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RIGA TECHNICAL UNIVERSITY

Līga Kurevska

DESIGNING REGULATORY FRAMEWORK FOR DEMAND RESPONSE SERVICE INTEGRATION IN BALTIC ELECTRICITY MARKETS

Summary of the Doctoral Thesis

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

To be granted the scientific degree of Doctor of Science (Ph. D.), the present Doctoral Thesis has been submitted for the defense at the open meeting of RTU Promotion Council "RTU P-05" on August 25, 2022 at 13:00 at the Faculty of Electrical and Environmental Engineering of Riga Technical University, 12 k-1 Azenes Street, Room 306.

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DECLARATION OF ACADEMIC INTEGRITY

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

Līga Kurevska ……………………………. (signature)
Date: ………………………

The Doctoral Thesis has been written in English. It consists of an Introduction, 4 chapters, Conclusions, 28 figures, 19 tables, 10 appendices; the total number of pages is 132, including appendices. The Bibliography contains 101 titles.

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INTRODUCTION

Background and relevance of the research

Mitigating climate change is professed to be one our generation's greatest challenges; however, similarly to many public goods where benefits are enjoyed by many while the costs are born by few, finding a balance between the pace of the change and cost borne by society is not an easy task. The Paris Agreement under the United Nations Framework Convention on Climate Change, which as of April 2017, has been ratified by 145 countries (including the Baltics) [1] and European Commission's "Clean Energy Package" published on 30 November 2016 [2] have already shown that the global policy makers are determined to lead the world towards stronger reliance on renewable energy sources and improved energy efficiency. This global trend is cemented even more within the newest set of European Commission policy initiatives under the umbrella of The European Green Deal which aims to make Europe climate neutral by 2050.

The objectives of The European Green Deal effectively cover wide range of economic activity starting from waste reduction, reforestation, transportation, and sustainable farming. However, energy sector is at the center of it. It is estimated by the policy makers that the energy sector is responsible for approximately 75 % of greenhouse gas emissions. The new requirements, objectives, and investment opportunities have created a space for emergence of new technologies and increased availability of previously prohibitively expensive ones.

The combination of the aforementioned conditions causes a fundamental paradigm shift in global legal framework, the energy sector experiences emergence of new products and services. Firstly, the continuous increase of energy system decentralization and higher reliance on less-controllable/ predictable intermittent generation requires redefinition of the roles and interdependencies of the energy system actors. Secondly, considerable increase in active energy users (prosumers) creates the demand for secondary services (technical, operational, financial support services). Thirdly, the rapid change in the fabric of the industry creates new challenges to system operators regarding technical, operational and pricing (tariff) aspects.

On top of the sheer pace of new technology uptake and the resulting dynamic changes in the industry, the policy makers also have to evaluate the least cost to ensure naturally conflicting objectives – technical system reliability, uptake of new, climate-neutral technology, and low energy costs.

Technical system reliability

The reliability of electric power system operation depends on the balance between power production and consumption [3]. To achieve this balance, every grid connection point needs to be accounted for [4]. Traditionally, this is managed by dividing the system in multiple imbalance areas each having a market participant, which is financially responsible for ensuring that all energy generated within the area is sold and all energy consumed within the imbalance areas is bought. These market participants are called balance responsible parties (BRPs). BRPs ensure the balance by forecasting demand and supply of energy within their imbalance areas and ensuring according energy trades via day-ahead and intraday markets.

When BRPs fail to forecast demand and supply accurately, it can result in excess/deficit energy in the power system. Forecasting errors are corrected in real time by transmission system operators (TSOs) via balancing market. Ensuring sufficient balancing energy reserves is pivotal to TSOs, as without them the power system balance cannot be maintained, which, depending on the interconnections to other power systems, can result in costly procurement of balancing energy from other control areas or in adverse system frequency fluctuations.

The costs of power system balancing are covered by the imbalance payments from those BRPs whose actual consumption/generation deviate from the forecast. Accordingly, the costlier balancing energy is, the more expensive penalty payments for forecasting errors are and consequently the costlier energy in retail markets becomes. The main driver for high balancing prices is balancing resource scarcity. Currently, in the Baltics, only electricity producers provide balancing resources. Furthermore, since the opening of the Common Baltic Balancing market and subsequent increased reliance on national balancing resources (instead of balancing energy resources from Russian TSO), we can observe preliminary indications of balancing resource scarcity [5].

Furthermore, according to the Baltic generation adequacy report, it is expected that during the next 10–15 years the capacity required for balancing reserves will increase due to rising intermittent generation and the planned Baltic power system desynchronization from UPS/ISP. At the same time, the generation from some of the sources typically used for balancing purposes in the Baltic states (thermal power plants in Estonia) will reduce by up to 50 % due to lost competitiveness of oil-shale power plants caused by the increasing costs of SO_2 and NO_2 emissions [5].

This gives clearly indicates that additional sources for balancing reserves are needed. Demand response (DR) is a promising source of balancing energy to consider. DR integration in balancing energy markets can provide significant financial savings for grid operators and market participants and promote optimal resource allocation [6]. Some large consumers in the Baltic states have already expressed preliminary interest in providing services to the TSOs. However, to facilitate DR participation in power system balancing, the service must provide economic gains for both the existing market participants and DR service providers. From the policy makers' point of view, the reliability of the power system is pivotal for functioning economy and must not be jeopardized or experimented with.

Facilitating uptake of climate neutral solutions

While availability of technology is a necessary precondition for behavioral changes in society, the opportunity itself is not sufficient for overall societal change. Based on the research, most rational market actors choose to engage in new initiatives based on three main considerations – the weight of financial and social benefits against administrative and organizational burden. A well-functioning regulatory framework would promote such technologies and consumer and supplier behaviors that generates more social wealth than the cost of introduction and maintenance of the said policies. On the contrary, poorly designed regulatory framework can promote inefficient allocation of resources by either over-subsidizing certain activities or promoting private investment that depletes the investors' wealth.

Low energy costs

The cost of electricity consists of three main components – cost of resource (in Latvia, electricity price constitutes approximately 40 % of the total costs); cost of maintenance and development of the infrastructure necessary to transport electricity (in Latvia, grid services constitute approximately 30 % of the total energy cost); and taxes and levies (in Latvia value added tax and mandatory procurement component together constitute approximately 30 %).

While the long run marginal cost of producing electricity from renewable sources decreases over time due to technological advancements, the increase in intermittent and distributed generation as well as continuous increase in demand for electricity not only promotes volatility electricity prices, but also creates new challenges for the power system infrastructure. An aspect of this is illustrated by the case of South Queensland (Australia), where during the period of 2009–2014 the total installed capacity of solar panels increased from 187 MW to 4092 MW [7] and percentage of residential consumers with rooftop solar panels reached 25 %. Such shift reduced electricity volumes consumed through distribution system but did not have considerable impact on the costs of the system, the volume-based distribution system tariffs increased by 112 % [8]. This illustrates that poorly designed or insufficiently flexible pricing strategy for system services can result in undesired consequences. With the emerging preference for electric transportation as well as electricity-based heating, ventilation and cooling systems, the demand for electricity has increased the tendency to cluster in high and low demand periods, which typically results in peak load demand outpacing overall increase in annual consumption. These trends continue to add further price pressures to the electricity and power system alike.

The potential of demand response

When considering alternative instruments for increasing system flexibility via climate and cost friendly solutions, one of the instruments is a product/service category broadly referred to as 'demand response'. According to the Federal Energy Regulatory Commission, demand response (DR) is defined as: "*Changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized*". DR can be broadly divided into two groups: implicit DR and explicit DR. Implicit DR ('price based' DR) refers to consumers choosing to be exposed to time-varying electricity prices and/or time-varying network tariffs that reflect the real cost of electricity at the time of use and allows the consumers to react to that price depending on their own preferences. Explicit DR refers to a program where demand competes directly with supply in the wholesale, balancing and ancillary services' markets directly or through the services of aggregators.

As discussed in [9]–[11], demand response is able to increase the system's adequacy and to substantially reduce the need for investment in grid development and peaking generation by shifting consumption away from times of high demand, as well as act as a cost-effective balancing resource for variable renewable generation. Adding stability to the system, it lowers the need for traditional and often ineffective sources of energy. It furthermore decreases the need for local network investments, as it shifts consumption away from peak hours in regions with tight network capacity [11]. DR delivers these benefits by providing consumers – residential, commercial, or industrial – with control signals and/or financial incentives to adjust their consumption at strategic times and by doing so promotes consumer engagement.

While there seems to be a consensus on the need for the energy sector to introduce and integrate DR in energy markets, the preferred choice of the market framework enjoys far less unambiguity both from policy makers' and industry representatives' point of view [12]–[19]. For example, in Austria the DR provider (incl. aggregator) has to agree bilaterally on data exchange and transfer pricing with the BRP before flexibly providing service to its customer; while in Switzerland the DR provider does not need such an agreement with the BRP, it has to compensate the BRP at transfer price determined by TSOs. Furthermore, in Ireland neither BRP nor aggregator is charged for the imbalance created [12], [13], [15]. Due to the increased role of DR and independent aggregator proposed in the European Commission "Clean Energy Package", the Member States have restarted discussion on the integration of DR in their respective energy markets with increased urgency. However, as mentioned above, when introducing new regulatory framework, considerable analysis is necessary to avoid loss of social wealth.

Hypothesis, objective and tasks of the Thesis

Hypothesis

By developing appropriate regulatory framework, the demand response services can provide a cost and energy efficient tool for improving system flexibility and mitigate resource price and system price volatility driven by increase in intermittent generation in the Baltic region.

Objective

To develop and assess an appropriate proposal for the main components of regulatory framework to facilitate the demand response service development and promote non-disruptive end-user engagement in energy transition.

Tasks

1. To develop compensation framework and determine roles and responsibilities between the demand response service provider and other market participants.
2. To develop methodology for estimating the volume of energy transferred in the event of demand response.
3. To evaluate and test the impact the demand response could have on electricity markets in the Baltics.
4. To evaluate and test potential financial benefits for the demand response asset holders' from engaging in explicit or implicit demand response.

Research methods and tools

Research studies presented in the Doctoral Thesis were performed employing various bespoke modelling tools and algorithms developed in-house at the RTU Institute of Power.

When modelling the different future scenarios (Chapters 2 and 3), MATLAB was employed to prepare the input data by scaling and adjusting the data according to the scenario assumptions. Furthermore, validation and analysis of the results obtained was performed in Excel. For solving optimization problem of the AOF parameter search tool presented in Chapter 3, MATLAB scripting environment and Global Optimization Toolbox was used to take advantage of its data processing abilities and solver *patternsearch.*

Monte Carlo simulation-based tool *DR Assess* tool employed in the case study presented in Chapter 4 was developed using the MATLAB scripting environment. To make it usable for any interested person, a stand-alone application was compiled, which can be deployed on a standard computer with the royalty-free MATLAB Runtime environment.

For testing and comparative analysis, data sets from NordPool, Elering AS, JSC "Augstsprieguma tīkls", SKM Market Predictor, and Latvian Environment, Geology and Meteorology Centre and specially obtained case study data were used.

Scientific novelty

To facilitate the demand response participation in any of the electricity markets, an algorithm for assessing the volume of electricity transferred is necessary. Considering the metering and market particularities in the Baltic region, alternative algorithms were tested on real metering data on randomly selected energy consumers based on three criteria – simplicity, accuracy, and robustness. From the four potential consumption baseline models analyzed the best performing model was identified. Furthermore, to tackle the issue of expected changes in imbalance settlement period (switching from hourly to 15-min periods), alternative interpolation methods on wind forecasting data were compared and the most precise one was identified. The results of the research assessing the volume of electricity transferred provide concrete assessment of the best performing algorithms in the context of Baltic energy markets.

Regarding compensation methodology a comprehensive overview of models employed in the European Union was reviewed and analyzed for their suitability for Latvian legal and market environment. The combination of integrated and centralized model was deemed to be the most appropriate. The proposal has been now partly introduced in national legislation.

To research how demand response would impact energy prices, two main markets were examined – the Baltic balancing market and the Baltic day-ahead market. For the needs of balancing market examination, the following assessments were made. Firstly, to facilitate optimal activation of balancing resources by the transmission system operator, a bespoke tool, AOF parameter search, has been developed. It includes a complex algorithm mimicking the activities of a TSO dispatch operator in ordering mFRR products to sustain the power system balance. For further assessment several mathematical models were used in order to assess the cost-benefit analysis. On the other hand, to assess the impact on the day-ahead market, multi-factor analysis of the day-ahead price determination was performed.

To evaluate the costs and benefits from demand side services for the asset owners, firstly, a demand response assessment tool has been developed. It is based on Monte-Carlo simulations to properly consider the uncertainties characteristic to electricity markets and provide probabilistic results on benefits the end-user can gain through provision of explicit DR to the market or via implementing implicit DR. While the tool has been tailored for the Latvian case, considering the existing common Baltic balancing market and Nord Pool day-ahead market frameworks, it could be easily applied also to other case studies with similar market setup. Furthermore, in 2020 the financial benefits from participation were tested in real-life environment based on heat-pump system. The alternative assessments provide a more transparent evaluation.

Practical significance of the research

Practical significance of the research studies carried out by the author during development of the Doctoral Thesis have contributed to several research and innovation projects. Listed below, they include not only national and international scientific projects but also contract work for a major industry stakeholder.

1. Research contract "Development of mathematical models for an economic assessment of demand-side flexibility resources and activation optimization of balancing reserves" (2017–2018), commissioned by "Augstsprieguma tīkls" JSC (the Latvian TSO).
2. Project "Management and Operation of an Intelligent Power System (I-POWER)" (2018–2021), funded by the Latvian Council of Science.
3. Project "Future-proof development of the Latvian power system in an integrated Europe (FutureProof)" (2018–2021), funded by the Ministry of Economics of the Republic of Latvia within the National Research Programme "Energy".

Author's personal contribution

During development of the Doctoral Thesis, the author participated in several collaborative projects implying tight cooperation with other staff members of the RTU Institute of Power Engineering. Namely, the AOF parameter search tool and DR Assess tool were developed by the author together with Researcher K. Baltputnis and Z. Broka under the supervision of Professor A. Sauhats. The author contributed to all stages of work and specifically in conceptualization and definition of the mathematical model, and performed the case studies and analysis of their results.

