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ELECTRICITY PRICE MODELLING AND THE ROLE OF NEW DEVELOPMENTS IN ELECTRICITY MARKETS

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ZAHVALE

Za vso podporo med študijem se želim zahvaliti družini in Ani. Za nasvete in pomoč pri pisanju disertacije se zahvaljujem mentorjema Miroslavu Verbiču in Jeleni Zorić. Zahvala pa gre tudi vsem prijateljem in bližnjim sodelovcem.

ELECTRICITY PRICE MODELLING AND THE ROLE OF NEW DEVELOPMENTS IN ELECTRICITY MARKETS

Summary

In recent years, European countries have moved from regulated regional monopolies to liberalised electricity markets. The power market has changed from a vertically integrated structure into a competitive market. The day-ahead electricity market is a wholesale market where standard hourly contracts are sold for day-ahead physical delivery. The market clearing price is determined at the intersection of the market's supply and demand curve. The main electricity characteristics significantly influencing electricity price determination in a competitive market are: non-storability, the required balance of production and consumption in every moment, it is an essential and homogenous commodity, has low demand elasticity, and there's a difference in physical and contract flows. Due to impossibility of economical storage of electricity and required real time balance of production and consumption, unlike other commodities markets, negative electricity prices can arise. Therefore, the dissertation thoroughly researches the performance of contemporary electricity price forecasting algorithms (EPF) and the role of new developments in electricity markets. Under the umbrella term "new developments in electricity markets," we individually research market impact of supported renewable generation and electricity market coupling. The dissertation relies on a publicly available data source ENTSO-E transparency platform, and thoroughly avoids data blending, to foster easy and fast research reproducibility.

In the first chapter, we provide a thorough systematic overview of electricity price forecasting accuracy for the major contemporary forecasting algorithms. Forecasting performance is assessed based on the evidence from the Greek & Hungarian Power Market simulation. We provide valuable and reliable information to the interested audience by comparing forecasting accuracy with the statistical Diebold-Mariano test applied on the simulation samples with more than 1000 days. Only the support vector machine algorithm statistically outperformed the econometric autoregressive benchmark model. Furthermore, we answer important research question on how the training sample size impacts forecasting accuracy. Our findings suggest that the training data sample size is positively correlated with the EPF accuracy however, models have a turning point after which the relationship is converted. An artificial neural network and long short-term memory model achieve better forecasting accuracy if trained on considerably larger training samples compared to the other major contemporary forecasting algorithms. Also, training on hourly clustered data samples can improve forecasting accuracy. However, the answer is ambiguous as it depends on the selected forecasting algorithm and electricity market. The introduced demand-supply ratio explanatory variable has a minor positive effect on the overall forecasting accuracy, but no significant effect in the case extreme price situations.

In the second chapter, we research the impact of market coupling on electricity markets. To do so, we propose a simulation framework that replicates day-ahead power exchange operations. Modelling coupled market areas consistently in one integrated framework is a specific challenge and is frequently overlooked in the electricity market research. The market coupling process is simulated at the junction of three regional power markets, namely the Central Western Europe, the Northern Italian, and the South Eastern Europe markets. The simulation results are compared against the market realisations at the time non-coupled electricity market's junction. The simulation results empirically confirm that in coupled electricity markets inefficient cross-border capacity usage is eliminated. Additionally, with the simulation results we can confirm improved electricity price convergence and price volatility in coupled electricity markets, which is in line with findings in the literature and market coupling objective. By the estimated Vector Autoregression model, we have for the first time analysed electricity price shock transmission in the European electricity markets. The model results suggest improved electricity price shock transmission in coupled electricity markets.

In the third chapter, we address the topic researchers pay the most attention in the context of supported renewable generation, the so-called 'merit order effect.' We empirically confirm the merit order effect in less mature and the yet unresearched Greek, Hungarian, and Romanian electricity markets. By researching the merit order effect, we provide a valuable addition to the existing literature focused on key EU energy areas in terms of installed renewable generation capacity and market maturity. To conduct the analysis, we used data from the ENTSO-E transparency platform blended with the Romanian transmission system operator data on realised production. Data blending was unavoidable due to the extensively missing data points and non-reported data types for the actual generation in the ENTSO-E TP data base. To simulate the adjustment of the realised day-ahead electricity prices in the non-renewable generation scenario, we developed a simulation framework intuitively close to DIME (Dispatch and Investment Model for Electricity Markets in Europe) model. Electricity generation dispatch can be efficiently simulated by the unit commitment models that minimises total dispatch costs of the power plant fleet. Due to the limited public data availability to develop a unit commitment model, we rely on a family of data mining algorithms to estimate the profile of the supply curves ranked by their short-run marginal costs in an increasing order, together with the dispatched energy – a so-called merit order. The applied approach efficiently handled the non-linear behaviour of the electricity price signals and bridged the gap in limited data availability to simulate electricity prices in non-renewable generation scenario.

Keywords: electricity price forecasting, machine learning**,** EU market coupling**,** renewable electricity sources, merit order effect, ENTSOE-E transparency platform

MODELIRANJE CEN ELEKTRIČNE ENERGIJE IN VPLIV NOVIH DEJAVNIKOV NA TRGE ELEKTRIČNE ENERGIJE

Povzetek

V zadnjih letih so evropske države prešle iz reguliranih regionalnih monopolnih tržnih struktur k liberaliziranemu trgu z električno energijo (EE). Trg z EE za dan vnaprej je veleprodajni trg, kjer se trguje s standardiziranimi urnimi pogodbami za fizično dobavo za dan vnaprej. Borzna cena EE je določena s presečiščem tržne premice ponudbe in povpraševanja. Njene glavne značilnosti, ki pomembno vplivajo na oblikovanje cen na konkurenčnem trgu, so: nezmožnost shranjevanja, zahtevano ravnovesje proizvodnje in potrošnje v realnem času, homogena dobrina, nizka elastičnost povpraševanja, razlikovanje fizičnih in pogodbenih tokov. Kot posledica nezmožnosti ekonomičnega shranjevanja, zahtevanega ravnovesja proizvodnje in porabe v realnem času se lahko oblikujejo negativne cene EE, ki niso značilne za trge ostalih surovin. Disertacija temeljito razišče uporabnost sodobnih napovedovalnih algoritmov za napovedovanje cen električne energije in vpliv novih dejavnikov na omenjene trge. Pod krovnim izrazom »vpliv novih dejavnikov na trge električne energije« individualno raziščemo tržni vpliv subvencionirane proizvodnje iz obnovljivih virov energije in proces spajanja trgov z EE. Omenjena trenda poglavitno vplivata na delovanje trga in sta predmet številnih raziskav. Doktorsko delo temelji na javno dostopnem podatkovnem viru ENTSO-E in se ob tem izogiba mešanju virov. Tako zagotovimo enostavno in hitro ponovljivost izvedenih podatkovnih simulacij.

V prvem poglavju podamo temeljit in sistematičen pregled natančnosti napovedovanja cen EE z najpomembnejšimi sodobnimi algoritmi. Z omenjenimi algoritmi smo napovedovali cene EE za dan v naprej na madžarskem in grškem tgu. S primerjavo napovedovalne natančnosti s statističnim Diebold-Marianovim testom na simulacijskih vzorcih z več kot 1000 napovedovalnimi dnevi zagotovimo zainteresiranemu bralcu dragocene in zanesljive informacije o lastnostih posameznih napovedovalnih algoritmov. Med izbranimi napovedovalnimi algoritmi je v primerjavi z ekonometričnim modelom časovnih vrst natančnejša samo metoda podpornih vektorjev statistično. Z raziskavo dodatno odgovorimo na pomembno raziskovalno vprašanje, kako velikost učnega vzorca vpliva na natančnost napovedi. Naše ugotovitve kažejo, da je velikost učnega vzorca pozitivno povezana z natančnostjo napovedovanja cen električne energije, vendar imajo modeli prelomno točko, po kateri se razmerje obrne. Nevronske mreže in model z dolgim kratkoročnim spominom (angl. *long short-term memory*, LSTM) v primeru učenja na bistveno večjih učnih vzorcih dosegata večjo natančnost napovedovanja kot drugi sodobni napovedovalni algoritmi. Poleg tega lahko učenje na urnih podatkih v gručah (angl. *hourly clusterd data samples*) izboljša natančnost napovedovanja, vendar odgovor ni enoznačen, saj je odvisen od izbranega napovedovalnega algoritma in trga z EE. Na splošno ima dodatna pojasnjevalna spremenljivka razmerja med

povpraševanjem in ponudbo (angl. *demand-supply ration*, DSR) manj izrazit pozitiven učinek na napovedovalno natančnost, v ekstremnih cenovnih situacijah pa je ta zanemarljiv.

V drugem poglavju raziščemo vpliv spajanja trgov z EE na njihovo delovanje. V ta namen razvijemo simulacijsko okolje, ki preslika delovanje borz z EE za dan v naprej na spojenih trgih. Modeliranje le teh oz. razvoj primernega simulacijskega okolja je poseben izziv, ki je v tržnih raziskavah pogosto spregledan. Proces spajanja je simuliran na stičišču treh regionalnih trgov, in sicer srednjezahodne Evrope, severne Italije in jugovzhodne Evrope. Rezultate simulacije primerjamo s tržnimi realizacijami na takrat še nespojenih trgih z EE in s tem empirično potrdimo, da je na spojenih trgih odpravljena neučinkovita raba čezmejnih prenosnih zmogljivosti. Z rezultati dodatno potrdimo izboljšano konvergenco in manjšo volatilnost cen na spojenih trgih, kar je v skladu z ugotovitvami v literaturi in ciljem spajanja trgov. Z ocenjenim modelom vektorske avtoregresije v nadaljevanju prvič analiziramo prenos cenovnih šokov EE na evropskih trgih. Izsledki modela kažejo na izboljšan prenos cenovnih šokov na spojenih trgih.

V tretjem poglavju obravnavamo proizvodnjo EE iz obnovljivih virov energije (OVE), ki ji raziskovalci posvečajo največjo pozornost in t. i. učinku izrivanja konvencionalnih virov električne energije (angl. *merit order effect*, MOE). Prisotnost omenjenega učinka empirično potrdimo na neraziskanem in manj zrelem grškem, madžarskem in romunskem trgu. Z učinkom zagotovimo doprinos k obstoječi literaturi, ki se osredotoča na ključna energetska področja Evropske unije (EU) glede na količino proizvodne zmogljivosti iz OVE in zrelost trga z EE. Za izvedbo analize smo uporabili podatke iz baze ENTSO-E, ki so združeni s podatki o realizirani proizvodnji romunskega operaterja prenosnega sistema. Zaradi manjkajočih opazovanj in podatkovnih tipov v bazi ENTSO-E TP je bilo mešanje podatkovnih virov neizogibno. Z uporabo modela, ki je intuitivno blizu modelu DIME (Dispatch and Investment Model for Electricity Markets in Europe), smo izvedli simulacijo prilagajanja realiziranih cen EE za dan vnaprej brez proizvodnje iz OVE. Proizvodnjo EE je mogoče učinkovito simulirati z optimizacijskimi modeli proizvodnje (angl. *unit commitment models*), ki minimizirajo skupne stroške proizvodnje elektrarn. Za razvoj takšnega modela smo zaradi omejene dostopnosti javnih podatkov s pomočjo algoritmov podatkovnega rudarjenja ocenili ponudbene krivulje konvencionalne proizvodnje. Te so razvrščene v naraščajočem vrstnem redu glede na kratkoročne mejne stroške proizvodnje, skupaj s količino proizvedene energije (angl. *merit order*). Omenjen pristop učinkovito obravnava nelinearnosti cenovnih signalov EE in premosti vrzel manjkajočih podatkov za implementacijo optimizacijskega modela proizvodnje.

Ključne besede: napovedovanje cen električne energije, strojno učenje, evropsko spajanje trgov električne energije, obnovljivi viri električne energije, učinek izrivanja, ENTSOE-E podatkovna baza

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INTRODUCTION

Description of the broader scientific area of the doctoral dissertation

Data availability and accessibility to qualified parties has historically limited applied power market research (Hirth et al., 2018). In Europe, this situation has changed with the commencement of publicly available power system data through the ENTSOE-TP data base (ENTSO-E TP, 2020). With the power market liberalisation, increased renewable production, and improved public data availability, electricity price forecasting (EPF) and market simulations have become an interdisciplinary research area attracting different professionals (economists, engineers, mathematicians, and statisticians).

