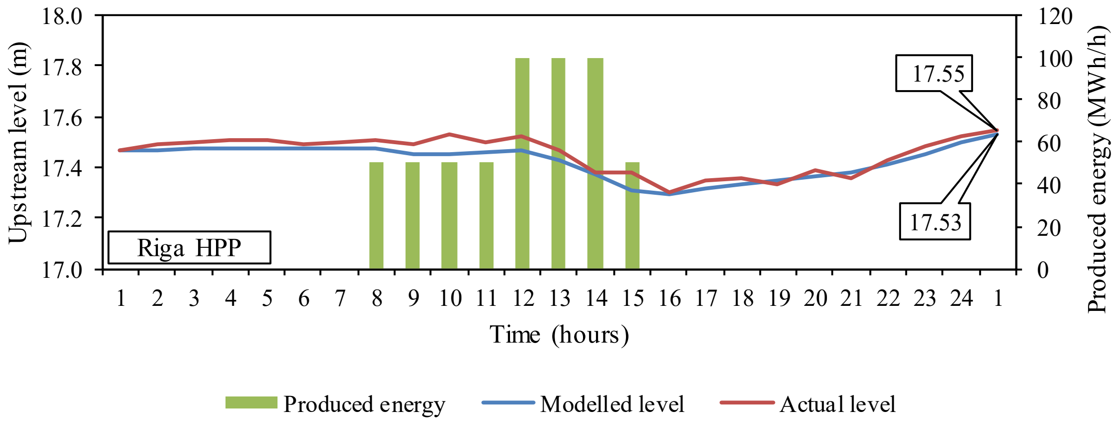


Fig. 2.10. Model accuracy test on data from September 25, 2015 for Riga HPP.

A closer inspection of the figures reveals that the overall modelled trajectory of changes in water level in the Plavinas HPP follows the registered data closely, whereas in Kegums HPP and Riga HPP the modelled trajectory is noticeably smoother than the historical data suggests. This implies there are factors yet unaccounted for in the downstream reservoir models. One possible explanation might be disturbances (e.g., waves) caused by the discharge in upstream HPPs as in the current implementation the discharge is modelled as uniform, dependent on power generation and water head. Another possible explanation might be the assumption on the constant nature of lateral inflow and the assumed 1 hour time delay for water traveling between two Daugava HPPs. However, further dedicated studies would be necessary to sufficiently explain this phenomenon.

2.5. Validation of the dynamic programming approach

After it has been established that the reservoir model and approximations of unit characteristics are accurate enough to be used in calculations it is also necessary to test the dynamic programming approach discussed in Section 2.2.

As was previously described, there are two ways how to employ DP to determine which units in an HPP should be operational and what their power should be within a given hour. If the input variable for each hour is the total amount of water to be used in the particular HPP, then DP solves a power maximization task. On the other hand, if the input variable for each hour is the desired sum of all units' generation, a discharge minimization is performed. Both approaches essentially strive to increase efficiency of operation and thus higher water value.

The following calculations are based on data from June 1, 2015[13].

2.5.1. Power (and by extension – revenue) maximization

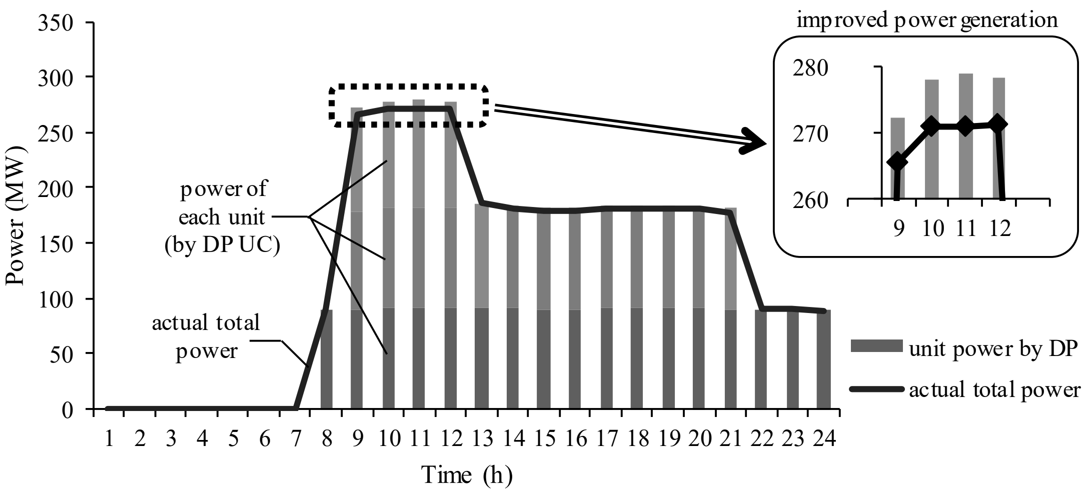


Fig. 2.11. Comparison of power generation with and without UC optimization.

Input data is hourly discharge which is obtained by calculations using the reservoir and hydroelectric unit characteristics and afterwards set as constraints analogous to (2.20) . For this example, optimization is performed on Plavinas HPP for each of the 24 hours. Results are compared to the actual statistics in Fig. 2.11.

The UC subtask solution offers to produce more electrical energy using the same amount of water. The improvement constitutes 45.6 MWh which is a 1.49% increase. Taking market prices into account it can be concluded that revenue from Plavinas HPP would thus increase by 2758.24 €, if the plant operators managed to sell this additional energy in the market.

[13] Data on the actual generated power and water levels – courtesy of the HPP operator, Latvenergo AS.

2.5.2. Discharge minimization

On the other hand, here the input constraint is hourly power generation. The objective is to find such a combination of units that produces the same power, but uses less water in doing so.

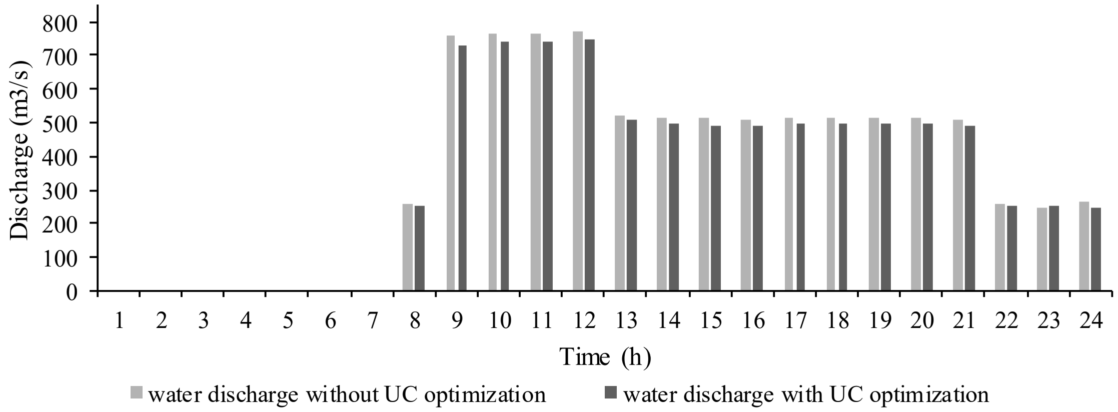


Fig. 2.12. Comparison of water discharge with and without UC optimization.

The solver achieves the given desired Plavinas HPP hourly power schedule by finding the most effective combinations of units. In this case those turn out to be units 5, 7 and 8. The differences in hourly discharge before and after solving the minimization task are displayed in Fig. 2.12. The saved water resources amount to 1.09 mill.m^3 which constitutes a 3.47% reduction, showing the importance of choosing the most effective units for any given time.

With the comparisons in Fig. 2.11 and Fig. 2.12, it can be concluded that the DP-based unit selection module proposed does provide beneficial results, thereby it can be included in the overall mathematical model and the main three-stage optimization tool. The following chapter analyses the performance of the full process as explained in Fig. 2.1.

2.6. Optimization results

2.6.1. Linear optimization

The performance of the developed model for the optimization of cascaded HPPs with medium-sized reservoirs was analyzed by carrying out a full run through all the modules of the tool based on the initial reservoir levels of September 25, 2015 and prior price and inflow data. The first step is price and inflow forecasting, which is followed by operator's decision on minimum and maximum price limits for the day-ahead (first 24 hours) horizon. Here we assume the limits to be 75% and 125% from the forecasted price respectively.

Figures 2.13–2.15 illustrate the distribution of water resources in each of the HPP for every of the three price scenarios. The water resource management is considered in terms of upstream reservoir level with hourly time resolution and two-week look-ahead horizon. Of course, as explained in model description in Section 2.2, we are interested in the water level at the end of the first 24 hours as those are used as constraints in the nonlinear stochastic optimization for the day-ahead horizon. The corresponding values along with the initial reservoir level are highlighted in the charts.

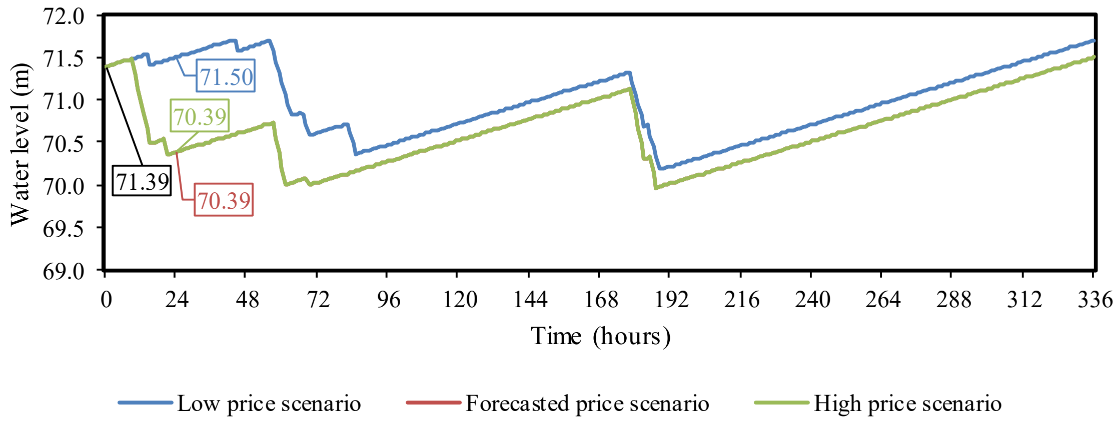


Fig. 2.13. Hourly water level in Plavinas HPP upstream reservoir in three price scenarios[14].

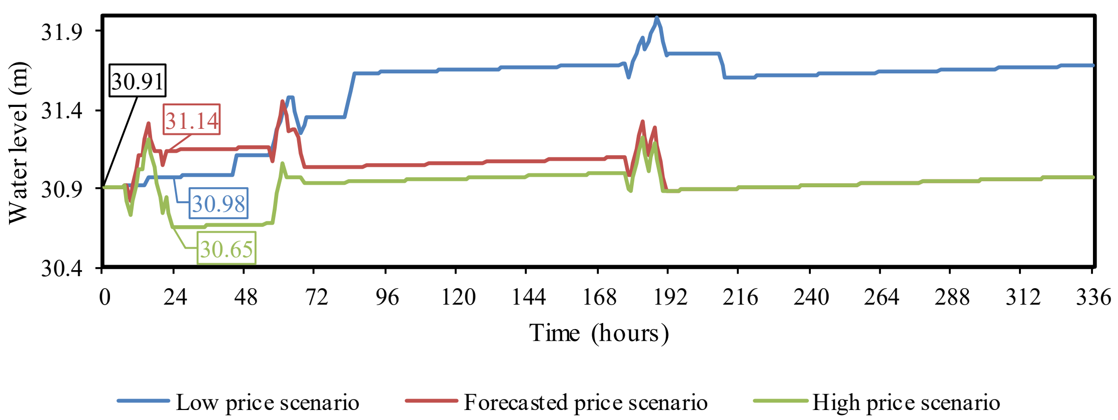


Fig. 2.14. Hourly water level in Kegums HPP upstream reservoir in three price scenarios.

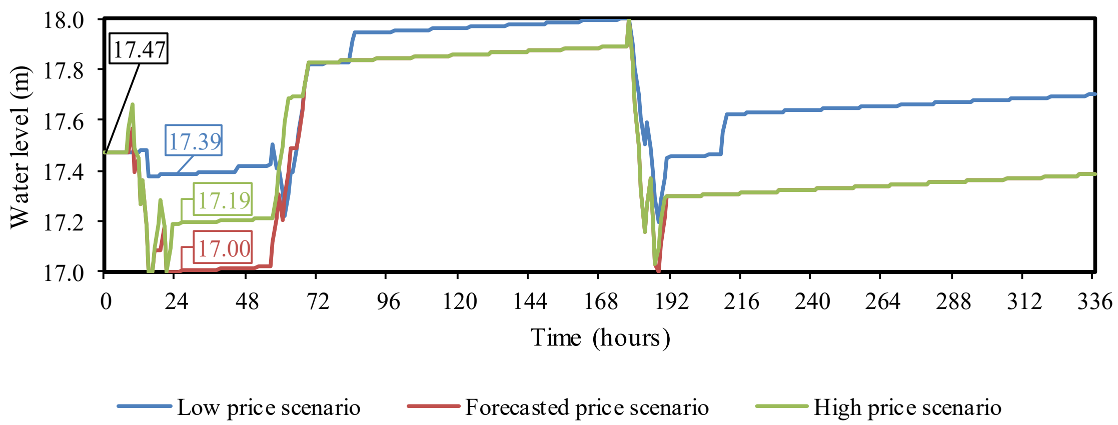


Fig. 2.15. Hourly water level in Riga HPP upstream reservoir in three price scenarios.

The visualization of the results of linear optimization allows noticing some peculiarities. Firstly, the Plavinas HPP has already achieved its daily discharge constraint (1 m) in the *Forecasted price* scenario at the end of the day-ahead horizon of first 24 hours. Hence, the HPP cannot produce more power in the *High price* scenario and both trajectories are the same.

[14] The *Forecasted price* scenario and *High price* scenario produce the same water level change trajectory for Plavinas HPP in the case study under consideration. Thereby, the red line corresponding to the Forecasted price scenario is not visible in Fig. 2.13.

Secondly, the trajectories for *Forecasted* and *High price* cases converge for the other two HPPs as well, but it happens noticeably later in the two-week period and the results for the first 24 hours differ.

Another peculiarity is that while in the *High price* scenario in Kegums HPP the reservoir is emptied more than in the normal price case (30.65 m vs 30.98 m level at the end of the day-ahead horizon), the opposite is true for the Riga HPP (respectively 17.19 m vs 17.00 m). This effect is explained by the inflow caused by discharge in the upstream reservoirs which raises the level in downstream reservoir with a slight delay.

As can be observed from Figures 2.13–2.15, the optimized reservoir levels correspond to the minimum and maximum level constraints. It can be seen that neither Plavinas nor Kegums HPP reach either of the constraints within the two-week period. However, in Riga HPP, which has the smallest operating range in terms of reservoir level variability, both upper and lower constraints are activated. It is important to notice this also happens in the *Forecasted price* scenario at the end of the day-ahead horizon when the reservoir level reaches its minimum 17 m. Thereby, it will be important to see how this constraint impacts the results when the more precise nonlinear model is employed.

The amount of power generated in each HPP within the day-ahead horizon in each scenario is summarized in Table 2.2. Since the linear optimization is expected to be more imprecise, these are indicative results and not yet the final values.

Table 2.2. Total produced energy in each HPP in the day-ahead horizon (linear model)

	Plavinas HPP	**Kegums HPP**	**Riga HPP**
Low price (75%) scenario	446.75 MWh	133.00 MWh	201.00 MWh
Forecasted price (100%) scenario	4098.53 MWh	1609.62 MWh	1467.02 MWh
High price (125%) scenario	4098.53 MWh	2368.00 MWh	1969.29 MWh

2.6.2. Nonlinear optimization

The next stage in the optimization tool envisions stochastic nonlinear optimization according to Eq. (2.2)–(2.10) and, additionally, using the water reservoir values at the end of the first 24 hours of the linear model run (highlighted in Figures 2.13–2.15) as constraints. Fig. 2.16 displays the forecasted day-ahead electricity price for September 25, 2015 along with the additional realizations obtained according to Section 2.2 and the actual historical market clearing price that day in the Latvian bidding area of the Nord Pool [9][15].

According to Fig. 2.16, the main one-point forecast obtained by the ANN has managed to capture two price peaks during the day (at 15 and 21 PM) and the low prices at night (from 1 to 5 AM). However, it has failed to correctly predict the first and largest peak at 7 and 8 AM. Fortunately, the additional price forecast realizations obtained by considering past residuals do include this peak within their distribution. Thereby, it remains to be seen if after simulated market clearing these points will be successfully taken advantage of.

[15] Data extracted from file *elspot-prices_2015_hourly_eur.xls*.

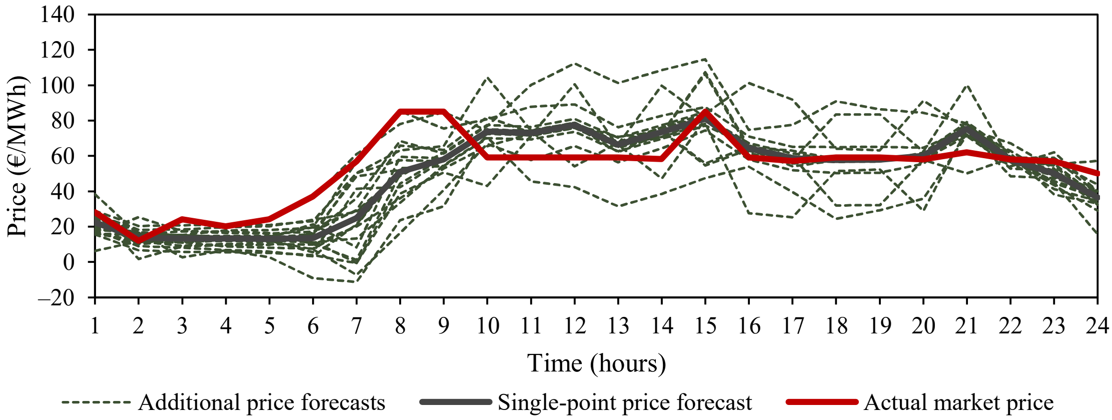


Fig. 2.16. Price forecasts and actual price on Sept. 25, 2015, LV price area in Nord Pool.

The results of nonlinear optimization for the *Low*, *Forecasted* and *High price* scenarios are summarized in Table 2.3.

Table 2.3. Summary of the results of nonlinear optimization

	Produced energy (MWh)			**Reservoir level at the end of 24 hours (m)**		
	Plavinas HPP	**Kegums HPP**	**Riga HPP**	**Plavinas HPP**	**Kegums HPP**	**Riga HPP**
Low price (75%) scenario	364.00	95.00	255.00	71.56	30.96	17.39
Forecasted price (100%) scenario	3780.00	1065.50	2055.00	70.39	31.07	17.03
High price (125%) scenario	3870.00	1357.50	2253.00	70.35	30.70	17.16

Contrary to previous concerns, the final reservoir levels have been successfully carried over from the linear to nonlinear models. Deviations of the nonlinear programming outcome from the output of the previous stage range from –0.07 m to 0.06 m. The total power produced, however, differs noticeably in both models, signifying that the power production estimated by the linear model has meaning in terms of its profile, but not in absolute value, because, clearly, the nonlinearities of the HPP plants and their reservoirs evidently play a significant role.

2.6.3. Unit commitment and dispatch

At last, bids at different price levels are obtained and the last stage of the model can be deployed. If normally the bids would be submitted to a power exchange, here this step is simulated by invoking the previous assumption – the price-taker nature of Daugava HPP plants – and using the historical price as the supposed price signal from the market. The total hourly power bids and the resulting (accepted) profile is displayed in Fig. 2.17.

The accepted bids are filled in black. No offers created by the *Low price* scenario have been accepted, but ten bids from the *Forecasted* and one from the *High price* scenarios have been accepted. In total, the market price cleared for 15 hours in the *Forecasted* and 9 hours in the *High price* scenario.

Evidently, during the first price peak, which was not forecasted (Fig. 2.16), only very minor bids were made and subsequently realized. The likelihood of a spike here was underestimated, however, the following peaks were successfully utilized.

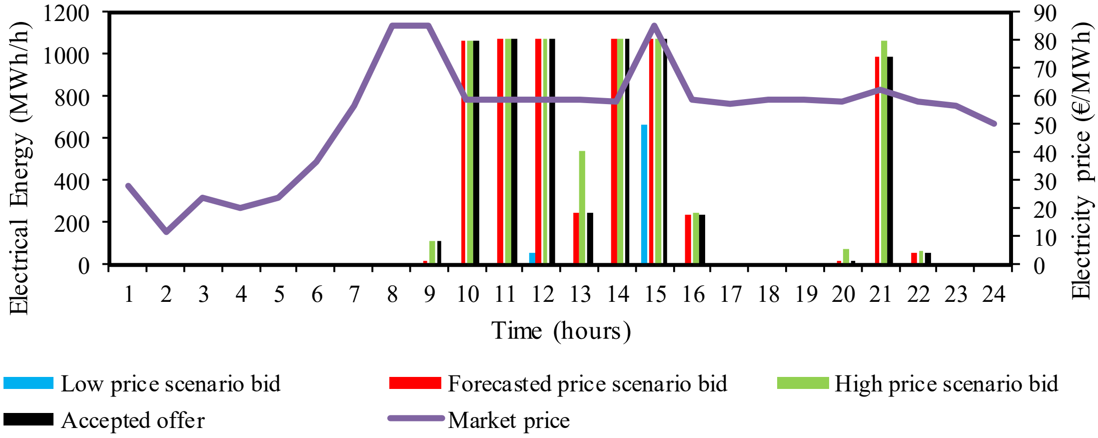


Fig. 2.17. The bids and accepted generation schedule.