Approbation of the results

The research results included in the Doctoral Thesis have been discussed at six international scientific conferences.

Scientific paper related to Chapter 1 "Compensation methodology"

1. **Sadovica, L**., Marcina, K., Lavrinovics, V., Junghans, G. "*Facilitating energy system flexibility by Demand Response in the Baltics – choice of the market model*". 58th International Scientific Conference on Power and Electrical Engineering of Riga Technical University, 2017, ISBN: 978-1-5386-3846-0, DOI 10.1109/RTUCON.2017.8124834.

Scientific papers related to Chapter 2 "Consumption baseline methodology"

2. **Sadovica, L**., Lavrinovics, V., Sauhats, A., Junghans, G.; Lehtmets, K. *"Estimating the energy transferred in the event of demand response activation: baseline model comparison for the Baltic States"*, 15th International European Energy Market Conference, 2018, ISBN: 978-1-5386-1488-4, DOI: 10.1109/EEM.2018.8469796.
3. **Kurevska, L**., Sile, T., Sauhats, A. *"Developing an economically advantageous wind forecasting method for electricity market design with a 15-minute imbalance settlement period"*; 16th International European Energy Market Conference, 2019, E-ISBN: 978-1-7281-3942-5 DOI, 10.1109/EEM.2019.8916574.
4. **Kurevska, L**., Lavrinovics, V., Junghans, G. "*Harmonization of Imbalance Settlement Period Across Europe: the Curious Case of Baltic Energy Markets*", *60th International Scientific Conference on Power and Electrical Engineering of Riga Technical University*, 2019, e-ISBN: 978-1-7281-3942-5; DOI: 10.1109/EEM.2019.8916254.

Scientific papers related to Chapter 3 "Impact assessment on market prices"

5. **Kurevska, L**., Lavrinovics, V., Junghans, G., Sauhats, A. *"Measuring the impact of demand response services on electricity prices in Latvian electricity market"*. 61st International Scientific Conference on Power and Electrical Engineering of Riga Technical University, 2020, e-ISBN: 978-1-7281-9510-0, DOI: 10.1109/RTUCON51174.2020.9316485.
6. Broka, Z., Baltputnis, K., Sauhats, A., Junghans, G., **Sadovica, L**., Lavrinovics V. "*Towards optimal activation of balancing energy to minimize regulation from neighboring control areas"*, 15th International European Energy Market Conference, 2018, e-ISBN: 978-1-5386-1488-4, DOI: 10.1109/EEM.2018.8469935.
7. Silis, A., Ertmanis, K., **Kurevska (Sadovica), L**., Junghans, G., Sauhats, A. "*Benefits of regional balancing areas*". 16th International European Energy Market 2019 Conference e-ISBN: 978-1-7281-1257-2, DOI: 10.1109/EEM.2019.8916254.

Scientific papers related to Chapter 4 "Cost-benefit assessment for demand response asset holder".

8. **Sadovica, L**., Lavrinovics, V., Sauhats, A., Junghans, G., Baltputnis, K., Broka, Z. *"Case study – assessing economic potential for demand response in Baltic balancing market"*; 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University, 2018, ISBN: 978-1-5386-6903-7, DOI: 10.1109/RTUCON.2018.8659901.
9. **Kurevska, L**., *"Heat Pump Optimization Strategies for Participation in Price-Controlled Demand Response in the Latvian Electricity Market".* Latvian Journal of Physics and Technical Sciences, vol. 58, no. 3, 2021, pp. 98–107. https://doi.org/10.2478/lpts-2021-0019.
10. Broka, Z., Baltputnis, K., Sauhats, A., **Sadovica, L**., Junghāns, G. *"Stochastic Model for Profitability Evaluation of Demand Response by Electric Thermal Storage". 2018 IEEE 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON 2018)*, Latvia, Riga, 12–14 November 2018. Piscataway, NJ: IEEE, 2018, pp. 449–454. ISBN 978-1-5386-6904-4. e-ISBN 978-1-5386-6903-7. doi:10.1109/RTUCON.2018.8659837.

Structure of the Thesis

This Thesis is written in English. It consists of an introduction, four main chapters, conclusions, and bibliography. It contains 28 figures and 19 tables.

Chapter 1 provides an introduction on how far the demand response services and flexibility services in general have advanced in the European Union. Furthermore, the chapter proposes a taxonomy and decision-making algorithm based on which a policy maker can evaluate the best approach for market roles and responsibilities given the market conditions. The chapter concludes with the evaluation of alternative compensation model comparison and a proposal of combination of central settlement model and integrated model as the most appropriate for the current market conditions in the Baltics.

Chapter 2 provides an overview of the alternative methodologies to determine the energy consumption level that would have occurred in case the demand response activation would not have taken place. This calculated consumption is pivotal for explicit demand response service integration in any of the wholesale markets or allowing the demand response to provide ancillary services to system operators. The chapter includes a comparison of four consumption baseline calculation models (two are proposed by the author). The comparative analysis is based on robustness (using netted mean forecast errors) and accuracy (using absolute mean forecast error). For comparison, real metering data from 40 randomly selected medium to large Baltic consumers. As a result, consumption baseline model UK CBM was identified as the best performing both in terms of accuracy and robustness. Acknowledging that smart meters in Baltics are currently using hourly time resolution, while starting from 2025 (the latest), imbalance should be calculated based on 15-minute resolution, alternative interpolation algorithms are compared based on the case study for wind generation forecasts. The best performing interpolation algorithm based on the study is Spline (Order 5).

Chapter 3 deals with estimating and examining the role of demand response in the Baltic electricity markets. To understand the potential impact the demand response participation might have, the factors influencing the electricity day-ahead price are evaluated and quantified. The chapter looks at the following variables: gas price, wind production, emission costs and consumption changes. Based on the day-ahead market data of 2019, it is estimated that the reduction of consumption by 1 MWh/h results in a daily average price decrease of 0.025 EUR/MWh (and decreases total expenditure for electricity procurement by 500–700 EUR or 20–30 EUR/MWh for each 'unconsumed' MWh). This estimation is a valuable input when considering regulatory tools for introduction of demand response. Furthermore, the chapter includes an overview of two additional fields of study related to the demand response participation in electricity markets. One is the potential benefits for regional coordination in balancing market, the other is the examination of the system balancing procedures (activation optimization function). Findings from both indicate an increased potential for demand response regarding the provision of ancillary services as well as clear benefits for common regulatory framework.

Chapter 4 provides an overview of findings of two case studies related to the financial benefits the demand response asset holder might enjoy from participation in demand response. One case is related to implicit demand response where the benefits are tested in real-life environment using heat-pumps during Q1 2021. The other is related to explicit demand response and participation in balancing market. In case of the explicit demand response, an assessment using Monte Carlo simulation based on load profiles of multiple fridges is used. The results suggest that, while the benefits for implicit demand are quite modest, the potential benefits for participation in balancing market can provide motivation to consumers to participate and invest in the tools and processes necessary.

Conclusions of the Thesis provide a summary of main findings.

1. COMPENSATION METHODOLOGY

1.1. Motivation and background

The Paris Agreement under the United Nations Framework Convention on Climate Change, which as of April 2017, has been ratified by 145 countries (including the Baltics) [1] and the European Commission's "Clean Energy Package" published on 30 November 2016 [2] have once again shown that the global policy makers are determined to lead the world towards stronger reliance on renewable energy sources and improved energy efficiency. As a result of this fundamental paradigm shift in global legal framework, the energy sector has seen emergence of new products and services. One especially prominent category of such products has been broadly referred to as 'demand response'. According to the Federal Energy Regulatory Commission, demand response (DR) is defined as: "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized".

As discussed in [9]–[11], demand response is able to increase the system's adequacy and to substantially reduce the need for investment in grid development and peaking generation by shifting consumption away from times of high demand as well as act as a cost-effective balancing resource for variable renewable generation. Adding stability to the system, it lowers the need for traditional and often ineffective sources of energy. It furthermore decreases the need for local network investments, as it shifts consumption away from peak hours in regions with tight network capacity [11]. DR delivers these benefits by providing consumers – residential, commercial, or industrial – with control signals and/or financial incentives to adjust their consumption at strategic times and by doing so promotes consumer engagement.

While there seem to be a consensus on the need for the energy sector to introduce and integrate demand response in energy markets, the preferred choice of the market framework enjoys far less unambiguity both from policy makers' and industry representatives' point of view [12]–[19]. For example, in Austria the DR provider (incl. aggregator) has to agree bilaterally on data exchange and transfer pricing with balance responsible party (BRP) before flexibly providing the service to its customer; while in Switzerland the DR provider does not need such an agreement with BRP, it has to compensate the BRP at transfer price determined by the transmission system operator (TSO). Furthermore, in Ireland neither BRP nor aggregator is charged for the imbalance created [12], [13], [15]. Due to the increased role of DR and independent aggregator proposed in the European Commission "Clean Energy Package", the Member States have restarted discussion on the integration of DR in their respective energy markets with increased urgency. The objective of this section is to present an overview of market models to be considered by the Baltic policy makers. The main contribution of this section is to review and categorize the market models currently employed in the EU and determination of the preliminary qualitative assessment criteria for model evaluation in the context of balancing market in the Baltic region.

Despite the fact that the Energy Efficiency Directive (2012/27/EU) has urged the Member states of EU to introduce the DR in all the energy markets, the majority of Member States still need to fully adopt the directive in practice. According to the latest survey on the DR, as of 2017, only in six countries (Switzerland, France, Belgium, Finland, Great Britain, and Ireland) the DR products are actively participating in wide range of energy markets (Fig. 1.1) [12], [13], [15]. However, even in these countries there are still some market design and/or regulatory challenges.

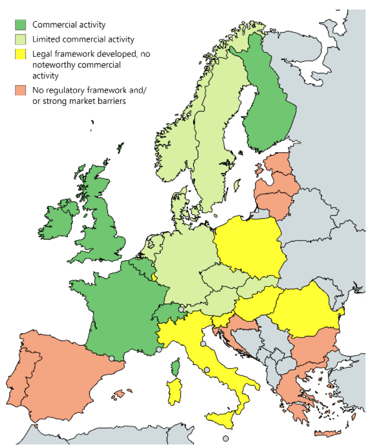

Fig. 1.1. Level of DR introduction in EU as of 2017 [13], [15]

When reviewing the countries with less substantial progress, three broad groups emerge. Countries where DR has been partly integrated; countries where the market models have been developed, but no noticeable commercial activity in the sector of DR has been observed, and lastly, countries where no regulatory framework has been introduced or very strong market barriers still persist.

The policy makers of Austria, Denmark, Germany, the Netherlands, Norway, Sweden, Czech Republic, and Slovakia have started working towards introduction, however, strong market barriers remain and the market growth is fairly limited. For example, Germany and the Nordic countries have started working towards introduction of independent aggregator, while Austria has been working to incrementally improve the bilateral agreement model currently employed. The policy makers of Slovenia, Italy, and Poland have been working towards initial introduction of DR in the energy markets and market activity is expected, while Romania, Hungry, and Luxemburg have developed regulatory framework but due to market barriers or energy system characteristics, have rendered those markets inactive. The policy makers of Spain, Portugal, Baltics, Greece, Croatia, and Bulgaria have yet to develop basic regulatory framework for DR or have to remove significant synthetic market barriers [12]–[14]. Overall, the situation in EU can be characterized as fairly heterogeneous.

1.1.1. The drivers for the DR in the Baltics

Increase in unpredictable generation

Similarly, to the trends in the Central and Southern Europe, the energy system in the Baltics becomes more reliant on the unpredictable distributed generation. Since 2010, the wind energy generation has increased more than three times, and currently the total wind capacity in the Baltics has reached almost 796 MW while solar capacity is 70 MW (Fig. 1.2). As of 2016, the installed capacity of unpredictable (distributed) generation (wind & solar) is more than 10 % of total generation capacity in the Baltics (Fig. 1.2). Furthermore, the trend is upwards sloping – the wind has already been one with the highest installed capacity increase rate, and it is expected to be further amplified by the upcoming oil shale production reduction in Estonia after 2020 due to facilitated lower CO_2 emissions.

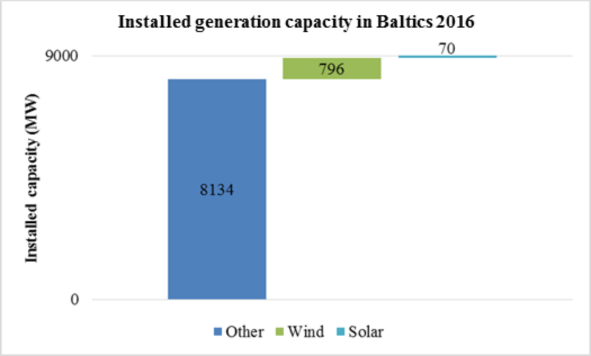

Fig. 1.2. Installed generation capacity in Baltics in 2016; data source: ENTSO-E

Higher balancing market liquidity

Currently in Latvia there is only one business entity participating in balancing market. While there has not yet been a situation where all submitted balancing bids are activated, having a single market participant is traditionally seen as suboptimal. Allowing new type of product (DR) would diversify the balancing market bid offer. Furthermore, the lack of demand side flexibility results in low energy price elasticity [20]. Increased demand side flexibility would have positive effect on market prices in all energy markets (including balancing market).

The legislative framework requirements

Both existing and upcoming requirements of the legislative framework designed by the European Commission have already emphasised that the Member States are to develop a market model where the demand response resource owners (both resident and non-resident) can freely participate in the respective energy markets. According to [12], [13], and [15], while none of the countries have special obstacles disallowing the demand response, the lack of appropriate framework for DR inclusion in different energy markets has made the DR inclusion virtually impossible. Furthermore, the "Clean Energy Package" originally published on 30 November 2016 continues to stipulate the requirements of the market model in a greater detail than before [2]. The precise requirements are reviewed in the following sections.