In regulated electricity markets dominated by publicly owned monopolies, price variations were minimal and under the control of government agencies. In such an environment, the attention was focused on demand forecasting and the most sophisticated statistical techniques have been proposed to achieve satisfactory short-run predictions (Fezzi, 2007). In contrast, in liberalised electricity markets price volatility has increased far beyond those of any other commodity or financial asset. This is especially true for spot prices (day-ahead market) where volatility can be as high as 50% on a daily scale, i.e., over 10 times higher than for other energy products (Weron & Misiorek, 2005). Due to considerable market risk on the competitive wholesale power market, electricity price forecasting (EPF) became an unavoidable task for both producers and consumers (Garcia-Martos et al., 2012). According to Weron's EPF review article in 2014, main forecasting methodologies include time series econometrics, machine learning and data mining, and agent-based modelling (Weron, 2014). Lago, De Ridder, & De Schutter (2018) presented the largest benchmark of EPF algorithms to date – although in a simulation environment in which market participants typically do not operate and without addressing open research question on optimal learning sample size.

One of the goals of the European Union (EU), related to energy markets, is the establishment of the Energy union, and consequently electricity price convergence. Neighbouring electricity markets are typically interconnected by the electricity transmission network – enabling cross-border energy exchange. Before the introduction of the market coupling mechanism, cross-border capacity and electricity energy were traded at two different auctions, thus the price information may not have been available instantaneously and frequently resulted in the inefficient use of cross-border capacities (CBC) (Kiesel & Kusterman, 2016). A market coupling mechanism ensures the optimal allocation of the CBC and supports electricity price convergence. Kiesel & Kusterman (2016) explained that in coupled markets it becomes crucial to model electricity prices in all areas consistently in one integrated framework. Thus, there is a consensus among researchers that coupled electricity markets cannot be efficiently analysed in isolation without accounting for the market coupling specialities. Additionally, Lago et al. (2018) argued that the effects of market integration can dramatically modify the dynamics of electricity prices, but there is a lack of general modelling framework that could model this effect and analyse its impact on the electricity market. These raise the argument that the development of an integrated modelling framework should be put at the heart of applied electricity market research.

The introduction of guaranteed feed-in-tariffs to support renewable electricity generation changed market dynamics as the required power to maintain the power system balance equal to the system load reduced for renewable generation. This situation required new terminology and Saint-Drenan et al. (2009) introduced a so-called "residual load." The theoretical concept that in the short-run increases in subsidised renewable energy generation reduce electricity prices was first introduced by Jensen and Skytte (2002). This theoretical concept, recognised as the merit order effect, is confirmed and thoroughly researched in the developed European electricity markets. Research by Würzburg, Labandeira, & Linares (2013) stands out as it econometrically confirms the concept in Germany and Austria, which can be considered as the most developed European market areas in terms of market maturity and share of renewable capacity in their generation mix. Delayed Power exchanges establishment in the region of Southeast Europe (SEE) and considerably higher volatility compared to other mature European markets, characterise SEE electricity markets as less developed (Božić et al., 2020). More scientific research is needed that would further study electricity market concepts in developing European markets.

Research questions addressed in this dissertation

The doctoral dissertation aims to address the following research questions, which can be aligned along three dimensions:

- Dimension 1: Electricity price forecasting (EPF) methods
- *Research question 1.1*: Do modern statistical approaches (data mining and machine learning) perform better than the linear econometric time series model in electricity price forecasting?
- *Research question 1.2*: What is the effect of training data set size on the forecasting performance?
- *Research question 1.3*: Does model training on hourly clustered data samples enhance electricity price forecasting performance?
- *Research question 1.4*: Does the demand-supply ratio (DSR) explanatory variable enhance electricity price forecasting performance in extreme price situations?

- Dimension 2: Market coupling simulation
- *Research question 2.1:* How should market simulations be designed in coupled electricity markets?
- *Research question 2.2:* Does electricity market coupling ensure efficient cross-border capacity allocation and electricity price convergence?

- *Research question 2.3:* What is the impact of market coupling on electricity price volatility?
- *Research question 2.4:* Does market coupling improve electricity price shock transmission?

- Dimension 3: Renewable energy sources (RES) and merit order effect
- *Research question 3.1:* Does crowding out of conventional electricity production sources by renewable energy sources lead to lower electricity prices on the Southeast Europe (SEE) electricity markets?
- *Research question 3.2:* Can modern statistical approaches bridge the gap in data availability and efficiently simulate electricity prices in the no-RES generation scenario?
- *Research question 3.3:* Does renewable energy source (RES) generation enhance electricity price volatility in the Southeast Europe (SEE) electricity markets?

Each dimension forms one of the three research topics the dissertation addresses. The research topics are detailed below.

Performance of alternative electricity price forecasting methods: Findings from the Greek & Hungarian power exchanges

The dissertation analyses the performance of modern statistical approaches for day-ahead electricity price forecasting. Forecasting performance of the alternative or modern statistical approaches from the data mining, machine learning and deep learning family is compared to the econometric autoregressive model with exogeneous explanatory variables. Due to the complexity of electricity price data generation process, the relationships between the dependent and explanatory variables are complex (non-linear). The ability of alternative models to adapt to a non-linear and fast-changing price signal behaviour may not necessarily result in better point forecasts (Weron, 2014). To statistically verify this open question, this dissertation evaluates the forecasting performance of selected contemporary models trained on Greek and Hungarian day-ahead electricity markets. In addition, with the study design we provide valuable insights on the impact of a different training sample size, as well as the impact of training on an hourly clustered sample on the forecasting performance.

An Integrated Model for Electricity Market Coupling Simulations: Evidence from the European Power Market Crossroad

Despite the fact that previously independent market areas have become connected through market-coupling auctions, many scholars usually analyse electricity markets independently. Kiesel and Kusterman (2016) explained that in coupled electricity markets it becomes crucial to model electricity prices in all areas consistently in one integrated framework. Coupled day-ahead markets increase the overall efficiency of trading by promoting effective competition, increasing liquidity, and enabling a more efficient utilisation of the cross-border capacities and generation resources across Europe (NEMO Committee, 2020b). This doctoral dissertation aims to add to the electricity price modelling literature an integrated simulation solution for electricity price determination and efficient cross-border capacity allocation. The proposed integrated simulation framework replicates day-ahead power exchange operations in coupled electricity markets. The dissertation applies the proposed solution to eliminate observed inefficient cross-border capacity allocations at a time of the simulation of non-coupled interconnectors, and adjusts market clearing prices in Austria, Italy, Slovenia, and Croatia, accordingly. Based on the simulation results, this dissertation empirically confirms the effects of market coupling on efficient cross-border capacity allocation, price convergence, and improved price shock transmission.

The crowding out of conventional electricity generation by renewable energy sources: Evidence from Greek, Hungarian, and Romanian electricity data

Due to the national promotion strategies on renewable energies in the electricity sector, and triggered by the Directive (2001/77/EC), all EU member states have introduced policies to support the market introduction of renewable energy sources (RES). Guaranteed feed-in-tariffs support for renewable electricity generation has led to the growth in the installed capacity of supported technologies. The theoretical consideration introduced by Jensen and Skytte (2002) predicts that in the short-run an increase in renewable energy sources generation reduces electricity prices. The price reducing impact is by scholars recognised as the merit-order effect. It is explained as the right shift of the system supply curve when supported RES generation with low variable costs is integrated into the supply curve. With the econometric model specified by Würzburg, Labandeira, & Linares (2013), the dissertation confirms the presence of the merit order effect in the less mature Central and South East European electricity markets. Further, the thesis simulates the adjustment of the realised day-ahead electricity prices to the no-RES generation scenario. With the simulation results, the thesis empirically analyses the effect of RES generation on the electricity price levels, price volatility, and electricity net export.

An assessment of the dissertation's contribution to the field of knowledge

By studying the presented dissertation topics and answering research questions, the dissertation provides several contributions to the electricity price modelling field of knowledge. To answer the research questions aligned along the first dimension, the dissertation provides independent electricity price forecasting simulations on yet unresearched Greek and Hungarian day-ahead electricity markets. Forecasting performance is evaluated on more than one thousand simulation days, which ensures reliable accuracy comparison of the alternative models and statistical Diebold-Mariano test execution. The dissertation offers one of the first systematic quantitative overviews of the forecasting performance of the respective contemporary forecasting algorithms. The electricity price forecasting field has experienced a massive increase in the number of published articles, as well as the number of citations. This suggests that the research field would benefit from the systematic overview article that statistically evaluates forecasting performance of the contemporary algorithms with respect to the applicative limitations in the day-ahead market operations. Further, the dissertation thoroughly studies the impact of training sample size on forecasting performance of algorithms and provides insights to this intriguing research question that remained open in a similar study by Lago, De Ridder, & De Schutter (2018). The dissertation offers relevant information to novice scholars, and as well to researchers with numerous years of experience and published articles in the field.

Motivated by the currently ongoing final steps in the EU electricity markets integration, the dissertation proposes a solution for applied simulations in coupled day-ahead electricity markets. Several scholars have agreed that electricity prices in coupled electricity markets must be modelled in all areas consistently in one integrated framework. However, proposed solutions typically rely on statistical methods that cannot provide insight into the market coupling process itself i.e., efficient CBC allocation. The EUPHEMIA algorithm, a single price-coupling solution calculates electricity prices across Europe respecting the cross-border capacity constraints on a day-ahead basis. The dissertation simulation framework relies on the EUPHEMIA algorithm developed by the European Power Exchanges and proposes an alternative orderbook generation process based on publicly available data. The orderbook generation is based on the econometrically estimated aggregate supply price elasticity functions for each market individually. The power market data accessibility to qualified parties limited the development of forecasting algorithms and applied power system research (Díaz et al., 2019). The proposed order book generation solution bridges the need for the publicly unavailable power exchange orderbook data and stimulates scholars to further research coupled electricity markets. Finally, the dissertation empirically provides answers to the research questions on improved electricity price convergence, reduced price volatility, and improved price shock transmission in coupled electricity markets.

The crowding out of conventional electricity generation by renewable energy sources (RES) recognised by the scholars as the merit order effect (MOE) is thoroughly researched in key EU energy areas (Denmark, Germany, Spain, etc.). These are areas with higher shares of renewable capacity in their generation mix and matured electricity markets. The dissertation empirically confirms and quantifies MOE in Greek, Hungarian, and Romanian day-ahead electricity markets. With the MOE analysis and simulation on yet unresearched SEE power markets, the dissertation supplements existing literature focused on key EU energy areas in terms of installed renewable generation capacity and market maturity. Data availability and accessibility historically limited applied power market research (Hirth et al., 2018). Due to the limited publicly availability data, traditional simulation models used in the power system or agent-based simulations cannot be applied to simulate electricity prices in a no-RES generation scenario. Therefore, the dissertation simulates the adjustment of the realised electricity prices to the no-RES generation scenario with a framework based on modern statistical methods. The proposed framework successfully bridges the gap in the limited public availability of data to solve simulation models intuitively close to power system or agent-based simulations.

Data and methodology

This dissertation is built upon a publicly available data source ENTSO-E TP, ensuring fast and easy study reproducibility. According to Hirth, Mühlenpfordt, & Bulkeley (2018), data availability and accessibility historically limited applied power market research. Power market research is data intensive, as it typically requires hourly data resolution on electricity consumption, generation, transmission, etc. The situation in Europe changed in 2015 with the commencement of the Transparency Platform (TP) operated by the European Network of Transmission System Operators for Electricity (ENTSO-E). According to ENTSO-E (2020), there are three channels of data collection, a graphical user interface (GUI), a restful application programming interface(API), and a file transfer protocol. From ENTSO-E TP, we utilised reported hourly data on forecasted and actual consumption, aggregated production for each type of power plants, reported power plant outages, forecasted solar and wind production, scheduled commercial exchanges (net-export), and day-ahead electricity prices. In the data collection phase, we noticed missing data points and non-reported data types in the ENTSO-E TP data base. Romania is not in the first chapter scope, evaluating the forecasting performance of alternative algorithms, as we could not find a replacement for the non-reported Romanian power plant outages data type. The Romanian data set utilised in the third chapter researching merit order effect is a blend of ENTSO-E TP data and Romanian national transmission system operator's data source (Transelectrica, 2020) for the reported aggregated production values. Except for the aforementioned exception, the dissertation data sets are obtained through API implementation in R software environment from ENTSO-E TP. Because ENTSO-E TP includes all European countries, it enables the study of differences among the individual electricity price indexes and other power market characteristics.