Table 2.4. The hourly schedules of particular hydroelectric sets in the Daugava cascade

	Energy production (MWh/h)																						
	Plavinas HPP										**Kegums HPP**							**Riga HPP**					
t	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**K1**	**K2**	**K3**	**K4**	**K5**	**K6**	**K7**	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	57	57	0	0	0	0	0	0	0
10	0	91	0	0	91	89	91	91	89	89	0	0	0	19	57	57	0	50	50	50	50	50	50
11	0	91	0	0	91	89	91	91	89	89	0	0	17	17	56	56	0	50	50	50	50	50	50
12	0	91	0	0	91	89	91	91	89	89	0	0	17	17	54	54	0	50	50	50	50	50	50
13	0	0	0	0	0	0	0	0	0	0	0	0	17	17	54	54	0	0	0	0	0	51	51
14	0	91	0	0	91	90	91	91	90	89	0	0	17	17	54	54	0	50	50	50	50	50	50
15	0	91	0	0	91	90	91	91	90	89	0	0	17	17	54	54	0	50	50	50	50	50	50
16	0	0	0	0	0	0	0	0	0	0	0	0	0	17	57	57	0	0	0	0	0	51	51
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0
21	0	90	0	0	90	90	90	90	90	90	0	0	0	0	0	55	0	51	50	50	51	50	50
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The output of the unit commitment subtask is summarized in Table 2.4. It displays the hourly power generation of each of the 23 hydroelectric sets in the cascaded HPPs on the Daugava river. The operation of units is generally uniform, which is beneficial for the durability of equipment as frequent start-ups and shut-downs are detrimental to the equipment and cause a necessity for more frequent maintenance [72]. Only at 13 PM some units have an hour-long disconnection and at 21 PM – a single consecutive hour in operation. The latter is justified by following the last price peak, which enables gaining additional profit as opposed to a situation if the operation of the units was entirely uniform throughout the day.

2.7. Discussion regarding the model

Overall, the model performance can be considered to be satisfactory. It managed to abide by environmental constraints and produced reasonable generation schedules. Most importantly, it operates within acceptable timeframes. While generally the exact amount of time a full model run takes depends on the user and the machine where it is deployed, the timeframe registered in this experiment (below 10 minutes) allows to deem it suitable for use by actual HPP operators in preparing and processing bids to a power exchange. The time an optimization model takes to reach a solution is not of much concern for academic endeavors, but it is of paramount importance when adapting or developing models for practical applications. The novelty of the decomposition approach described in this study allows decreased computational time without sacrificing accuracy or abidance to environmental constraints. Furthermore, unlike in [53], the necessity to aggregate similar units into a united generator is evaded, instead modeling each of them individually at the last stage of the proposed approach. This enables both more detailed characterization of every hydroelectric set and easier model recalibration in case some units have undergone reconstruction.

While the model was tested on a case study basis, particularly, on the parameters of Daugava HPPs in Latvia and the corresponding environmental and electricity market data, the mathematical description can be adjusted to change the hydraulic scheme of reservoirs. Thus, by supplying the model with the characteristics of different HPPs and their reservoirs, the tool can easily be repurposed for a different case study or practical application.

There are, however, certain limitations currently in the proposed model. Firstly, as the results of the case study suggested, the forecasting procedure can fail to predict some price peaks, despite the fact that it employs ANN. While this can fully be explained by influences on the power market that cannot be identified by this particular implementation of ANN (e.g., disconnection of large generating units, transmission congestion etc.), a dedicated electricity market simulator [73] might be better suited for more accurate price forecasts. On the other hand, the ANN module can be enhanced further by incorporating seasonal variations, as in [74].

Secondly, the application of this model for other cascaded HPP systems might be hindered if sufficiently trustworthy data for the construction and validation of relationship curves is not available. Hence, close corporation between researchers and industry is necessary for meaningful testing and successful adaptation of any mathematical models and tools aimed at improving power plant scheduling.

Nevertheless, the model described in Section 2.2 and the subsequent case study confirms the feasibility of its use in practical power system application. It also opens the door for further studies. Two areas where this tool could be further refined is incorporation with the models of thermal plants for co-optimized hydro-thermal scheduling and, subsequently, detailed modelling of thermal and hydroelectric unit start-ups and associated costs. However, already at the current state the model can be and has been used for research purposes, such as evaluating the ability and costs of reserve provision [75], estimating the lost profit incurred due to environmental constraints [76] and generating HPP production time series data to be used in overall power system economic and reliability models.

2.8. Multi-objective approach

Most of the real-world problems involve several objectives (often conflicting) that need to be considered, thus leading to multi-objective optimization. For example, a generating company interested in maximizing its profit might also want to minimize the amount of emissions (called economic emission load dispatch [77] or economic environmental dispatch [78]) or, in another case, minimize risk and maximize reliability at the same time. In such a case, the solution should be provided as a set of optimal solutions instead of one optimum, because no single solution can be considered to be better than any others with respect to all objective functions [78]. A feasible solution to a multi-objective problem is efficient (also called non-inferior or Pareto optimal) if it is not possible to improve one of the objectives without depraving the others. The efficient set (also known as Pareto front or trade-off curve) represents the values of the objectives for efficient solutions [79].

One of the most widely used methods for generating efficient solutions is the weighted-sums approach [79], where the trade-off curve is obtained by changing the weight contribution of each single objective to the general objective. The weight factors can be adjusted depending on the importance of each objective [80]. For example, [77] proposes weighted minimax method and employs a stochastic approach (treating uncertainties as random variables) for economic emission load dispatch. In [78], solution for a similar problem in a hydrothermal system is presented by using multi-objective differential evolution. DP is employed in [79], whereby the multi-objective problem is formulated as weighted sum of objectives.

A GENCO operating HPPs aims to reduce the number of startups since it involves various costs due to loss of water during startup, wear and tear of equipment (generator windings as well as mechanical equipment), possible malfunctions of the control equipment during the startup and the resulting need of maintenance and loss of water during the maintenance [81]. It is even more important when operating cascade HPPs, since malfunction of control equipment in one of the plants can require rescheduling of the entire cascade and decrease energy production of the cascade. Minimization of the number of startups is also considered in [82] by employing a two-step genetic algorithm. The first objective considered in [82] is the maximization of hourly plant efficiency according to efficiency curves of each hydro unit.

In the following subchapters, the previously described cascaded HPP three-stage optimization tool (Section 2.2) is supplemented with additional functionality by the inclusion of an additional sub-objective, namely, the minimization of the number of startups and shutdowns. Solution of the multi-objective problem is provided as a Pareto optimal set, leaving the final choice up to the power plant operator.

In the overall model, the minimization of startups is assessed by constraining the minimum operating time of the units to respectively one, two and three hours, whereby the dispatch of hydro units is rescheduled retaining the objective of profit maximization. The HPP operators can thereby choose from a set of Pareto optimal solutions a strategy which either maximizes its profit in the short-term or allows more cost-effective scheduling of the hydro units in the longer term.

2.8.1. Case study: multi-objective optimization

For the purposes of testing the added multi-objective functionality of the overall optimization model, the case study will be based on one HPP, namely, the Plavinas HPP. In Figures 2.18–2.20, the schedule of the power plant is presented in both aggregated and per-unit basis, in order to illustrate the effect of the added constraint.

The charts on the left present the hourly power generation and cumulative profit, while the charts on the right indicate which units are online at each hour (marked by **X**). Evidently, the hydro units are operating only a part of the day given the amount of water available.

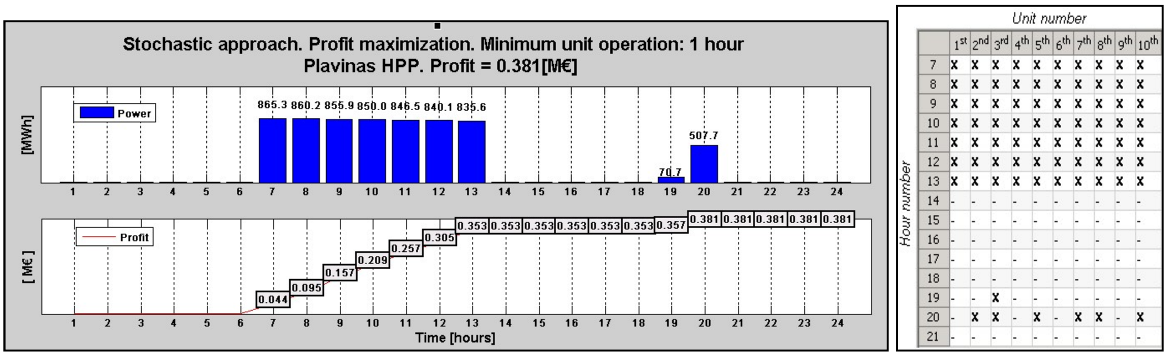


Fig. 2.18. Dispatch schedule of the HPP with 1-hour constraint (A).

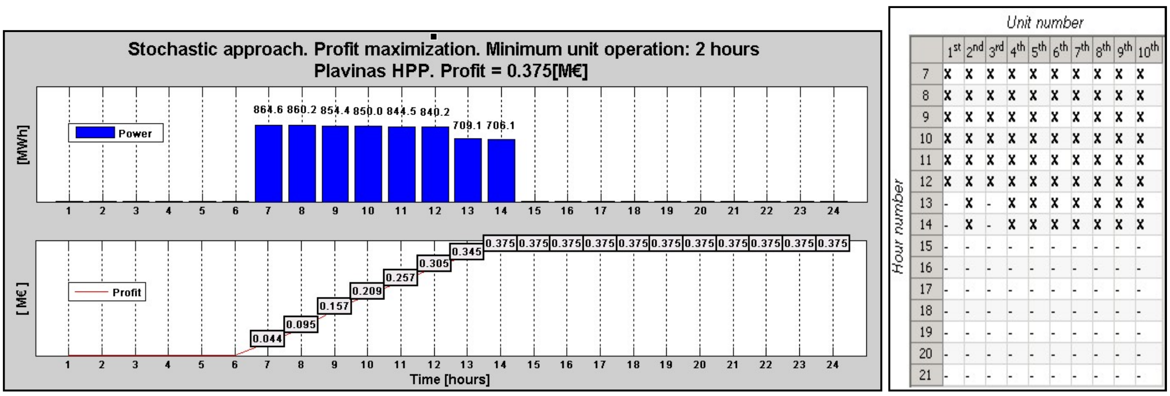


Fig. 2.19. Dispatch schedule of the HPP with 2-hour constraint (B).

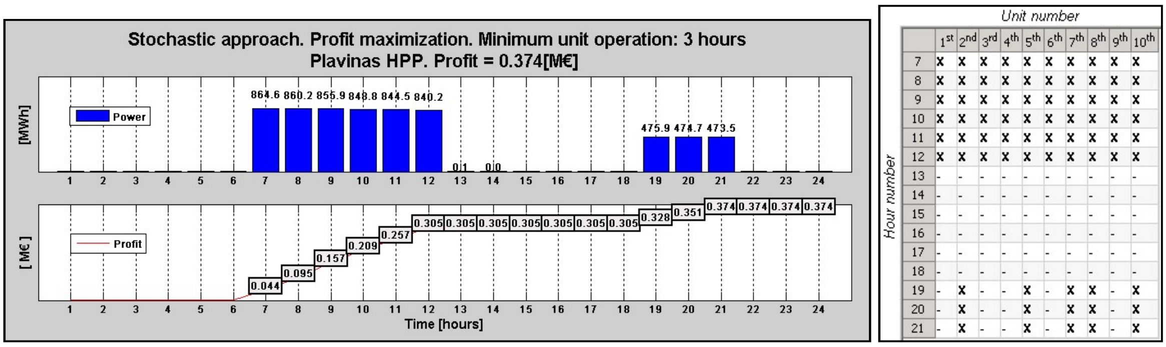


Fig. 2.20. Dispatch schedule of the HPP with 3-hour constraint (C).

Comparing all the three dispatch schedules, the maximum difference of the profit is about 7 000 €, while the number of startups varies from 10 to 16. The given results allow construction of a Pareto front (Fig. 2.21). Points A and B represent the non-dominant solutions and belong to the Pareto front since none of them is better than the other one with respect to both objective functions. However, point C is not on the Pareto front because it is entirely dominated by B in regard to both the profit and the number of startups.

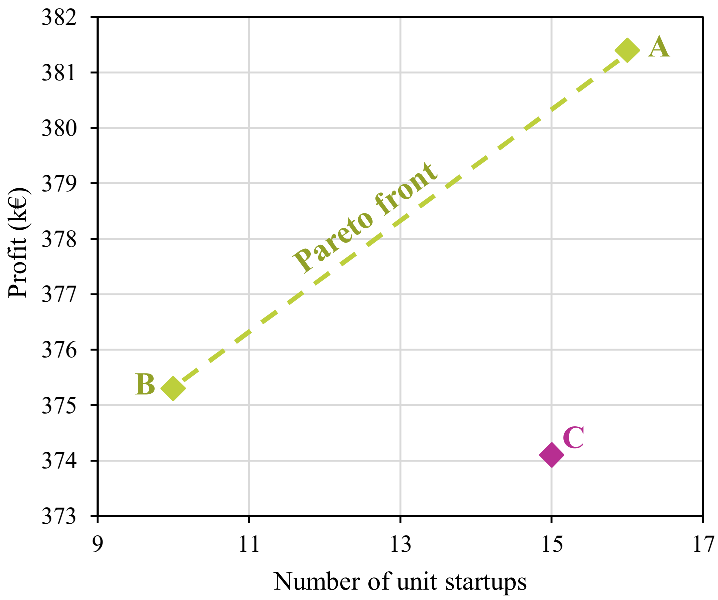


Fig. 2.21. Pareto optimal set of solutions for the case study.

The set of Pareto optimal solutions allows the HPP operator to make the final decision on the operating strategy to maximize its profit by also considering the number of startups.

2.9. Chapter conclusions

This chapter presented a practical stochastic modelling tool for obtaining the optimum profit-based daily and hourly schedules of cascaded hydropower plants, whereby the final model outcome is the generation schedule for each particular hydroelectric set. The optimization problem is stated and solved in accordance to a competition-driven electricity market structure, as opposed to vertically integrated power system. Additionally, the model is especially suited for HPPs with medium-sized reservoirs, i.e., poundage power plants that are not strictly run-of-river, but cannot provide seasonal regulation either. Hence, the first stage of the optimization problem is solved for a two-week horizon, increasing the complexity of the problem statement and model accuracy with each consecutive stage.

The stochastic nature of electricity price and water inflow is considered by using a self-adaptive ANN. All the modules of the tool, both forecasting and optimization models, were developed in the MATLAB scripting environment utilizing its toolboxes where possible. The mathematical model for the first two optimization stages was created by the team from RTU Institute of Power Engineering led by Professor A. Sauhats, whereby the software implementation was mainly carried out by Dr. sc. ing. R. Petrichenko. The author has contributed to all the development phases of the model, but especially so in regards to the final optimization stage – the unit commitment using dynamic programming, both in terms of the theoretical model definition and its integration in the overall software tool, as well as the incorporation of detailed reservoir and unit characteristics within the model. All the case study results presented throughout this chapter where obtained by the author.

Furthermore, the functionality of the HPP scheduling optimization tool has been further appended to allow for multi-objective approach. In the particular implementation, an ability to also consider the number of unit start-ups alongside the main objective (profit maximization) was tested. Various solutions and their adherence to multi-objective criteria can be well summarized by employing visualizations of the Pareto optimal set of solutions.

Apart from practical application by HPP operators, the model can also be further used for research purposes by incorporating it in larger power system models or, with some modifications, more directly in the assessment of reserve provision, wind power balancing or water value.

3. CHP PLANT MODELLING TO ASSESS IMPACT ON ELECTRICITY MARKET PRICE

3.1. Motivation for CHP and electricity market modelling

Several European countries have established support mechanisms for certain categories of electricity producers. There are primarily two reasons for this – increasing the share of renewable generation in the national portfolio and ensuring generation adequacy.

The latter is of particular importance in power systems that operate under energy-only electricity markets. Large power plants necessary for system reliability are often incapable of recouping their investments as the market price does not cover all of their marginal and fixed costs. It both puts the continued operation of current peak plants at risk and hinders investments in new reliable and flexible capacities which are necessary as backup generation to renewables [83]–[85].

On the one hand, capacity payments have been identified as an effective way to promote new gas-fired generators and prevent the mothballing of existing ones [86]. Furthermore, they have also been linked to electricity price spike reduction [84], [87]. On the other hand, capacity mechanisms are also viewed as problematic due to the risk of market distortions [88]. Consequently, the European Parliament has expressed in 2015 that "national capacity mechanisms should only be used as a last resort, once all other options have been considered" [89].

Support schemes for renewables and cogeneration in Latvia have been implemented since the mid-1990s and continued with several amendments until 2012 after which no new beneficiaries are accepted in the scheme [90]. However, support granted to the power plants before the moratorium is continued for up to 20 years depending on the generation technology. E.g., the large cogeneration plants studied in this chapter have been granted the support for 15 years since commissioning. It is estimated that the total support costs for all types of power plants under the scheme in place on 2017 would comprise around 4 billion € up to 2037 [90].

The support for renewables and cogeneration is largely covered by all electricity end-users in Latvia as a levy on their energy bills. By 2017, it formed a relatively large cost burden to customers [91], particularly to energy-intensive industries, and resulted in a noncompetitive final price of electricity compared to other European countries in the region [92]. This, along with the huge pressure from society, forced the responsible authority, the Ministry of Economics of Latvia, to reconsider the amount of support and this served as the main motivation for the study presented in this chapter of the Thesis. The work laid out here was carried out in the first half of 2017 and originally presented to the Ministry and wider public in the report "*Price of Electricity and Its Influencing Factors*" [93] and, subsequently, to the academic community in an article [94] presented at the 15th International Conference on the European Energy Market (EEM 2018). It should thereby be noted that input data, forecasts and assumptions utilized in this chapter are based on information and data available in the first half of 2017.

Similarly to other Northern European countries, there is a significant presence of district heating (DH) networks in Latvia. Meanwhile, support to cogeneration plants amounted to a significant part of the national support scheme. Consequently, as a first remedy to reducing the support payments, two high-efficiency combined heat and power (CHP) plants in Riga were considered – CHP-1 (with installed power of 144 MW_{el}) and CHP-2 (881 MW_{el}). These plants comprise about 35% of the total installed generation capacity in Latvia [95] and were first awarded state support in 2007. The support continues until 2021 for CHP-1 and until 2028 for CHP-2.

The Latvian transmission system operator (TSO) had already acknowledged the reliability and self-sufficiency value these plants bring [95]. Thus, the objective for this research was twofold: to assess the impact of the two CHP plants on the electricity wholesale price formation in Latvia through long-term modelling up to 2030 and to evaluate if support can be reduced without the risk of mothballing the power plants. A hypothesis was put forward that these plants are fundamental in restricting excessive price rise in the Latvian bidding area of Nord Pool. It was then verified through electricity market price simulations and techno-economic assessment of the feasibility of CHP operation with support payments reduced to a varying degree. The research presented in this chapter was carried out by the author of this Thesis in cooperation with Zane Broka under the supervision of Prof. Antans Sauhats. The main contribution of the author consists of the conceptualization and implementation of the simulation model as well as analysis and assessment of its results.

3.2. Factors influencing the electricity market price

3.2.1. Characterization of the Nord Pool market

As already described previously in Chapter 1.1, electricity wholesale trading in Latvia is carried out in the Nord Pool exchange. The Latvian bidding area there was opened on June 3, 2013, for day-ahead trading (Elspot) and on December 10, 2013, for intraday trading (Elbas) [96]. However, since nearly all of the electricity trades in the Latvian bidding area are performed in the day-ahead market[16], the subsequent considerations and analysis are focused on Elspot.

In terms of the volumes traded, Nord Pool is one of the largest electricity exchanges in Europe and it is operating in a number of countries, but most notably in Northern Europe (Norway, Denmark, Sweden, Finland) and the Baltic states (Estonia, Latvia, Lithuania). The large number of participants ensure high market liquidity and thereby also conceivably the lowest costs for electricity wholesale purchase.

The electricity market clearing price, called Nord Pool system price, is found at the intersection of the supply and demand curves (Fig. 3.1 [97][17]). This point represents the market equilibrium. For the day-ahead market these curves are constructed in the previous day by

[16] For instance, 99.8% of the electricity bought and 98.1% of the electricity sold in Latvia in 2016 [9]. Data assessed using Nord Pool database categories *Consumption*, *Production* and *Elspot volumes*.

[17] Data extracted from file *mcp_data_report_27-12-2016-00_00_00.xls*

aggregating for each particular hour the supply and demand bids according to their price and volume. The merit order list is obtained by ranking the bids according to their price. The bid price limits in Nord Pool are set equal to -500 €/MWh and 3 000 €/MWh as the lower and upper constraint respectively.