The desynchronization from the Integrated Unified Power System

The desynchronization from the Integrated Unified Power System (IPS/ UPS) is one of the priorities outlined in the EU Energy Strategy. While the exact date of the desynchronization has not yet been set, it is the common understanding of the Baltic TSOs that preparations for this task should be started already now. The following three scenarios have been suggested as the most feasible options for the desynchronization plan:

- Baltic States' synchronous operation with continental Europe (HVAC Lithuania-Poland interconnector), including soft coupling supported by existing HVDC links;
- Baltic States' synchronous operation with the Nordic countries (HVAC Estonia-Finland), including soft coupling supported by existing HVDC links;
- Baltic States' isolated island operation, including soft coupling supported by existing HVDC links.

While these approaches differ vastly in technical specification and costs, they all share the essential precondition for the Baltic States' energy system having higher flexibility [21].

When comparing the Baltics with other EU countries in regards to the main drivers behind the development of DR, it is clear that many aspects overlap. The increase in unpredictable generation to at least some extent is present in all EU countries. Similarly, the need for higher liquidity in balancing market is almost universal across the EU. Given that the Baltic region is in IPS/UPS and that the wind & solar energy penetration for the Baltics is still below Western Europe, it follows that the pressure to integrate DR in the energy markets is comparatively lower in the Baltics than in, for example, Ireland or Denmark. Furthermore, the EU policy/ regulatory requirements are the same for all EU countries, and this aspect, though important, also does not distinguish the Baltics among the other EU countries either. The most unique driver for DR in the Baltic region is the upcoming desynchronization from IPS/UPS. It is already known that when the Baltics do desynchronize, the market of DR must be already in place, especially for balancing and reserve markets. Based on experience in the EU, the length of time required for the DR market to become commercially active is five or even more years [13]. Accordingly, market regulations should be developed and implemented already now.

1.1.2. Review of legal requirements for the Baltics

Before the European Commission (EC) published the project for “Clean Energy Package” on 30 November 2016, the key EC regulation in regard to demand response and aggregation had been the Energy Efficiency Directive (2012/27/EU) [22]. The main requirements towards demand response under the Energy Efficiency Directive can be divided into four sections [15]:

- Demand response should be encouraged to participate alongside supply within the wholesale, balancing and ancillary services markets;
- TSOs and DSOs must treat the demand response providers, including aggregators, in a non-discriminatory manner and on the basis of their technical capabilities;
- national regulatory authorities should define technical modalities for the participation in these markets on the basis of participants’ capabilities;
- these specifications should include enabling aggregators.

The “Clean Energy Package” further includes more detailed and more concrete requirements for the Member States. The two regulations most discussed regarding DR are: Proposal for the Directive on the internal market for electricity and Proposal for the Directive on the internal market for electricity.

The draft proposal for the Directive on the internal market for electricity develops on the initial stance and provides Member States with further details (particularly Articles 13 and 15). The directive stipulates the importance of [2]:

- granting the demand side resources (private and professional) access to all markets (wholesale, balancing, ancillary services) at all timeframes and introducing a new obligation to remunerate customers for the flexibility;
- empowering the consumer to participate in DR (directly or through aggregation) without the consent of the supplier and to switch aggregation service provider without penalty;
- empowering independent aggregators by ensuring that they can enter the market without the consent from the supplier and can participate in the energy markets without compensating the supplier and/or generator.

The Directive on the internal market for electricity should have been fully transposed by the Member States by January 2021. All three Baltic countries are currently in process of including appropriate provisions in their national legislation.

1.2. Overview of alternative compensation models

The models presented in EU [11]–[19] can be broadly categorized into six main types. Within each of the architype, different variations of the model are possible. There are two main groups of the model architypes: models where the aggregator directly or indirectly compensates the supplier for the energy transferred (Supplier Settlement Model, Consumer Settlement Model, Central Settlement Model) and models where aggregators do not compensate either directly or indirectly the supplier for the energy transfer (Socialized Settlement Model, No Settlement model). The

Integrated model does not have any energy transfer (and no compensation mechanism is necessary). Each of the groups has a subdivision. For the ‘compensation group’ the subdivision is determined by the party through which the compensation is granted to the supplier. For the ‘no compensation group’ the subdivision is determined by the group of customers who ultimately compensate the supplier (Fig. 1.3). The relationships between different market parties in each of the models are presented in Fig. 1.4.

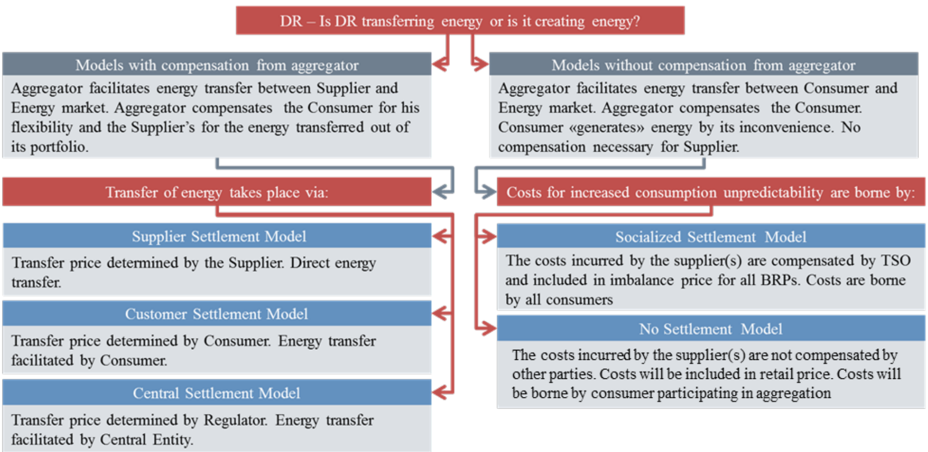

Fig. 1.4. Proposed market model taxonomy

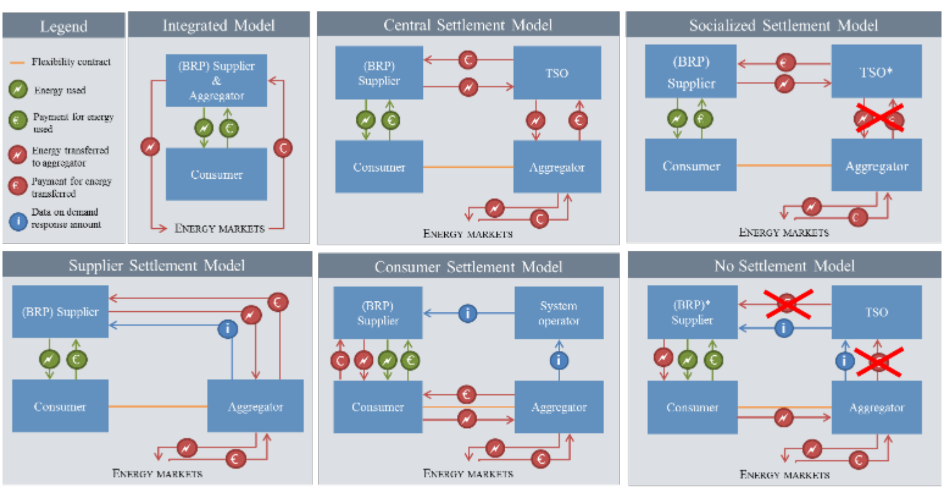

Fig. 1.3. Roles and responsibilities in different market models [11], [14], [16]–[19]

1.3. Qualitative analysis

The overview presented in the previous sections sets up the basis for the evaluation of the models in the context of the Baltic region. The best practices along with the drivers for the DR integration in the Baltic energy market and the upcoming changes in the legislative framework suggest that a model should not only be in line with the current legislation but should also have the following characteristics:

- inclusive – meaning that the market model ensures there are no barriers of entry for the independent aggregator;
- fair – meaning that the market model treats the aggregators as energy transfer facilitators between market participants;
- simple – the market model is compatible with the existing data exchange processes and does not require significant investments in IT infrastructure/administrative processes for other market participants.

In Fig. 1.5 the summary of model comparison is presented.

Market model	Inclusive	Fair	Simple
Integrated	×	✓	✓
Supplier settlement model	×	✓	✓
Consumer settlement model	✓	✓	×
Central settlement model	✓	✓	✓
Socialized settlement	✓	×	✓
No settlement	✓	×	✓

Fig. 1.5. Comparison of the market models

The preliminary qualitative comparison of the models suggests that the best approach for the integration of DR in the Baltic Balancing market is to combine two models:

- the integrated model is the most appropriate for suppliers who are interested in developing new products for their customer portfolio;
- the centralized settlement model is the most appropriate for independent business interested in providing aggregation service.

Such combination of models will provide the best opportunity for the existing and the potential market participants and ultimately will ensure that each and every customer has an option to participate in the balancing market. Further research should focus on the analysis of how the market model impacts the prices within energy wholesale and retail markets, as well as assessment of the most suitable market model or combination of market models for energy wholesale markets.

2. CONSUMPTION BASELINE METHODOLOGY

2.1. Motivation and background

Demand response service (DR) is a temporal change in consumer's energy consumption due to a reaction to price signals or by other measures [23]. DR is associated with multiple benefits such as increased system flexibility, improved network congestion, cost-effective alternative to grid investments, and improved energy efficiency [24], [25].

DR can be broadly divided into two groups: implicit DR and explicit DR. Implicit DR ('price based' DR) refers to consumers choosing to be exposed to time-varying electricity prices and/or time-varying network tariffs that reflect the real cost of electricity at the time of use and allows the consumers to react to that price depending on their own preferences. Explicit DR refers to a program where demand competes directly with supply in the wholesale, balancing and ancillary services' markets directly or through the services of aggregators. This is achieved through the controlled changes in the load that are traded in the electricity markets, providing a comparable resource to generation, and receiving comparable prices [26], [27]. Currently, implicit DR in Latvia and Estonia is available to consumers via electricity supply contracts where retail price is linked to the spot price. Starting from late 2017, there is an ongoing DR aggregation pilot study in Estonia; however, the explicit DR is not commercially active there or anywhere else in the Baltics [28].

For explicit DR to become commercially active, a market framework describing the financial settlement among the market parties (such as consumers, aggregators, system operators and balance responsible parties) needs to be developed. Estimate of DR delivered also known as the electricity reduction amount (ERA) is a pivotal part of such a framework. ERA is the difference between the actual consumption that occurred and the forecasted consumption that would have occurred in the absence of DR activation event. This forecast is called a baseline, and a method for baseline estimation is called consumption baseline model (CBM) (Fig. 2.1) [29].

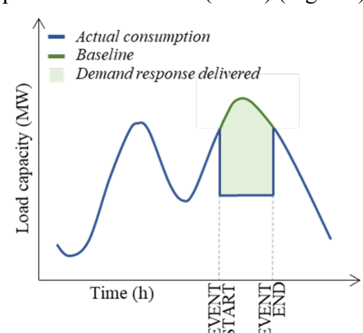

Fig. 2.1. Consumption baseline explained

As of now there is no universal consensus on the best performing CBM, and even in countries where the DR commercial activity is relatively high (e.g., UK, France, Belgium, USA) the choice of the model tends to be rather fluid and CBMs are regularly updated to reflect the reduced costs of data collection and processing as well as improved understanding of the underlying processes [24], [26], [27], [29]–[34]. Regional CBM compatibility studies have been performed in USA [29], [30], UK [35], Australia [36] and EU in general [26], [27] among others. When considering a CBM proposal for the Baltic region, we need to take into account the additional challenges regarding the data resolution. Traditionally, DR events for a single metering point can be shorter than 15 minutes. Currently the imbalance settlement period in the Baltics is 1 hour and the metering data that can be used for the financial settlement are collected at the same time resolution [28]. The mismatch between the length of a DR event and the time resolution of available metering data further complicates the development of acceptable CBM [33]. The main contribution of this section is testing of CBMs' accuracy and skewness on a lower resolution metering data (using the hourly data that are typically used in the Baltics instead of more popular 5-minute or 15-minute resolution usually used in the previous research). Such tests are important because the change in data resolution can have an impact on the relative performance of CBMs.

2.2. Overview of alternative consumption baseline models

A CBM is used to forecast the consumption in the absence of DR activation event. A well-designed CBM enables grid operators and utilities to measure the performance of DR resources and correctly attribute the imbalance caused. Such a CBM benefits all stakeholders by aligning the incentives, actions and interests of consumers, aggregators, utilities, and grid operators; however, not all CBMs can be considered well-designed [33]. A CBM that systematically over-estimates the forecasted consumption will over-value the contribution of the participating DR resource and result in overestimation of positive imbalance for the balance responsible party of the said resource. Conversely, a CBM that systematically underestimates the forecasted load will under-value the contribution of the participating DR resource and result in overestimation of negative imbalance for the balance responsible party [33].

Based on the literature review, CBMs are characterized by the following parameters: accuracy (low average expected error); robustness (absence of systematic error in either direction and lack of obvious data manipulation exploitation possibilities for opportunistic market participants); and transparency (market parties can apply the CBM and get the same results as the grid operator) [29], [36]. It is important to note that at times these characteristics are at odds with each other –very accurate models based on advanced data processing methodologies tend to be fairly complex and non-transparent, while very simplistic models tend to be fairly vulnerable to data manipulation [24], [33]. Accordingly, the choice of the CBM is ultimately dependent on the relative importance attributed to accuracy, robustness, and simplicity. This implies the necessity for tradeoffs when designing a CBM for a particular market and at least partly explains the exotic variety of CBMs already in place.

All CBMs can be broadly divided into two categories – a day-matching forecast and a regression forecast [34]. In the Baltics the concept of explicit DR is still fairly novel and the new market participants (such as independent aggregators) still face limited enthusiasm from the incumbent market participants. Based on the market maturity and the Baltics market participants' views presented in public consultation summary, it is obvious that a CBM relying on advanced statistic and data processing tools would currently not be feasible [24], [29], [36], [37]. Similar approach can be observed in the EU, where, as of now, only in France the balancing market has employed long-term statistics-based model, while all other EU states, where CBM is present, have opted for day-matching CBMs [26], [27], [33]. Furthermore, our position on regression-based models was further cemented by EnerNOC (2009) that stated that regression models have been rejected in the USA due to the lack of support from the market participants. Accordingly, the regression-based models are not reviewed in this section on the basis of not fulfilling the minimum requirements of simplicity parameter [33].