The dissertation employs several quantitative methodological approaches executed in R software environment. The first chapter evaluates a forecasting performance of alternative electricity price forecasting methods from the family of machine learning and artificial intelligence algorithms. The econometric autoregressive model with exogeneous explanatory variables is a benchmark model, as the other alternative approaches are used to overcome the linearity bias in the ordinary least squares estimator. In the second chapter, we propose an integrated model for electricity market coupling simulations. Power exchange orderbooks are generated based on the estimated supply price elasticity functions. The relationship between the supply prices and equilibrium quantity may introduce a bias as a consequence of a possible reverse causality, therefore, we estimate supply price elasticity functions by the method of instrumental variables. Electricity prices and cross border capacity allocations in coupled market areas are determined by the mathematical optimisation model. Electricity price shock transmission in coupled market areas is analysed by the estimated vector autoregressive models, as they allow to characterise the joint distribution of power prices in the studied coupled electricity markets. In the third chapter, we quantify and confirm the crowding out of conventional electricity generation by renewable energy sources by the estimated multivariate regression model. As well, we simulate the adjustment of the realised day-ahead electricity prices to the no-RES generation scenario. In the simulation, we account for the changed international net export dynamics and conventional generation dispatch adjustment to the omitted RES generation. The impact of the omitted RES generation on electricity net export is estimated by the multivariate regression model, whereas the dynamic adaptation of generation mix is approximated by the machine learning algorithms.

Structure of the doctoral dissertation

The dissertation is organised in three chapters, each investigating a different, but interrelated topic connected to electricity market price modelling:

- Chapter 1: Performance of alternative electricity price forecasting methods: findings from the Greek & Hungarian power exchanges;
- Chapter 2: An integrated model for electricity market coupling simulations: A Slovenian day-ahead market case study;
- Chapter 3: Crowding out of conventional electricity generation by renewable energy sources: evidence from Greek, Hungarian, and Romanian electricity markets.

The chapters can be read individually, which may lead to certain repetition when describing the related literature, the data sources used, and the methods. They are followed by a conclusion, which summarises the findings and assesses the scientific contribution of the dissertation to the literature. The dissertation is supplemented by several appendices, which provide modelling results in more detail, and concluded with an extended abstract in the Slovenian language.

1 PERFORMANCE OF ALTERNATIVE ELECTRICITY PRICE FORECASTING METHODS: FINDINGS FROM THE GREEK & HUNGARIAN POWER EXCHANGES

1.1 Introduction

The liberalisation of the power market has led to a change from a centralised structure where the only variable of interest in terms of prediction was demand, to a competitive environment where the prediction of price is an unavoidable task for both producers and consumers (Garcia-Martos et al., 2012). Risk related to the daily market operations is derived from high price volatility. This is especially valid for spot prices, where volatility can be as high as 50% on a daily scale, i.e., over 10 times higher than for other energy products (natural gas and crude oil) (Weron & Misiorek, 2005). According to study examining the economic impact of price forecast inaccuracies on forecast users in a day-ahead market operations, a 1% mean absolute percentage error (MAPE) accuracy metrics improvement resulted in a 0.1-0.35% cost reduction (Zareipour et al., 2010).

According to Misiorek & Weron (2014) existing EPF methods are: multi-agent models, fundamental models, reduced-form models, statistical model and computational intelligence models. We can differentiate between three forecasting time horizons: short- , medium- and long-term EPF (Cerjan et al., 2013). In the day-ahead markets (short-term) most important EPF methods are statistical models and computational intelligence (CI) techniques. Statistical models are frequently criticized for linearity bias. Linearity bias implies the inability to model non-linear electricity price behaviour (Weron, 2014) and rapid changes in the price signal (Chan et al., 2012), ultimately resulting in poorer forecasting performance. Today there is an important subfield of deep learning in the artificial neural networks models (Lago, De Ridder, & De Schutter, 2018).

In the reviewed EPF literature considering CI models, training and testing data sets used in the point forecast simulations are typically fixed over the considered time series. Such experiment setting indicates that once the EPF models are calibrated, market participants would rely on the non-recalibrated model version for the indefinite period, i.e., during the whole out-of-sample testing period. This rather arguable experiment setting in case of the applied EPF practice in the day-ahead market operations, is in our study bridged by the simulation of a typical daily EPF process. Analysis of the training data set size effect on the forecasting accuracy remains open in the review study of neural network based approaches and traditional algorithms in Lago, De Ridder, & De Schutter (2018). With the study design we can provide insights to the yet unaddressed research question. To improve forecasting accuracy some researches include dummy variables associated with the individual hours of the day into the EPF models (Díaz et al., 2019; Panapakidis & Dagoumas, 2016). To fully extract individual hour predictive information, we have implemented an EPF model for each single hour of the day. Linearity bias reduction i.e. superior forecasting accuracy of the alternative models compared to the statistical benchmark model is usually confirmed by lower forecasting error and the statistically significant Diebold-Mariano test (DM) (Grossi & Nan, 2019; Lago, De Ridder, & De Schutter, 2018; Lago, De Ridder, Vrancx et al. 2018; Nowotarski & Weron, 2018; Weron, 2014). However, a typical model back-test period varies markedly e.g. from one week per season to over a year period. Similar EPF model review study by Lago, De Ridder, & De Schutter (2018) used a year of data for the out-of-sample forecasting accuracy analysis. We use considerably longer time series which make accuracy comparison of alternative models and statistical DM test more reliable. In the studied research papers data set is typically a blend of various data sources. Blended data sets are limiting fast and easy research reproducibility. Our study is based on a single publicly available data source. There is a substantial amount of EPF papers focusing on Western, Northern and Southern European countries. To the best of our knowledge there is no similar EPF study, researching countries of the Central and Eastern Europe (CEE) and Southeast Europe. We aspire to bridge this gap by providing EPF evidence from Greek and Hungarian power markets.

To simulate sound application of the most important EPF methods in the day-ahead markets we have executed computationally intensive dynamic forecasting by the rolling-window approach. Furthermore, simulation is exclusively based on hourly data set available on the ENTSOE-TP before the power exchange order book closure. The optimal training data set size is determined by incrementing the number of included days in the training data set by the increment of 28 days (from 28 to 336 days) and further analysis of the forecasting accuracy under different training data sample sizes. Full individual hour predictive information extraction is done with the calibration of 24 smaller models on hourly clustered samples. In our analysis, we used a data set based on a time series of 1,368 days (almost a 4-year period). Maximum training sample size of 332 days allows analysis of the out of sample model behaviour on over a more than 1,000-day period. This makes accuracy comparison of alternative models and statistical DM test more reliable. The analysis is based upon a single publicly available data source ENTSOE-TP, ensuring an easy study reproducibility.

Although number of authors reported superior forecasting accuracy of the computational intelligence EPF models, they have overlooked the importance of the applicative nature of the experiment in the day-ahead electricity markets. Our research will further investigate the superiority of the most important alternative models, however based on a considerably longer time series and by a rolling window analysis simulating sound application of the EPF tools in the day-ahead markets. Furthermore, with the computationally intensive study design we can answer intriguing research questions associated with the EPF simulation settings: does training sample size in matter, does model training on hourly clustered data samples enhance EPF accuracy and can the demand-supply ratio (DSR) explanatory variable enhance EPF accuracy in extreme price situations?

The chapter is structured as follows. In Section 1.2 is a literature review of the most important research papers with a specific focus on the data sample size used in the out-of-sample forecasting. Section 1.3 outlines electricity price formation process with a focus on Greek and Hungarian electricity market. Study design and a concise explanation of the selected models are in Section 1.4. In Section 1.5 represent ENTSOE TP, data collection process and used data set. In Section 1.6 are positioned simulation results with their interpretation and discussion. In Section 1.7 is located research conclusion with outlined research findings.

1.2 Electricity price forecasting methods

The power system data accessibility was historically limited to the qualified parties with direct participation in the electricity markets. This situation has limited the development of EPF and applied power system research (Díaz et al., 2019).With the power market liberalisation and increased renewable production, EPF has become an interdisciplinary research area attracting many researches. In the EPF extensively used statistical time series model are of ARX type models, where AR stands for the autoregressive variable (historical price) and X for exogeneous explanatory variables (e.g. load, wind production etc.). Adding a moving average in the model, results in ARMAX model and integration of the former, results in ARIMAX model. Implementation of the artificial neural network (ANN) based models and other CI approaches is complex, as the definition of the free parameters (in case of ANN models additional network architecture definition) is mainly dependent on experience (Yang et al., 2017). Number of authors have reported their superior performance compared to the statistical EPF models. An EPF review article by Weron (2014) continues to serve as a good reference point to many researches interested in the topic. In our research autoregressive time series model with the exogeneous variables (ARX) serves as a benchmark model. Proposed alternative models to bridge the linearity bias in the benchmark model are: K-Nearest Neighbours (KNN), Regression Tree (M5P), Random Forest Regression (RFR), Support Vector Machine (SVM), Artifical Neural Net (ANN) and Long Short-Term Memory (LSTM). Regression tree approaches and KNN algorithm used in this chapter are not part of the revision in Weron (2014). As the regression tree based model won the Global Energy Forecasting Competition (GEFCOM) in price and load forecasting section, we have considered this methods in our study (Gaillard et al., 2016). Application of KNN in GEFCOM solar power forecasting competition is used by Zhang & Wang (2015) for the identification of similar days with regards to the weather conditions.

In the initial phase of EPF commonly used models are statistical time series models. Presumably due to the before mentioned data accessibility issue there are many publications researching univariate time series approaches. In one of the earliest publications ARMA model is applied for the Germany day-ahead price forecasting (Crespo Cuaresma et al., 2004). Models are calibrated on approximately a year and a half of data, and the performance is evaluated based on the month and half data. Better forecasting performance is reported for models calibrated on the hourly clustered data samples. Comparison of EPF accuracy of a univariate

ARMA model with ARMAX model base on Californian data is done by Weron & Misiorek (2005). Exogeneous variable added to base ARMA model is forecasted load value. Models are calibrated on approximately one-year period whereas testing is based on 8 months out-of-sample test period. ARMAX model performed on average better. Statistically based univariate EPF of Nord Pool market by rolling approach is conducted in Raviv, Bouwman, & van Dijk (2015). Authors used in the study 18 years of data, with a single rolling window setting of 365 days. Models compared forecasting performance of multivariate models with additional variables associated with hourly, daily and weekly dynamics compared to the base univariate statistical models. Multivariate models had higher accuracy. EPF with rolling window analysis with advanced statistical methods based on the Italian day ahead market data is done by Grossi & Nan (2019). Authors compared forecasting accuracy of univariate Self- Exciting Threshold Auto Regressive model (SETAR) with the SETARX model, where X stands for the renewable system generation. Authors generated 365 day-ahead forecasts with models estimated on a 2-year long rolling window. Multivariate model SETARX model outperformed univariate SETAR model.