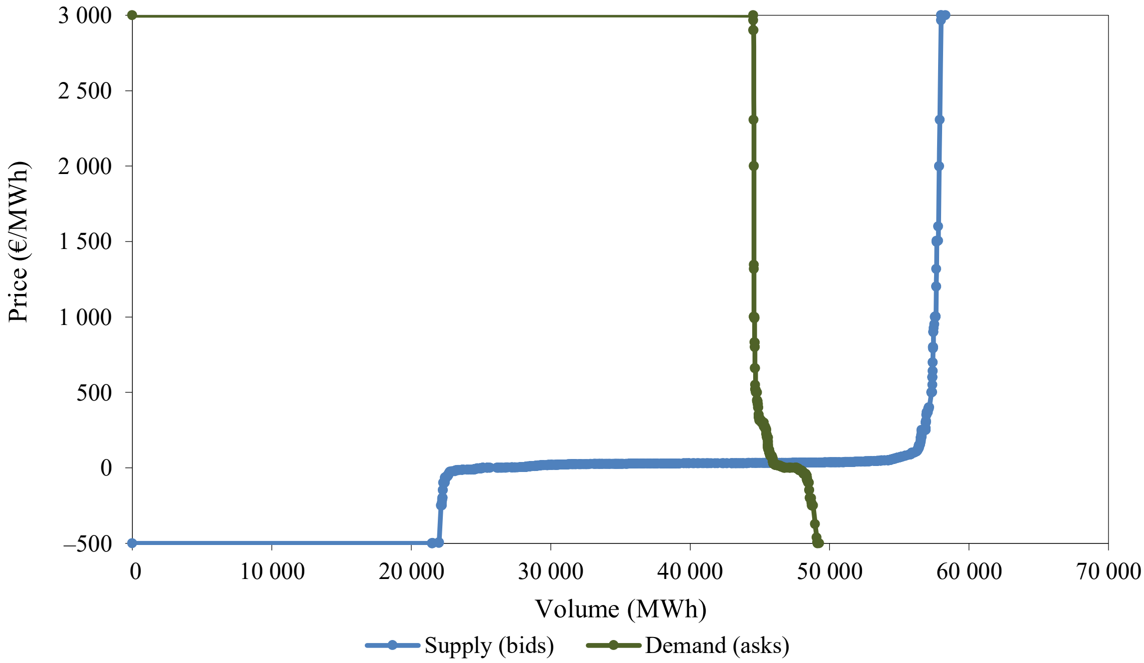


Fig. 3.1. Example of Nord Pool supply and demand curves (27.12.2016 at 10–11 AM CET).

The full price setting algorithm, however, is more complex as there are also other order types and not only single hourly orders. In the case of Nord Pool, there are also block orders (consisting of a number of consecutive hours), exclusive groups (a cluster of blocks whereby only one of them can be activated) and flexi orders (a block order where the time of activation is determined by the clearing algorithm). Nevertheless, "the largest share of the day-ahead trading is matched on single hourly orders" [98]. The peculiarities involved with the alternative order types introduce significant complexity to the market clearing process [99]. However, these issues are handled by the common European electricity market clearing algorithm EUPHEMIA [100]. Furthermore, the final system price also depends on the electricity market coupling flows to other bidding areas neighboring the Nord Pool region.

The main principle of electricity market clearing is maximization of the social welfare[18] [7]. In practice, this means that the electricity demand is covered by the least expansive generation units capable of covering the demand. Under conditions of perfect plant availability and divisibility with no transmission constraints (i.e., perfect competition), the equilibrium in energy-only markets is found at a price equal to the short run marginal costs of the most expensive accepted generating unit [101]. These marginal costs are mostly composed of the fuel, CO_2 emission and other operational & maintenance (O&M) costs per unit of energy produced.

[18] The social welfare is the sum of the consumer surplus, the supplier surplus and the congestion rent [100]

The system price resulting from the market clearing process serves as a reference for futures and forwards trades in electricity. However, to obtain the actual market clearing price in each of the Nord Pool bidding areas (as illustrated previously in Fig. 1.1), it is necessary to take into account the transmission constraints in all the interconnections. If a transmission constraint is violated in the market clearing process, a more expensive marginal offer has to be accepted in the area in direction to which transmission is congested, until the constraint is satisfied. Thereby, the clearing price in the deficit area increases and price differences between bidding areas arise.

As was already established in Chapter 1.1 and Table 1.1, the area prices in Latvia and Lithuania have consistently been very similar, in fact, equal for the vast majority of hours. This allows them to be considered, in essence, as the same price area for modelling purposes. However, in regards to Estonia, price equality is rarer, with the price normally being higher in Latvia whenever congestions on the Estonia-Latvia interconnector emerge. The trend did change notably in 2016[19] with the launch of the new 700 MW interconnector NordBalt[20] between Sweden (SE4) and Lithuania [102]. Previously, electricity imports from Scandinavia reached Latvia only through the interconnection with Estonia (via Finland), but the launch of NordBalt allowed for electricity to be imported to the Latvian/Lithuanian area directly from Sweden.

3.2.2. Characterization of the Latvian and Lithuanian power systems

Nearly 88% of the installed power in Latvia is operated by one producer's – Latvenergo AS[21] – five power plants:

- Daugava HPP cascade (1 536 MW) – Pļaviņas, Rīga and Ķegums HPP;
- Riga CHP-1 (144 MW);
- Riga CHP-2 (881 MW).

However, the production of the HPPs is to some degree influenced by weather conditions (i.e., natural inflow), whereas the CHP plants are also providing heating energy to the district heating network of the right bank of Riga.

The rest of the production sources can be separated in six groups [103]:

- small natural gas CHP plants (172 MW);
- wind power plants (71 MW);
- biogas power plants (66 MW);
- biomass power plants (58 MW);
- small HPP plants (29 MW);
- solar power plants (0.4 MW).

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[19] Price between the Estonian and Latvian bidding areas differed for 69.6% of hours in 2014, 66.1% in 2015, but only 29.2% of hours in 2016 [9].

[20] This HVDC cable became available for trading in the middle of February, 2016.

[21] Here and elsewhere in this subchapter the power systems are described as they were during the time of carrying out the modelling work, i.e., in the first half of 2017.

On the other hand, the total installed capacity of the Lithuanian power system at the beginning of 2017 was 3 558 MW. However, due to the high marginal costs and low competitiveness of the thermal plants, it is generally more cost-effective to mostly import electricity and start-up the more expensive plants only during cases of such necessity (i.e., scarcity). When that happens, it is sharply reflected in the electricity price spikes. Most of the installed power comes from cogeneration plants Lietuvos elektrinė (1 045 MW), Vilnius 3 (360 MW), Kaunas (170 MW) and producers at manufacturing facilities (292 MW) [104]. Water resources are significantly less developed than in Latvia (Kaunas HPP – 101 MW; small HPPs – 27 MW), however, the Kruonis pumped storage plant (900 MW) is significant. The total capacity of biomass, biogas and waste power plants constituted 108 MW and solar – 73 MW. The wind power capacity was six times larger than in Latvia – 438 MW [104].

The short-run marginal costs of producing electricity with hydropower or wind are very small. However, production from these resources in the Latvian and Lithuanian area is usually insufficient to cover the whole demand, thereby the market clearing price is mostly set by either electricity import or local thermal plants. As found by M. Balodis in [105], the highest prices in the region (150..200 €/MWh) occur if the marginal production unit is a heavy fuel oil or gas turbine plant.

3.2.3. Correlation analysis

In order to analyze what factors have the most influence on the electricity day-ahead market clearing price, correlation analysis is performed on various variables. For this analysis, hourly resolution data from May 1, 2016, to April 30, 2017, is used. This period was chosen to account for changes in price dynamics introduced by the commissioning of the NordBalt (SE4–LT) and LitPol (LT-PL) interconnectors at the beginning of 2016, and it constitutes a full year of data as available at the time of performing the analysis.

The correlation versus electricity day-ahead market clearing price in Latvia is assessed for the following variables:

- Nord Pool system price,
- electricity consumption,
- electricity production,
- usage (loading) of the most important interconnections,
- price of natural gas,
- price of CO_2 emission allowances,
- ambient air temperature.

Pearson's correlation coefficient [106] is used for the assessment as it is suitable for finding the linear correlation of a pair of samples of variables x and y, as in:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}, \tag{3.1}$$

where x_i , y_i – individual sample points of the variables;

$\overline{x}$, $\overline{y}$ – the mean values of the samples;

n – sample size.

The coefficient r describes the strength of the correlation and its value can be from –1 to 1. The closer it is to the bounds, the stronger is the correlation between the two studied samples of variables x and y. If its value is 0, then there is no linear correlation between the two variables. A positive coefficient means that an increase in x corresponds to an increase in y, but for a negative coefficient the opposite is true. The absolute value of the correlation coefficient $|r|$ can be interpreted as follows [107]:

- 0.80–1.00: very strong correlation,
- 0.60–0.79: strong correlation,
- 0.40–0.59: moderate correlation,
- 0.20–0.39: weak correlation,
- 0.00–0.19: very weak correlation.

However, results of correlation analysis ought to be considered cautiously – a strong correlation does not necessarily imply causation. Thereby, it is necessary to also take into account the potential influence of other parameters. The sample size is also of importance – the larger it is the more statistically significant are the results and vice versa. The results of the correlation analysis are as follows:

- Nord Pool system and bidding area prices

The correlation coefficient for Nord Pool day-ahead system (SYS) price and the price in the Latvian (LV) bidding area [9][22] from 05.2016 to 04.2017 is 0.45, which shows a moderate correlation between the two prices. If we plot the correlation (Fig. 3.2), several data points can be seen where the difference between the prices is very significant. For instance, for 70 hours the price in LV area exceeds 80 €/MWh (averaging 126.98 €/MWh), while the average SYS price in the same hours is only 32.60 €/MWh.

If these hours are excluded from the analysis, the correlation coefficient for the remaining 8 680 hours is 0.62, showing a stronger correlation. Notably, if we look at the 70 hours with the most expensive price, a common feature manifesting in 62 of them is the inability of the largest plant (Riga CHP-2) to participate in the market with full capacity (in 25 of these hours both Riga CHP-2 production units were down for maintenance and in the remaining 37 – one of the units [108], [109][23]) .

[22] Here and further on, Nord Pool price data extracted from data files *elspot-prices_2016_hourly_eur.xls* and *elspot-prices_2017_hourly_eur.xls*.

[23] Here and further on, power plant unavailability data extracted from Nord Pool *Urgent Market Messages* (UMM) service and ENTSO-E Transparency Platform section *Unavailability of Production and Generation Units*.

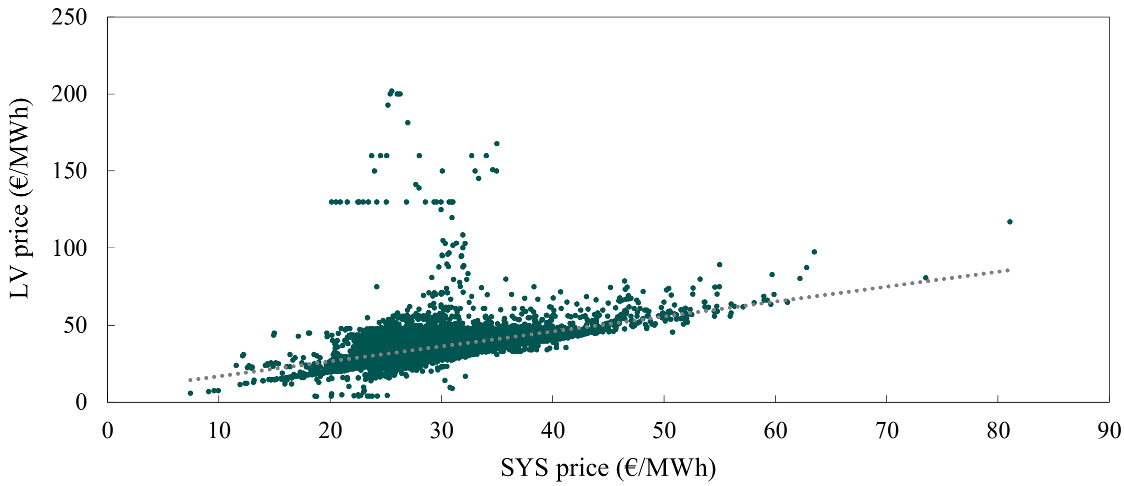

Fig. 3.2. SYS and LV day-ahead hourly market price correlation.

In those same 70 hours the price in the Lithuanian (LT) area was as high as in the LV area, and, in 50 of those, the NordBalt cable (connecting the Lithuanian and Swedish bidding area SE4) was unavailable. Furthermore, in 35 of these hours the maximum import capacity in the link between Estonia and Latvia (EE-LV) had been reached [9][24]. Since price differences are caused precisely because of reaching the allocated cross-border transfer capacities, in further analysis, it is useful to assess not only the whole year (8 760 hours) as a whole, but also separately analyze those hours when due to transmission congestions different area prices emerge. Thereby the overall data sample is divided in three additional subsets – 2 009 hours when there are different prices in Estonia and Latvia (designated as EE≠LV); 5 204 hours when the price is equal in Finland, Estonia, Latvia and Sweden SE4 (designated as FI=EE=LV=SE4) and another small subset of 162 hours for specifically when the SYS price equals the LV area price (SYS=LV).

Table 3.1. Correlation of the day-ahead market price of various Nord Pool bidding areas

	SYS	**SE1**	**SE2**	**SE3**	**SE4**	**FI**	**DK1**	**DK2**	**EE**	**LT**
SYS	1									
SE1	0.782	1								
SE2	0.782	1.000	1							
SE3	0.782	0.997	0.997	1						
SE4	0.772	0.958	0.958	0.963	1					
FI	0.692	0.886	0.886	0.890	0.871	1				
DK1	0.732	0.718	0.718	0.724	0.715	0.652	1			
DK2	0.705	0.888	0.888	0.892	0.929	0.826	0.804	1		
EE	0.681	0.879	0.879	0.883	0.864	0.979	0.648	0.820	1	
LT	0.440	0.627	0.627	0.631	0.649	0.708	0.458	0.629	0.725	1
LV	0.451	0.652	0.652	0.655	0.652	**0.729**	0.467	0.633	**0.746**	**0.967**

[24] Here and further on, the transfer capacities available for trading are extracted from the corresponding data files of *Elspot capacities*, whereas market flows – from the data files regarding *Elspot flow*.

In Table 3.1, the correlation coefficients between Nord Pool bidding area prices are summarized[25]. For the LV area price, there is nearly full correlation (0.967) with the LT area price, and it is notable also with the EE and FI area price (0.746 and 0.729 respectively), followed by SE4 and DK2.

- Electricity consumption in Latvia and Lithuania

The correlation coefficient of the total electricity consumption in Latvia and Lithuania in hourly resolution with the LV area price in the studied period (Fig. 3.3) is 0.52, which signifies a moderate correlation. If the 70 hours with the atypically high prices (> 80 €/MWh) are excluded, the coefficient becomes 0.69, showing high correlation between the market price and electricity consumption. This is in line with the principles of setting the market clearing price, whereby consumption is covered by the generating units with the least expensive marginal costs, i.e. with increased consumption it is necessary to accept more expensive units.

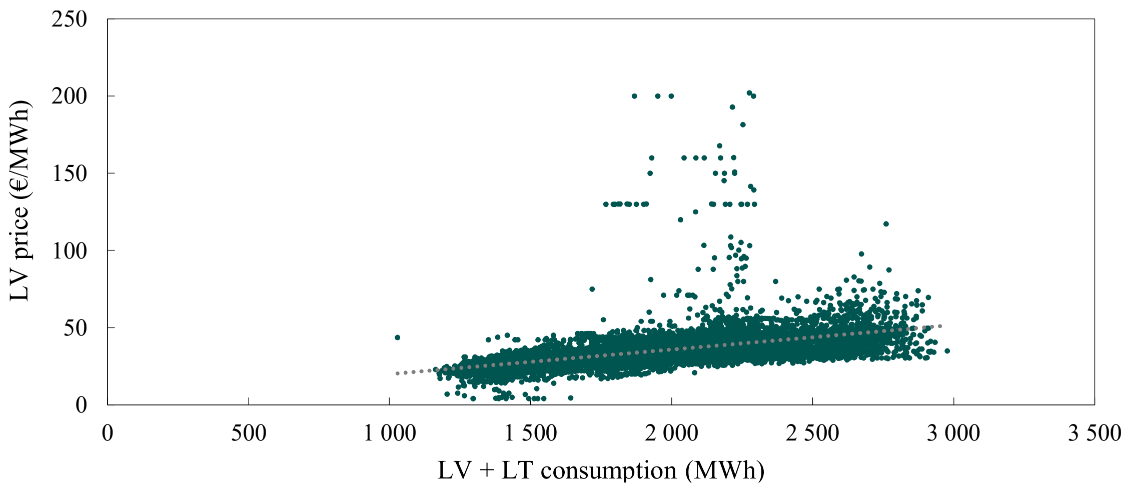

Fig. 3.3. LV and LT consumption and LV day-ahead hourly market price correlation.

If we look at the FI=EE=LV=SE4 subset, $r = 0.66$, but, in the EE≠LV subset, $r = 0.32$, and, in the SYS=LV subset $r = 0.55$. The more equal are the prices in Nord Pool areas, the higher is the LV area price correlation with the consumption in Latvia and Lithuania. This is influenced by effective operation of the market in the corresponding time periods, which reduces the need for expensive and rarely activated generation units, and also by smaller demand in the corresponding hours, due to which it is not necessary to fully utilize interconnections and thereby price differences do not emerge.

- Electricity generation in Latvia and Lithuania

When looking at the correlation of electricity production in Latvia and Lithuania with the local area price, the situation is very similar (Fig. 3.4). For the whole sample $r = 0.45$, but, when the 70 most expensive hours are excluded, $r = 0.57$, which, in whole, implies a moderate correlation.

[25] With the exception of the Norwegian bidding areas, since very low correlation was identified there.

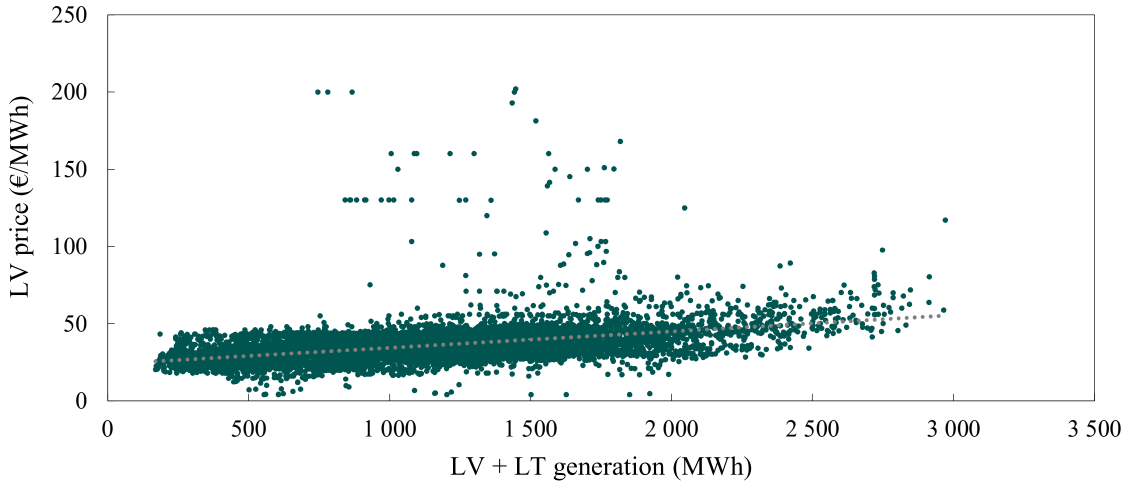

Fig. 3.4. LV and LT generation and LV day-ahead hourly market price correlation.

For FI=EE=LV=SE4, $r = 0.59$; for SYS=LV, $r = 0.53$; but for EE≠LV, $r = 0.36$.

- Electricity generation by source in Latvia, Lithuania and Estonia

In order to assess the correlation of the day-ahead market clearing price in Latvia with the electricity production per type of energy source, data from the ENTSO-E Transparency Platform is used [108][26]. In the results (Table 3.2–Table 3.4), those sources for which the hourly production in the period is relatively small (not exceeding 100 MWh/h) are considered statistically insignificant and subsequently colored in light grey.

Within the generation sources in Latvia (Table 3.2), the highest market price correlation (albeit moderate, $r = 0.424$) was found with electricity production in natural gas power plants. The positive correlation can be explained by the fact, that natural gas power plants normally would not be in operation when the market price is the lowest, due to higher marginal production costs. Their profitable operation can only be possible if the market clearing price reaches a sufficiently high level.

On the other hand, production in HPPs is mainly dictated by the natural inflow, thereby its correlation with the market price is very weak ($r = 0.132$, i.e., Latvian HPP plants in general are price takers). For the remaining generation sources in Latvia, the correlation with market price is also very weak.

This is also at least partially caused by the RES support schemes in place (i.e., mandatory procurement) which does not motivate the owners of these power plants to adjust their production schedules according to market-based factors [105]. Instead, for instance, biomass and biogas cogeneration plants schedule their operation in accordance to the heat demand profile, or maintain it relatively constant.

[26] Data extracted from section *Actual Generation per Production Type*.