The day-matching CBMs can be further divided into two sub-categories – models using only the data from before the DR activation event and models using data from both before and after the DR activation event. In the EU, the CBMs using only ex-ante metering data seem to enjoy higher popularity [26], [27], which might be linked to the ex-ante/ex-post CBMs being more vulnerable to data manipulation exploits.

Baseline consumption methodology forecast models

We tested four day-matching CBMs – three of those only use metering data from before DR activation event and one uses the data from both before and after activation. Description of the CBMs tested is presented in Table 1.

1. EnerNOC CBM has been used and tested in North America (USA) and is one of the earlier baseline models tested in markets. EnerNOC original variation operates with a time resolution of 1 hour [33].
2. The UK model is adopted from the paper by Imperial College London (2014) and for some time had been used in the UK. The model originally operates with higher time resolution and has been adjusted to the use of hourly metering data [35].
3. Average CBM is the only model in our test that uses both before and after DR activation event data. The model broadly follows the concepts present in the CBM employed in Ireland [26], [27].
4. The daily profile CBM is loosely based on the methodology present in Belgium [26], [27]. Similar to the Daily profile, the Belgium model does not fully use day-matching approach, since only the data from the same day is employed in the CBM. Furthermore, Belgium uses 15 min time resolution.

Based on the paper presented by DNV KEMA (2013) on the basic CBM calculation type, a separate calculation can be applied to align the baseline with the observed conditions of the event day – baseline adjustment method. The CBM adjustment method can improve the performance of the model significantly. The factors used for adjustment rules may be based on, but are not limited to: temperature, humidity, calendar data, sunrise/sunset time, and/or event day operating conditions (the most widely used factor). There are two main types of baseline adjustment methods:

1. Additive, which adds a fixed amount to the provisional baseline load in each hour, such that the adjusted baseline will equal the observed load at a time shortly before the start of the event period.
2. Scalar, which multiplies the provisional baseline load at each hour by a fixed amount or scalar, such that the adjusted baseline will equal the observed load on average during a window of time shortly before the start of the event period [34].

In our analysis, additive adjustment is used in EnerNOC CBM, UK CBM and Average CBM, while scalar is used in Daily profile CBM (Table 2.1).

Table 2.1

Summary of Alternative Consumption Baseline Models

CBM	Short description
EnerNOC	Baseline is equal to the average consumption of 5 corresponding hours with the highest consumption within 10 last non-event days. Baseline is adjusted upwards by the average difference between the last two hours' actual consumption and their baseline. Formula $b_t = \frac{c_1 + c_2 + c_3 + c_4 + c_5}{5} + \max\left[\frac{c_{t-1} - b_{t-1} + c_{t-2} - b_{t-2}}{2};0\right]$ (2.1)
UK	Baseline is equal to the average consumption of 5 corresponding hours within 5 days with the highest daily consumption (out of 10 last non-event days). Baseline is adjusted upwards and downwards by the difference between the last two hours' actual consumption and their baseline. Formula $b_t = \frac{c_1 + c_2 + c_3 + c_4 + c_5}{5} + \frac{c_{t-1} - b_{t-1} - b_{t-2}}{2}$ (2.2)
Average	Baseline is equal to the average of consumption one hour before and one hour after the DR event. Formula $b_t = \frac{c_{t-1} + c_{t+1}}{2}$ (2.3)
Daily profile	Baseline is equal to the consumption within preceding hour multiplied by the fraction of increase/decrease of consumption in the corresponding hours a day before the event. Formula $b_t = \frac{c_{d,t-1} \times c_{d-1,t}}{c_{d-1,t-1}}$ (2.4)

b_t – baseline at hour t;
c_1 – highest corresponding hourly consumption within 10 last non-event days;
C_1 – highest corresponding hourly consumption in a day with highest daily consumption within 10 last non-event days.

2.3. Quantitative analysis

2.3.1. Methodology

We used hourly metering data that represents annual consumption of 40 randomly selected medium to large electricity end-users from the Baltic region. The set of consumers included different consumption patterns with the hourly average consumption varying from 50 kWh to 3 MWh. In our analysis, we mainly focus on the medium and large consumers due to two reasons: such consumers usually are characterized by higher consumption pattern volatility, such consumers have higher DR potential.

To ensure that the sample is heterogeneous and represents different consumption patterns, correlation analysis was performed for all pattern pairs. The results of the correlation analysis indicated a well diverse sample and indicated that no pattern type is over-represented.

The total number of hours used in the analysis is 8760. Since each model requires different number of days or hours before the event, the number of hours with forecasted baseline differs among the models tested.

Analysis

Based on the literature review, all the analysed CBMs fulfil the simplicity parameter. Accordingly, the objective of the analysis was to quantify each model's accuracy and robustness.

For robustness comparison, we calculated netted mean forecast errors (NMFE), and for the accuracy measurement, we used absolute mean forecast error (AMFE). If NMFE is equal (close) to zero, it is expected that in the long term, inaccuracy will not have impact on total amounts of energy transferred – in other words, NMFE measure the extent to which the model is systematically skewed in either direction. AMFE measures the expected deviation in a single instance. As a benchmark for the AMFE we use the results from the study covering different CBMs in USA, where the model accuracy for models with adjustments ranged from 10–14 % [34].

The baseline error was calculated as follows:

$$Er_{BL} = E_F - E_A, \text{ where} \qquad (2.5)$$

Er_{BL}– baseline error, kWh;
E_F – baseline or forecasted energy consumption, kWh;
E_A – actual consumption, kWh.

Sample error at a trading interval (t) is calculated as follows:

$$Er_{\%_t} = \frac{\sum_{i=1}^{I} \frac{Er_{BLi,t}}{Er_{Ai,t}}}{I}, \qquad (2.6)$$

where
$Er_{\%_t}$ – baseline error at a trading interval *t*;
I – number of consumption patterns in the testing sample;
i – consumption pattern.

Accordingly, if the baseline error is above 0, the baseline is overestimated, while if the baseline error is below 0, the baseline is underestimated.

NMFE is calculated as follows:

$$NMFE = \frac{\sum_{t=1}^{T} Er\%_t}{T}, \qquad (2.7)$$

where
NMFE – netted mean forecast error for all trading periods within the sample;
t – trading interval;
T – all trading intervals in the sample.

AMFE is calculated as follows:

$$AMFE = \frac{\sum_{t=1}^{T} |Er\%_t|}{T}, \qquad (2.8)$$

where AMFE is absolute mean forecast error for all trading periods within the sample.

To estimate the statistical significance of the average accuracy differences observed for both MNFE and AMFE, we ran F test for the difference in two variances for all CBM pairs at a significance level of 99 %. The results indicated that all CBMs' variances are significantly different from each other. We continued with *t*-test for differences in error means of CBMs. The results are presented in the next section.

2.3.2. Results and discussion

The descriptive statistics of NMFE and AMFE is presented in Tables 2.2 and 2.3.

Table 2.2

NMFE Descriptive Statistics

	EnerNOC CBM	**UK CBM**	**Average CBM**	**Daily prof. CBM**
SD	33.21 %	7.54 %	3.52 %	6.64 %
Variance	1103 $\%^2$	57 $\%^2$	12 $\%^2$	44 $\%^2$
Max	727 %	66 %	182 %	389 %
Mean	36.6 %	0.7 %	1.1 %	1.1 %
Min	1 %	–43 %	–23 %	–100 %
Sample	8312	5797	8759	8686

Table 2.3

AMFE Descriptive Statistics

	EnerNOC CBM	**UK CBM**	**Average CBM**	**Daily prof. CBM**
SD	33.15 %	6.24 %	3.27 %	6.49 %
Variance	1099 $\%^2$	39 $\%^2$	11 $\%^2$	42 $\%^2$
Mean	37.8 %	9.5 %	4.8 %	7.1 %
Sample	8312	5797	8759	8686

The density distribution for the forecast errors of the CBMs tested is presented in Fig 2.2.

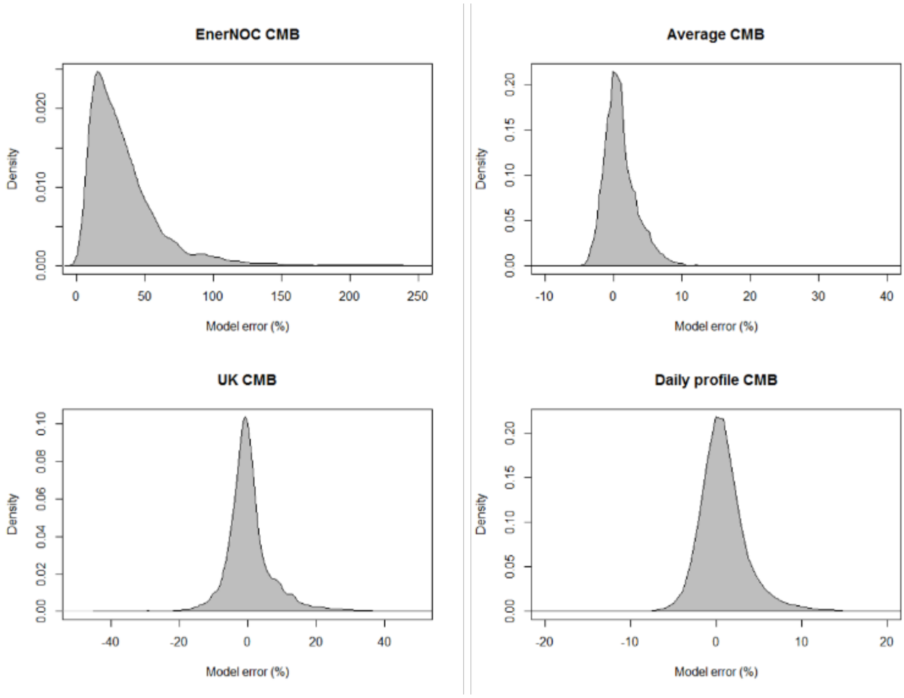

Fig. 2.2. Density distribution for the forecast errors of the CBMs tested

The results of the t-test for the mean difference for the model pairs for NMFE and AMFE values are presented in Tables 2.4. and 2.5, accordingly.

Table 2.4

NMFE t-test Results

t-value for differences of error means			
	UK CBM	**Average CBM**	**Daily prof. CBM**
EnerNOC CBM	95.280***	97.068***	95.691***
UK CBM		3.969***	3.677***
Average CBM			0.366

Significance: ***1 % level; ** 5 % level; *10 % level.

The results of the t-test for NMFE indicate that there is no significant difference between the NMFE of Average CBM and Daily profile CBM. All other differences are statistically significant at a significance level 1 %.

Table 2.5

AMFE t-test Results

t-value for differences of error means			
	UK CBM	**Average CBM**	**Daily prof. CBM**
EnerNOC CBM	72.895***	90.306***	83.059***
UK CBM		– 52.781***	–22.906***
Average CBM			–28.738***

Significance: ***1 % level; ** 5 % level; *10 % level.

The results of the t-test for AMFE indicate that the CBMs present significantly different AMFE at the 1 % significance level.

The UK CBM shows the lowest NMFE (0.7 %). The results indicate that if this model were applied, there would be no substantial long-term inaccuracy of ERA in either direction. The EnerNOC CBM shows the poorest results, which is associated with overestimation of ERA for more than one third of the total energy volume.

The analysis of AMFE indicates that all models, except for EnerNOC CBM, perform better than the benchmark value of 10–14 % and as such is considered to fulfill the minimum accuracy condition.

2.4. Comparison of alternative time resolution increase algorithms

2.4.1. Background and motivation

According to Article 53 of the European Union Electricity Balancing Guidelines, the transmission system operators (TSOs) should implement the 15-minute imbalance settlement period (ISP-15min) until 18 December 2020, with Article 62 indicating that the introduction can be postponed until up to 1 January 2025. Most smart-metering devices in the Baltics are capable only to support hourly time resolution for metering data. Similar issue can be observed in wind generation forecasting. To test alternatives transposing algorithms, a study based on the needs of wind forecasting in the context of 15-minute ISP, was performed.

Imbalance calculation and ISP

It is generally agreed that finer time resolution for imbalance settlement improves system forecast accuracy (Fig. 2.3) [38]–[40]. The longer the ISP, the more the deviations from the forecasted schedule are netted within the ISP and the lower imbalance amount is recorded. The netting effect is beneficial to market participants with volatile loads, but it hurts the other market participants. Regardless of netting, the system must be balanced at every moment, so the costs of balancing are still incurred and are translated into higher imbalance costs per MWh.

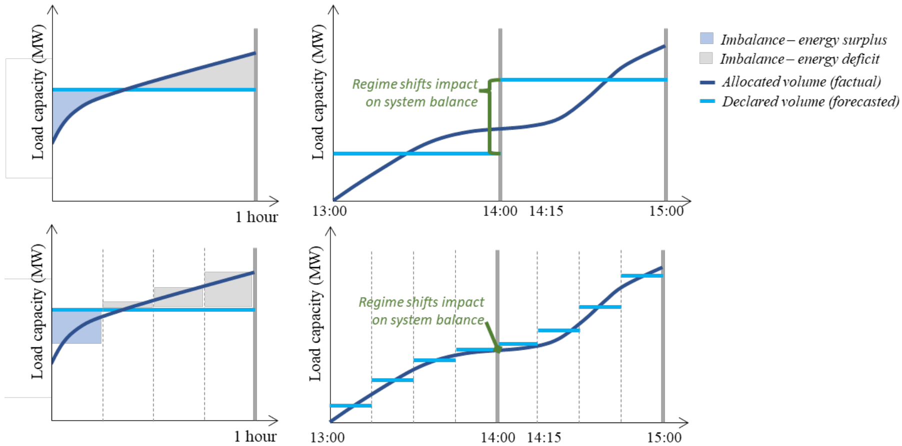

Fig. 2.3. Imbalance misattribution due to netting effect and regime change effect

Furthermore, the highest imbalance in the Baltic system is typically recorded at the beginning of the hour when the generation units change regimes. This is caused by the slow ramping rates of the conventional generation plants; by introducing shorter ISPs the ramping rates can be better acknowledged and more accurate system balance forecast could be created (Fig. 2.3).