Comparison of the statistical ARIMA, SVM and ANN model based on Californian data is done by Che & Wang (2010). Models were calibrated on 28 days of data and tested on two out-of-sample forecasted weeks. The only exogenous variable used in the analysis is wind power generation. ARIMA model was outperformed by both alternative methods, with SVM model having the highest accuracy. The empirical comparison of the deep learning neural network approaches and traditional algorithms based on the Belgium data is analysed by Lago, De Ridder, & De Schutter (2018). Models were trained on five-year period and back-tested on a one year out-of-sample period. Explanatory variables used in the analysis are load forecast and the reported generation availability in the system. Neural network models were the models with highest reported accuracy. Based on univariate time series ANN with wavelet transformation and ARIMA model with wavelet transformation are tested based on the Californian and Spanish data in Catalão, Pousinho, & Mendes (2010). Models were back-tested on 4 representative weeks of yearly seasons. Calibration for each week was done on 42 days period. ANN models outperformed statistical ARIMA model. In paper by Panapakidis & Dagoumas (2016) Italian Southern region day ahead price is forecasted based on the artificial neural network models with different topologies in combination with additional clustering algorithm. Models are trained on approximately 3 years of data and back tested on 4 months period. Additional included explanatory variables are weekday dummies, load, renewable production and natural gas price. ANN models with rich explanatory variables data set and additional clustering algorithm outperformed univariate ANN models. ANN method with wrapper function fort the feature selection is tested and compared to a Pattern Sequence-based Forecasting method (PSF) on Australian, New-Yorker and Spanish market by Neupane, Perera, Aung, & Woon (2012). Explanatory variables (features) in the models are past electricity data, weather data and calendar data. Models were trained on 3 years period and back tested on 1-year period. ANN method had higher accuracy compared to the PSF method. Price forecasting and price spike probability forecasting for Finish Nord Pool day-ahead market is done by

Voronin & Partanen (2013). Exogenous explanatory variables in the models are load and reported total generation. ARIMA time series model is compared to the ANN model. Models are trained on 2-year period and back tested on a year of out-of-sample data. In both cases ANN model had higher reported forecasting accuracy. Gradient boosted regression trees tested on Spanish market outperformed linear regression model in paper by Díaz et al. (2019). Gradient boosted regression tree is an ensemble machine learning technique closely tied to random forest algorithm (RFR) used in our study. Researchers trained models on 30 months period and back tested proposed methods on 6 months of the out-of-sample test data. Study is based upon a rich set of explanatory variables.

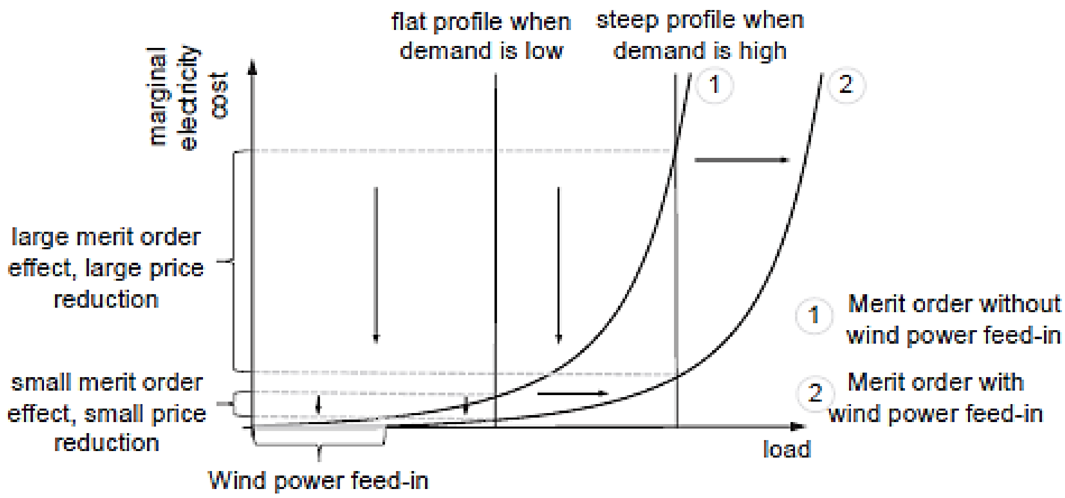
Rolling window analysis simulating typical day-ahead application of EPF tools is newer applied in studies using CI approaches. This might be associated with the time-consuming computation of such an analysis. Training and testing sample sizes vary from study to study markedly. With the research on optimal training size our chapter provides indicative optimum values for frequently used EPF algorithms. We use considerably longer out-of-sample back test period compared to the reviewed articles. This makes our accuracy comparison of alternative models and statistical DM test more reliable. Data set used in the studied researches is typically a blend of fundamental data provided by the national transmission system operator (TSO) and power exchange closing prices from different sources. Non-of the papers analysing European countries based their study upon ENTSOE-TP data source. There can be found only few studies that explore EPF performance in more than one country.

1.3 Greek and Hungarian day-ahead markets

The day-ahead market is a wholesale market where the standard hourly contracts are traded for the day-ahead physical delivery (24 hourly contracts). The competitive price is determined by the intersection of a market supply and demand curve as illustrated in Figure 1.1. The profile of the supply curve is defined by the ranking of the production units by their short-run marginal costs in increasing order, together with the dispatched energy, in merit order (Sensfuß et al., 2008). Electricity is an essential commodity, and as such in the short-term exhibits inelastic demand, therefore is typically represented by a flat vertical line (Cerjan et al., 2013). Renewable production is supported by the feed-in tariffs. As a natural consequence, the purchased load in the electricity markets is reduced accordingly for the subsidised renewable production (Keles et al., 2013). Renewable generation availability has a negative impact on electricity prices, and this fact is recognised as a merit order effect (Martin de Lagarde & Lantz, 2018).

Recent reforms in the Greek power market in 2018 resulted in the establishment of Hellenic Energy Exchange (HEE), which undertook all the responsibilities that previously belonged to the LAGIE market operator. The Greek day-ahead market refers to wholesale transactions during each D-1 calendar day, where electricity supply contracts are auctioned for each market time unit (1 hr.) of physical delivery on day D. The delivery day (D) consists of 24 purchased time units, starting at 01:00 Eastern Europe Time (EET) on calendar day D, and ending at 01:00 EET on the next calendar day D+1. The orderbook opens at 10:30 (D-1) and remains open for 150 min., closing at 13:00 (D-1) (Ioannidis et al., 2019).

Figure 1.1: Merit order effect



Source: Keles, D., Genoese, M., Möst, D., Ortlieb, S., & Fichtner, W., A combined modelling approach for wind power feed-in and electricity spot prices, 2013, p. 214.

The 'residual load' or the reduced load that has to be bought in the market is defined as:

$$\boldsymbol{Residual\ load = Load - Wind - Solar} \tag{1.1}$$

Hungarian power exchange (HUPX) was established in 2010. It operates organized Hungarian spot power market where standard hourly and block day-ahead electricity products can be traded. HUPX has a leading position in Central and Eastern Europe (HUPX, 2020). According to the market rules, orderbook closes at 11:00 (D-1) (HUPX, 2019).

Table 1.1 summarises the Greek power generation mix from 1.1.2015 to 30.9.2018. On average, the total generation is just above the 40 TWh per annum.[1] Lignite-fired power plants historically represent the biggest share of production, however, in 2017 and 2018 this share was balanced with the gas production. In 2015, wind and solar power production reached production of 7.1 TWh. Since 2015, renewable generation has an upward production trend and reached a total production of 8 TWh in the 3rd quarter of 2018.

[1] Please note that ENTSO-E TP reports for Greece-only generation periods for hydro-pumped storage power plants, causing a bias due to the non-reported consumption periods.

Table 1.1: Greek generation mix production in TWh

Year	Lignite	Gas	Oil	Pumped Storage	Water Reservoir	Solar	Wind	Total
2015	18.9	8.4	0.0	0.9	4.5	3.6	3.5	39.8
2016	15.1	13.7	0.0	0.6	4.2	3.6	3.7	41.0
2017	16.8	16.6	0.0	0.4	3.0	3.6	4.2	44.7
2018^{3rd}	14.4	14.4	0.0	0.6	4.3	3.3	4.6	41.7

Source: ENTSO-E TP (2019).

As detailed in Table 1.2, there is no solar generation and only moderate wind generation in the overall Hungarian generation mix. Nuclear power plants accounts for a major share in the Hungarian generation mix. As in Greece, lignite-fired power production decline is compensated with the gas production increase.

Table 1.2: Hungarian generation mix production in TWh

Year	Biomass	Lignite	Gas	Nuclear	Other	Run of river	Water reservoir	Wind	Total
2015	0.8	6.0	4.3	14.9	0.9	0.1	0.1	0.1	27.1
2016	0.8	5.5	5.4	15.1	0.8	0.1	0.1	0.1	28.0
2017	0.9	4.8	6.9	15.2	0.8	0.1	0.1	0.1	28.9
2018^{3rd}	0.6	3.5	4.2	11.1	0.6	0.1	0.1	0.1	20.3

Source: ENTSO-E TP (2019).

According to Table 1.3, Greece can be characterised as a natural electricity importer with the average yearly total net imports above 6 TWh. The country imports electricity on all interconnections with the neighbouring countries. The sole exceptions were the Turkish border in 2016 and on the Italian border in 2018.

Table 1.3: Greek net import per border in TWh

Year	GR-AL	GR-BG	GR-IT	GR-MK	GR-TR	Total
2015	0.8	2.4	1.1	1.9	0.3	6.4
2016	1.3	3.8	1.7	2.4	–0.6	8.6
2017	0.3	2.9	1.3	1.2	0.5	6.2
2018^{3rd}	1.0	2.9	–0.7	1.4	0.5	5.3

Source: ENTSO-E TP (2019).

Hungary is an electricity importer with the average yearly total net imports around 13 TWh. As detailed in Table 1.3, Hungary on average imports energy on all interconnected borders with the exceptions on the Croatian and Romanian border.

Table 1.4: Hungarian net import per border in TWh

Year	HU-AT	HU-HR	HU-SR	HU-RO	HU-UA	HU-SK	Total
2015	3.4	-3.5	2.5	-0.4	4.2	7.5	13.7
2016	2.9	-1.1	1.0	0.0	3.3	6.6	12.7
2017	4.1	-3.0	0.7	-1.7	3.9	8.8	12.8
2018^{3rd}	1.5	-0.8	1.3	1.7	2.9	5.0	11.6

Source: ENTSO-E TP (2019).

In the survey literature, there is a considerable number of articles addressing EPF of Spanish PX (Díaz et al., 2019; Yang et al., 2017; J.-L. Zhang et al., 2019). In Table 1.5, we can observe that the Greek and Spanish[2] PX indexes exhibit similar price patterns according to the price levels and the overall variance. Price levels in Greece and Spain are significantly higher compared to Germany, whereas the price variance in Germany is higher. Hungarian PX index is on average above the German PX index and bellow the Greek and Spanish indexes. Variance in Hungary is almost twice higher compared to the variance in Greece and Spain. From 2014 to the end of year 2017, the monthly average volume of energy exchanged on the Greek PX is above 4 TWh, in Hungary above 1 TWh, in Spain under 15 TWh, and in Germany close to 20 TWh (The European Commission, 2017).

Table 1.5: PX index in €/MWh and overall variance

Year	GR	HU	DE	ES
2015	51.9	40.6	31.8	/
2016	42.8	35.5	29.0	39.7
2017	54.7	50.4	34.2	52.2
2018	56.9	46.5	41.7	55.4
VAR	178.3	355.3	241.4	178.2

Source: ENTSO-E TP (2019).

1.4 Methodology

The sole superiority of the forecasting accuracy does not necessarily imply that forecasts from other models contain no additional information (Diebold & Mariano, 1995). The superiority of the alternative models compared to the benchmark model is therefore mutually confirmed by lower forecasting error and the statistically significant Diebold-Mariano test (DM).

In the surveyed literature, considering hourly EPF, a single EPF model typically serves as a forecaster for all hours of the day, i.e., calibration of a single model on an hourly non-clustered sample. In order to extract useful predictive information, some authors introduce dummy variables associated with the individual hours of the day (Díaz et al., 2019; Panapakidis & Dagoumas, 2016) into the EPF models. To fully extract individual hour predictive information, we have implemented an EPF model for each single hour of the day, i.e., calibration of 24 models on hourly clustered samples. A direct consequence of this implementation is the reduced size of the learning sample by the multiple of 24 on the same data. The hourly non-clustered yearly data sample consists of 8,760 hourly data points (365 days x 24 hours = 8,760 data points), whereas hourly clustered samples consist of 365 hourly data points (365 days x 1 hour = 365 hours).