Table 3.2. Correlation of electricity production sources in Latvia with the LV day-ahead hourly market price

	Natural gas	HPPs	Biomass	Other	Wind
All hours	**0.424**	0.132	0.082	-0.075	-0.124
EE≠LV	0.192	0.181	0.082	-0.044	-0.071
FI=EE=LV=SE4	**0.634**	0.177	0.314	0.124	-0.124

While analyzing the correlation of various Lithuanian electricity generation sources with the market price (Table 3.3), it is important to take into account the fact that, in total, a fairly small amount of electricity is generated there (about one quarter of the national consumption in the analyzed time period). The market price is moderately correlated with natural gas power plants (r = 0.401), however, the highest (but still moderate, r = 0.474) correlation is with the Kruonis PSHP[27]. This correlation points to this pumped storage plant having adapted to operation under liberalized market conditions. Furthermore, unlike in the Latvian HPPs which can operate at full capacity only during the spring flood season, Kruonis HPP is capable of full operation in the market all year round (except for periods of maintenance). The correlation with heavy fuel oil (HFO) plant production is even higher, but the overall volume of generation from this source is notably small[28]. On the other hand, electricity production in Lithuanian wind power plants is very weakly and negatively correlated with the market price.

Table 3.3. Correlation of electricity production sources in Lithuania with the LV day-ahead hourly market price

	Kruonis PSHP	Natural gas	Wind	HPPs	HFO	Solar	Waste	Biomass	Other
All hours	**0.474**	0.401	-0.153	0.080	0.542	0.331	-0.061	-0.033	0.038
EE≠LV	0.358	0.377	-0.123	0.045	0.545	0.307	-0.014	-0.064	0.063
FI=EE=LV=SE4	**0.491**	0.472	-0.120	0.233	0.515	0.188	-0.039	0.075	0.012

For Estonia (Table 3.4), there is some correlation with the LV area market price with production in oil shale power plants (r = 0.328). However, it is weaker than with Latvian or Lithuanian natural gas plants, possibly due to fuel costs of oil shale plants, whereby despite higher CO_2 emissions, their marginal costs are lower than in natural gas plants. As in Lithuania, Estonian wind power production is very weakly negatively correlated to the LV area price.

Table 3.4. Correlation of electricity production sources in Estonia with the LV day-ahead hourly market price

	Oil shale	Wind	Peat	Natural gas	Biomass	HPPs	Other RES	Waste
All hours	**0.328**	-0.145	-0.097	0.119	-0.085	-0.042	0.021	0.018
EE≠LV	0.148	-0.099	-0.123	0.163	-0.124	-0.052	0.041	0.041
FI=EE=LV=SE4	**0.488**	-0.115	-0.092	0.177	0.012	-0.081	-0.104	0.057

[27] In this analysis, Kruonis PSHP was considered in both consumption (pumping) and generation modes.
[28] Average hourly production from HFO – 15 MWh/h, maximum hourly production – 63 MWh/h [108].

- Electricity production and consumption in Nordic countries

When analyzing the correlation of the day-ahead market hourly price with consumption and production time series of the Nordic countries[29] (Table 3.5), a strong correlation between Nordic consumption and the system price can be identified ($r = 0.757$). Furthermore, it is greater than the correlation between Latvian and Lithuanian electricity consumption and the respective area price (0.520). This can be linked with the consumption in Northern Europe having more pronounced seasonal characteristics than in Latvia or Lithuania.

In terms of generation sources, Nordic HPP production strongly correlates with the SYS price and moderately – the LV area price ($r = 0.663$ and 0.492 respectively). On the other hand, price correlation with production in nuclear power plants (NPPs) and wind power plants is weak or very weak. This is because wind production mainly depends on weather factors, while NPPs try to maintain generally smooth profile and do not notably react to price signals. However, for HPPs, significant range for regulating their output is available, thereby adjusting to the consumption patterns. This allows Swedish and especially Norwegian HPPs to be used for covering the maximum demand, which also explains the notable correlation with system price.

Table 3.5. Correlation of Nordic electricity consumption and production with Nord Pool SYS price and LV area price

	Consumption	**Production (total)**	**Production (NPPs)**	**Production (HPPs)**	**Production (wind)**
LV price	0.282	0.308	-0.152	0.492	-0.108
SYS price	**0.757**	0.349	0.396	**0.663**	0.055

- Interconnection capacity utilization

Market flow in the four most important cross-border interconnections has been analyzed in terms of effect on the LV area price. For this assessment, the FI=EE=LV=SE4 subset of the sample (i.e., when the market clearing price is equal in the Finnish, Estonian, Latvian and Swedish 4th bidding area) is used. Hours when the market flow in a particular interconnection is zero are also excluded, since those correspond to interconnector unavailability, but the aim is to assess correlation in normal operating conditions.

Table 3.6. Correlation of electricity market flow with the LV day-ahead hourly market price

Interconnection	SE4–LT	FI–EE	EE–LV	LV–LT
Coefficient *r*	-0.169	**-0.205**	-0.094	**0.301**

Even though the correlation is overall small (Table 3.6, Figures 3.5–3.8), a trend is observable whereby the electricity market flow in directions SE4→LT, FI→EE and EE→LV decreases the market price in Latvia. On the other hand, flow in the direction LV→LT increases it. This is in line with electricity market principles – electricity flows from areas with lower local marginal production cost to areas where the cost is higher, thereby equalizing the prices across the regions (as long as transmission constraints are not active).

[29] Those Nordic countries who have Nord Pool bidding areas – Norway, Sweden, Denmark and Finland.

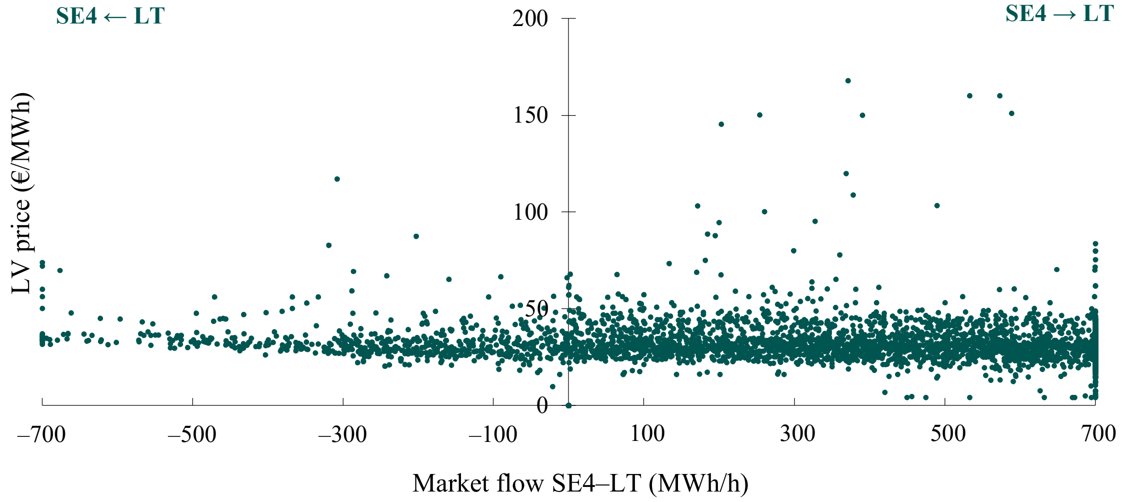

Fig. 3.5. Market flow SE4–LT and LV day-ahead hourly market price correlation.

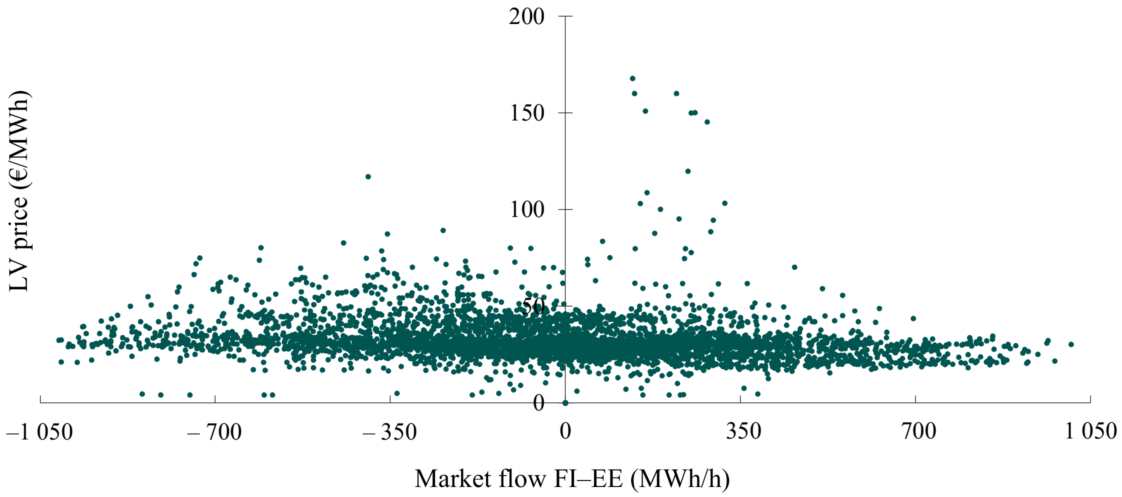

Fig. 3.6. Market flow FI–EE and LV day-ahead hourly market price correlation.

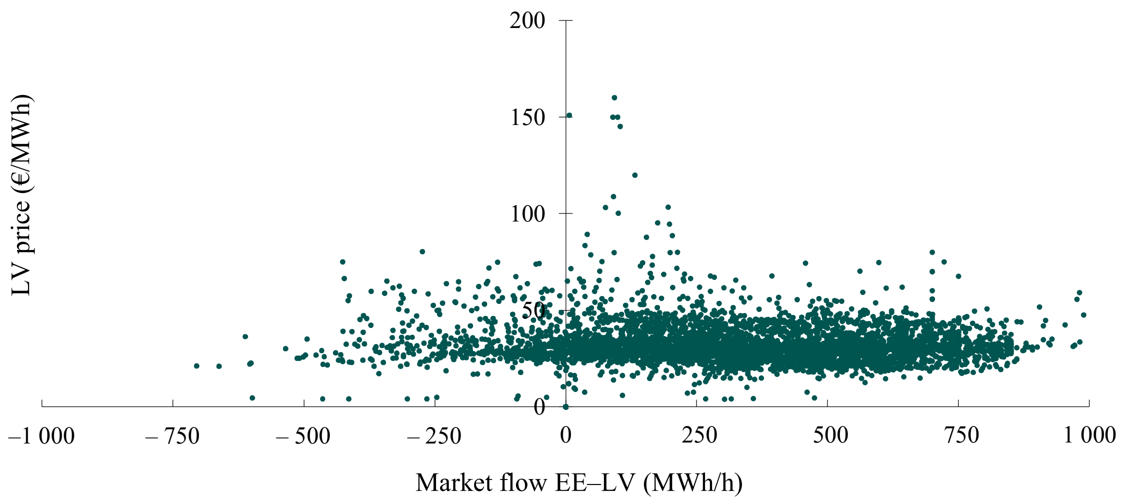

Fig. 3.7. Market flow EE–LV and LV day-ahead hourly market price correlation.

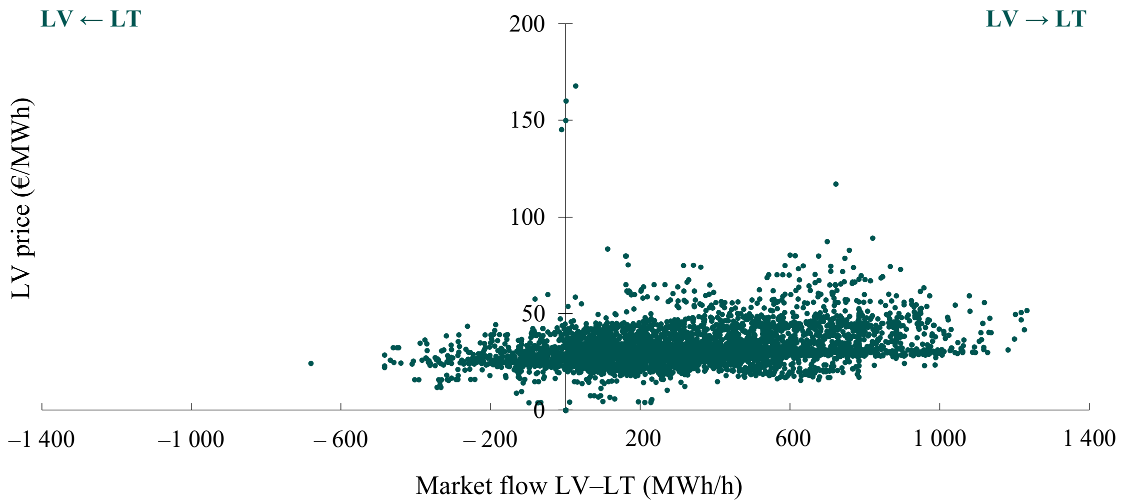

Fig. 3.8. Market flow LV–LT and LV day-ahead hourly market price correlation.

- Price of natural gas

To assess the correlation between electricity market price and natural gas price (Fig. 3.9), the monthly gas trading price of the incumbent natural gas trader Latvijas Gāze AS[30] was used [110]. Accordingly, instead of hourly day-ahead electricity market prices, here the monthly weighted average prices[31] were utilized. The resulting correlation coefficient r = -0.626 shows a strong, but, unexpectedly, negative correlation. On the one hand, this could be explained by peculiarities in the gas procurement process. However, more importantly, the sample size is overly small for this analysis (n = 12) to be of significance due to the necessity to use monthly values instead of hourly as before. Consequently, this result should be viewed with caution.

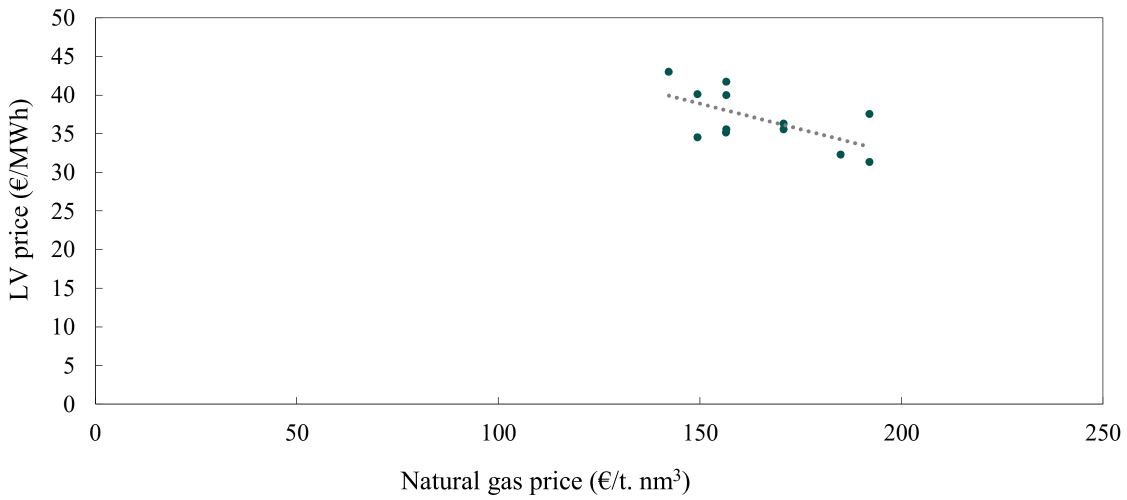

Fig. 3.9. Natural gas monthly price and LV day-ahead weighted monthly average market price correlation.

[30] This corresponds to the natural gas trading monopoly situation in Latvia as it was before April 2017, when the market was liberalized.

[31] Here and further on, the weighted average electricity market prices are weighted taking into account the volumes of electricity traded in each trading interval (i.e., hour) within the analyzed period.

- Price of CO_2 emission allowances

Emission allowance auctions are not hourly, thereby, for the purposes or performing this analysis, the correlation between weighted weekly average day-ahead electricity market price and weekly average CO_2 allowance price at the last auction [111][32] was studied (Fig. 3.10). The coefficient (r = 0.060) in conjunction with the limited sample size (n = 52) do not allow to establish a correlation between these two variables in the sample studied. Furthermore, in the time period considered, CO_2 allowances constituted a fairly minor part of the whole production marginal costs, especially compared to the fuel costs.

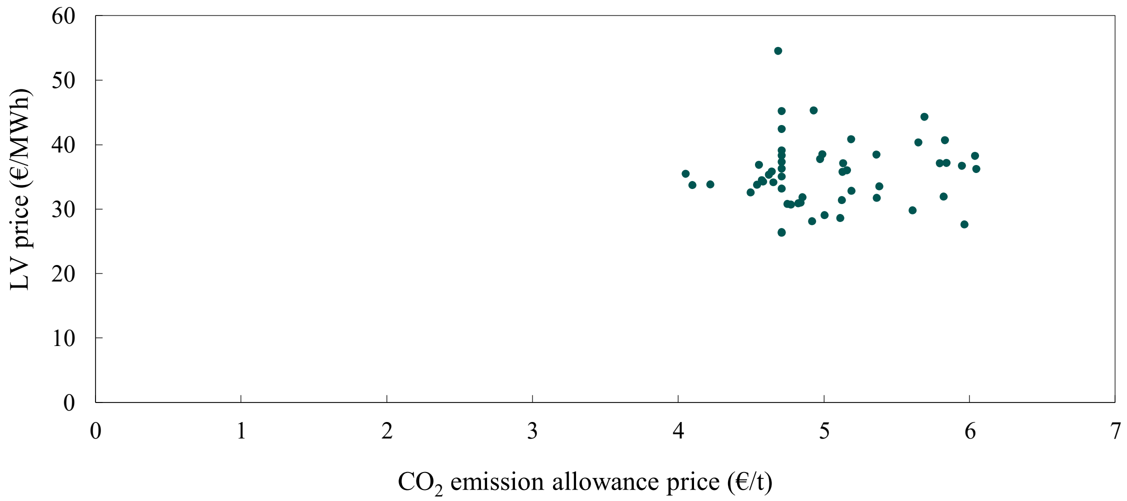

Fig. 3.10. CO_2 emission allowance price and LV day-ahead weighted weekly average market price correlation.

- Ambient air temperature

For this analysis, the actual registered hourly ambient air temperature in the capital of Latvia, Riga, is used [112][33]. For the whole year, r = 0.066; for the EE≠LV subset, r = 0.103; for the FI=EE=LV=SE4 subset, r = -0.211. The negative coefficient in the last case shows that the electricity market price tends to increase as the air temperature decreases and vice versa. Partly, this can be explained by more pronounced need for thermal power plant participation in the market and rising electricity consumption in the winter (especially pronounced in the Nordic countries). Nevertheless, the correlation identified ranges from very weak to weak.

To summarize the correlation analysis laid out in Chapter 3.2.3, it can be concluded that electricity day-ahead market price in the Latvian bidding area has the strongest positive correlation with consumption and production in Latvia and Lithuania, as well as the production from certain types of energy sources – Baltic natural gas and oil shale plants, Kruonis PSHP and Nordic HPPs. In other words, larger consumption is met by larger production, which

[32] Data extracted from files *emission-spot-primary-market-auction-report-2016-data.xls* and *emission-spot-primary-market-auction-report-2017-data.xls*.

[33] Data parameter: *Air temperature, actual*; Observation station: *Rīga – Universitāte*.

increases the market clearing price, and thus allows the activation of production plants with higher marginal costs.

The price in the Latvian bidding area is very strongly correlated with the price in the Lithuanian area, and strong correlation is also with Estonia and Finland, moderate – with Sweden. Electricity market flow from Finland and Estonia to Latvia aids in decreasing the price, whereas the flow from Latvia to Lithuania, increases it.

In the time period studied (May 1, 2016 – April 30, 2017), no strong correlation could be identified between electricity market prices and natural gas or CO_2 allowance price. On the other hand, there is minor negative correlation with the ambient air temperature in the FI=EE=LV=SE4 subset.

The most important factors analyzed in this subchapter are used further on in modelling the electricity market and assessing the role of Riga CHPs in setting the market clearing price in Latvia.

3.2.4. Analysis of hourly prices in the Latvian bidding area

To more thoroughly assess under what conditions do exceptionally high price spikes occur in the Latvian bidding area of the Nord Pool day-ahead market, the hourly prices from 2016 were analyzed. This period was selected as it contains more hours with atypically high prices than, for instance, 2017.

Nevertheless, also in 2016 exceptionally high price spikes were observed relatively rarely and in 92.4% of hours the price did not exceed 50 €/MWh (Table 3.7). Most often (~29.3% of hours) the price was in the range 25–33 €/MWh, followed by 33–41 €/MWh (in 25.8% of hours) and 41–50 €/MWh (19.9%).

Price higher than 50 €/MWh occurred only in 671 hours within the year. Higher than 100 €/MWh it was only in 105 hours (1.2% of all hours), higher than 150 €/MWh – 39 hours (0.4%). The highest price, above 200 €/MWh, occurred in only 19 hours (0.2%).

Table 3.7. Rate of occurrence of various day-ahead prices in LV bidding area (2016)

Price range	Number of hours	% of all hours
≤ 50 €/MWh	7 950	92.4%
> 50 €/MWh	671	7.6%
> 100 €/MWh	105	1.2%
> 150 €/MWh	39	0.4%
> 200 €/MWh	19	0.2%

The occurrence of prices in the equal or below 50 €/MWh range is further broken down in a histogram in Fig. 3.11, and a duration curve of the recorded day-ahead price statistics is presented in Fig. 3.12.