Overall, it is expected that the cost allocation among market participants will better reflect cost creation. However, real benefits for system stability and balancing cost reduction can only be achieved if market participants adjust and improve their forecasting methodologies.

2.4.2. Methodology

Objective and scope

The typical time resolution of a mesoscale model output is 60 minutes. In order to get a qualitative improvement in load forecasting and consequently reduce imbalance costs, the 60-minute data must be translated into higher time resolution. The aim of the analysis is to explore the benefits of facilitation of this translation via interpolation and to test and compare the performance of the approaches. To exclude particularities outside of the scope of current research step, the author opted to interpolate data from a single model. To test the quality of the interpolation, the available wind observation data from 2018 with 10-minute time resolution was used. Accordingly, also the interpolation methods' performance is determined for 10-minute intervals. For the purpose of this study it is acceptable to assume that the method's performance at 10-minute resolution is a proxy for the method's performance at 15-minute resolution.

To provide a rough comparison of economic performance the authors also accounted for the differences between the imbalance cost of overestimation of wind speed and underestimation of wind speed and the used absolute (as opposed to netted) forecasting error.

Methodology

The Weather Research and Forecast model has been used to create a mesoscale model dataset. Although a 30-min model data are available, the data were down-sampled to the time resolution of one hour. In total the author tested 9 different interpolation methods. These approaches can be divided into three groups: ‘the nearest neighbor’, ‘polynomial interpolation’, and ‘spline interpolation’.

- The nearest neighbor interpolation is the simplest method, as it substitutes the unknown value with the closest available value, namely, for all ISPs between 14:00 and 15:00 the available modeled value for 14:00 is used. ‘The nearest neighbor’ approach serves as a baseline approach to which the other eight methods are compared.
- Polynomial interpolations use a polynomial function to obtain the values between known points. Polynomial interpolation can have different orders, depending on the order of the function used. The author tested three polynomial interpolation approaches – a linear function, where a straight line is drawn between known points (first order), a quadratic function (second order), and a cubic function (third order).
- Spline interpolation is an approach where the interpolating function is required to have smoothness properties, by ensuring the continuity of derivatives. The author tested five approaches based on spline interpolation (order 1 to 5).

After obtaining the interpolated model data, the author converted both real observation and interpolated model data in energy generated by using a power curve of a small wind power station. The difference between energy calculations based on the forecasted and observed data is considered imbalance. Furthermore, the annual expected cost of imbalance was calculated based on a difference between average imbalance prices (both directions) and corresponding spot prices for 2018. Lastly, the relative performance of each interpolation approach was calculated assuming the ‘nearest neighbor’ method’s performance as a reference.

Inputs

The author used the following data for the analysis:

- Model data was extracted from the mesoscale NEWA [41] dataset [42] for the nearest gridpoint and vertically logarithmically interpolated in each timestep to the observational height.
- For observational data, the available high mast measurements carried out using cellular communication masts for the station near Ventspils, Staldzene were used. Observational data are available for 10-minute intervals for one full year (2018) for the measurement height of 80 m [42].
- As a sample power curve for converting wind power in capacity, a power curve from Vestas V100/2000 (2MW) was used.
- For day-ahead price calculations the author used NordPool spot prices for 2018 (Baltic/Latvian bidding zone).
- For imbalance price calculations the author used the imbalance price data for 2018 of the Baltic TSOs (Baltic/ Latvian bidding zone).

2.4.3. Results and discussion

Overall deviations between observations and forecast are quite high (netted error is ~20 %). The calculations also show that the error rates from the mesoscale model data are skewed in the direction of overestimation. 60 % of modeled values suggested the wind speed higher than the observed, while 40 % suggested the wind speed lower than the observed. In other words, the modeled data, when used for electricity generation scheduling, would result in 60 % of ISPs with negative imbalance (imbalance energy bought by the power station operator) and 40 % of ISPs with positive imbalance (imbalance energy sold by the power station operator) (Table 2.7). The author did not detect statistically significant difference regarding systematic bias in one or the other direction among the interpolation methods tested.

While overall deviations between the observed and modeled (forecasted) value are quite high, the overall costs of imbalance remain adequate (7 % of electricity sales). That is related to favorable market conditions that rendered small price differences between the imbalance price and spot price (8.22 EUR/MWh for deficit and 5.97 EUR/MWh for overproduction) [43].

While comparing interpolation approaches, the best performing model is Spline (Order 5). Compared to the simplistic approach (assuming modeled hourly value is unchanged for all ISPs within an hour), Spline (Order 5) provides a 5.1 % reduction of imbalance costs against the 'nearest neighbor'. Similar level of reduced annual imbalance costs is associated with Spline (Order 3) (Table 2.6).

Table 2.6

Model Performance Comparison

Method name	Expected annual imbalance costs	Performance against 'the nearest neighbor'
Nearest neighbor	23 766.22 €	n/a
Linear	23 645.44 €	–0.51 %
Quadratic	23 782.04 €	0.07 %
Cubic	23 788.40 €	0.09 %
Slinear	23 645.44 €	–0.51 %
Spline (Order 2)	22 732.82 €	–4.37 %
Spline (Order 3)	22 620.24 €	–5.04 %
Spline (Order 4)	22 691.34 €	–4.75 %
Spline (Order 5)	22 609.88 €	–5.10 %

Table 2.7

Model Comparison – Imbalance Costs (Both Directions)

Parameter	Standard approach	Polynomial interpolation			Spline inerpolations				
	Nearest neighbor	Linear	Quadratic	Cubic	Slinear	Spilne (order 2)	Spline (order 3)	Spline (order 4)	Spilne (order 5)
% of ISPs where imbalance energy is bought	60.05	60.59	60.61	60.64	60.59	60.49	60.78	60.58	60.57
Imbalance energy bought annually (MWh)	2 189.38	2 178.26	2 190.69	2 191.30	2 178.26	2 072.72	2 058.34	2 070.00	2 058.03
Price of underproduction (EUR/MWh)	8.22	8.22	8.22	8.22	8.22	8.22	8.22	8.22	8.22
Costs incurred in deficit hours (EUR)	18 002.09	17 910.63	18 012.88	18 017.86	17 910.63	17 042.82	16 924.60	17 020.52	16 922.04
% of ISPs where imbalance energy is sold	39.35	39.41	39.39	39.36	39.41	39.51	39.22	39.42	39.43
Imbalance energy sold annually (MWh)	–965.31	–960.40	–966.15	–966.39	–960.40	–952.90	–953.84	–949.69	–952.54
Price of overproduction (EUR/MWh)	5.97	5.97	5.97	5.97	5.97	5.97	5.97	5.97	5.97
Costs incurred in overproduction hours (EUR)	5 764.13	5 734.81	5 769.15	5 770.54	5 734.81	5 690.00	5 695.64	5 670.82	5 687.83

3. IMPACT ASSESSMENT OF MARKET PRICES

3.1. Motivation and background

In the context of Baltic synchronization with the Continental Europe synchronous area, the discussion on alternative sources for fast acting reserves (FCR and aFRR balancing products) has gained prominence. The demand response services has been considered as one of the less expensive technological options compared to storage facilities and conventional gas turbines [44], [45]. To facilitate faster adoption of the demand response role in Latvian electricity market, a new Cabinet of Ministers regulation has been developed for aggregators (in force from 24 March 2020). This regulation allows the demand response services to participate not only in providing ancillary services for system operators, but also to participate in wholesale electricity markets [46].

According to the report published by the Latvian transmission system operator, electricity consumption is expected to grow by less than 1 % per annum (base scenario) [47]. The growth of consumption in a conservative scenario (with average winter temperatures above –3.5 °C) is forecasted at ~0.5 %. Similarly, the model developed by Skribans, V. & Balodis, M. (2017) the forecasts of electrical consumption in Latvia only slightly increase (i.e., 10 % within 10 years) [48]. From the supply-demand perspective this means that lower prices for electricity can be achieved only by shifting the demand from peak periods to, for instance, night hours, when electricity consumption in Latvia and the region is lowest [49].

Day-ahead price characterization

Latvian electricity market operates under the Nord Pool electricity exchange, which provides services for the Nordic and Baltic regions and Northern Europe (Germany, France, the United Kingdom, etc.). Nord Pool is the largest electricity exchange in Europe – in 2019 the total of 494 TWh was traded on the exchange [50]. For comparison, Latvian total consumption of electricity in 2019 was 7.3 TWh, or 1.4 % of traded on Nord Pool. Such traded amounts and large number of market participants (more than 400 entities) guarantee high competition and liquidity both for producers and consumers.

In 2019, average day-ahead price in Latvia was by 16 % higher than in Sweden (Zone 4), and by 5 % higher than in Finland. While prices in Latvia, Lithuania, and Estonia are quite close to each other, they are significantly higher than the prices in the Nordics (especially in Sweden and Norway). This difference becomes even more pronounced when accounting for electricity consumption profile. Consumption is considerably higher during the business hours, so the demand in Nord Pool cannot be covered by the relatively cheap renewable and nuclear energy. In these hours cheap energy is mainly consumed in the bidding zone where it is produced. In other bidding zones, the day-ahead closing prices are determined by more expensive producers.

Day-ahead prices in Latvia are not only the highest but also the most volatile when compared to other bidding zones. Figure 3.1 shows that Latvian prices vary from 12 €/MWh to

114.6€/MWh. In contrast, daily average prices in neighboring bidding zones never crossed 100 €/MWh level during the last 4 years from 2016 to 2019.

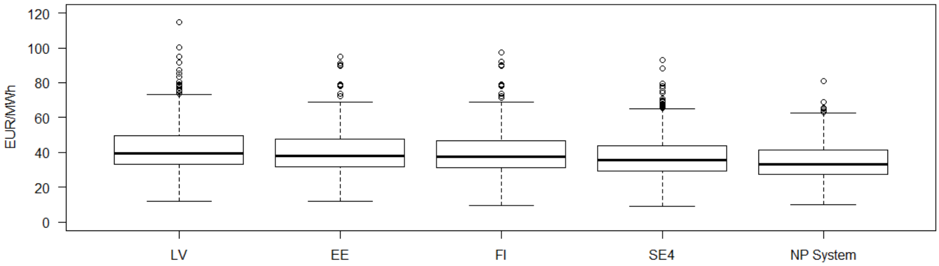

Fig. 3.1. Box plot of daily average day-ahead prices, 2016–2019; source: Nord Pool (author's calculations)

In Latvia, where only a couple of electricity retailers have their own production facilities, which can be used as a natural hedge against electricity price fluctuations, most traders are very sensitive to volatility of day-ahead prices. Introducing the demand response services could provide additional hedging options for these traders.

3.2. Methodology

Framework

To determine the impact of demand response services on the prices of the day-ahead market, the day-ahead price factor analysis is performed. To do this, the author uses the time series methodology, which is the most widely used technique in studies focused on price determination [51]–[53]. The multiple linear regression model is employed to evaluate if the chosen set of k variables has a statistically significant impact on electricity prices (Y). The general form of multiple regression model is as follows:

$$Y_t = \beta_0 + \beta_1 x_{t,1} + \beta_2 x_{t,2} + \ldots + \beta_i x_{t,1k} + \varepsilon_t . \quad (3.1)$$

The use of multiple regressions is associated with multicollinearity issues – the situation when two or more independent variables have high correlation, which may result in unstable solutions of regression models. According to [54], multicollinearity makes the regression coefficients unidentifiable. To minimize multicollinearity, the correlation matrix analysis is performed and regressions variables that have high mutual correlation are removed. Furthermore, for the regression model with the highest explanatory power (measured as adjusted R-squared) standard model diagnostic tests are performed.

Factors analyzed

To estimate the impact of consumption changes on the day-ahead electricity price, the author analyzes the relationships between fundamental factors and electricity prices in Latvia, such as oil, coal, natural gas. The CO_2 emission allowances have a statistically significant influence on day-ahead prices in Latvia, as the price of the fuels and CO_2 emission allowances constitute the biggest part of short-term marginal costs for generators [45]. Furthermore, the availability of renewable resources such as hydro and wind have a statistically significant influence on the day-ahead prices in Latvia because the short-term marginal costs of hydro and wind stations are negligible [55].

Factors considered in the analysis:

- Electricity spot price (€/MWh) – the Nord Pool traded day-ahead electricity price for a specific bidding zone (Nord Pool).
- Electricity consumption/production prognosis (MWh) – expected consumption/production volume according to the day-ahead Merit Order Curve result in a specific bidding zone (Nord Pool).
- Wind production prognosis (MWh) – expected wind production volume according to the day-ahead Merit Order Curve results in a specific bidding zone (Nord Pool).
- CO_2 emission allowance price (€/ 1000t) – CO2 daily closing price of continuously traded EUA future contract on ICE (SKM).
- Natural gas (TTF) price (€/MWh) – daily closing price of continuously traded future contracts on ICE (SKM).

The results of multicollinearity correlation matrix analysis are presented in Table 3.1.

Table 3.1

Correlation Matrix Based on Daily Data from 2016 to 2019 (inclusive)

Variable	[1]	[2]	[3]	[4]	[5]
Price LV [1]	100 %				
Consumpt. prog. LV [2]	24 %	100 %			
TTF price [3]	36 %	15 %	100 %		
CO_2 price [4]	51 %	1 %	5 %	100 %	
Wind prod. NordPool [5]	–10 %	26 %	14 %	27 %	100 %

3.3. Results and discussion

Analysis

The results of the regression with four independent variables (prognosis of electricity consumption in Latvia, forecasted electricity amount from wind stations at Nord Pool territory, CO_2 emission allowances and natural gas (TTF) future contract prices) indicate that all of them are statistically significant predictors of the day-ahead price in Latvia. The equation of the model is as follows:

$$Price_d = \beta_0 + \beta_1 Consumption\ prog_d + \beta_2 CO_2price_{m-1} + \beta_3 TTFprice_{m-1} + \beta_4 + \varepsilon_d \qquad (3.2)$$

All variables are significant at 1 % level. The results suggest that higher forecasted consumption, CO_2 emission allowances, and natural gas prices result in higher day-ahead prices. In contrast, higher wind production is associated with lower day-ahead prices. The regression's adjusted R-squared is 61.35 % – more than half of the variance of the day-ahead prices is explained by the variance of these four independent variables. The variance inflator factor indicates no multicollinearity in the equation.