Luo & Weng (2019) observed that the training mean squared error (MSE) fluctuates around the minimum value as we increase the training sample size, while the testing MSE becomes extremely large. One of their findings due to the overfitting is that more training data is not necessarily connected with the higher out-of-sample forecasting accuracy (Luo & Weng, 2019). We have determined the optimal training data set size by increasing the number of

[2] Please note that ENTSO-E TP does not report the Spanish PX index for the whole year of 2015.

included days in the training data set from 28 to 336 days (28, 56, …, 336 days). The increment of 28 days replicates an increment of a month, with such setting we have analysed the effect over a year's time horizon.

A price spike is characterised by a sudden departure of prices from the normal regime for a very short time interval (Grossi & Nan, 2019). Such a situation could be predominantly associated with electricity demand, generation outages, transmission congestions, market participant behaviours, etc. (Hong et al., 2016). To control for the generation outages, we have added a demand-supply ratio (DSR) defined as:

$$DSR = \frac{Residual\ load}{Installed\ available\ generation\ capacity} \tag{1.2}$$

to the base set of explanatory variables. DSR summarises the share of the available installed generation capacity to cover the residual load. High DSR index values indicate low availability of free generation capacities and tight market conditions (Alexander & Dominique, 2007).

As the models are calibrated on the realised data set, we have additionally executed out-of-sample accuracy tests on the forecasted fundamental explanatory variables. This simulates a typical use of forecasters in the day-ahead markets and tests their robustness. Day-ahead publicly available forecasts in the domain of load and renewable generation are published on the ENTSO-E TP no later than two hours before the gate closure of the day-ahead market (ENTSO-E TP, 2020).

1.4.1 ARX model

The linear ARX forecaster serves as a benchmark EPF model estimated by the Ordinary Least Squares (OLS) method. All the alternative models are implemented to overcome the linearity bias in the ARX approach. The workhorse linear model is defined as:

$$Price_t = \alpha + \beta\ Price_{t-24} + \delta\ Residual\ Load_t + \sum_{i=1}^{6} \theta_i\ Weekday\ Dummy_{it} + \varepsilon_t \tag{1.3}$$

$Price_{t-24}$ in Equation 1.3 is an autoregressive term that brings in the model's previous day price level information. Variable $Price_{t-24}$ is included instead of $Price_{t-1}$, as at the time of forecasting for the next delivery day (*D+1*) the variable $Price_{t-1}$ is observable only for the first hour of the *D+1*. This is a natural consequence of a day-ahead market design (explained in Section 3), as the whole set of daily hours is quoted at once. The $Residual\ Load_t$ term is calculated according to the Equation 1.1. As the only fundamental variable in this model is Residual Load, this model is referenced as *RL Model*.

The demand-supply ratio defined in the Equation 1.2 is specifically addressed to improve the EPF accuracy during the price spike events. Equation 1.4 is for the DSR variable extended Equation 1.3 and is referenced as *RL + DSR Model*:

$$Price_t = \alpha + \beta\ Price_{t-24} + \delta\ Residual\ Load_t + \gamma\ DSR_t + \sum_{i=1}^{6} \theta_i\ Weekday\ Dummy_{it} + \varepsilon_t \quad (1.4)$$

The ARX model is a time series model where 'AR' stands for the autoregressive term, i.e., $Price_{t-24}$, and '*X*' for the exogenous variables (Residual Load & Weekday dummies). Exogenous variables are not part of the dependent variable time series, as is the case for the *AR* terms. The ARX model is estimated by the OLS estimator. OLS is not the best way of estimating the derived Equation 1.3, as it imposes a linear relationship on the whole data space (Wang & Witten, 1996). This is deemed to be the main weakness of the model, causing poorer forecastin1.g performance.

1.4.2 K-nearest neighbours – the k-NN algorithm

The K-NN algorithm is a non-parametric method used for classification and regression (Altman, 1992). The algorithm itself is popular due to the straightforward interpretability. The results of the model are based on the selected number of past observations that are closest to the current state of the explanatory variables according to the predefined metrics. Regression predictions are obtained by averaging the output variables that are considered *k* nearest neighbours by the selected distance metrics (Mangalova & Agafonov, 2014).

Common distance metrics is the Euclidian distance, defined for points $A(x_1, x_2, \ldots, x_m)$ and $B(y_1, y_2, \ldots, y_m)$, i.e., two different observations, as:

$$dist(A, B) = \sqrt{\frac{\sum_{i=1}^{m}(x_i - y_i)^2}{m}} \quad (1.5)$$

where *m* is the dimensionality of a feature space (*Price, Residual Load*, …, *Weekday Dummy*). The number of data point's neighbours (K) is a free parameter that must be adjusted during the model implementation.

1.4.3 Regression Tree – the M5P algorithm

The M5P algorithm enables application of the decision tree building logic used in the classification problems (class variables) for the purpose of continuous prediction. The concept used to overcome the linearity, is that it initially builds a tree based on the splitting criteria which minimises intra-subset variation in the class values down each branch (Wang & Witten, 1996). Intra-subset variation minimisation stands for 'Standard Deviation Reduction' (SDR) computed as:

$$\boldsymbol{SDR} = \boldsymbol{sd}(\boldsymbol{T}) - \sum_i \frac{|\boldsymbol{T}_i|}{|\boldsymbol{T}|} \times \boldsymbol{sd}(\boldsymbol{T}_i) \tag{1.6}$$

where T is the set of examples that reach each node, and $T_1, T_2 \dots T_n$ are the sets that result from splitting the node according to the chosen attribute. Linear regression is applied in every leaf node of the constructed tree. The number of the linear regression models equals the number of the leaf nodes. Explanatory variables or attributes used in the linear regression in each leaf node are those that are referenced by the tests or linear models somewhere in the subtree at this node (Quinlan, 1992). The minimum number of instances at each leaf is a stopping criterion for a tree growth and an adjustable parameter.

1.4.4 Random forest regression – RFR

Random forest regression is an ensemble method closely related to the regression tree MP5 algorithm. The algorithm produces a collection of regression trees and takes a mean prediction of the built regression trees as an output. A forest is built upon the principle of bagging, i.e., combining models with low bias and high variance error in order to reduce the variance, while keeping the bias low (Lago, De Ridder, & De Schutter, 2018). Random forests are a combination of tree predictors where each tree depends on the values of a random vector sampled independently, and with the same distribution for all trees in the forest (Breiman, 2001). A set of free parameters must be predefined or tuned during the model implementation. Free parameters are several trees to grow and several variables to be sampled as a candidate at each split.

1.4.5 Support vector machine – SVM

SVM is a computationally-intensive method used for classification and regression tasks. SVM performs a non-linear mapping of the data into a higher dimensional space to create linear decision boundaries in the new space by simple linear functions (Weron, 2014):

$$y_t = f(X_t) = \langle W, \varphi(X_t) \rangle + b \tag{1.7}$$

In Equation 1.7, $\langle \cdot \rangle$ denotes the dot product, W a weight vector, b the bias, and $\varphi(\cdot)$ the non-linear mapping function. In order to find the optimum linear decision boundaries, the convex quadratic optimisation problem must be solved (Yan & Chowdhury, 2014). A detailed description of a full derivation procedure can be found in Yan & Chowdhury (2014) and Thissen, van Brakel, de Weijer, Melssen, & Buydens (2003). The data set used in the SVM model is normalised to achieve an easier training process. We have to choose three parameters when applying SVM with Radial Basis Function (RBF) kernel, C (connected with a loss function), ε (defines bandwidth of a 2 ε tube), and γ (parameter of a RBF kernel).

1.4.6 Artificial neural net – ANN

In the last decade, the field of neural networks has experienced several innovations that have led to what is known as 'deep learning' (DL) (Yang et al., 2017). In particular, one of the traditional issues of neural networks had always been the large computational cost of large models training (Lago, De Ridder, & De Schutter, 2018). The situation changed once, showing that such networks could be trained efficiently by a so-called 'greedy layer-wise pre-training algorithm' (Hinton et al., 2006). There is no generally agreed threshold dividing shallow learning from deep learning. According to Schmidhuber, models with more than 10 hidden layers are classified as extremely deep learning algorithms (Schmidhuber, 2015). The implementation of neural network based approaches is complex, as the definition of parameters and network architecture is mainly dependent on experience (Yang et al., 2017). For this chapter, we have implemented feedforward neural networks, sometimes called 'multilayer perceptrons.' The feedforward mechanism relates to the fact that there are no feedback connections in which outputs of the model are fed back into itself (Ian et al., 2016). The depth of the model is associated with the number of the network layers. In its simplest form, it is called a 'single-layer perceptron,' as there are no hidden layers and it is equivalent to linear regression (Weron, 2014). The ANN weights are determined by a learning algorithm that minimises the cost function. For full model derivations, please refer to (Ian et al., 2016). Applied ANN models have two hidden layers, returning a single continuous value. The used data set was normalised to achieve an easier training process.

1.4.7 Long short-term memory model – LSTM

Long short-term memory (LSTM) is a frequently used deep learning artificial recurrent neural network architecture. There are numbers of LSTM applications in the field of voice and handwriting recognition. Feed-forward artificial neural networks (ANNs) are memoryless, as their response to an input is independent of the previous network state. They are static in the sense that they produce only one set of output values, not a sequence of values from a given input (Weron, 2014). ANNs with the feedback connections are dynamic systems referred to as 'recurrent neural networks' (RNN). When a new input pattern is presented, the neuron outputs are computed. Because of the feedback, the inputs to each neuron are modified, which leads the network to enter a new state (Weron, 2014). In LSTMs, a memory cell containing a node with a self-connected recurrent edge of fixed weight one is introduced to maintain its state value over a long time, such that the gradient can pass across many time steps without vanishing (Lipton et al., 2015). It has been shown that LSTMs work better than simple RNNs for training long-term sequence data. The complex model structure of LSTMs makes the training and decoding of LSTM models more expensive (Miao et al., 2016). Due to the network architecture with feedback connections they are suitable for forecasting complex nonlinear time series. For a full model description, please refer to (Hochreiter & Schmidhuber, 1997).We have trained a LSTM model for 10 epochs with two connected hidden layers and an output layer returning a single continuous value.

1.5 Data, model implementation & forecast measurement

Data availability and accessibility in a user-friendly format is specifically a problem in the less matured power markets. Such conditions in Europe have changed with the commencement of the Transparency Platform (TP) operated by the European Network of Transmission System Operators for Electricity (ENTSO-E). The sole purpose of the TP is to foster transparency in the power market, and level the playing field between small and large parties (Hirth et al., 2018). Besides the free access to the historical power system data on an hourly resolution, TP offers access to the historical load forecasts, renewable generation forecasts, and outage information. This information is available in the standardised format on the TP from 5 January 2015 on. In the studied research papers, the data set is typically a blend of various data sources. Our analysis is based upon a single publicly available data source ENTSOE-TP, which is not a common point in the reviewed literature. ENTSOE-TP has three channels of data collection, a graphical user interface (GUI), a restful application programming interface (API), and a file transfer protocol (FTP) (ENTSO-E TP, 2020). There are existing *R* and *Python* libraries for easier data transfer through API and FTP channels. The data collection process was carried out by the API-related code executed in *R*. The working data set spans from 1.1.2015 to 30.9.2018, resulting in a time series of 1,368 days or 32,832 hourly observations.

Weron concluded in his EPF review study that many of the time series regression approaches are hybrid solutions, as they use additional fundamental explanatory variables Weron (2014). The common set of fundamental explanatory variables are ambient weather conditions, load, generation capacity, wind power, gas, and coal prices (González et al., 2005; Karakatsani & Bunn, 2008; Kristiansen, 2012; Uniejewski et al., 2016; Weron & Misiorek, 2008). We have used the following set of variables for the EPF simulation:

- **DA market clearing price**: for every market time unit the day-ahead prices in the bidding zone.
- **Actual load**: actual total load per bidding zone per market time unit, the total load being defined as equal to the sum of power generated by plants on both TSO/DSO networks, from which is deduced:
  - the balance (export-import) of exchanges on interconnections between neighbouring bidding zones
  - the power absorbed by energy storage resources.
- **Forecasted load**: day-ahead forecast of total load per market time unit per bidding zone. Publication at the latest two hours before the gate closure time of the day-ahead market in the bidding area.
- **Actual solar generation**: actual aggregated solar net generation output (MW) per market time unit.
- **Forecasted solar generation**: forecast of solar power generation (MW) per bidding zone, per each market time unit of the following day. The information is published no later than 18:00 (CET), one day before actual delivery takes place.