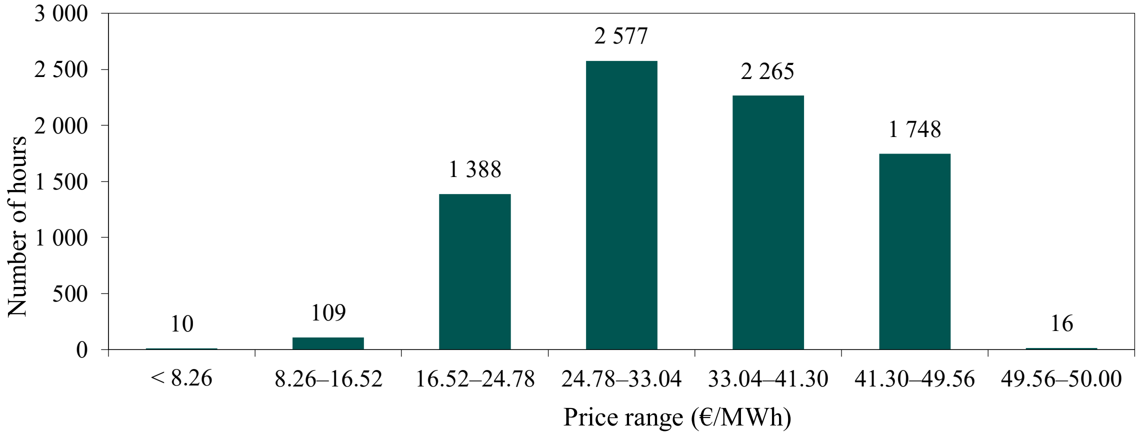

Fig. 3.11. Histogram of the day-ahead prices (≤ 50 €/MWh) in LV bidding area in 2016.

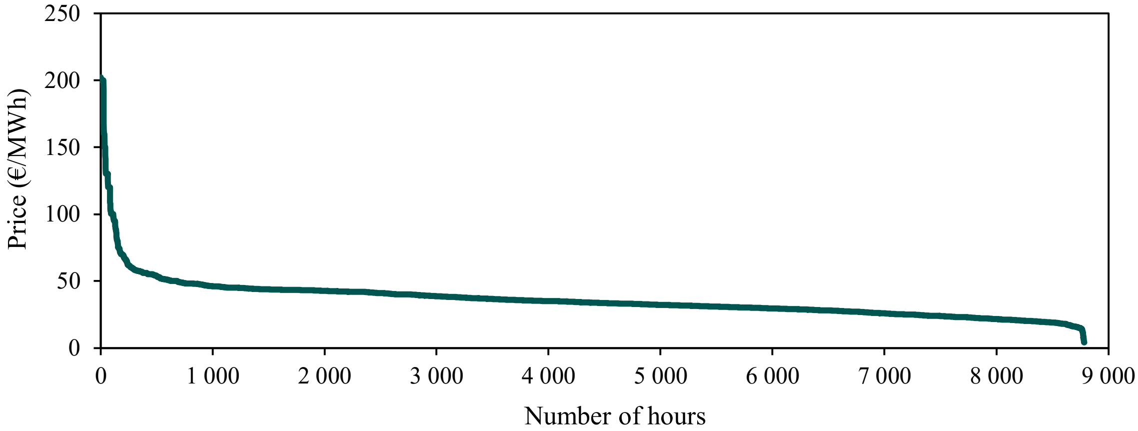

Fig. 3.12. Duration curve of the day-ahead prices in LV bidding area in 2016.

If we assume the marginal costs of Riga CHPs to be in the range of 30–50 €/MWh, evidently the market price falls within this range for 5 176 hours or 58.9% of the year. By estimating the marginal production costs of Riga CHPs in more detail for each hour of the year, and using the actual statistics of the plant operation in 2016, it is possible to identify the hours when either Riga CHP-1 or CHP-2 have been the price setting generation unit in the Latvian bidding area. Afterwards a hypothesis can be made, stating that if these plants were unavailable then taking also into account the transmission congestions, generation units with greater marginal costs (i.e. in the range of 100–200 €/MWh), would become the price setters.

A common trait of the 105 of most expensive hours in 2016 (> 100 €/MWh) is that in 93 of them the NordBalt cable was not available for market transactions. Evidently, whenever this cable is out of service or with limited transmission capacity, the role of local generation sources significantly increases. Another important characteristic of the most expansive hours is that in only 19 of them both units of Riga CHP-2 were operational (for 58 hours either of the units were unavailable, but for 28 – both of them).

The impact of Riga CHP-2 on the market clearing price can be observed all through 2016. For instance, whenever it was unavailable due to planned or unforeseen maintenance, the average day-ahead price was 68.30 €/MWh, but whenever Riga CHP-2 was available to participate in the market, the average price in Latvia was 39.09 €/MWh.

3.3. Modelling methodology

The overarching task of the research work presented in Chapter 3 is assessing the impact natural gas cogeneration plants Riga CHP-1 and Riga CHP-2 have on the market clearing price in the Latvian bidding area of Nord Pool till 2030 by employing mathematical modelling. Both plants received capacity payments in accordance to Cabinet Regulation No. 221 [113]. In addition, the possibilities to receive the support payments to 75%, 50%, 25% and 0% of the current level, and the subsequent impact of such actions is analyzed. In accordance to information published by the Ministry of Economics [114], the annual capacity payment to Riga CHP plants constituted 99.88 mill. €[34].

As described in the previous subchapter, electricity market price is affected by a number of factors: consumption, production in various countries and various types of power plants, production costs, transmission capacities and flows etc. All of these parameters vary in time, thereby for long-term modelling forecasts have to be used based on assumptions. However, it is important to keep in mind that for long-term scenario modelling it is not possible to obtain results with absolute certainty, i.e., scenario modelling results are not and should not be interpreted as forecasts. Instead, they are useful indicators to evaluate the possible effect of certain decisions.

3.3.1. Modelling approach

To quantitatively assess the impact of both CHP plants on the day-ahead market clearing price, a market simulation model was devised (shown in Fig. 3.13). The model includes approximated bids of all types of power plants in the considered bidding areas and a more accurate production model of the Riga CHP plants to enable detailed techno-economic feasibility calculations.

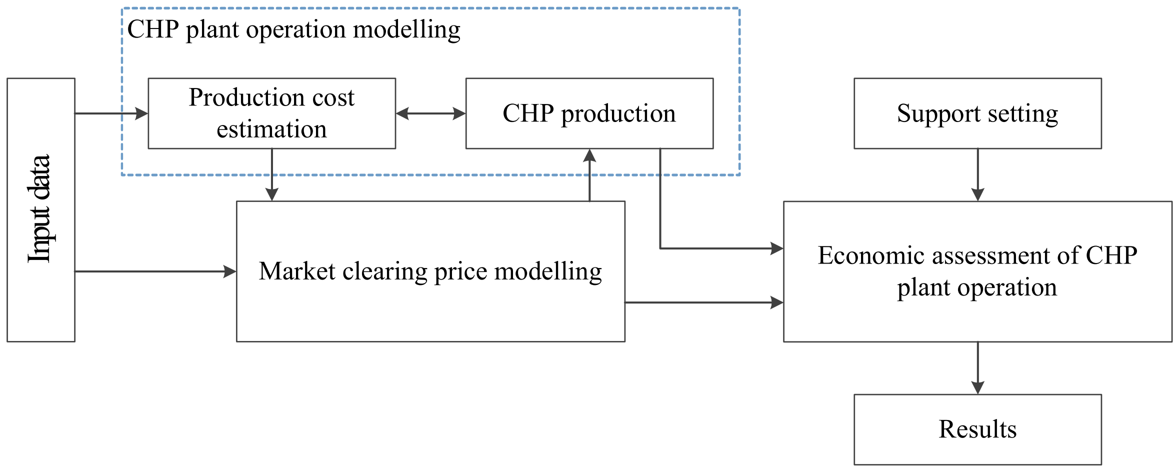

Fig. 3.13. The overall structure of the model.

[34] This is the maximum amount of annual support, not taking into account subsidized electricity tax and capacity payment correction. However, the deductions are accounted for in the mathematical model.

The algorithm is comprised of the following main steps:

1. Read the input data for each particular year.
2. Taking into account the price of natural gas and CO_2 emission allowances, as well as the heating load demand, calculate the variable production costs (short-run marginal costs) for each of the CHP unit in cogeneration, condensing and mixed modes[35].
3. Model the supply-demand equilibrium to estimate the market clearing price for each hour of the year as follows:
   a) consumption, non-fossil generation and interconnector power flow time series are used as input based on historical data and future assumptions;
   b) local fossil sources, including Riga CHP plants, are activated in a step-wise manner based on their marginal costs until the demand is met (i.e., following a merit order list).
4. Return the resulting market price signal to the CHP model, which calculates and selects the operational mode and amount of energy to be produced corresponding to the price.
5. Finally, calculate and compare various Riga CHP plants expenditure and income positions to evaluate profitability of the plant operation in the particular year modelled.

3.3.2. CHP production model

In the overall structure of the algorithm (Fig. 3.13), CHP operation modelling is utilized twice in each iteration. Firstly, it is used to estimate the short-run marginal costs and pass them to the market simulation model. Secondly, once the market clearing price is known, the CHP model is used to generate the production profile and calculate the corresponding indicators in accordance to the market situation.

The following technical parameters of the Riga CHP plants are incorporated in the model[36]:

- Both plants supply the same district heating network. It is assumed that during the heating season CHP-1 supplies 40% of the demand, but CHP-2 – 60%[37], whereas in summer (hot water provision), it is covered fully by CHP-1.
- Electricity self-consumption in the plants is assumed to be 5%[38].
- The technical minimum of electrical power – 185 MW (CHP-2.1), 148 MW (CHP-2.2) and 45 MW (CHP-1).
- Installed electrical power – 407 MW and 419 MW for CHP-2.1 and CHP-2.2 in cogeneration mode and respectively 437 MW and 439 MW in condensing mode [115]; 144 MW for CHP-1 (only cogeneration mode) [116].

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[35] Both Riga CHP-1 (one unit) and CHP-2 (two units) are capable of high efficiency cogeneration modes, whereas condensing (no heat energy production) and mixed modes are only possible in the two units of CHP-2.

[36] All the input data and assumptions used for the research described in Chapter 3 were sourced only from publicly available data and no proprietary information was used. The reason for this was twofold – firstly, the final report would have to be publicly accessible, and, secondly, the policy-maker decisions stemming from the conclusions of this research would directly affect the company holding any potentially useful proprietary data. Thereby, to avoid any conflicts of interest, such data was neither requested nor utilized.

[37] This ratio is obtained by analyzing the total annual heat production data as presented in the plant operator Latvenergo AS annual reports [11].

[38] Obtained from annual reports [11] by comparing the amounts of produced and supplied electricity.

- Installed heat power – 274 MW, 270 MW and 145 MW in respectively CHP-2.1, CHP-2.2 and CHP-1, whereas installed power of heating boilers on CHP-2 premises is 580 MW, but on CHP-1 premises – 348 MW.
- The ratio of electrical vs heating energy production in cogeneration mode is assumed to be 1.49 (CHP-2.1), 1.55 (CHP-2.2) and 0.99 (CHP-1)[39].
- Efficiency – 0.8690 and 0.8819 in cogeneration and 0.5577 and 0.5561 in condensing mode for CHP-2.1 and CHP-2.2, but 0.8854 for CHP-1. In reality, the efficiency coefficients are dependent on various factors, e.g., electrical power, ambient air temperature, however, to correctly approximate such nonlinearities, multi-year data of operational parameters of the plants would be required, which is sensitive proprietary information. Since within this research only publicly available data has been used, the coefficients in the model are considered to be constant.
- The CO_2 emission factor for natural gas is assumed to be 0.2002 t/MWh [117].
- the efficiency of the water heating boilers is assumed to be 0.92 (akin to high efficiency boilers).

The hot water boilers are installed to cover peak demand of heating during cold spells or to supply heating when the cogeneration mode is either technically or economically unfeasible.

The procedure to estimate the cost of energy produced starts with distribution of the heating load among the plants:

$$Q^t_{\text{CHP-1}} + Q^t_{\text{CHP-2}} = k \cdot Q^t_{\Sigma} + \left(1-k\right) \cdot Q^t_{\Sigma}, \tag{3.2}$$

where Q^t_{Σ} – total heat demand (MWh) during hour t;

$Q^t_{\text{CHP-1}}$, $Q^t_{\text{CHP-2}}$ – heat load to be covered by each plant (MWh);

k – coefficient to expresses the division of the heat load in the DH network.

The amount of electricity to be produced by each power unit n of the CHP plants depends on the hourly heating load assigned to it, Q^t_n. Thus, the amount of electricity to be produced in cogeneration mode by power unit n (MWh):

$$E^t_{n\ \text{cog.}} = \begin{cases} a_n \cdot Q^t_n \cdot A^t_n & \text{if } \ Q^{\min}_{n\ \text{cog.}} \le Q^t_n \le Q^{\max}_{n\ \text{cog.}} \\ a_n \cdot Q^{\max}_{n\ \text{cog.}} \cdot A^t_n & \text{if } \ Q^t_n > Q^{\max}_{n\ \text{cog.}} \\ 0 & \text{if } \ Q^t_n < Q^{\min}_{n\ \text{cog.}} \end{cases} \tag{3.3}$$

where a_n – coefficient expressing the proportion of electricity production versus heat production;

A^t_n – binary variable designating the availability of power unit n at hour t;

$Q^{\min}_{n\ \text{cog.}}$, $Q^{\max}_{n\ \text{cog.}}$ – technical constraints on the heat production in the power unit.

[39] Obtained as a ratio of the installed electrical and heating power.

Similar calculations are carried out also for the condensing and mixed operation modes of CHP-2. For the condensing mode, no heat load is necessary, but the efficiency is thereby lower, whereas for the mixed mode, some heat energy is produced, thereby the overall efficiency depends on the heating demand covered by the units.

The cost of electricity produced in any of the modes, $C^t_{n\ \mathrm{E}}$, is comprised of two main components: the cost of fuel and the cost of carbon emissions:

$$C^t_{n\ \mathrm{E}} = C^t_{n\ \mathrm{E,\,G}} + C^t_{n\ \mathrm{E,\,CO_2}} \tag{3.4}$$

of which

$$C^t_{n\ \mathrm{E,\,G}} = \underbrace{\frac{E^t_n}{E^t_n + Q^t_n} \cdot G^t_n}_{G^t_{n\ \mathrm{E}}} \cdot c_{\mathrm{G}} \cdot 10^{-3}, \tag{3.5}$$

where E^t_n – the amount of electricity produced (MWh);

η_n – efficiency of generation unit;

G^t_n – total fuel (natural gas) consumption of the power unit (nm^3);

$G^t_{n\ \mathrm{E}}$ – fuel consumption for electricity production (nm^3);

c_G – fuel price (€/t.nm^3);

and

$$C^t_{n\ \mathrm{E,\,CO_2}} = \underbrace{G^t_{n\ \mathrm{E}} \cdot Q_{\mathrm{LHV}} \cdot f_{\mathrm{CO_2}}}_{Em^t_{n\ \mathrm{cog.\,E}}} \cdot c_{\mathrm{CO_2}}, \tag{3.6}$$

where Q_{LHV} – lower heating value of the fuel (MWh/nm^3);

$f_{\mathrm{CO_2}}$ – CO_2 emission factor (t/MWh);

$Em^t_{n\ \mathrm{cog.\,E}}$ – CO_2 emissions from electricity production (t);

$c_{\mathrm{CO_2}}$ – cost of CO_2 emission allowances (€/t);

Finally, the marginal cost of electricity (€/MWh) used for bidding to the market is determined for each operation mode:

$$c^t_{n\ \mathrm{E}} = \frac{C^t_{n\ \mathrm{E}}}{E^t_n - E^t_{n\ \mathrm{s.c.}}}, \tag{3.7}$$

where $E^t_{n\ \mathrm{s.c.}}$ is the self-consumption energy of power unit n at time t (MWh).

The resulting marginal costs along with the corresponding amounts of generation for all technically feasible modes of CHP plants are then passed to the overall market simulation model.

The market clearing model outputs the wholesale price signal based on the established supply-demand equilibrium which is then compared to the marginal costs of the CHP plants to select the operational mode for each power unit as illustrated in Fig. 3.14. The variable c^t_{LV} represents the market clearing price in the bidding area where the CHP plants in question operate – in this case, it is the Latvian area of the Nord Pool.

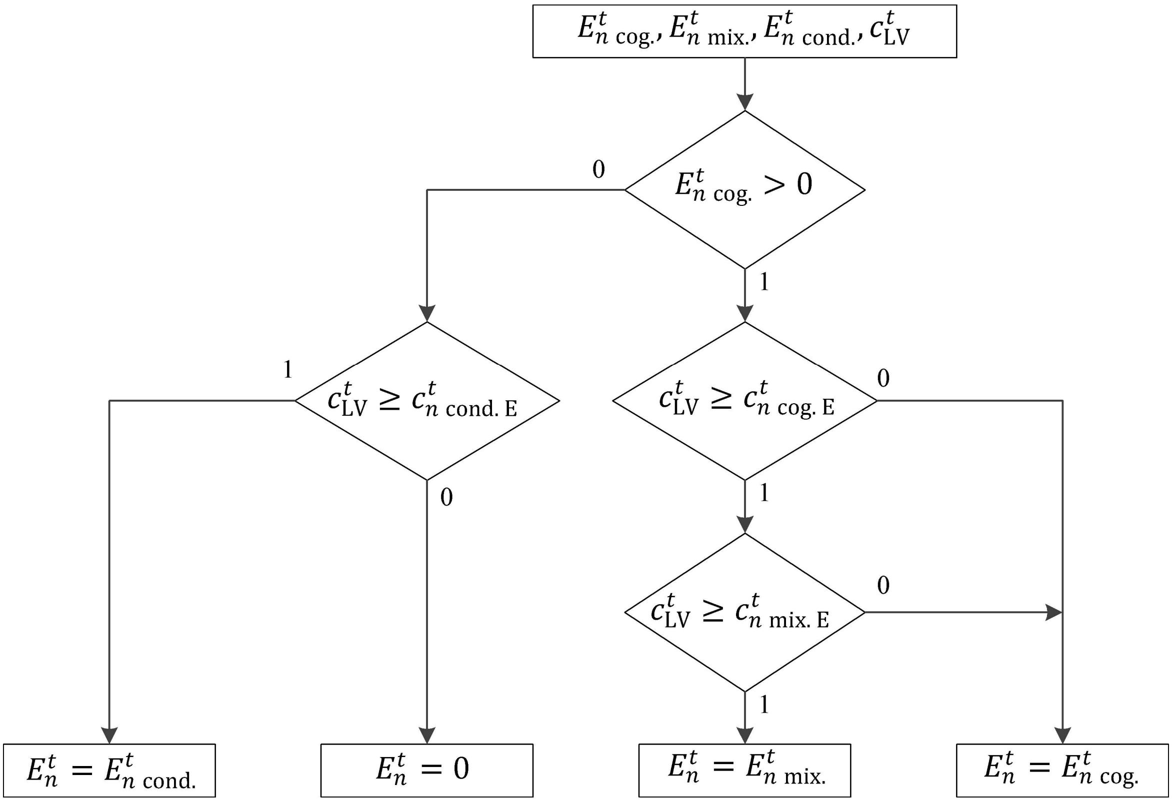

Fig. 3.14. Decision logic for power generation mode selection of CHP plants.

Once the operational mode and amount of electricity production is known, as well as the heating energy production and means of doing it (in cogeneration or with hot water boilers), it is possible to calculate all the costs of energy production, as well as the income from selling the electricity in the market and the heating energy to the district heating network operator.

However, as follows from Eq. (3.3), the heating load to be covered by the CHP plants significantly affects the amount of electricity which can be produced in cogeneration or mixed modes and subsequently also its marginal cost. Thereby hourly heating demand time series is required for the operation of the model.

In this study, the hourly heating demand time series is simulated utilizing some public data sources. Namely, the sum amount of heating energy sold to the district heating network operator in 2016 (2 416 GWh [11]) and the actual registered hourly ambient air temperature in Riga [112]. This data is used to construct an equation to approximate hourly heating demand from hourly ambient air temperature.

Firstly, the off-season (summer) heating demand is assessed. For purposes of simplification, it is assumed to be equal for each hour within the off-season. Based on Latvenergo AS public annual reports [11], it is found that in the 3rd quarter of 2016 (01.07–30.09), the sum heating energy production was 179 GWh or, on average, 81 MWh/h. Secondly, by assuming the time period of the off-season to be from 01.05.2016 to 30.09.2016, it can be estimated that during the heating season the sum production of heating energy is about 2 118.6 GWh.

To obtain the heating demand hourly profile during the heating season, an optimization task is solved to find the coefficients of a 2nd order polynomial approximating heating demand from ambient temperature. The objective function is error minimization, whereby an error is the mismatch between the set total heating load in the season and the sum load of the hourly approximated values.

Of course, such a problem statement can produce many solutions most of which would not resemble a realistic demand profile, thereby to obtain a result which allows constructing believable and trustworthy hourly heating demand profiles, additional constraints are introduced – during the warmest hour of the heating season the heating load must be exactly 100 MWh, but during the coldest hour, it must be within the constraints of 990 to 1100 MWh. The resulting heating demand approximation polynomial is as follows:

$$Q(T) = 0.418 \cdot T^2 - 25.152 \cdot T + 407.877, \tag{3.8}$$

where T – the actual ambient air temperature at any given hour (°C);

$Q(T)$ – hourly heat demand corresponding to the ambient air temperature (MWh/h).