Table 3.2

Regression Analysis using the Consumption Prognosis, CO_2 Price, TTF Price, and Wind Production Prognosis in Nord Pool as Independent Variables

	Estimate	**St. Err.**	***t*-value**
Intercept	1.601	1.590	1.007
Consumpt. progn. LV	0.025***	0.002	13.767
CO_2 price	0.805***	0.021	39.041
TTF price	0.960***	0.042	22.757
Wind prod. Nord Pool	–0.081***	0.004	–21.401
# of observations	1387		
Adj. R-squared	0.6135		
F-statistics	551		
p-value	$2.2e^{-16}$		

*Significance: *** 1 % level; ** 5 % level; * 10 % level*

Furthermore, the author uses Multivariate Adaptive Regression Splines (MARS) to model independent variable relationship with the day-ahead prices in Latvia. This allows to evaluate non-constant linear relationship between the predictor and response variable. The results of MARS are presented in Fig. 3.2.

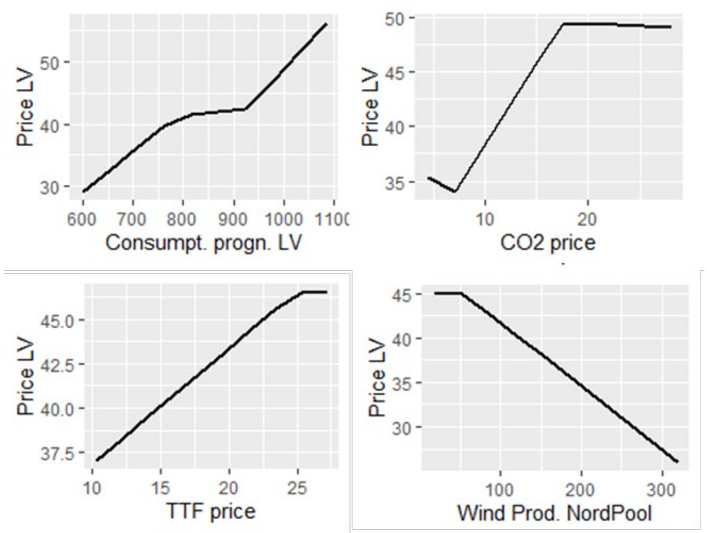

Fig. 3.2. Output of regression analysis using consumption prognosis, CO_2 price, TTF price, and wind production prognosis in Nord Pool as independent variables.

Estimated impact – changes in consumption

The results suggest that an additional 1 MWh/h of electricity consumed results on average in increase of 0.025 EUR/MWh in the day-ahead electricity price. Furthermore, the MARS analysis identifies that on days with average hourly consumption below 780 MWh or above 930 MWh, additional consumed electricity results in higher price response than on days with average hourly consumption between 780–930 MWh. This can be explained by nature of generating resources in the region. The costs of production remain quite flat when, with certain level of generation, producers are ready to sell electricity without major increase in prices in order not to stop the production by conventional stations. In contrast, when the consumption is growing and tends towards its peak levels, the producers face start-up costs of less efficient plants. This leads to a more pronounced electricity price response to increasing demands.

Estimated impact – other factors

CO_2 prices have significant impact on the electricity price in day-ahead market. CO_2 price increase by 1 € results in 0.81 €/MWh increase of day-ahead electricity prices in Latvia. Similar conclusion is reported by Bariss et al. (2016) who demonstrate that 1€ increase of CO_2 emissions would increase electricity prices in the Baltics by 0.67 €/MWh [53]. This finding identifies a clear need to hedge risks associated with volatility of CO_2 emission allowance prices. For example, the retailers can enter yearly or monthly forwards under the EUA scheme, thus, fixing the CO_2 price level. This effectively would result in lower financial risks from electricity price changes on the day-ahead market.

Natural gas prices significantly affect the day-ahead electricity prices in Latvia. Regression estimates suggest that, *ceteris paribus*, a 1€ increase of TTF forward prices translates in 0.96 €/MWh growth of the day-ahead electricity prices in Latvia. So, hedging via gas derivatives removes substantial price risks for traders.

Increased wind generation availability has negative impact on day-ahead prices. The estimates of all regressions show robust results – additional 1 MWh/h of electricity produced during the day from wind reduces Latvian day-ahead prices, on average, by 0.081 €/MWh. These findings are in line with the conclusions presented by Jonsson et al. (2012), who studied the relationship between electricity volumes generated by wind stations and Elspot prices in Western Danish price area [56]. Similarly, Fabra N. & Reguant M. (2014) report positive correlation between the wind speed and electricity prices in Spain [57].

3.4. Optimization of imbalance price

3.4.1. Motivation and background

While most commercial activity takes place in the day-ahead timeframe, a part of the electricity price in retail is related to imbalance costs. Accordingly, as additional field of study the potential opportunities for improving balancing costs were examined. Firstly, it was the regional coordination among the Baltic states based on the preliminary results of coordinated balancing area (CoBA). Secondly, the author participated in the development of improved balancing energy optimization with the goal to minimize the total cost of balancing (and therefore imbalance price).

Baltic coordinated balancing area

The Baltic area balancing mechanism was developed to establish a common balancing area starting from 2018. To achieve this, the TSOs established procedures for coordinated balance control, exchange of the balancing energy, imbalance netting, and balance settlement. The objective of harmonized Baltic balancing market was to increase the safe operation of the power system by promoting the availability of balancing resources and reducing the power system balancing costs. Establishing the Baltic balancing market involved harmonization of the balancing market framework and introduction of a common balancing IT platform.

One of the building blocks of the common balancing system is the Activation Optimization Function (AOF). As stipulated in guidelines [58] developed by ENTSO-E, the AOF determines the most efficient activation of the incoming balancing request while respecting some capacity and operational restrictions. The Baltic TSOs intend to implement the AOF as an automatic algorithm the main inputs to which are the available bids from the CMOL (considering transmission constraints) and activation volume proposal [59], the latter being the focus of this section. Specifically, it implies an algorithm for the suggestion of activation volume of balancing reserves along with a time schedule based on the historic ACE data with minute resolution and the current ACE forecast. It is meant to support the decision making by the human operator of the transmission system, and thus constitutes the first steps towards building a fully automatic system for the activation of balancing reserves. As of now, the decision to order the balancing energy is left solely to the human operator with a very short timeframe for decision-making. However, since the power system is a very complex structure with a large number of variable and uncertain parameters, an automated tool should provide a more optimal solution. Nevertheless, human operators usually have significant hands-on experience which is challenging and sometimes outright impossible to represent mathematically within an automated algorithm. Thus, one of the tasks of this study has been to investigate the pros and cons of automated vs manual regulation activation.

3.4.2. Results and discussion – regional coordination

To estimate the impact of coordinated procedures and harmonized regulation data sets from 2017 (year before CoBA operations) and 2018 (first year of CoBA operations) were compared regarding the following aspects: area control error (precision of regulation); balancing market liquidity (price efficiency of the market); and imbalance price. The results indicate that the common Baltic market performs better in all of the aspects.

Area control error

The analysis of the of historical data of the Baltic CoBA performance revealed that centralized balancing market approach led to significant decrease of the Baltic ACE. Average ACE decreased by 43 % from 42 MWh to 24 MWh per imbalance settlement period in 2018 compared to year 2017. Similarly, improved results on maintaining ACE close to 0 MWh were observed. In 2018, ACE was within 50 MWh range in 89 % of operational hours compared to 65 % in 2017 (Fig. 3.3).

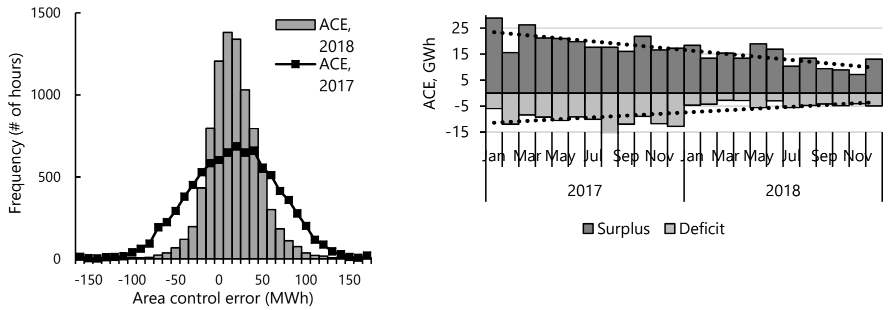

Fig. 3.3. Frequency and monthly trend in changes in area control error

Market liquidity

The reduced ACE was mostly achieved by improved and coordinated balancing. In 2018, the Baltic TSOs ordered mFRR products in 79 % of hours, which is twice as much as in 2017 (36 % of hours). This higher demand for balancing resources increased the balancing market liquidity and made it more attractive to local generation. Therefore, the amount of used balancing energy in 2018 tripled compared to 2017, while at the same time the share of local balancing resources stayed at the level of 66 % (Fig. 3.4).

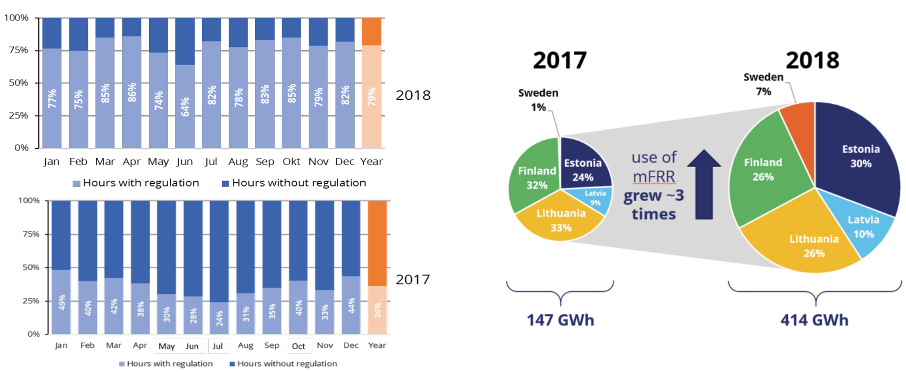

Fig. 3.4. Increase in balancing energy used after operation of CoBA

Imbalance costs

Changes in imbalance pricing system created more level playing field for pan-Baltic BRPs and BSPs. Total Baltic BRP balancing costs decreased from 19.9 M.EUR in 2017 to 15.1 M.EUR in 2018. To evaluate the impact of changes in imbalance pricing model on pan-Baltic BRP's imbalance costs, we simulated the BRP's portfolio.

Pan-Baltic BRP was created with average hourly planned consumption of 100 MWh in each country. Hourly consumption was profiled according to the Baltic weekly average consumption profile, and different imbalance scenarios (300) were simulated. As a result, the simulated BRP cost reduced significantly comparing 2017 to 2018 and the BRP can benefit from netting its imbalances between the Baltic countries, therefore reducing the cost of balancing (Fig. 3.5).

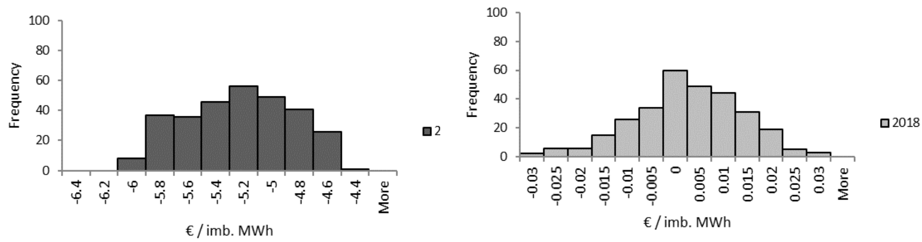

Fig. 3.5. Comparison of imbalance costs for simulated BRP

Overall, the introduction of Baltic CoBA created considerable benefits by reducing the reliance on open balance provider (reduced ACE), improving local generation asset participation in balancing market and reducing the imbalance costs for balance responsible parties. The increased demand for balancing resources provides more opportunities also for the demand response assets.

3.4.3. Results and discussion – improved activation optimization function

The objective of optimization is to minimize expected activation costs by considering both ACE and cost of bid activation. The author participated in the development of a software tool with an algorithm for deriving optimal activation parameters of mFRR for balancing of the Baltic power system. The algorithm operates under the assumption that the mFRR should be activated one or a few times within the given imbalance settlement period (in this case study, no more than five activations within an imbalance settlement period were considered). The algorithm itself is based on three main parameters: the time of activation (minutes from the beginning of each ISP), the percentage of the ACE forecast to be regulated against, and the ignorance level (the minimum value of the ACE forecast for regulation to be activated). Consequently, the time series of ACE forecast with minute resolution is provided as input data. Real-life historic data from 2016 provided by the TSO was used for numerical simulations.

After testing of the developed software, the following results were obtained when comparing the alternative frequency of regulation (Fig. 3.6).

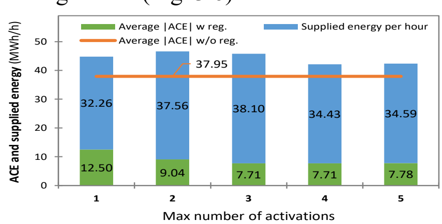

Fig. 3.6. Comparison of alternative activation frequencies.

Furthermore, the alternative scenarios were compared assuming the set balancing and ACE costs (Table 3.3).

Table 3.3

Comparison of Costs of Alternative Activation Frequencies

Max. number of activations	**1**	**2**	**3**	**4**	**5**
	Cost of ACE with local regulation (€)				
Energy bought @ 100 €/MWh	205 643.77	137 685.42	133 461.79	126 568.68	133 142.01
Surplus sold @ 5 €/MWh	–21 540.16	–16 118.70	–12 948.91	–13 285.65	–13 148.32
Cost of ACE	***184 103.60***	***121 566.72***	***120 512.88***	***113 283.03***	***119 993.69***
	Cost of supplied local regulation energy (€)				
Energy bought @ 50 €/MWh	188 740.31	246 043.25	238 190.36	194 939.63	194 561.59
Surplus sold @ 10 €/MWh	–126 444.67	–141 952.35	–146 298.99	–136 286.05	–137 142.43
Cost of supplied local energy	***62 295.64***	***104 090.90***	***91 891.37***	***58 653.58***	***57 419.15***
Total cost with local regulation	**246 399.25**	**225 657.63**	**212 404.26**	**171 936.61**	**177 412.84**
	Cost of ACE without local regulation (€)				
Energy bought @ 100 €/MWh	409 669.61				
Surplus sold @ 5 €/MWh	–76 089.76				
Total cost without local regulation	**333 579.85**				

Overall results suggest that the more precise and more frequent activation of balancing energy produces better results for the market. As demand response typically provides lower volume balancing bids, the shift towards more frequent balancing would provide potential future opportunities.