- **Actual wind generation**: actual aggregated wind net generation output (MW) per market time unit.
- **Forecasted wind generation**: forecast of wind power generation (MW) per bidding zone, per each market time unit of the following day. The information is published no later than 18:00 (CET), one day before actual delivery takes place.
- **Installed generation capacity availability**: The planned unavailability of 100 MW or more of a generation unit, including changes of 100 MW or more in the planned unavailability of that generation unit, expected to last for at least one market time unit up to three years ahead.

In addition to the aforementioned fundamental explanatory variables, we have considered the dummy variables associated with each weekday and price time series autoregressive terms.

In the time series of 32,832 hourly observations, we have registered for some of the variables missing data points. In the Greek data set there were 395 missing hourly observations, and in the Hungarian data set there were 616 missing hourly observations. The missing data points were replaced by averaging two respective nearest available observations. Except for these artificially calculated data points and normalisation for the support vector machine, the neural network model and long short-term memory model, we use raw, non-processed data in the analysis.

Tables A1 and A2 of the Appendix present key statistical metrics of the Greek and Hungarian price time series from 1.1.2015 to 30.9.2018. The lowest prices are on average observed during the night-time. Prices start rising during the morning rush hours, and the maximum prices are observed in the evening peak hours (18:00-21:00). Evening peak hours are also the hours where minimum prices were never close to 0 €/MWh. The standard deviation in these hours almost doubles, implying that these are the hours with the highest price volatility.

In the reviewed literature, training and testing data sets are ordinarily fixed over the considered time series. It would be reasonable to assume that market participants would execute their market operations according to the indications of the utmost updated and recently calibrated EPF models. For this purpose, we have implemented dynamic model calibration and testing by the rolling-window approach over the available data set.

As summarized in Table 1.6 each model is recalibrated 14,232 times to obtain the forecasts for the whole time series subject to different training sample sizes. Introduction of the DSR explanatory variable in the workhorse model defined by the Equation 1.3, triggers an additional set of calibrations.

Table 1.6: Number of calibrations per model – hourly non-clustered training regime

Total sample size (days)	Training sample size (days)	Forecasting sample size (days)	Number of calibrations per Model
1,368	28	1,340	1,340
1,368	56	1,312	1,312
1,368	...	...	...
1,368	...	...	...
1,368	336	1,032	1,032
			14,232

Source: Own work.

Investigation of the EPF accuracy under the hourly clustered training regime has a consequence of having a small individual model for each hour of the day. The number of 14,232 calibrations under hourly non-clustered training regime must be consequently multiplied by 24 to obtain the number of calibrations under the hourly clustered training regime.

The main outcome of such an experiment setting is considerable computational time, especially for the more complex methods such as the support vector machine (SVM) and artificial neural network (ANN) models. All alternative approaches have free parameters that must be fine-tuned to obtain the optimal results. Consequently, fine tuning of free parameters is only executed on the first run calibration.

Forecasting performance of the proposed alternative models compared to the benchmark model is analysed by comparing different accuracy metrics. The statistical significance of the error differential between the base and alternative models is then further statistically confirmed by the positive outcome of the Diebold-Mariano test (DM).

For evaluating an hourly point forecast, the simplest performance metric is a mean absolute error (MAE) defined as:

$$\boldsymbol{MAE = \frac{1}{N}\sum_{t=1}^{N}|A_t - F_t|} \tag{1.8}$$

In Equation 1.8, A_t stands for the observed price and F_t for the forecasted price. As it is hard to compare forecasting accuracy on different data sets by the MAE measure, mean absolute percentage error (MAPE) is by far the most popular evaluating approach in point electricity price forecasts (Weron, 2014):

$$\boldsymbol{MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|} \tag{1.9}$$

MAPE metrics can be misleading in cases when electricity prices are close to zero, as the values become very large. In the case of high prices, errors become relatively smaller. The pitfalls of the MAPE metrics can be seized by the symmetric MAPE measurement proposed and discussed by Spyros Makridakis (1993) as:

$$\boldsymbol{sMAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{(A_t + F_t)/2}\right| \tag{1.10}$$

Another frequently used metric in the domain of EPF is the 'root mean squared error' (RMSE) defined by Equation 1.11 (Weron & Misiorek, 2005):

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(A_t - F_t)^2} \tag{1.11}$$

The quadratic term in the equation penalizes harsher forecasts with higher errors, which is adequate in cases of price spikes. The drawback of this metric compared to the MAE is an unnatural interpretability, unambiguity, and some other issues discussed by (Willmott & Matsuura (2005).

The Diebold-Mariano (DM) test is used to test the statistical difference between the two pairs of forecasts. In our case, the ARX model is pairwise tested against the alternative CI models. The null hypothesis of alternative models (CI) having an accuracy equal to or worse than a benchmark ARX model is tested. Considering time series $\{y_t\}_{t=1}^{T}$, the benchmark forecast $\{\hat{y}_{ARX,t}\}_{t=1}^{T}$ and the alternative forecasts $\{\hat{y}_{CI,t}\}_{t=1}^{T}$, with the associated error terms $\{\varepsilon_{ARX,t}\}_{t=1}^{T}$ and $\{\varepsilon_{CI,t}\}_{t=1}^{T}$, the DM tests the hypothesis that the mean of the loss differential series defined as $d_t^{CI,ARX} = L(\varepsilon_{CI,t}) - L(\varepsilon_{ARX,t})$ is greater than or equal to zero. The loss function $L(\varepsilon_{ARX,t})$ can be of the absolute or square type, e.g. $|\varepsilon_{ARX,t}|$ or $\varepsilon_{ARX,t}{}^2$.

In the one-sided DM test version, the H_o (null) and H_1 (alternative) hypotheses are defined as:

$$\begin{cases} \boldsymbol{H_o}: \boldsymbol{E}[\boldsymbol{d_t}^{CI,ARX}] \geq \boldsymbol{0} \\ \boldsymbol{H_1}: \boldsymbol{E}[\boldsymbol{d_t}^{CI,ARX}] < \boldsymbol{0} \end{cases} \tag{1.12}$$

If the null hypothesis is rejected, we can confirm that the alternative forecast $\{\hat{y}_{CI,t}\}_{t=1}^{T}$ has statistically significantly better performance. We tested the hypothesis with the modified version of the DM test as discussed by Harvey, Leybourne, & Newbold (1997).

1.6 Results & discussion

According to the reported best performance metrics for the Greek market in Table 1.7, we conclude that four out of six alternative EPF models turned out to have higher accuracy than the benchmark ARX model. The support vector machine (SVM) model (8.30% sMAPE) had the best performance, with MAE metrics 0.71 €/MWh lower than the benchmark ARX model (9.60% sMAPE). In the Hungarian market EPF simulation, only the SVM model (16.50% sMAPE) outperformed the benchmark ARX model (17.00% sMAPE). The difference in the reported MAE metrics value is 0.26/MWh in favour of the SVM model. Table A3 of the

Appendix summarizes the forecasting statistics on working days, and Table A4 of the Appendix over the weekends. Dummy variables associated with each weekday were included in the models to address weekly price dynamics. In Greece, sMAPE accuracy metrics drop on weekends on average by 2 percentage points compared to the forecasts on weekdays and in Hungary by 7 percentage points.

In both markets the DM test null hypothesis is rejected in one of the settings of the SVM model. Reported p-values for all the other alternative models are above the threshold p-value of 0.05. A mutual condition for overcoming the linearity bias in the benchmark model, i.e., better forecasting accuracy and a statistically significant DM test is fulfilled only by the SVM model. Figures 1.2 and 1.3 further present the dependency between the forecasting performance and learning sample size for the studied markets. In both markets, the K-nearest neighbour (KNN) model has the best performance with smaller sample sizes, whereas other models on average reach their best performance with larger training sample sizes. ANN and LSTM model achieved best forecasting performance with the largest training sample. The best performance of later models is reached with the learning sample sizes between 84 and 112 days. Once the optimum forecasting performance is reached, it starts with larger learning samples notably declining. Based on the shape of the forecasting errors curves, we conclude that models have a turning point that coincides with the optimum training size after which their performance starts notably deteriorating.

The typical use of the forecasters in the day-ahead markets is simulated with the out-of-sample forecasts based on the forecasted fundamental variables values. In Figures 1.2 and 1.3, this set of forecasts is plotted with the dashed line type, whereas the solid line presents forecasts based on the actual, realised data. Forecasts of models trained on hourly clustered data are plotted in red colour, whereas models trained on hourly non-clustered data are plotted in blue colour. Out-of-sample forecasts with the actual test data are plotted with a solid line, whereas out-of-sample forecasts with the forecasted test data inputs are plotted with a dashed line. The performance metrics of the forecasters under both scenarios are reported in Table 1.4. Based on the Greek data set, EPF models have equivalent accuracy metrics under both test data sets except for the KNN, LSTM, and ANN models. Models trained on Hungarian data have a constant drop in sMAPE metrics when forecasting based on the forecasted explanatory variable values. According to the ENTSO-E TP knowledge base, explanatory variables forecasts are provided by the transmission system operators no later than two hours before the PX gate closure (ENTSO-E TP, 2020). A residual load forecast could be considered of good quality, as the reported sMAPE forecasting metrics are almost alike under both scenarios. A detailed examination is beyond the scope of this chapter.

The DSR ratio is added to the models to integrate the supply side market tightness information and to improve the price spikes forecasting accuracy. Figures 1.4 and 1.5 compare the forecasting performance between the models built upon the residual load (*RL Model,* defined in Equation 1.3) and extended models by the DSR ratio (*RL+DSR Model,* defined in Equation

1.4). In Greece, the best forecasting performance is reached with the added DSR ratio. In Hungary, only the ANN model has the highest accuracy with added DSR ratio. However, under both data sets accuracy improvement is trivial, this is especially true considering the price spikes forecasting accuracy. Figures A1 and A2 of the Appendix visualize forecasting behaviour on 50 highest and 50 lowest observed prices in each market. The average forecasted price of all *RL models* is almost perfectly aligned with the average forecasted price of all *RL+DSR models*. A reason for the insignificant impact might be that on the ENTSO-E TP information is available only for the planned outages. For the considered time series unplanned outages for Greece and Hungary are not reported. This is a rather unexpected result, but a similar conclusion is also found by Alexander & Dominique (2007).