3.3.3. Market clearing price modelling

The estimation of hourly market clearing price in the Latvian bidding area of Nord Pool is based of indirect simulation of the demand and supply curves. However, the demand is considered to be price-inelastic as is the case in power systems without well-developed demand response programs [118]. Since the Latvian and Lithuanian bidding areas are very well interconnected as established in Chapter 3.2.3, the amount of electricity demand in the market is obtained by summing the demand in these two countries within each modelled hour. For future scenarios, historical exogenous time series are used as input, scaling them to adjust to the forecasts of the expected value in any given year. Thereby, for instance, to obtain the hourly electricity consumption in Latvia in a given year $YYYY$, the 2016 time series can be used as base as in the following equation[40]:

$$E^t_{\text{cons.,LV},YYYY} = E^t_{\text{cons.,LV,2016}} \cdot \frac{E^\Sigma_{\text{cons.,LV},YYYY}}{E^\Sigma_{\text{cons.,LV,2016}}}, \tag{3.9}$$

where $E^t_{\text{cons.,LV,2016}}$ – the actual electricity consumption in Latvia in hour t in 2016;

$E^t_{\text{cons.,LV},YYYY}$ – the estimated electricity consumption in Latvia in hour t in year $YYYY$;

$E^\Sigma_{\text{cons.,LV,2016}}$ – the actual total electricity consumption in Latvia in 2016;

$E^\Sigma_{\text{cons.,LV},YYYY}$ – the forecasted/assumed total electricity consumption in Latvia in year $YYYY$.

40 Such scaling is performed for various exogenous time series used in the model.

Note, when scaling the electricity demand in the Lithuanian bidding area, the demand due to the Kruonis PSHP operation mode is subtracted from the historical time series, since its operation is modelled separately.

From the supply side, several energy sources that otherwise would be modelled via optimal dispatch are instead in the model implemented as non-dispatchable due to the support scheme (i.e., feed-in tariffs) in place in Latvia. This support scheme demotivates the owners of small hydropower and cogeneration plants from planning their schedules following market signals [105].

The large HPP plants are also assumed to operate based on historical data, assuming that the peculiarities of their production profiles are captured in it, namely, larger production whenever the market price is higher, which normally is during consumption peaks, consequently the production is reduced during nights and weekends. The seasonality of HPP production is also implicitly present in the historical data, whereby production is significantly lower during the summer due to low inflow, and noticeably higher during the spring flood season.

All exogenous time series (production of small and intermittent plants from ENTSO-E Transparency Platform [108], consumption, electricity import price from other Nord Pool areas) [9] are obtained by scaling historical data using April 2016 to March 2017 as the base year. Earlier data was not used as the market situation has changed significantly after NordBalt cable (LT–SE4) started its regular operation at the beginning of 2016. The choice of scaling factors, however, is scenario based. Also, historical data on unavailability of interconnectors from ENTSO-E Transparency Platform is used.

If import capacities are sufficient for covering the consumption in Latvia and Lithuania without activating additional local fossil units, the marginal price is assumed to be defined by import from the SE4 area of Nord Pool market. The assumption is based on the historic market trends and the price series for SE4 are derived from Energinet's future projections [119]. The same source is used for fuel and CO_2 emission price projections for the time period from 2018 to 2030.

Additionally, the Kruonis PSHP in Lithuania has been modelled to purchase electricity whenever its market price is below 80% and sell when it is above 111% of the two-week average[41]. This follows from the 0.72 round-trip efficiency of the plant and other factors discussed and assessed in Chapter 1.4. The constraints related to water reservoir levels are also respected by tracking the amount of stored energy in hourly resolution throughout each modelled year.

Thereby, in the first approximation, the electricity market balance in hour t is approximated without local fossil fuel plants as follows:

$$\begin{aligned} E^t_{\text{LV+LT}} = &-E^t_{\text{cons.,LV}} - E^t_{\text{cons.,LT}} + E^t_{\text{hydro,LV}} + E^t_{\text{biom.,LV}} + E^t_{\text{wind,LV}} + E^t_{\text{oth.sm.,LV}} + E^t_{\text{biom.,LT}} + \\ &+ E^t_{\text{sol.,LT}} + E^t_{\text{waste,LT}} + E^t_{\text{wind,LT}} + E^t_{\text{oth.sm.,LT}} + E^t_{\text{imp.,EE}} + E^t_{\text{imp.,SE4}} \end{aligned} \tag{3.10}$$

[41] Using two of its four hydroelectric sets, assuming the other two to be restricted for reserve provision.

If $E^{t}_{\mathrm{LV+LT}}$ is negative (i.e., the consumption is not covered by the stated production sources or electricity import), in the next iteration, the next cheapest thermal power plant bid is accepted, repeating the process until the balance is either zero or positive, which means that electricity market equilibrium has been found (in case of positive balance, there is electricity market export from the LV+LT areas). The resulting market clearing price in Latvia is then set by the most expensive of the accepted bids, i.e., the production costs of the marginal power plant.

Table 3.8 summarizes the remaining local fossil plants [120] that can be activated in the model to meet the demand of electricity, apart from the Riga CHP plants which are modelled and included with each of the possible operation modes in the merit order list separately. The last entry in the table (a low efficiency oil plant) is the price setting one if consumption is not met otherwise, i.e., it is the final marginal unit, hence its max power is not constrained.

Table 3.8. Fossil power plants modelled in the merit order

Parameter / **Type**	**Natural gas (cogeneration)**				**Natural gas (condens.)**	**Oil (condens.)**	
Max. power (MW)	360	60	110	335	455	600	–
Efficiency	0.915	0.9065	0.8087	0.7988	0.58	0.38	0.22

The market clearing price modelling module was tested on the historical data of 2016, where the actual average market price in the Latvian bidding area was 36.09 €/MWh, but the weighted average – 38.55 €/MWh. The results obtained from the model test run were sufficiently close to the actual data – the modelled average price is 35.53 €/MWh and modelled weighted average price is 37.58 €/MWh. The relatively minor difference allows the model to be considered capable of estimating electricity day-ahead market clearing price.

3.3.4. CHP plant operation economic assessment

To assess the profitability of Riga CHP plants' operation with varying degrees of support, it is necessary to know both income and expenditure positions related to the plants. The income from sold electricity and heating energy is obtained using the outputs of the CHP operation and market clearing models. Electricity is sold at the modelled market price, whereas heating energy is sold at the procurement price set by the district heating network operator.

It is assumed that Riga CHP units are in operation if the market clearing price in any of the feasible operation modes exceeds the marginal cost. Only heating energy produced in the cogeneration units and not in the hot water boilers is considered in these calculations, since only the cogeneration units are subject to state support in the form of capacity payments. The variable production costs are obtained from the CHP operation model.

Furthermore, the capacity payments received by Riga CHP plants are subject to additional conditions, which also need to be included in the assessment model. The payment is reduced if market situation has been favorable to CHP plant operation. The procedure of support reduction is laid out in Cabinet Regulation No. 221 [113], and this correction is only applied starting from the 1 201$^{\mathrm{st}}$ hour of full-load operation.

As stipulated by the regulation, the correction of the capacity payment is considered per monthly basis, by comparing the market price of the electricity sold at each hour with approximate production cost estimated according to Eq. (3.11).

$$\frac{Tr_{\mathrm{g}} + Tr_{\mathrm{e}}}{9.3} \cdot 1.2 + c_{\mathrm{CO_2}} \cdot 0.17 + 3.55, \tag{3.11}$$

where Tr_{g} – the end tariff (without VAT) of natural gas (€/t.nm^3);

Tr_{e} – natural gas excess tax (€/t.nm^3);

$c_{\mathrm{CO_2}}$ – carbon dioxide emission allowance (EUA) price (€/t).

The approximated hourly production costs as per Eq. (3.11) multiplied by the produced energy are subtracted from the hourly income from the day-ahead market (the produced electricity multiplied by electricity market price). The difference in each hour constitutes either an additional market income or a perceived loss. The hourly differences within each calendar month are summed up, and if the sum is positive, it is considered to be additional income. The capacity payment for the particular month is reduced by an amount equal to 75% of the additional income.

Capital expenditure and maintenance costs are the final parameters required for the assessment of CHP plant profitability under various support conditions. These indicators are summarized in Table 3.9.

Table 3.9. Expenditure assumptions for the financial assessment of Riga CHP plant operation

Parameter	CHP-1	CHP-2.1	CHP-2.2	Source
Investment cost (M€)	106	178	320	[121]–[123]
WACC[42] (%)	7.8%			[124]
Service life (years)	15	20	15	In accordance with the regulated support period
Time of operation	2006–2020	2009–2028	2014–2028	
Fixed maintenance costs (€/kW/y)	24.3	19.8		[120]
Variable maintenance costs (€/MWh)	1.4	0.7		
Capital expenditure per year of modelled operation (M€)	12.23	17.86	36.93	Calculated with the assumed WACC

3.3.5. Long-term assumptions and forecasts

There are several assumption-driven factors impacting the market clearing model at specific points in the long-term outlook:

- Beginning with 2021, the maximum EE-LV transmission capacity is assumed to increase by 600 MW [103].
- Beginning with 2021, Riga CHP-1 no longer participates in the market due to end of the support period.

[42] Weighted Average Cost of Capital

- Beginning with 2025, the maximum EE-LV transmission capacity is assumed to increase by 1400 MW [103].
- Beginning with 2029, Riga CHP-2 units no longer participate in the market due to end of the support period.

As stated previously, forecasts of the yearly average electricity market price in Nord Pool SE4 bidding area, as well as the price of natural gas, heavy fuel oil and CO_2 emission allowances are taken from the Danish transmission system operator Energinet modelling assumption database [119][43].

The total annual electricity consumption and installed capacity of electricity production sources in Latvia till 2026 is extracted from the national TSOs Augstsprieguma tīkls AS projections made in the Base scenario of the 2015 report [125]. The corresponding data for Lithuania is taken from Litgrid's projections [126].

Historical hourly time series of SE4 price, hourly consumption and interconnection capacity are taken from Nord Pool database [9], time series of various production sources (hydro, wind, solar etc.) are taken from ENTSO-E Transparency Platform [108], and the hourly unavailability of both Riga CHP plants is obtained from Nord Pool REMIT UMM (Urgent Market Message) system [109] – the 2016 unavailability profile for each unit is assumed to repeat in the subsequent years.

The amount of emission allowances is modelled in accordance to Cabinet Regulation No. 499 [127] till 2020. For the following years, it is assumed to gradually decrease by reaching zero in 2027.

Various long-term assumptions are summarized in Annex I. The grey cells are interpolation or extrapolation results for years to which no values could be found in the information sources used. As can be seen from Fig. 3.15, the long-term assumptions are driven by expectations of notable fuel price and emission allowance price increases, as well as an overall steady increase in the electricity market price (as inferred from the SE4 price projections).

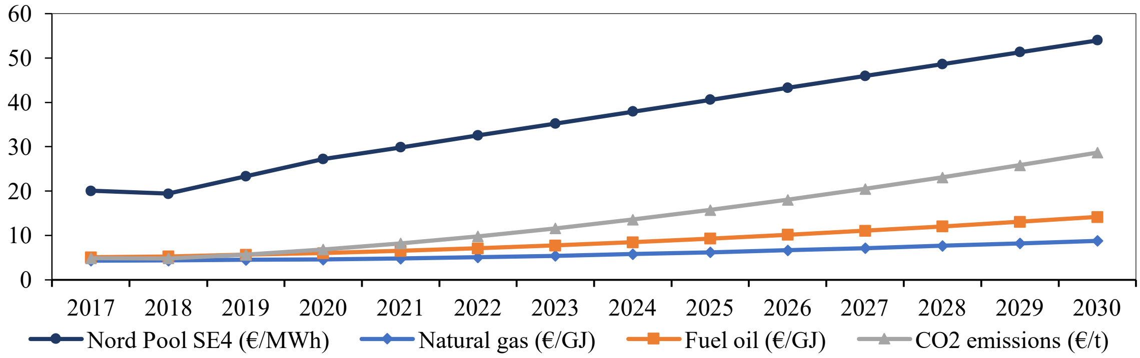

Fig. 3.15. Fuel, emission allowance and electricity price projections used in the modelling.

[43] Energinet's projections of fuel and emission allowance prices trends are partly based on futures contracts (EEX EUA, Europe ICE Brent, Germany ICE Endex), partly on IEA World Energy Outlook New Policies Scenario (for 2030). SE4 price projections are based on forward prices and Energinet's own modelling exercises.

3.3.6. Analyzed scenarios

Overall, two different future scenarios have been considered for market simulations. They both use the assumptions and projections described previously, but they differ in two notable aspects – firstly, the unavailability profile of the NordBalt cable, which allows the import of generally cheap electricity from Scandinavia, and, secondly, they consider different developments in the heating energy system of Riga.

First of the scenarios (*Conservative Scenario*) envisions the same unavailability profile of the NordBalt interconnector as in the base period (April, 2016–March, 2017). In the first months of 2016, the cable was operating in test mode and often was unavailable to the market. However, also in the considered period a pronounced characteristic of the interconnection was frequent disconnections and, overall, in the base period it was available to the market for only 72% of the hours. In the *Conservative Scenario*, the electricity market price is modelled and Riga CHP plants profitability assessed with varying degrees of support by assuming that also in the future the NordBalt cable will encounter technical difficulties with the same pattern as until the time this study was carried out. The second defining characteristic of the *Conservative Scenario* is an assumption that the situation in the heating energy demand and supply in Riga remains as before, i.e., the demand profile is as in the base year and can be supplied by the Riga CHP plants in cogeneration mode or their hot water boilers.

The other modelled scenario (*Development Scenario*), foresees two major deviations in regards to these assumptions:

1) Significant technical improvements have been carried out to the most fault-vulnerable parts of the NordBalt cable, as a consequence of which, starting from 2018 it no longer disconnects as frequently as before. The unavailability profile is thereby assumed to be similar to that of a comparable submarine cable (Estlink-2, 650 MW), which, in 2016, was available to the market for 95.7% of the hours. Thereby this assumption signifies a notable improvement in electricity import capabilities from Scandinavia.
2) Beginning from 2018, new biomass thermal energy plants start operation in the district heating network where Riga CHP plants supply their thermal energy. The total installed thermal capacity of these new developments is assumed to be 80 MW, and it is also assumed that these sources outcompete Riga CHP plants in the thermal energy market. A direct consequence of this assumption is the inability of Riga CHP plants to operate in cogeneration mode during summer, due to lack of heating load to be supplied.

The purpose of these scenarios is assessment of Riga CHP plants impact on the electricity market price and evaluation of options to decrease the capacity payments they receive (to 75%, 50%, 25% or 0% of the current level). The previously described considerations allow to hypothesize that in the *Development Scenario* the price constraining effect of Riga CHP plants will be smaller, while support reduction will more considerably decrease their operational profitability and increase the risk of mothballing them.

3.4. Results and discussion

3.4.1. Conservative Scenario

The results from the *Conservative Scenario* are summarized in Figures 3.16–3.18. The impact of Riga CHP plants on the electricity price is estimated by comparing modelling runs with and without their participation in the market.

Fig. 3.16 shows the price in SE4 as a reference for electricity imports and the simulated weighted average market price in Latvia. The price here is averaged over four different types of hours based on the availability of the NordBalt connection and Riga CHP plants. We see that in 2018, 2023 and 2028, the CHP plants contribute to a decrease of the price by 5.71, 12.74 and 29.65 €/MWh respectively during the hours when the NordBalt is operational and by 32.32, 48.97 and 82.45 €/MWh respectively when it is not. The price limiting effect of the CHP plants is indeed the most prominent when the import link from Sweden is out of service.

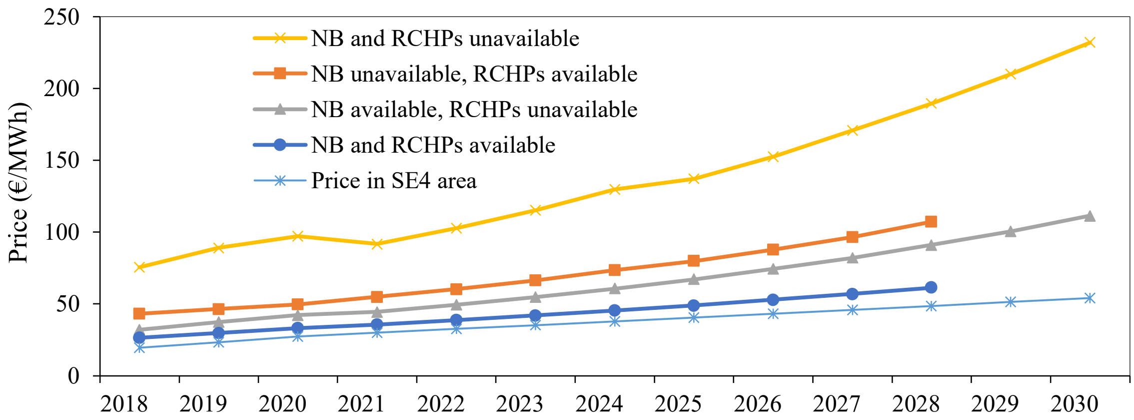

Fig. 3.16. Annual weighted average electricity price in selected hours based on the availability of NordBalt and Riga CHP plants (*Conservative Scenario*).

An example of the electricity market price dynamics during one modelled year is provided in Annex II. It is evident that without Riga CHP plants the price tends to be noticeably higher. When the price is averaged over the whole year, the unavailability of Riga CHPs causes an increase by 13.00, 22.77 and 44.26 €/MWh in 2018, 2023 and 2030 respectively (Fig. 3.17). However, one should be wary of long-term prognosis as the degree of uncertainty increases the further in the future we model [128].

Increased electricity prices would put a strain on the national economy. We can estimate the overall escalation in costs by using the annual consumption of electricity. The total expenditure on electricity would increase by 95.44 M€ in 2018, by 175.27 M€ in 2023 and by 357.94 M€ in 2028 if Riga CHPs would not participate in the day-ahead market.

Of course, the input assumptions and projections used envisioned a gradual but steep increase in electricity production costs due to fuel price increases and other factors in the future. Because of this, the price limiting effect of Riga CHP plants is more pronounced (in absolute terms) in the long term, resulting in larger cost increases in each subsequent year, except for 2021, when CHP-1 was assumed to be decommissioned.

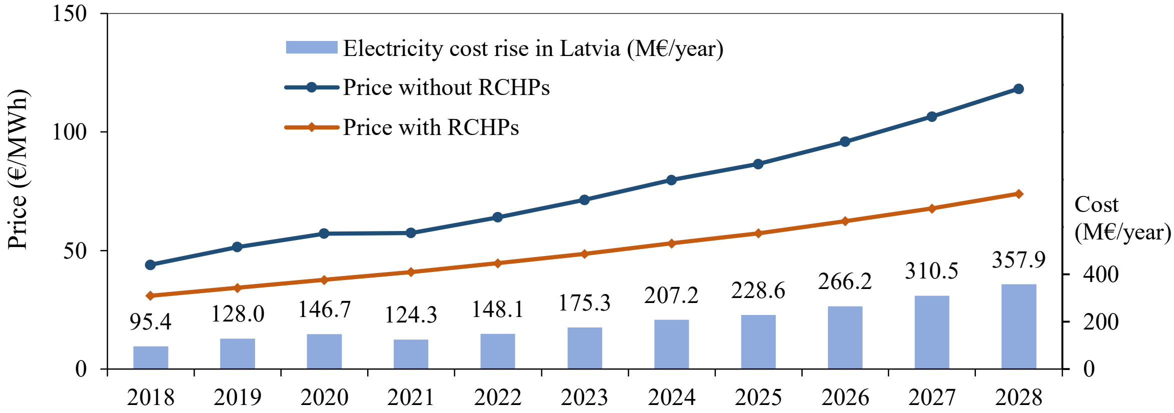

Fig. 3.17. Weighted average electricity price of the whole year with/without Riga CHP plants and electricity cost rise w/o RCHPs (*Conservative Scenario*).

In Fig. 3.18, we can see the results of techno-economic assessment of the overall profitability of Riga CHP plants with different support schemes in mind. The capital costs and fixed annual costs of the power plants are sourced from public data, whereas the variable costs and income from the spot market are output by the model. 100% designation here corresponds to the full amount of support in effect for 2017. It provisioned capacity payments of 8 525 €/MW/month with a condition of operating at least for 1 200 hours/year in cogeneration mode. Furthermore, starting with hour 1 201, if the monthly income in the spot market was more than the marginal cost in any of the remaining months of the year, the support would be reduced by 75% of the monthly operational profit from the spot market [113].

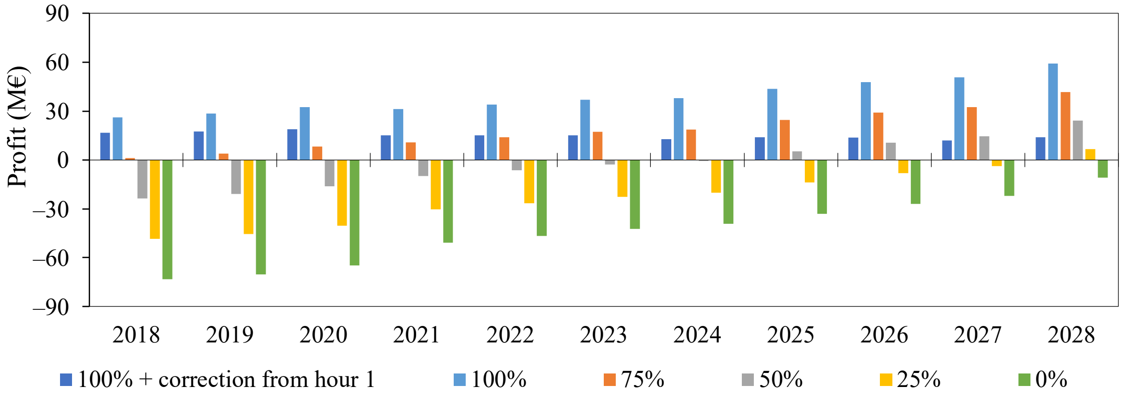

Fig. 3.18. Profit of CHP plants with differing amounts of support (*Conservative Scenario*).