4. COST-BENEFIT ASSESSMENT FOR DEMAND RESPONSE ASSET HOLDER

4.1. Case study: Implicit demand response

4.1.1. Motivation and background

Traditionally the balance between demand and supply in a power system is maintained by adjusting centrally controlled supply to the largely inelastic demand. The increase in intermittent and distributed generation [60] as well as continuous increase in demand for electricity not only promotes volatility of electricity prices, but also creates new challenges for the power system infrastructure. An aspect of this is illustrated by the case of South Queensland (Australia), where during the period of 2009–2014 the total installed capacity of solar panels increased from 187 MW to 4092 MW [7] and the percentage of residential consumers with rooftop solar panels reached 25 %. Such shift reduced electricity volumes consumed through distribution system but did not have considerable impact on the costs of the system, the volume-based distribution system tariffs increased by 112 % [8].

With the emerging preference for electric transportation and heating the demand for electricity has even a greater tendency to cluster in high and low demand periods, which may result in peak load demands increasing faster than the total annual consumption, adding additional price pressures to the electricity as resource and power system alike. On the other hand, the technologies enabling demand response offer an opportunity to mitigate the volatility of energy consumption patterns, which could help the power system to adjust to the emerging and in some cases already established market requirements. The consideration that improving of system flexibility is a key factor in reducing the costs of integrating intermittent generation, has also been reinforced by recent studies [61]–[63]. For this reason, encouraging consumer engagement in demand response activities has become an increasingly important energy policy topic [61], [64]–[66]. While there might be consensus on whether facilitation of consumer engagement in electricity market is necessary, how to achieve it is a challenge with a less clear solution. The objective of this case study is to compare in alternative and easy to apply cost optimization scenarios for air-to-air heat-pump based heating system.

The EU energy policy foresees increased importance and integration of demand response, facilitated by smart meter rollouts, supportive legal framework and active consumer education. The Council Directive 2019/944/EU (2019) foresees that "[..]Consumers should have the possibility of participating in all forms of demand response. They should therefore have the possibility of benefiting from the full deployment of smart metering systems and, where such deployment has been negatively assessed, of choosing to have a smart metering system and a dynamic electricity price contract. This should allow them to adjust their consumption according to real-time price signals that reflect the value and cost of electricity or transportation in different time periods, while Member States should ensure the reasonable exposure of consumers to wholesale price risk. Consumers should be informed about benefits and potential price risks of dynamic electricity price contracts. [..]" while Article 11 stipulates that "Member States shall ensure that the national regulatory framework enables suppliers to offer dynamic electricity price contracts. Member States shall ensure that final customers who have a smart meter installed can request to conclude a dynamic electricity price contract with at least one supplier and with every supplier that has more than 200 000 final customers" [67]. According to CEER in 2018, 21 out of 27 Member States offered some type of variable price contracts, and only in 15 out of 27 Member States spot-price tied contracts are available to residential users [68].

Electricity market liberalization in Latvia started in 2007 when the option to freely choose electricity supplier was offered to business consumers with high consumption. Furthermore, they were joined by business consumers with medium consumption on April 1, 2012 and all other business consumers on November 1, 2012. The market was opened to residential consumers on January 1, 2015. While the electricity suppliers in Latvia are required to offer 'universal product' to residential consumers, the Latvian legal framework does not require electricity suppliers to offer dynamic electricity price contracts. According to the data published by the Public Utilities Commission of Latvia, 12.5 % (three-fold increase from the end of 2017) of residential consumers and 42.8 % of business consumers (~30 % increase from the end of 2017) had chosen the dynamic pricing type of contract [69]. Currently, most of electricity suppliers provide some type of dynamic price contracts (either time-of-use [70] or spot-price tied [71]) to both business and residential consumers.

To look at overall consumption pattern trends in Latvia, year 2020 is excluded due to considerable but not easily measurable impact of the pandemic. By comparing the day-ahead market volumes for 2017 and 2019, it can be observed that while the overall volumes increased, the volatility of the volumes bought decreased (Table 4.1) [72]. While a positive trend and more research should be done to explore the drivers behind it, the data also shows high variations between the peak and off-peak demand and the potential for implicit demand response to facilitate it.

Table 4.1

Comparative Descriptive Statistics for Energy Volumes Sold on Nord Pool Day-ahead Market in 2017 and 2019 [71]

Parameter	2017	2019	Deviation
Sum	7.2 TWh	7.3 TWh	+0.7 %
Mean	828 MWh	834 MWh	+0.7 %
Standard deviation	177 MWh	167 MWh	–5.9 %
Range	828 MWh	742 MWh	–10.4 %
Minimum volume	444 MWh	479 MWh	+7.9 %
Maximum volume	1 272 MWh	1 222 MWh	–4.0 %

Barriers for consumer engagement in demand response

Residential consumer's engagement (or lack of it) can be divided into stages, each characterized by different preconditions. EPRI (2012), proposes the following three step structure: participation (being enrolled in demand response), performance (responding in the desired way), and persistence of effects over time (Fig. 4.1) [61], [73].

Fig. 4.1. Three stages of consumer engagement in demand response. Adapted from [8]

Understanding the barriers and enablers of long-term active participation in demand response can allow policy makers and market actors to identify and foster consumer engagement in a more cost-effective approach and assess the potential for demand side response participation in more precise manner.

In literature the following types of motivators were identified: financial, environmental, and social. Based on multiple studies, the financial incentives are the most important [61], [74]–[80]. Financial incentives include a reduced monthly bill, rewards for specific consumption patterns, and free or reduced cost technology [61]. Environmental motivators are less studied and seem to play less important role, as participation in demand response does not necessarily decrease the overall consumption [61], [81]. Social motivators include increased perceived control over energy consumption [74], [81], finding the experience novel and entertaining [74], or taking pride in being socially responsible or supportive to energy system [61], [82], [83].

These benefits or motivators are usually weighed against effort, time, convenience, and comfort [61], [84]–[86]. Based on the systemic review by [61], real financial benefits are a necessary precondition for meaningful participation in implicit demand response activities.

4.1.2. Case study design

Heating, ventilation, and air conditioning systems (HVAC) have tendency in developed countries to become more prevalent over time [87]. The latest data for Latvia is from 2015, when 6 % of residential buildings in Latvia had electricity-based heating and ~2 % of residential buildings in Latvia had air conditioning [88]. Furthermore, HVAC tends to be one of the most energy intensive type of residential type of electric appliances. The exact estimation for the proportion of electricity consumption for which HVAC is responsible is hard to come by, as these estimates differ depending on climate, building, and other appliances. On average it is considered that heating is responsible for up to 50 % of the monthly electricity consumption during the peak demand period [89].

By reviewing the existing literature on HVAC control system testing and designing, it can be observed that while there are different energy efficiency objectives or particular challenges of multi-building or multi-zonal systems, the general approach for introducing deterministically controlled HVAC system is fairly simple and requires data collection, algorithm, and the load controller device [90]–[92]. The objective of this study is to evaluate in real data setting the most appropriate algorithm for implementing automatic and cost-efficient HVAC system management that relies on publicly available data. To achieve that for a set period of time (in December 2020 and January 2021), four HVAC systems were monitored. Afterwards, alternative optimization approaches were tested. The best performing algorithm is further intended to be used for HVAC management. Tables 4.2 and 4.3 present the environment and data description.

Table 4.2

Description of the Case Study Environment

HVAC systems used	One Toshiba Premium air-air type of heat pumps (RAS-25PAVPG-ND), with heating capacity 0.7–6.70 kW and three Toshiba Optimum (RAS-25PKVSG-ND) 1.00–6.50 kW were chosen
Area	Two isolated rooms: 26 m^2 (set indoor temperature 17 °C) and 23 m^2 (set indoor temperature 17 °C) and a large hall: 70 m^2 (set indoor temperature 19 °C with some HVAC unrelated temperature fluctuations due to ventilation or use of other devices)
Period	24 days, December 2020 – January 2021

Table 4.3

Description of the Data Used in the Case Study

Outside temperature	Factual hourly data from meteorological data from the Latvian Environment, Geology and Meteorological Centre (°C) [93]
Day-ahead prices	Factual hourly data from Nord Pool exchange (EUR/MWh) [72]
Heat pump load	Measured every minute (MW)

In the context of this study the following assumptions (simplifications) were made – firstly, the load is only shifted and there is no reduction of total consumption (rebound effect expected to be 100 %). The consumption from the hour where the system is turned off is shifted to the next two hours. The determination of the exact nature of the rebound effects in different conditions is outside the scope of this study and is left for further research. This assumption prescribes that switching off may not occur more often than once every two hours (the condition is observed also during the date change). The following optimization scenarios were devised (Table 4.4).

Table 4.4

Optimization Scenarios Used in the Case Study

Scenario	Conditions	Objective
Selecting two hours in every given day when the HVAC is switched off based on the following criteria:		
2–1	The lowest temperature	Representation of the highest expected consumption [94]
2–2	The highest day-ahead price	Representation of the highest cost per MWh
2–3	The highest forecasted cost savings from load shifting	Representation of the highest total gains from shifted consumption
Selecting three hours in every given day when the HVAC is switched off based on the following criteria:		
3–1	The lowest temperature	Representation of the highest expected consumption
3–2	The highest day-ahead price	Representation of the highest cost per MWh
3–3	The highest forecasted cost savings from load shifting	Representation of the highest total gains from shifted consumption

The highest forecasted cost savings (C_{H0}) from load shifting were calculated as follows:

$$C_{H0} = E_{H0} \times P_{H0} - E_{H0} \times \frac{P_{H1}+P_{H2}}{2}, \qquad (4.1)$$

where

C_{H0} – expected cost savings from load shifting (EUR);

E_{H0} – energy volume shifted from hour H_0 to hour H_1 and H_2 (MWh);

P_{H0}, P_{H1}, P_{H2} – day-ahead price for hour H_0, hour H_1, hour H_2 (EUR/MWh).

The expected volume E_{H0} shifted is calculated based on empirically obtained relationship for the particular HVAC system.

$$E_{H0} = 0.001288 - 0{,}00015\, T_{H0}, \qquad (4.2)$$

where T_{H0} is the expected temperature at hour H_0 (°C).

The empirical equation (Fig. 4.2) was obtained by applying linear regression on the empirical consumption and factual temperature data from the case study.

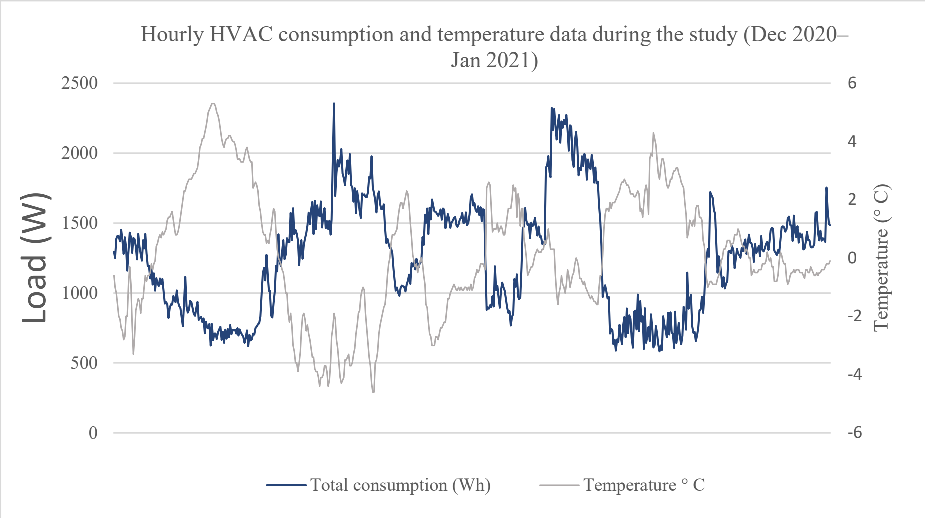

Fig. 4.2. Hourly HVAC consumption and temperature data during the study. Temperature data source [91]

The optimization algorithm selects the best fit based on the conditions described above. In case the best fit violates the condition that HVAC may only be switched off no more often than once every three hours, the next best fit is selected.

4.1.3. Results and discussion

During the observation period the following data was collected in regard to outdoor temperature, day-ahead price, and actual HAVC consumption (Table 4.5).

Table 4.5

Descriptive Statistics of Temperature, Electricity Price, and HVAC Consumption During the case Study. Data sources: temperature [91], electricity prices [71]

Parameter	Temperature (°C)	Day-ahead price (EUR/MWh)	HVAC actual consumption (kWh)
Mean	0.1	43.89	1.26
Range	9.9	197.21	1.77
Minimum	– 4.6	2.75	0.58
Maximum	5.3	199.96	2.36

The previously described scenarios provide the outcomes shown in Table 4.6.