Table 1.7: EPF models best performance – ascending sMAPE ordering

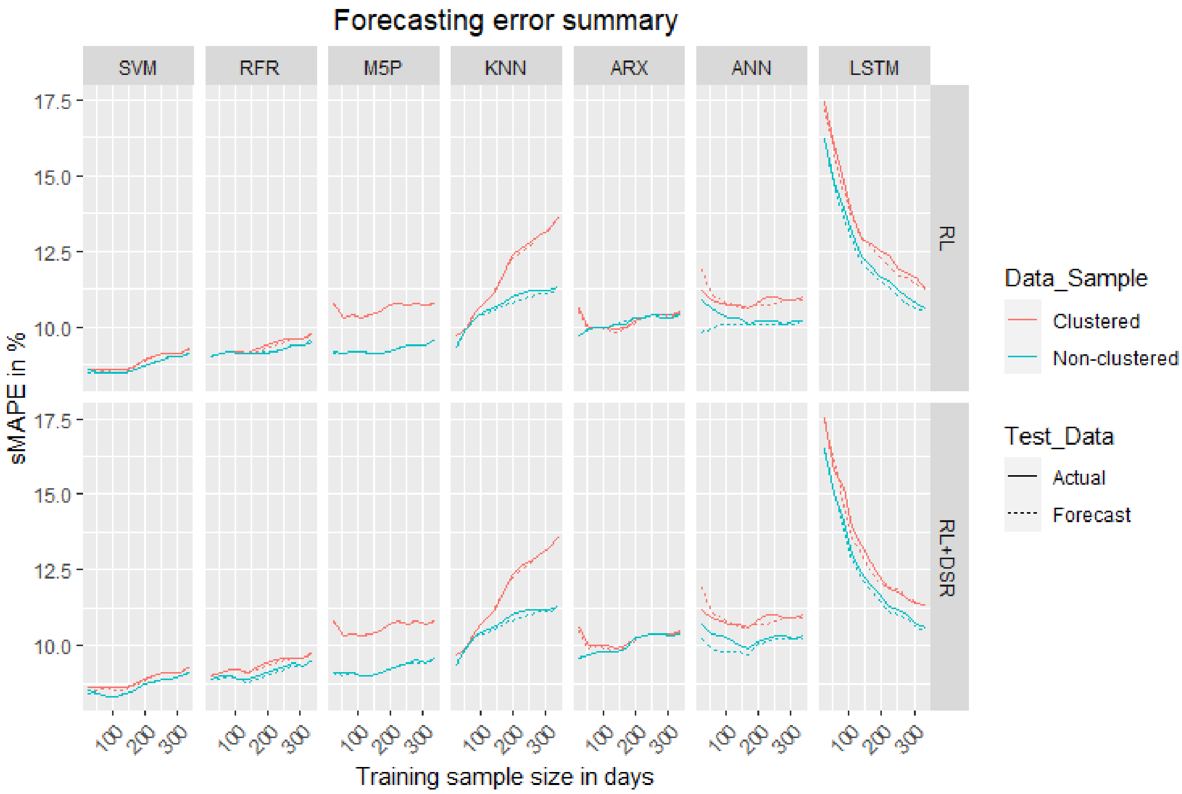
Country	Method	RL/DSR	Data sample	Test input	Window	MAE	RMSE	SMAPE	MAPE	DM test p-value
GR	SVM	DSR	Non-clustered	Actual	84	4.03	8.04	8.30%	17.20%	0.04
GR	SVM	DSR	Non-clustered	Forecast	84	4.03	8.07	8.30%	17.30%	0.30
GR	RFR	DSR	Non-clustered	Actual	28	4.38	8.40	8.90%	16.70%	0.61
GR	RFR	DSR	Non-clustered	Forecast	28	4.35	8.34	8.90%	16.80%	0.11
GR	M5P	DSR	Non-clustered	Actual	112	4.43	8.47	9.00%	17.20%	1.00
GR	M5P	DSR	Non-clustered	Forecast	112	4.42	8.42	9.00%	17.20%	1.00
GR	KNN	DSR	Non-clustered	Actual	28	4.70	9.05	9.40%	17.50%	1.00
GR	KNN	DSR	Non-clustered	Forecast	28	4.67	9.01	9.30%	17.50%	1.00
GR	ARX	DSR	Non-clustered	Actual	28	4.74	8.38	9.60%	17.60%	/
GR	ARX	DSR	Non-clustered	Forecast	28	4.74	8.41	9.60%	17.80%	/
GR	ANN	DSR	Non-clustered	Actual	168	4.92	8.81	9.90%	18.10%	1.00
GR	ANN	DSR	Non-clustered	Forecast	168	4.83	8.58	9.70%	18.00%	1.00
GR	LSTM	DSR	Non-clustered	Actual	336	5.25	8.66	10.60%	18.20%	1.00
GR	LSTM	DSR	Non-clustered	Forecast	336	5.24	8.68	10.50%	18.30%	1.00
HU	SVM	RL	Clustered	Actual	28	6.43	9.93	16.50%	23.90%	0.13
HU	SVM	RL	Clustered	Forecast	28	6.69	10.22	17.20%	24.00%	0.03
HU	ARX	RL	Clustered	Actual	112	6.69	10.31	17.00%	22.00%	/
HU	ARX	RL	Clustered	Forecast	112	7.07	10.73	18.30%	22.00%	/
HU	LSTM	RL	Clustered	Actual	112	6.69	10.31	17.00%	22.00%	0.99
HU	LSTM	RL	Clustered	Forecast	112	7.07	10.73	18.30%	22.00%	0.92
HU	RFR	RL	Clustered	Actual	28	6.74	10.07	17.20%	24.50%	0.69
HU	RFR	RL	Clustered	Forecast	28	6.86	10.24	17.70%	24.30%	0.12
HU	ANN	DSR	Non-clustered	Actual	224	7.08	11.04	17.70%	24.80%	1.00
HU	ANN	DSR	Non-clustered	Forecast	224	7.17	11.10	17.90%	25.10%	1.00
HU	M5P	RL	Non-clustered	Actual	112	7.20	10.64	18.00%	25.20%	0.95
HU	M5P	RL	Non-clustered	Forecast	112	7.40	10.95	18.70%	24.60%	0.88
HU	KNN	RL	Non-clustered	Actual	28	7.17	10.37	18.40%	25.30%	0.85
HU	KNN	RL	Non-clustered	Forecast	28	7.66	11.02	20.10%	25.10%	0.98

Source: Own work.

The superiority of eliminating the linearity bias by the proposed alternative models is, according to our experiment design, confirmed by the mutual condition of the better forecasting accuracy and positive DM test. In both markets the mutual condition is fulfilled only by the SVM model. Based on Greek data set, K-nearest neighbours (k-NN), regression tree (M5P), and random forest regression (RFR) models achieve on the best run better forecasting accuracy compared to the benchmark, but the DM test is found insignificant. The artificial neural net (ANN) model and long short-term memory (LSTM) model are compared to the benchmark model inferior in terms of accuracy and have an insignificant DM test. SVM model trained on Hungarian data set is the only model out of six proposed alternative models where the reported accuracy metrics are lower compared to the benchmark ARX model. Conducted DM test is as well statistically positive with the forecasted explanatory values. All other tested approaches have lower accuracy and statistically insignificant DM tests.

All models out-of-sample forecasting error density functions have the shape of a normal distribution (Figure 1.4 and 1.5). Distributions are centred around 0€, and the three standard deviations interval approximately spans from –25 € to +25 €. In both markets, the highest peak is observed by the SVM density function, meaning that the SVM model has the highest probability of committing 0 € forecasting error. Hungarian density functions are wider and have lower peaks at 0 € forecasting error. This a natural consequence, as the models forecasting accuracy in Hungary notably drops compared to Greek results.

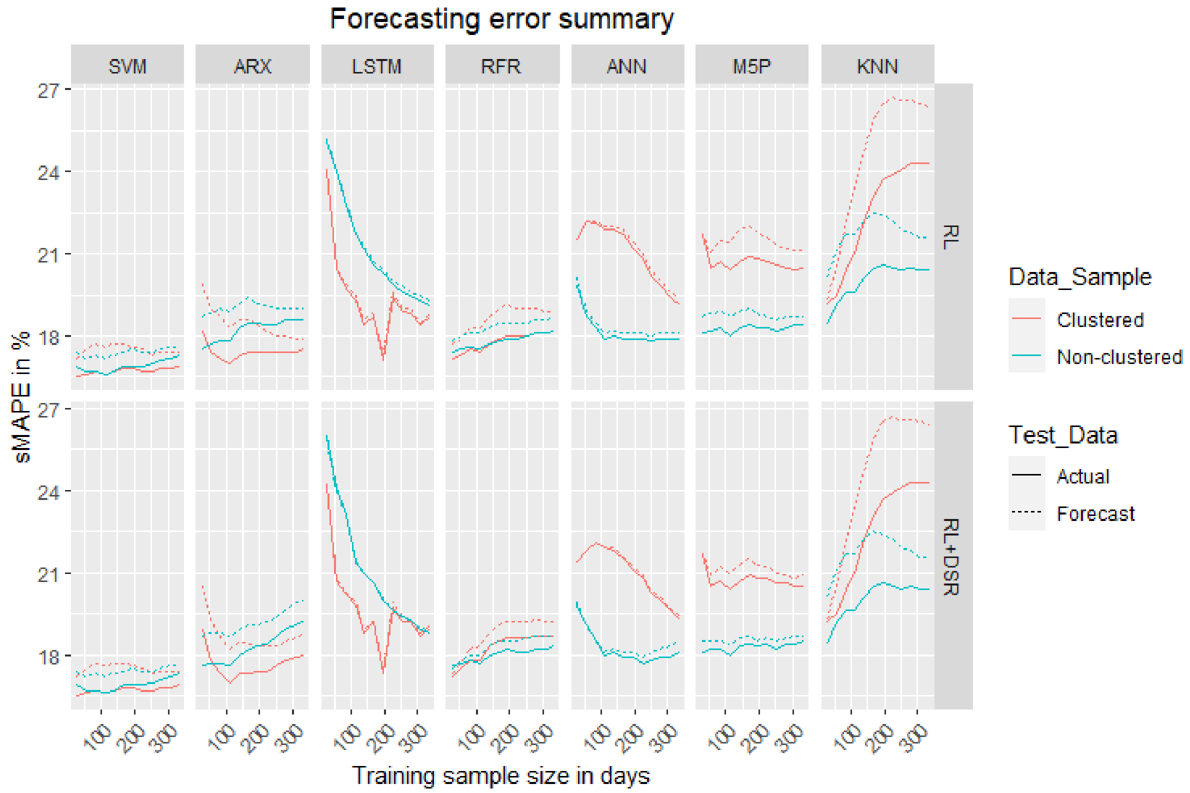
Figure 1.2: Greece – out of sample sMAPE forecasting error



Source: Own work.

To some extent, larger training sample sizes indeed contributed to the higher EPF accuracy of the promising ANN and LSTM models, however, they did not outperform the benchmark model on their best run. The poor performance of the neural network-based approaches might be associated with the initial free parameters setting, that is deemed to be optimal for all the consequent calibrations. The parameters defining depth and number of neurons were thoroughly discussed in Lago, De Ridder, & De Schutter (2018), where the authors reported sMAPE metrics for the suboptimal parameter setting of 14.30% vs. 13.27% for the optimal parameter setting. The ability of CI models to adapt to non-linear and fast-changing price signal behaviour may not necessarily result in better point forecasts (Weron, 2014). Albeit computational intensity and complex implementation of the neural net-based models, there are instances where such sophisticated methods were outperformed by the other forecasters (Conejo et al., 2005; Lin et al., 2010; Pousinho et al., 2012; Shafie-khah et al., 2011; Vahidinasab et al., 2008; Yang et al., 2017). Conversely, a comprehensive analysis on the Belgium data set has statistically confirmed superior performance of the neural network approach compared to other models (Lago, De Ridder, & De Schutter, 2018). The performance of the SVM, ANN, and ARIMA models is tested over a 2-week period in the Californian market in Che & Wang (2010). In one of the setups, the SVM model (0.75 RMSE) notably outperformed an alternative ANN model (1.41 RMSE) and a traditional ARIMA model (3.98 RMSE) in terms of forecasting accuracy.

Figure 1.3: Hungary – out-of-sample sMAPE forecasting error



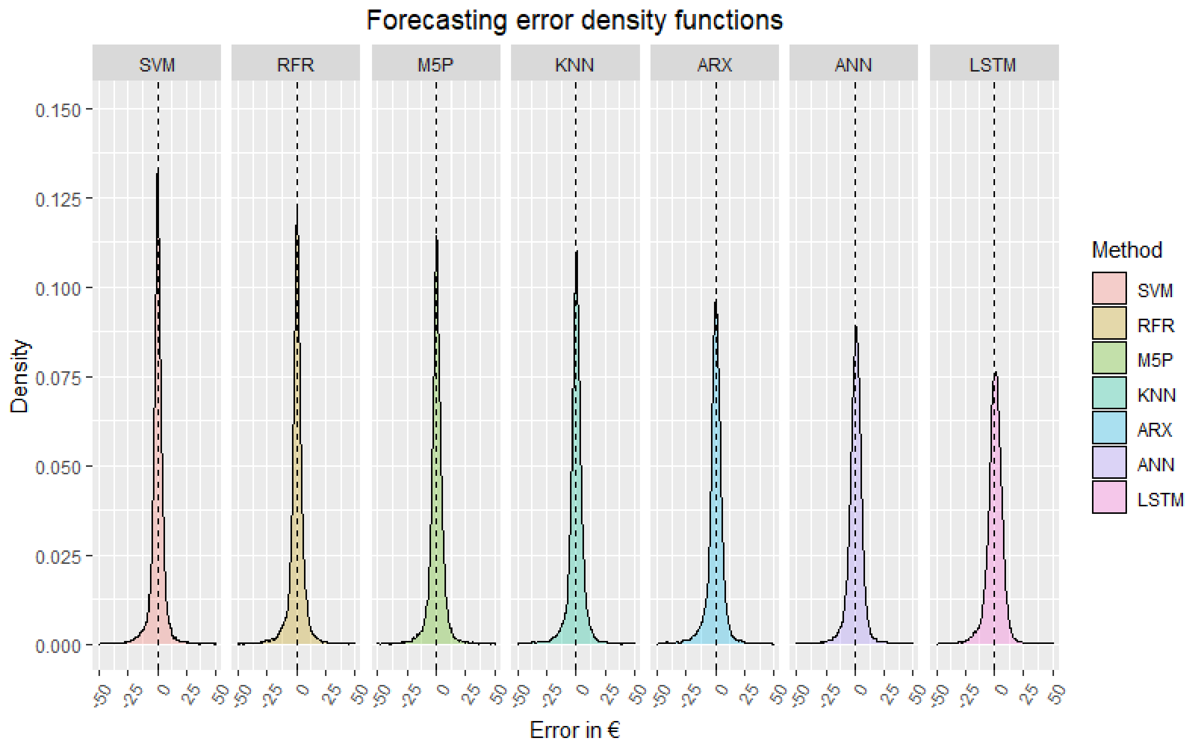
Source: Own work.