Evidently, the support can be decreased to 75% of the current level without endangering the feasibility of continued power plant operation. If support is reduced to 50%, the operation becomes feasible only starting from 2025, but with 25% support it is only feasible in 2028, i.e., in all previous years the plants would operate at a loss and thus would unlikely still be maintained. In case of immediate complete support withdrawal, the CHP plants would suffer a 73 M€ loss already in 2018.

Interestingly, the current amount of support with altered correction condition (from the 1st hour instead of 1 201st) would keep the profitability metrics reasonably positive (without exceeding 20 M€/year) – the more favorable market conditions, the less support is necessary.

3.4.2. Development Scenario

When compared to the *Conservative Scenario*, this case envisions a slower electricity price increase due to more stable operation of the NordBalt cable (Fig. 3.19). For instance, if previously the weighted average price for 2018 was 30.95 €/MWh, then in this scenario it is merely 26.73 €/MWh. The example of modelled price provided in Annex II also shows that the average price peaks have decreased almost twofold.

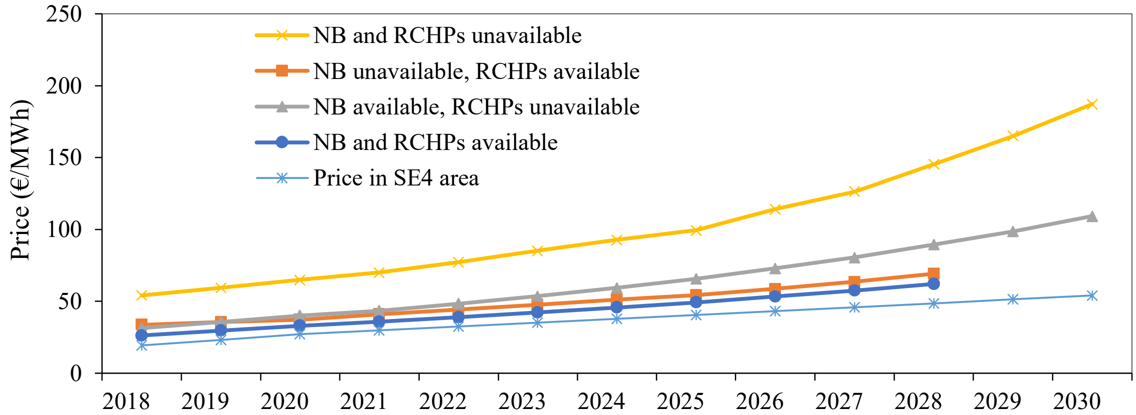

Fig. 3.19. Annual weighted average electricity price in selected hours based on the availability of NordBalt and Riga CHP plants (*Development Scenario*).

The cost increase brought by the absence of CHP plants (Fig. 3.20) would be by 54–120 M€/year less than in the *Conservative Scenario*, but still quite significant (41.69 M€ in 2018, 95.88 M€ in 2023 and 238.09 M€ in 2028).

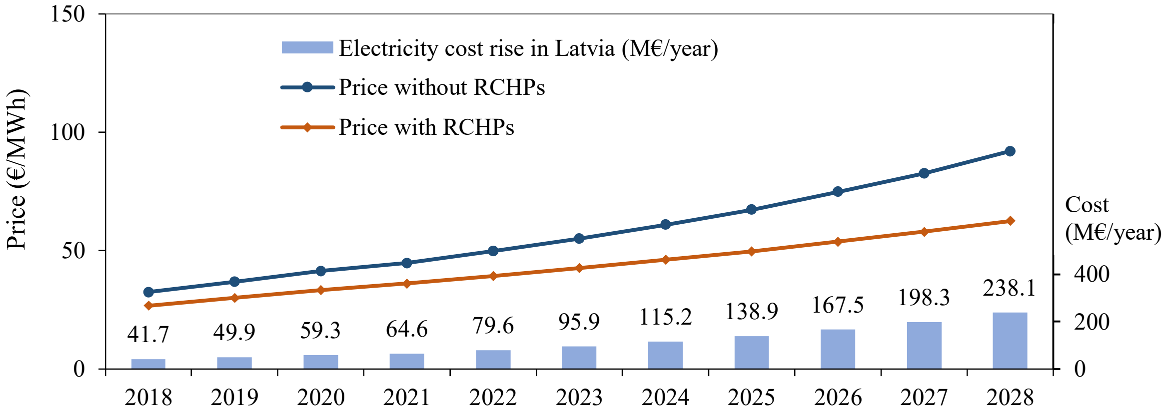

Fig. 3.20. Weighted average electricity price of the whole year with/without Riga CHP plants and electricity cost rise w/o RCHPs (*Development Scenario*).

The profitability in this scenario (Fig. 3.21) is more limited due to inability of the CHP plants to operate in the summer (because of the assumption of new heat sources outcompeting the large CHPs in district hot water provision) and close competition with imported electricity from Scandinavia. In the case of 75% support, the plants would operate at a loss till 2021. Any further support reduction would make the operation of CHP plants unfeasible. In the case of full support withdrawal, the plants would have an 85.5 M€ loss already in 2018.

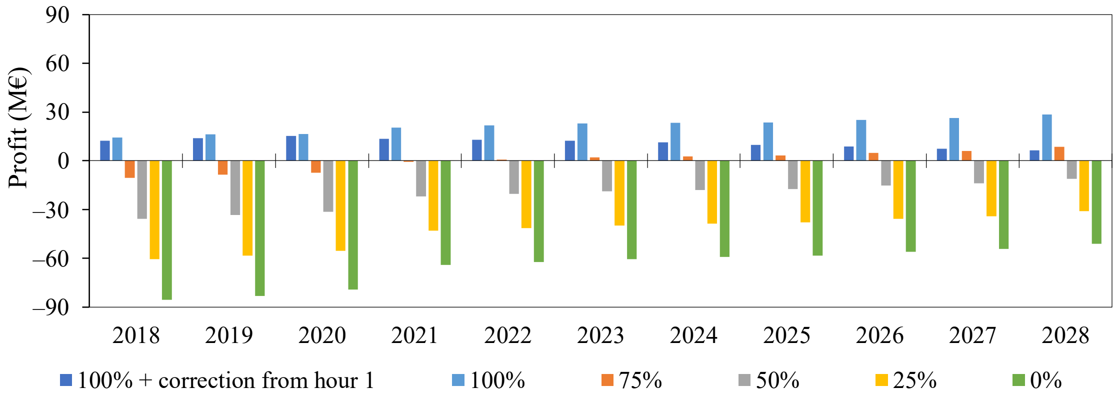

Fig. 3.21. Profit of CHP plants with differing amounts of support (*Development Scenario*).

Similarly to the *Conservative Scenario*, a revised support scheme, whereby a correction of the capacity payment is applied already from the first hour of operation, allows keeping the profitability at reasonable levels and a positive cash-flow in all the modelled years. The relative profit[44] does not exceed 15 M€ in any of the years. A positive aspect of such a scheme is the option to noticeably decrease the support payments whenever the market conditions in Nord Pool enable profitable operation of the CHP plants.

3.4.3. Discussion

It becomes evident from the modelling results that decrease in state support to the Riga CHP plants to 50% of the level envisioned in 2017 or lower would significantly reduce the profitability and economic feasibility of continued power plant operation as they would be unable to cover the annual expenses.

However, reduction to 75% only shows negative financial metrics until 2022 in the *Development scenario* and 2018 in the *Conservative Scenario* and would be well manageable in the later years.

The electricity and fuel price assumptions in Scandinavia used in the model envision favorable market conditions for natural gas plants in future years enabling them not only to cover variable costs but also to finance at least a part of the capital expenditure. Nevertheless, price projections up to ten years in the future have to be viewed with caution, especially since the price assumptions for the closest few years are based on futures contracts, but further developments are results of modelling [119]. Of course, the results of this study are input and assumption sensitive, but they are nevertheless useful in comparative terms. Overall, they do affirm the hypothesis of the significant role of Riga CHP plants in limiting the wholesale price of electricity, especially when other significant market infrastructure objects (e.g., the interconnector to Sweden) are disconnected.

[44] The annual *relative profit* in this research is the sum of the positive and negative cash flows related to the operation, maintenance and capital expenditure of the Riga CHP plants. It is relative in the sense that parts of the expenditure are sourced and estimated solely from publicly available information sources. It follows, that these results are mainly to be interpreted as an illustration of modelled trends and tendencies as needed for the purposes of this research, rather than an authoritative financial indicator analysis.

3.5. Chapter conclusions

During the study presented in this chapter, factors influencing electricity wholesale price were analyzed and Nord Pool day-ahead market clearing price in the Latvian bidding area until 2030 was simulated with the aim of assessing the impact of Riga CHP plants on it. The various possible operating modes of the power plants were modelled in hourly resolution in order to construct the merit order list necessary for clearing price identification. Furthermore, the options to decrease capacity payments these plants receive were considered through calculating financial indicators related to their operation.

The Riga CHP plants have a very important role in the Latvian power system not only in terms of generation self-sufficiency and reliability, but also in ensuring efficient electricity wholesale market operation by limiting excessive price rises. The absence of these power plants would result in significantly higher costs of electricity for all consumers. Their importance in limiting excessive wholesale market spikes is especially pronounced when the ability to import relatively cheaper electricity from Scandinavia is hindered, e.g., by interconnector disconnections, as shown by the comparison of the two analyzed scenarios. Another takeaway of the scenario analysis is the necessity for adequate heating demand which the CHP plants could supply in cogeneration mode, which ensures high efficiency of their operation and competitiveness in the market.

On the other hand, the market situation as analyzed in 2017 was not favorable to natural gas cogeneration plants yet despite their high efficiency and comparatively low emissions. Hence, support schemes have to be applied to ensure continued availability of these large power plants.

However, evidently there is merit in reevaluating the amount of support these power plants receive. In the research work presented here, options to decrease the support payments were identified. It was found that the support payments, in principle, can be reduced without risking making the sustained operation and maintenance of these power plants economically detrimental. From the various options assessed, reduction to 75% of the current level or application of payment correction from the first hour of operation were found to be feasible.

The results of this study were presented to the Ministry of Economics of Latvia, who incorporated them in the "*Conceptual Report on Complex Measures for the Development of the Electricity Market*" [129]. As a consequence of the aforementioned report and other factors, the support payment system in regards to the Riga CHP plants was changed starting from January 1, 2018 [130].

4. HEATING DEMAND FORECASTING FOR CHP PLANT OPTIMAL SCHEDULING

4.1. Motivation for research in heating demand forecasting

Combined heat and power plants are an important source of heating energy in district heating (DH) networks around the world. As pointed out in the previous chapter, these plants are characterized by high efficiency due to the electricity produced alongside heat, which allows them to have lesser fuel consumption and smaller carbon footprint compared to when the two types of energy are produced separately [131].

The primary task of CHP plants connected to DH networks, in general, is supplying the heating energy, whereas electricity is often treated as a byproduct. However, as pointed out in Chapter 3, for worthwhile participation in electricity markets, an adequate level of certainty is necessary regarding the heating demand. Although there are measures which allow more flexibility in the production of electrical energy by somewhat untying it from the heat demand, i.e., heat storage tanks, peak water boilers, improved cycling operation [131], [132], proper scheduling and operational control of CHP plants nevertheless heavily relies on heating demand forecasts.

The forecasts necessary for CHP plant operation can be categorized in two groups depending on the prediction horizon: operational (sub-hourly to several hours-ahead) for near real time adjustments of the production output and day-ahead for unit scheduling and preparation of bids to a wholesale market [133].

A great variety of methods for DH heating demand forecasting can be found in recent literature, for instance, feed-forward neural networks [133]–[138], support vector machines [134], [136]–[141], random trees regression [134], [137], [142], ridge regression [139], [143], random forest [139], deep learning [143], extreme learning machines [135], [142], genetic programming [135], [136], [138] and even linear regression [134], [137], [143]–[145]. The methods vary in complexity and therefore also presumably in their time of execution, unfortunately, few authors provide comparable data on computational time.

However, several studies suggest that the simpler regression models can provide similar [134] or even better [143], [145] forecasting accuracy than machine learning approaches. The study presented in this chapter aims to expand the literature on heating demand forecasting in DH networks with regression models by employing a very straightforward and effective polynomial approach and exploring the benefits of improving it with three types of modifications – decoupling hot water (HW) consumption from space heating demand, taking into account the residuals of the fitted regression model and filtering the input and output series. Furthermore, as currently the size of the overall historical dataset to be used for forecasting is seldom tested in the literature, this study provides insights into identifying a reasonable look-back horizon for forecasting heating demand with regression methods.

The research work presented here was carried out together with Dr. sc. ing. Roman Petrichenko and Dmitry Sobolevsky and it has been presented in the IEEE 6th Workshop on

Advances in Information, Electronic and Electrical Engineering (AIEEE) in 2018. The author contributed in all the phases of this research, but particularly in conceptualizing the approach, developing code in MATLAB scripting environment for running the forecasting experiments and analyzing the results.

4.2. Methodology

4.2.1. The underlying regression model

In general, regression allows us to approximate a mathematical relationship between two or more variables if their values are known in a number of points. Eq. (4.1) illustrates a multiple regression model (a polynomial), where the right-side terms can be both independent variables and functions of independent variables.

$$y_i = a_0 + \sum_{n=1}^{k} a_n \cdot x_i^n + \varepsilon_i, \tag{4.1}$$

where y_i – dependent variable at point i;

x_i – independent variable at point i;

n – power of each term;

k – power of the last term (i.e., order of the polynomial);

ε_i – error term at point i;

a_0 – the intercept term;

a_n – coefficient for the corresponding function of the independent variable.

In heat load forecasting, the dependent variable is, of course, the heating demand itself, whereas various different factors can serve as the independent variables or predictors. All of the reviewed studies agree on outdoor temperature as the most important predictor in heating demand forecasting. However, some additional parameters have been employed as well. For instance, papers [134]–[136], [138], [143] also consider time-lagged heating demand values. Time factors like hour-of-day, day-of-week and day-of-year are also sometimes used for forecasting [134], [137], [143]. If the forecasting algorithm is intended to be applied for a smaller supply area (i.e., one substation as opposed to the whole DH network), the physical parameters of the DH substation can be used as well [134]. Study [139] stands out in that it considers dew point as a predictor variable. Finally, solar irradiation [141] and wind speed [141], [144] is employed as well, however, the impact of wind on the forecasts can vary a lot across different buildings and, on a larger scale (i.e. the whole DH network), can even out [144].

However, the inclusion of multiple input variables in predictive models can negatively affect their interpretability and predictive power. Additionally, it can reduce their generalization capability [146]. Consequently, in this research, we focus on outdoor temperature as the most influential predictor [139], [141], [146].

Thus, we can formulate the function for heating demand forecasting. If we assume a third order polynomial relationship, the model can be expressed as in Eq. (4.2).

$$\widehat{Q}_t = a_0 + a_1 \cdot \widehat{T}_t + a_2 \cdot \widehat{T}_t^2 + a_3 \cdot \widehat{T}_t^3, \tag{4.2}$$

where $\widehat{Q}_t$ – the forecasted heating demand (model output) at hour t;

$\widehat{T}_t$ – the temperature forecast (model input) at hour t;

a_0, a_1, a_2, a_3 – polynomial coefficients (model parameters).

The model parameters are obtained by solving a least squares problem where the sum of the model residuals is minimized. The solution can be expressed in matrix formulation as:

$$\begin{bmatrix} a_3 \\ a_2 \\ a_1 \\ a_0 \end{bmatrix} = (V' \times V)^{-1} \times (V' \times Y), \tag{4.3}$$

where Y – a vector of dependent variable values (in this case, heating demand);

V – the Vandermonde matrix [147] for the independent variable (outdoor temperature).

4.2.2. Modifications

Ref. [144] identified HW as an important social component in the heating demand curve. In this study, it will be tested if a polynomial regression model can provide higher accuracy for testing datasets[45] if it is supplemented by an additional component for HW handling. Since the recorded heating demand data does not discriminate between space heating and HW, the energy spent on water heating has to be identified implicitly.

For this, it is assumed that most of the consumption during summer is specifically for HW and thus the social component can be obtained by averaging the recorded points over the corresponding time period. Afterwards, the approximate HW hourly profile can be subtracted from the model training dataset and added back to the forecast as a temperature-independent component.

Another addition to the polynomial regression model described in this chapter lays in handling the residuals of the fit. It is done by assigning information on hour-of-day to the error term ε_i from Eq. (4.1) for each element *i*. The residuals are then grouped by the respective hours of the day and, thus, an average error profile for a full day is obtained. This profile is subtracted from the forecast in an expectation to decrease the inaccuracy:

$$\widehat{Q}_t = a_0 + a_1 \cdot \widehat{T}_t + a_2 \cdot \widehat{T}_t^2 + a_3 \cdot \widehat{T}_t^3 - \overline{\varepsilon_t}, \tag{4.4}$$

[45] Unlike in Chapter 3, for the purposes of the research described here, some proprietary information has been used – testing of the developed forecasting techniques was carried out on datasets provided by the operators of the CHP plants under study with the purpose of developing a tool for improved CHP operational planning.

where $\overline{\varepsilon_t}$ is the average error of the model in the training dataset for each particular hour of the day t (1..24, since the aim is to use the forecasting model for day-ahead scheduling of CHP plants).

The third modification to be tested is applying a smoothening filter by calculating the weighted double-sided moving average of different lengths. This can be applied to either the model training data (historical heating demand, dubbed input hereinafter), the forecasted demand series (output), both or neither. The smoothening technique to be utilized here is the same which was used in processing forecasts of water inflow and market price for HPP optimization in Chapter 2.2.4, i.e., Eq. (2.11), assuming $T = 24$.

Finally, the size of the training dataset is also a model feature to be determined. 24 different setups are tested, from seven days (one week) to 168 days (roughly 6 months).

4.2.3. Setup of the simulations

The performance of the forecasting model is evaluated using mean absolute percentage error (MAPE) [148]:

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Q_i - \widehat{Q}_i}{Q_i}\right|, \tag{4.5}$$

where Q_i – the actual heating demand at point i;

m – total number of points in the forecast.

In order to simulate the intended application of the forecasting model (i.e., in day-ahead scheduling), the model is utilized in a rolling horizon manner – it moves iteratively though each day in the testing dataset and performs a 24-hour prediction; the MAPE for the day is calculated and saved; afterwards, the current day is added to the training dataset and a forecast for the next 24-hour period is performed. Once MAPEs for each of the days in the testing dataset are obtained, they are averaged out to find the mean error for the whole set. In order to test the effect of the features described in subchapter 4.2.2, the model runs are carried out a total of 384 times.

Finally, another approach to using the previously described additional multiple regression model features is tested, whereupon the model selects those features (HW exclusion on or off, model residual subtraction on or off, type of data filtering and, lastly, size of the training dataset) before each 24-hour period by exhaustively enumerating the possible model configurations on data from the previous day and selecting the best performer for the following day. It is expected that such and automated approach could provide better overall accuracy compared to if the preferred features are selected only once, e.g., at the beginning of the heating season.

4.2.4. Data set

For validation of the proposed multiple regression model and its modifications, historical data from Riga, Latvia, particularly, the largest DH network on the right bank of the city, which is supplied by Riga CHP-1 and CHP-2, is used. The dataset employed contains heating demand and outdoor temperature records from Jan. 1, 2015 to Oct. 31, 2016.

The forecasting simulation experiments will be run twice in this dataset. Case Study 1 will forecast demand for days from Jan. 1, 2016 to Mar. 1, 2016 (91 days), whereas Case Study 2 will perform forecasts from Oct. 15 to Oct. 31, 2016 (17 days). The former represents the middle of the heating season, while the latter – the beginning. It should be noted that only period when the heating season is assumed to be in full effect is included in the regression model (i.e., period from April to mid-October is excluded). The hourly forecasts are performed in a sliding horizon manner with 24-hour increments, but, for comparison purposes, only the final MAPE for each case study (and each model setup) will be presented.

In the results described below, the recorded temperatures are used as predictors instead of temperature forecasts. This is to isolate the effects from the regression model configuration, since the external temperature forecasts would introduce inaccuracies independent from the setup of the tested model. An evaluation of the impact of temperature forecast imperfections is already offered in, e.g., [142] and also by the author in a previously published paper [133].

4.3. Results

4.3.1. Selection of polynomial order

Multiple regression with polynomials up to the 5th order was tested. In Case Study 1, the 2nd order polynomial proved to provide the best accuracy with a MAPE of 5.98%, while the 3rd order was close behind with 6.07%. In Case Study 2, both of these parameters again showed very similar results albeit with the 3rd order prevailing (at 4.64% vs 4.68%).