Table 4.6

Comparison of Optimization Scenario Outputs

Scenario	# of hours selected per day	Total consumption (kWh)	Total cons. shifted (kWh)	Percentage of cons. shifted	Total cost of electricity (EUR)	Cost difference from base scenario
Base	0 h	748.42	–	–	33.58	–
2–1	2 h	748.42	70.94	9.5 %	33.58	0.01 %
2–2	2 h	748.42	65.37	8.7 %	32.94	–1.90 %
2–3	2 h	748.42	67.42	9.0 %	32.18	–4.18 %
3–1	3 h	748.42	104.64	14.0 %	33.54	–0.13 %
3–2	3 h	748.42	97.36	13.0 %	32.68	–2.69 %
3–3	3 h	748.42	99.43	13.3 %	31.97	–4.81 %

The relative performance of the scenarios was similar in both two-hour and three-hour scenario group. The highest load shift is observed in the scenario where the load is shifted away from the coldest hours (in two-hour scenario – 9.5 % of total load was selected, while in three-hour scenario 14.0 % of load was shifted). However, neither scenario 2–1 nor 3–1 resulted in noticeably different total costs regarding the base case scenario. This might be related to the following: the coldest hours are typically during night, when the electricity price dynamic is less pronounced. Scenarios 2–2 and 3–2 in both two-hour and three-hour group demonstrate the best performing similar relative performance in their respective scenario group, however, the best performing scenarios were 2–3 and 3–3 that considered both the expected difference in price as well as the expected loads. The improved economic performance in scenarios 2–2 and 2–3 is considerably higher than the increased load shift. This indicates that considering only the day-ahead prices and not considering the expected consumption level is the sub-optimal choice.

Overall, the results of the case study suggest that the immediate benefits from load-shifting are modest. Taking this into account, if the energy policy maker considers and identifies that active engagement from residential consumers in implicit demand response activities is pivotal for better integration of intermittent and distributed generation as well as power system optimization, additional incentives reflecting overall system benefits from more moderate peak and off-peak loads might be considered.

4.2. Case study: Explicit demand response

4.2.1. Motivation and background

Large industrial plants in Europe (e.g., in the Nordics, Poland, Croatia, the Netherlands, Germany) have been involved in DR provision for ancillary services for considerable time [95], [96]. These large consumers can participate in the market individually. In the Baltics, the energy intensive industry is not highly developed, accordingly, the DR potential is locked in smaller consumers (i.e., SMB, residential). A rough estimate suggests that both for residential and commercial buildings (such as schools, hotels, retailers) approximately 50 % of energy consumption stems from heating, cooling, ventilation, and lighting [97]. This a indicates substantial flexibility potential; however, given that the minimum bid size for mFRR product is 1 MW, these consumers can only participate in the balancing market if their loads are aggregated and coordinated. Advancements in information technology render such aggregation and resource coordination feasible.

While it is an energy related product, DR aggregation requires different business processes in place compared to a typical energy supplier. To ensure that all consumers willing to participate in DR are allowed to without switching their supplier, a new market participant – an independent aggregator – emerged. In essence, an independent aggregator is a DR aggregation service provider that delivers balancing energy sourced from end-users that are included in imbalance areas different to the aggregator [98]. There is no consensus on the best market framework for the integration of independent DR aggregators, since optimal choice of model differs by countries and types of electricity markets [95], [96]. The settlement model currently favored by the Baltic TSOs is a centralized model [98]. Detailed explanation of this model is provided in Chapter 1 of the Thesis Summary.

4.2.2. Case study design

Assumptions for energy transfer

When DR activation takes place, it has the following impact on the consumption curve (Fig. 4.3). When DR activation for upward regulation (i.e., reduced consumption) takes place, the consumption is curtailed.

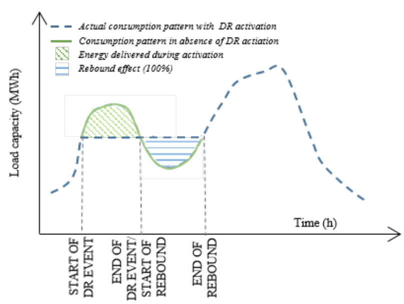

Fig. 4.3. DR activation explained

Depending on the resource type, the energy unconsumed during the activation will be consumed to some extent during one or the few following hours. Based on the results of the pilot with fridges [3], the assumed recovery effect in our simulations is 100 % and it takes place during the next hour. Within our simulation framework, it is assumed that the volumes of energy transferred can be determined without an error.

Assumptions for the settlement model (cash-flows)

Within the simulation, it is assumed that the following prices are equal:

- retail price is equal to the day-ahead price;
- balancing price is equal to the imbalance price.

In line with the centralized settlement model, the following trades for the energy delivered during activation take place:

1. Before an operational hour, the supplier/BRP buys energy in the day-ahead market at a day-ahead price (P_{DA}).
2. During the operational hour, the TSO orders balancing energy from aggregator at a balancing price (P_{bal}).
3. During the operational hour, the consumer does not consume the energy it would consume in the absence of the TSO's activation order.
4. During the settlement phase, the TSO makes an imbalance adjustment for the declared position of the impacted BRP.
5. During the settlement phase, the TSO pays to the BRP a compensation for the energy taken from its portfolio at a reference price (P_{ref}).
6. During the settlement phase, the TSO pays to the aggregator the difference between P_{bal} and P_{ref}.
7. During the settlement phase, the consumer does not pay for the energy unconsumed and may receive part of the profit generated by the difference between P_{bal} and P_{ref}.

The following trades for the consumption pattern deviation caused by the recovery effect take place:

1. During the settlement phase, the consumer pays to the BRP/Supplier a retail price (P_{ret}) of the recovery hour for the energy consumed due to the recovery effect.
2. During the settlement phase, the BRP pays the imbalance price (P_{bal}) of the recovery hour to the TSO for the energy consumed due to the recovery effect.

The simulation tool

The modelling for the case study was carried out using a Monte-Carlo simulations-based tool introduced and elaborated in [99]. The stochastic nature of the model requires the output to be probabilistic instead of deterministic. Consequently, most of the input settings concern the expected mean of a particular parameter across scenarios and the output is provided in the form of probability distributions.

The main modules of the tool are day-ahead price scenario generation, balancing liquidity and price scenario generation, balancing activation simulation, and short-term and long-term economic assessment.

Input assumptions and DR resource characterization

The assumptions for day-ahead market were made based on the historical values from the Nord Pool day-ahead market data for the Baltics in 2017. The assumptions are presented in Table 4.7.

Table 4.7

Day-ahead Market Data Simulation Parameters

Price simulation parameters	Value (st. dev.)
Mean price for 99.5 % of hours	34.02 €/MWh (10 %)
Mean value for weekdays divided by mean value for weekends	1.23 (10 %)
Mean value for a day (06:00–22:00) divided by mean value of the night (22:00–06:00)	1.38 (10 %)
Minimum price	2.99 €/MWh (10 %)
Maximum price for 99.5 % of hours	75.34 €/MWh (10 %)
Maximum price for 100 % of hours	130.05 €/ MWh (10 %)
Number of scenarios	300

The assumptions for the balancing market were made based on the historical values for the Baltic balancing market data for the first quarter of 2018. These reference values were chosen due to the significant market changes implemented on January 1, 2018. The assumptions are presented in Table 4.8.

Table 4.8.

Balancing Market Data Simulation Parameters

Price simulation parameters	Value
% of hours when the regulation takes place	70 %
% of regulation hours, where upward regulation is required (load reduction)	45 %
Balancing price for upward regulation (expectation)	1.6 P_{DA}
Balancing price for downward regulation (expectation)	0.6 P_{DA}
Number of scenarios	300

We based technical assumptions about the DR resource on the data presented in a pilot study by Lakshmanan et Al. (2016) [3]. We set the total load capacity at 2.5 MW (25 fridges). The load profile for a typical day is depicted in Fig. 4.4.

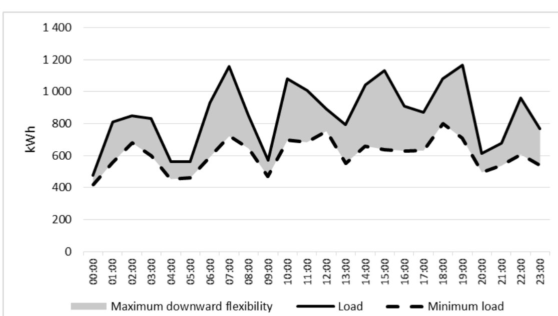

Fig. 4.4. Load profile of the DR resource simulated

The DR activation parameters are presented in Table 4.9. Minimum DR bid price is set at 45 €/MWh to limit events where the DR activation causes losses due to the price difference between the day-ahead price and balancing price. Based on the historical data of 2017, the day-ahead price in the Baltic region was below 45 €/MWh 85 % of times.

Table 4.9

DR Resource Simulation Parameters

DR resource simulation parameter	Value
Maximum number of events during 24 hours	6
Minimum time between the events	2 h
Maximum period before rebound	2 h
Rebound effect/DR energy delivery	100 %
Minimum DR bid price	45 €/MWh
Discount rate used for NPV calculations	3 %

We assume that the resource participates only in upward regulation. Furthermore, it is assumed that participation in DR does not damage the resource and consequently does not add other additional costs.

4.3. Results and discussion

The portfolio's expected average annual income from participation in balancing market is 8 622.89 €. 85 % of that is the revenue from the balancing market payments and 15 % stem from day-ahead price difference between the activation hour and recovery hour (Fig. 4.5). There is no benefit from energy savings in this case study, since we assumed that all the curtailed consumption would be recovered later.

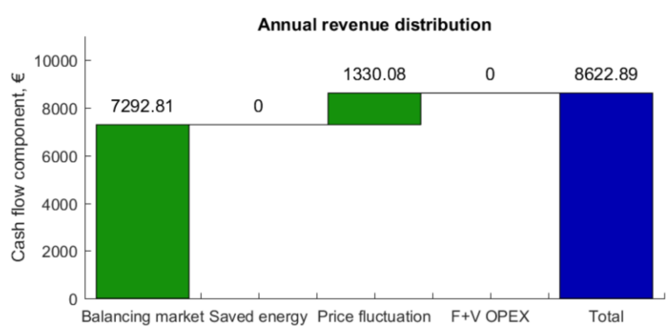

Fig. 4.5. Average annual revenue distribution

Assuming a 10-year asset service life and 3 % discount rate, the expected net present value (NPV) of the simulation described in the previous section is 73 555.01 €. In other words, the project would be profitable if the initial investment was below 73 555.01 € or below 2 942.20 € per fridge (Fig. 4.6).

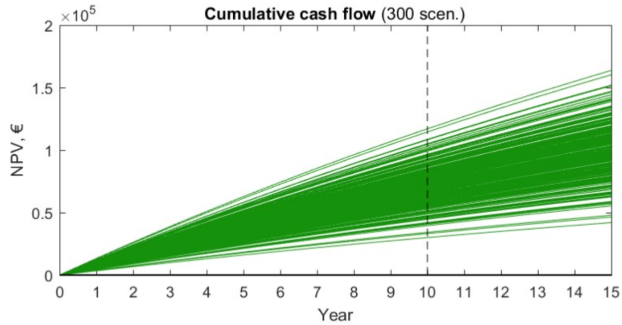

Fig. 4.6. Cumulative cash-flow for 15 years (all scenarios)

It is expected that on average the portfolio will annually deliver 326.24 MWh of balancing energy by participating in 32 % of all hours (1257 hours annually) when downward regulation is used. Accordingly, on average, the portfolio earns 26.43 € per each MWh delivered to the balancing market (Fig. 4.7).

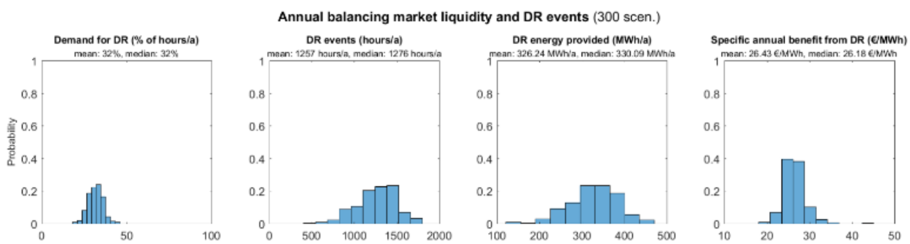

Fig. 4.7. Overview of simulated DR events and balancing market prices

The expected average annual cash inflow for the portfolio is equal to 19 661.18 €, while the expected average cash outflow for the portfolio is 11 038.29 € (Fig. 4.8).

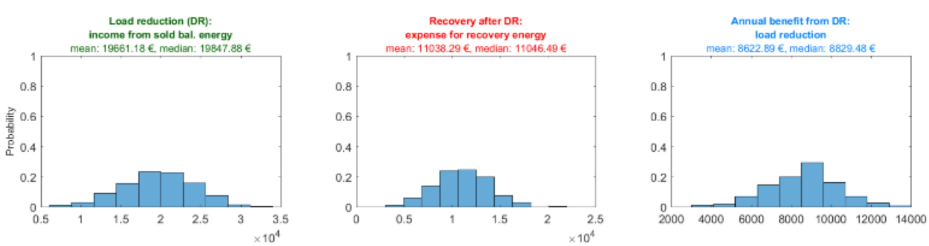

Fig. 4.8. Breakdown of the DR asset owner's estimated annual profit.

CONCLUSIONS

1. The performed cost-benefit assessment tests performed confirm the hypothesis that by developing an appropriate regulatory framework the demand response services can provide a cost and energy efficient tool for improving the system flexibility and mitigate the resource price increase and regional price volatility driven by the increase in intermittent generation in the Baltic region.
2. The market framework proposed in this research (*centralized settlement model*) for allowing the demand response services to participate in the Baltic region ancillary services market avoids abnormal returns to any of the market participants and provides, inclusive, fair, and simple allocation of roles and responsibilities.
3. The algorithm proposed in this research (*UK CBM*) for estimating the volume of the demand response services (energy) delivered provides an easy-to-introduce method that offers reasonably robust and accurate results.
4. The interpolation algorithm proposed in this research (*Spline* (*Order 5*)) offers better results than the alternative eight models when considering transposing hourly metering data to 15-minute time resolution.
5. There are identifiable financial benefits from the demand response participation in providing ancillary services to both service providers and other market participants.
6. The algorithm proposed in this research for optimizing the heat-pump system for implicit demand response provides an affordable method that relies on publicly available data and can be used by any owner of the HVAC type of demand response asset. The proposed algorithm offers up to 5 cost reduction.
7. Based on historical data (2016–2019) on the Baltic electricity market and day-ahead price drivers, the financial benefits from introducing demand response services in the day-ahead market or from customers engaging in implicit demand response are quite modest. The existing market conditions do not suggest that additional regulatory stimuli for faster demand response uptake are currently necessary. The situation might change after synchronization with the Continental Europe Synchronous Area.

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