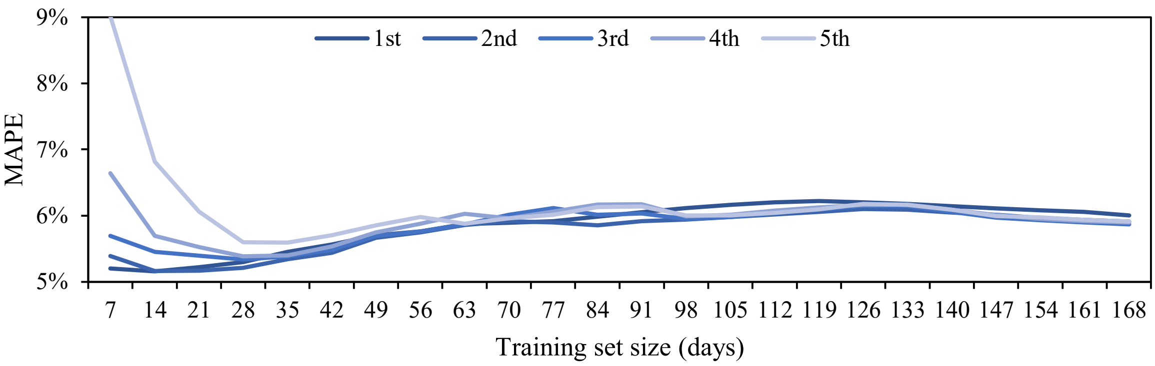

Fig. 4.1. MAPE per different polynomial orders and look-back horizon.

The performance of each of the five models depending on the training set size is summarized in Fig. 4.1 (for both case studies combined). Evidently, higher order models tend to overfit if the training set is small, but the more the training set is increased, the more similar the performance of the various polynomials becomes.

In the subsequent forecasting tests presented here, the 3rd order model is used, and this parameter is not varied further, as it is not the main subject of the study.

4.3.2. Effect of modifications and look-back horizon

Results from the various modified model runs for Case Study 1 are summarized in Table 4.1. These are the MAPE values averaged over the different look-back horizons. Fig. 4.2 and Fig. 4.3 present the disaggregated results with the impact of the training set size observable.

Evidently, in Case Study 1, the impact of time series filtering is very small – in the range of 0.05 percentage points. The best result is achieved if only the output is filtered. The inclusion of a social component for HW handling has not improved the model performance. The explicit correction of hour-of-day specific model residuals, however, has more notably improved the forecasting performance, i.e., by 0.27 percentage points. In terms of training set size, the best results were achieved with a look-back horizon of 28 days (5.34%). The results are similarly accurate for the range 14–49 days, but with larger training sets the MAPE quickly increases.

Table 4.1. Results of Case Study 1 (MAPEs)

Filtering		Error correction		Hot water component	
no filtering	5.92%	**included**	5.78%	**included**	5.92%
filtered input	5.96%	**not included**	6.05%	**not included**	5.92%
filtered output	5.86%				
filtered I/O	5.91%				

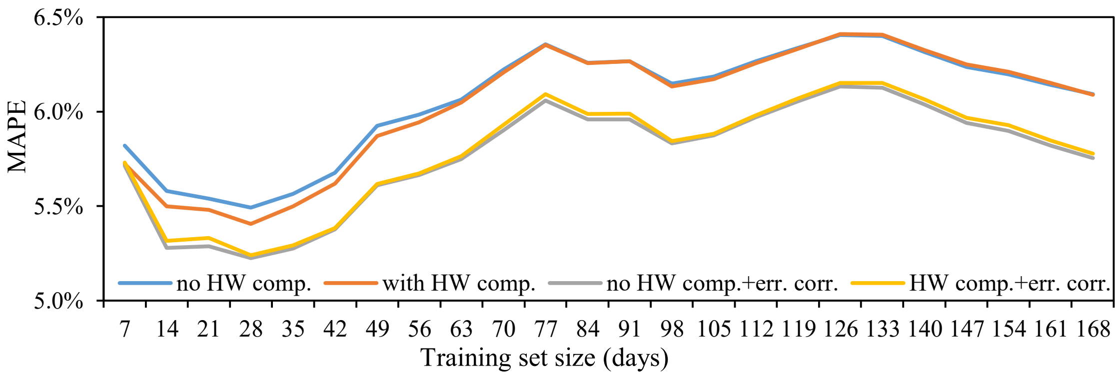

Fig. 4.2. MAPE per model modification and training set size (Case Study 1).

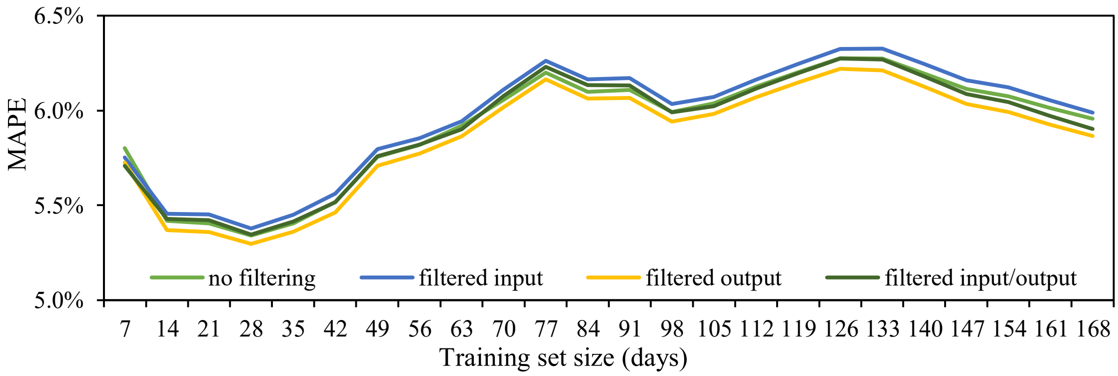

Fig. 4.3. MAPE per filtering type and training set size (Case Study 1).

The results of the Case Study 2 are similarly summarized in Table 4.2 (averaged over all the look-back horizons) and Fig. 4.4, Fig. 4.5 (disaggregated to show also the impact of the look-back horizon).

Table 4.2. Results of Case Study 2 (MAPEs)

Filtering		Error correction		Hot water component	
no filtering	4.40%	**included**	4.18%	**included**	4.36%
filtered input	4.37%	**not included**	4.59%	**not included**	4.42%
filtered output	4.38%				
filtered I/O	4.40%				

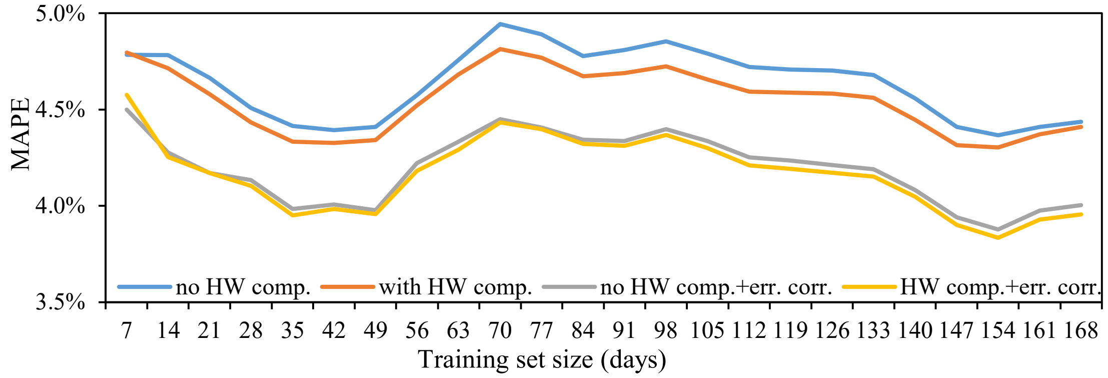

Fig. 4.4. MAPE per model modification and training set size (Case Study 2).

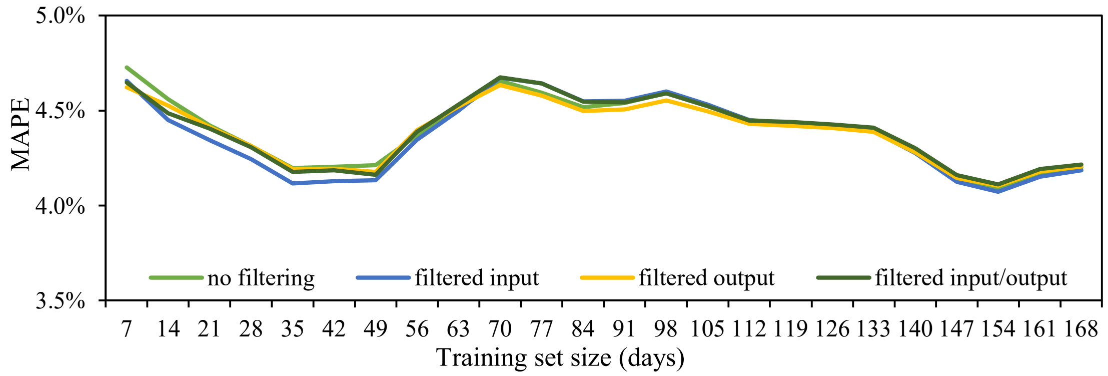

Fig. 4.5. MAPE per filtering type and training set size (Case Study 2).

The MAPE of Case Study 2 is overall notably smaller. This signifies a season-specific reason for the inaccuracies. Similar to the previous case, filtering does little to affect the results (range of only 0.03 percentage points) with input filtering providing the smallest error (4.37%). In this case, however, HW component has slightly improved the results (by 0.06 percentage points). The residual component once again provides the most notable accuracy improvements (by 0.41 percentage points). Unlike in Case Study 1, here the best results are obtained by a 154 day look-back horizon (4.09%), but there is also a range with low error estimates in the 28 to 49 days period.

4.3.3. Automatic feature selection

One of the main takeaways of the previous subsection is the difficulty to draw strong conclusions on the best forecasting model setup, since if applied to different portions of the dataset, the modified features offer varying advantages and disadvantages. Due to this uncertainty and the low computational effort the regression model requires (the 91 day testing dataset for Case Study 1 is handled by the forecasting algorithm[46] in less than a second), an automatic model setup is proposed and tested.

If before each day-ahead forecast the model can self-select those parameters which would have provided the best forecast for the previous day, the overall MAPE for the testing dataset decreases more significantly – 5.19% in Case Study 1 and 4.27% in Case Study 2, a 0.73 and 0.12 percentage point improvement versus the average MAPE in the previous simulations respectively.

The automatic forecasting algorithm chose to employ the HW component for 30.77% of days in Case Study 1 and 35.29 % of days in Case Study 2. The usage of the residual handling feature was more active – 72.53 % and 70.59 % respectively. Filtering wise, in both cases, I/O filtering was used most often (35.16 %, 35.29 %) while solely input filtering was the least used (13.19%, 17.65%).

Fig. 4.6 summarizes the frequency of training dataset size selected in both case studies. While generally this model feature has varied a lot, a tendency to cluster towards smaller look-back horizons can be observed.

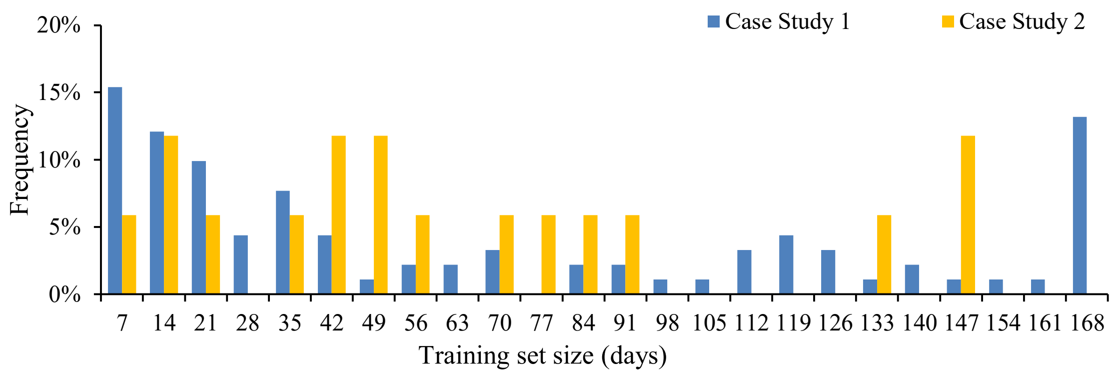

Fig. 4.6. Frequency of look-back horizon used in both case studies.

4.4. Chapter conclusions

Multiple (polynomial) regression has proven to be an effective tool for heating demand forecasting. One of its main strengths is the negligible computational time it takes to perform forecasts without losing much in terms of accuracy.

Furthermore, the forecasting model can be improved by certain modifications, the most promising of which has turned out to be subtraction of the model residuals averaged over hour-of-day. While other modifications (HW component and time series filtration) did not produce a consistently beneficial effect over the whole dataset, there were days when their inclusion

[46] The algorithm is implemented in MATLAB R2017a.

aided in improving the accuracy. Thus, a model which automatically selects the features the forecasting program should consider before each daily forecast is advisable. Additionally, it should consider automatic selection of the training set size, since the optimum look-back horizon tends to vary during the heating season.

While the model presented here already provides forecasts with adequate accuracy, further improvements are necessary. One promising venue for future work lays in improving the combined ANN/multiple linear regression forecasting model introduced in [145] with the modifications described here. It should also be tested what further forecasting accuracy improvements can be achieved if this algorithm is supplemented with advanced input data pre-processing techniques as in [149]. Another important research topic concerns forecasting the heat energy demand in the DH network specifically during the very beginning and end of the heating season, when space heating is gradually connected/disconnected by building managers.

CONCLUSIONS

1. The overall hypothesis of the work has been proven. Through the various case studies and analyses carried out in the main chapters of this Thesis, it is evident that application of well-functioning decision-making support methods, algorithms and tools by power plant operators and policy-makers can increase the benefits from efficient electricity market operation both to individual electricity wholesale market participants (e.g., storage and generator operators) and to the end-consumers at large.
2. The tasks of the Thesis have also been successfully carried out:
   - A method and algorithm for the optimized scheduling of and decision-support for large-scale energy storage plants participating in electricity wholesale market have been devised and tested in various case studies.
   - An algorithm and tool for cascaded hydropower plant optimized scheduling, including hydroelectric set selection subtask and multi-objective approach, have been improved and subsequently validated.
   - A method for the assessment of large combined heat and power plant impact on the electricity market price and evaluation of options to reduce state support received by such plants, in order to support policy-makers' decision-making process, has been devised and applied.
   - A computationally inexpensive heating demand forecasting algorithm, to aid the scheduling decision-making of combined heat and power plants' operators, has been devised and tested.
3. The electricity market conditions in the Latvian and Lithuanian bidding areas of the Nord Pool market are sufficient for profitable operation of already existing large-scale storage plants, but for the construction of new facilities to be feasible, additional revenue streams apart from price arbitrage need to be considered.
4. Coordinated participation of wind power and storage plants in the day-ahead market was found to be beneficial for both the wind power traders and storage operators. In the time period considered, this cooperation proved to provide slightly better net revenue than if the storage plant had operated independently. Furthermore, it offers additional environmental and societal benefits by avoiding wind power curtailment and making a maximum use of the available renewable energy.
5. Dynamic programming was found to be an effective approach for the optimized selection of hydroelectric sets in hydropower plants. Consequently, it was incorporated in a multi-stage cascaded HPP scheduling optimization model.
6. Furthermore, the functionality of the HPP scheduling optimization tool was further appended to allow for multi-objective approach (in the particular implementation – an ability to also consider the number of unit start-ups alongside the main objective, profit maximization). As a consequence, the plant operators could be provided with a tool to aid in their decision-making process.
7. Apart from practical application by HPP operators, the model can also be further used for research purposes by incorporating it in larger power system models or, with some

modifications, more directly in the assessment of reserve provision, wind power balancing or water value.

8. The Riga CHP plants have a very important role in the Latvian power system in terms of ensuring efficient electricity wholesale market operation by limiting excessive price rises. This is especially pronounced when the ability to import relatively cheaper electricity from Scandinavia is hindered. However, for maintained competitiveness, sufficient heating demand is necessary to ensure the ability to operate in cogeneration mode.
9. However, the market situation at the time of carrying out this analysis was not favorable for profitable CHP plant operation in the energy-only Nord Pool market, unless a certain level of capacity payments were available. Nevertheless, options to reduce the amount of support were identified.
10. Multiple (polynomial) regression has proven to be an effective tool for heating demand forecasting. One of its main strengths is the negligible computational time it takes to perform forecasts without losing much in terms of accuracy. Furthermore, the forecasting model can be improved by certain modifications, the most promising of which has turned out to be subtraction of the model residuals averaged over hour-of-day.

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ANNEXES

Annex I

Long-term modelling input data and sources

	Annual average price	Total consumption		Installed capacity									Price		
	SE4 area	LV	LT	HPP, LV	Biomass, LV.	Wind, LV	Other, LV	Biomass, LT	HPP, LT	Solar, LT	Other, LT	Wind, LT	Natural gas	HFO	CO_2 em. all.
	€/MWh	GWh	GWh	MW	MW	MW	MW	MW	MW	MW	MW	MW	€/GJ	€/GJ	€/t
								108	128	73	292	438			
2017	20.06	7248	10250	1580	80	81	290	122	130	73	294	467	4.32	5.08	4.85
2018	19.41	7307	10400	1588	85	90	297	136	131	74	296	496	4.36	5.26	4.81
2019	23.30	7378	10550	1588	90	99	304	150	133	74	299	525	4.50	5.64	5.65
2020	27.20	7453	10700	1588	95	109	310	164	134	75	301	554	4.57	6.02	6.83
2021	29.88	7530	10850	1588	100	118	317	179	136	75	303	584	4.80	6.51	8.21
2022	32.56	7606	11000	1588	105	127	324	193	137	76	305	613	5.08	7.08	9.79
2023	35.24	7703	11150	1588	110	161	331	207	139	76	308	642	5.40	7.74	11.58
2024	37.92	7780	11300	1588	115	186	338	221	140	77	310	671	5.78	8.47	13.56
2025	40.60	7857	11450	1588	120	211	345	235	142	77	312	700	6.19	9.27	15.71
2026	43.28	7945	11600	1588	125	235	353	249	144	77	314	729	6.64	10.13	18.02
2027	45.96	8013	11750	1588	130	264	360	263	145	78	316	758	7.13	11.05	20.48
2028	48.64	8091	11900	1588	135	290	367	277	147	78	319	787	7.64	12.03	23.07
2029	51.32	8170	12050	1588	140	317	374	291	148	79	321	816	8.19	13.05	25.80
2030	54.00	8248	12200	1588	145	344	381	306	150	79	323	846	8.77	14.12	28.65

Energinet.dk projections and modelling outputs [119]
Augstsprieguma tīkls AS Base Scenario [103]
Litgrid AB Base Scenario [126]
Linear interpolation/extrapolation

Market price clearing model output example

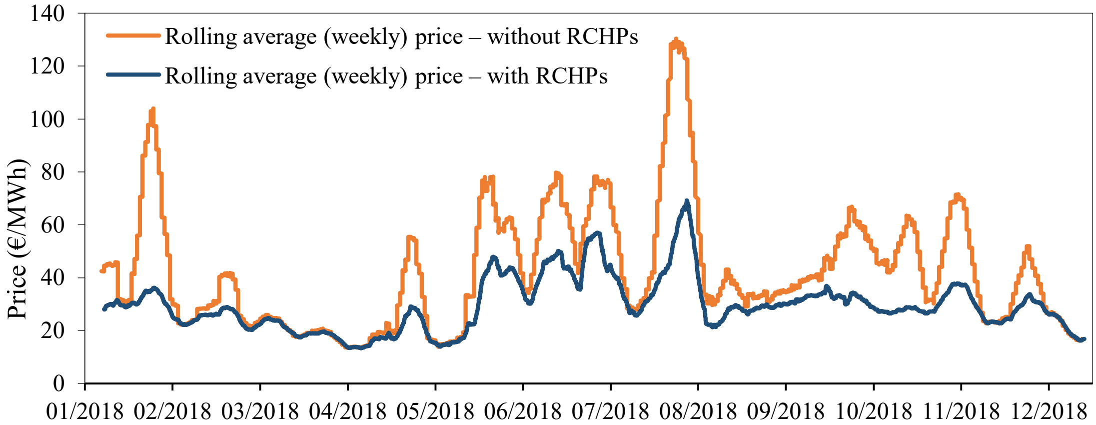

Fig. A.1. Example of modelled electricity prices during one year (*Conservative Scenario*).

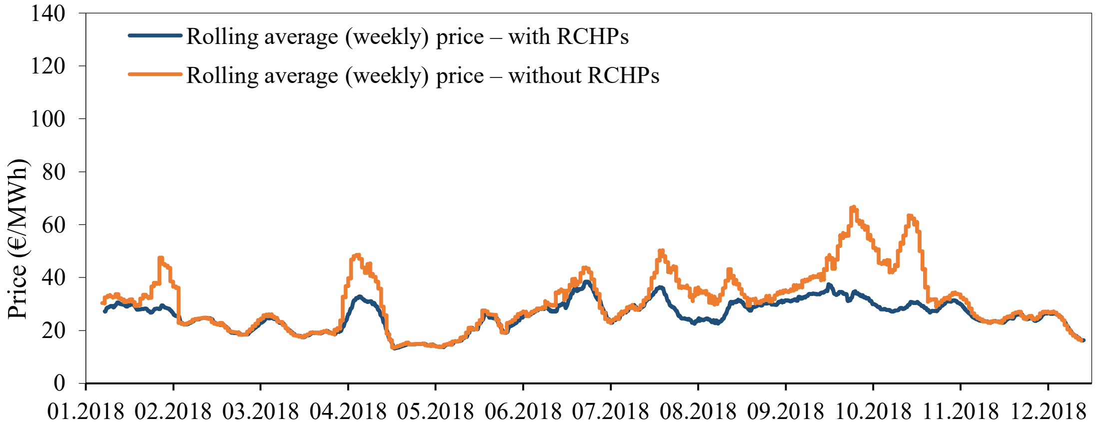

Fig. A.2. Example of modelled electricity prices during one year (*Development Scenario*).