In the literature survey in Lago, De Ridder, & De Schutter (2018), it is concluded that the out-of-sample accuracy test periods typically correspond to four representative weeks, i.e., one best week per season. Even if the forecasting accuracy is reported for the same market, and for the same out-of-sample (forecasting) test period, the errors of the individual methods are not truly comparable unless identical in-sample (calibration) periods are used, and therefore they cannot be used to formulate general statements about a method's efficiency unless such is the case (Weron, 2014).

To our knowledge, there has been no EPF article in the literature exclusively relying on the ENTSO-E TP data source. Data blending is a common feature in the reviewed literature. In

Lago, et al. (2018), Lago, De Ridder, & De Schutter (2018) and Lagarde & Lantz (2018) ENTSO-E TP data is combined with the national transmission system operator's data sources. The main advantage of a centralised data source is simple and rapid data accessibility and study reproducibility. During the data collection phase, we noticed that there are missing data points and non-reported data types in the ENTSO-E TP database. In addition, there is missing data history for Greece before 1.1.2015. To sum up, we believe there are further opportunities for improving data availability & consistency on the ENTSO-E TP with data reporting consistency and data quality checks as discussed in Hirth et al. (2018).

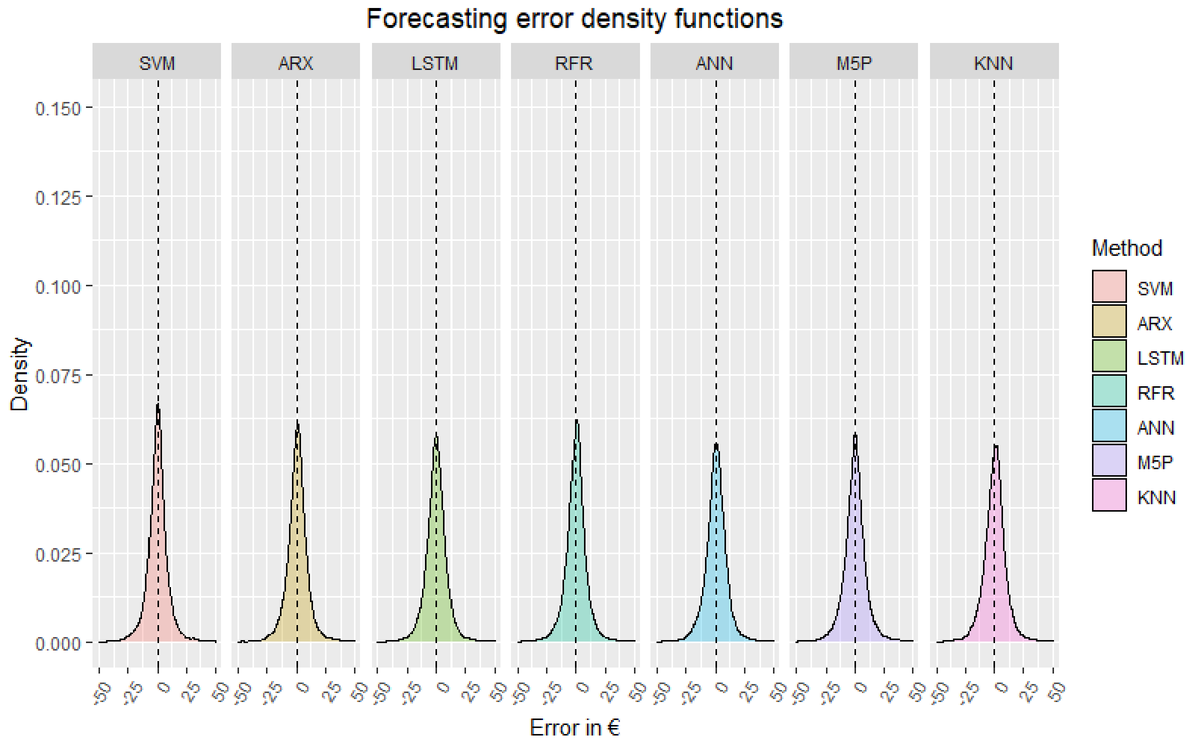
Figure 1.4: Greek out-of-sample forecasting error density functions



Source: Own work.

Our EPF simulation, based on the seven different forecasters with a typically used explanatory variables set, and a different scenario analysis (learning sample size, hourly clustered training, and demand-supply ratio explanatory variable), suggest that the key to notably improve the forecasting accuracy lies in higher data quality and more importantly in the extended set of explanatory variables. The data quality issue is related to the fact that we have registered missing hourly data points in the data set. In addition, unavailability of the unplanned outages information, which should be part of the demand-supply ratio, might have affected poor forecasting accuracy in the price spikes events. We have limited our analysis to the residual load and demand-supply ratio fundamental explanatory variables, as the main purpose of the research is to analyse forecasting performance of the alternative forecasting models. Consequently, the supply side dynamics associated with the production profit optimisation is overlooked and requires special attention in future research. This could be addressed with variables such as fuel costs and CO2 price, related to the marginal costs of production as addressed by Panapakidis & Dagoumas (2016) and Sensfuß et al. (2008). Market integration is effectively handled by Lago et al. (2018) by incorporating fundamental variables from neighbouring markets and by simultaneous EPF of the connected markets. Greece and Hungary are characterised as natural electricity importers. To potentially further enhance EPF accuracy in both analysed countries, in future research electricity price developments in the neighbouring markets should be controlled.

Figure 1.5: Hungarian out-of-sample forecasting error density functions



Source: Own work.

1.7 Conclusion

Closing a gap of the yet unresearched power markets of Central and Eastern Europe and Southeast Europe was primarily feasible due to publicly available Greek and Hungarian data set on the ENTSOE transparency platform. The electricity price forecasting with a single data source turned out to be practical as the data collection process is user friendly. Simulation of a typical daily forecasting process with the selected econometric, data mining and machine learning algorithms resulted in implementation of computationally very intensive dynamic forecasting by the rolling-window approach.

Based on more than one thousand day long back-test period, only the support vector machine model successfully bridges the linearity bias in the benchmark, econometric autoregressive model with exogeneous explanatory variables, by lower forecasting accuracy metrics and a statistically significant Diebold-Mariano test. A random forest, regression tree, and k-nearest neighbour algorithm trained on Greek data set, have higher forecasting accuracy compared to the benchmark econometric model, however, with the statistically insignificant Diebold-Mariano test. The support vector machine model trained on the Hungarian data set is the only model with improved forecasting accuracy compared to the benchmark econometric model.

Models trained on the Greek data set have better results with training on the hourly non-clustered data samples. Training on hourly clustered Hungarian data samples on average resulted in higher forecasting accuracy. The main difference between the Greek and Hungarian data sets is a markedly higher Hungarian price variance. The training data sample size is positively correlated with the EPF accuracy; however, models have a turning point after which the relationship is converted. Artificial neural network based models achieve higher accuracy if trained on considerably larger training samples compared to the other proposed alternative models.

In future work, it is possible to extend our research to other yet unresearched European markets with a specific focus on having enough results to establish if model training on hourly clustered data samples gives better results in electricity markets with relatively higher price variance. For fostering such comparative analysis, it is of key importance to put additional effort in further improving data availability and quality.

2 AN INTEGRATED MODEL FOR ELECTRICITY MARKET COUPLING: EVIDENCE FROM THE EUROPEAN POWER MARKET CROSSROAD

2.1 Introduction

One of the major changes in the European electricity markets is – besides the increasing share of a renewable infeed – the fact that previously independent market areas have become connected through market-coupling auctions. Day-ahead auctions are no longer organised separately for cross-border capacities (CBCs) and electricity. Instead, CBCs are implicitly auctioned in the day-ahead auction of electricity such that price differences between market areas are minimised, implying that the overall welfare is maximised (Kiesel & Kusterman, 2016). An implicit auction system has been introduced to solve inefficient network usage in non-coupled electricity market design with the additional beneficial side effects of price convergence, improved market liquidity, and less volatile electricity prices (Gómez, 2016). In Europe, a Single Day-ahead Coupling (SDAC) project is currently ongoing, with the goal to finalize the creation of a single pan-European cross zonal day-ahead electricity market. An integrated day-ahead market will increase the overall efficiency of trading by promoting effective competition, increasing liquidity, and enabling a more efficient utilisation of the generation resources across Europe (NEMO Committee, 2020b).

This study researches the inefficient CBCs utilisation and the underlying effect on electricity prices in non-coupled day-ahead electricity markets. As a case study, we have simulated market coupling, i.e. implicit CBCs allocation on historical realisations on Austrian-Italian (ATIT), Austrian-Slovenian (ATSI), and Croatia-Slovenian (HRSI) cross-border interconnectors. The simulation goal is to eliminate the observed inefficient CBCs utilisation at the time of the simulation non-coupled interconnectors, and to adjust market clearing prices in Austria, Italy, Slovenia, and Croatia, accordingly. With the simulation results we can empirically confirm the implications and benefits from market coupling on CBC usage efficiency, electricity price convergence, price volatility, and price shock transmission. The proposed market coupling simulation framework is integrated as the CBCs allocations and electricity prices are determined by the solution of a single mathematical optimisation problem.

The novelties of our paper are: (i) simulation of market coupling impact on the suppliers' and consumers' income; (ii) visual comparison of CBC utilisation and electricity prices in non-coupled and simulated coupled markets for the same market time-unit; (iii) a market coupling simulation with the social welfare maximisation algorithm (EUPHEMIA); (iv) the use of an alternative order book generation process based on the econometrically estimated aggregate supply price elasticities; and (v) an electricity price shock transmission analysis with a vector autoregressive (VAR) model and the underlying impulse response functions (IRF).

To the best of our knowledge regional market coupling on ATIT, ATSI, and HRSI cross-border interconnectors has not been jointly researched yet. We aspire to bridge this gap by providing simulation results and impact assessment on suppliers' and consumers' income. Further, this is the first study that intuitively presents market coupling benefits on CBCs utilisation and electricity prices. In the reviewed literature considering electricity market coupling, benefits are typically presented non-intuitively i.e. numerically. With the simulation results, we can analyse CBCs utilisation and its implications on electricity price dynamics in non-coupled and simulated market coupling environments. A visual comparison of the CBC utilisation and the underlying effect on electricity prices, under both market regimes for the same market time-unit, intuitively presents market coupling benefits.

Modelling coupled electricity markets with statistical models (Grossia et al., 2018; Hellwig et al., 2020; Parisio & Pelagatti, 2014) or advanced computational intelligence models (Dagoumas et al., 2017; Lago et al., 2018; Li & Becker, 2021) is not convenient for a detailed electricity price and the CBCs utilisation analysis. Kiesel & Kusterman (2016) explained that in coupled markets it becomes crucial to model electricity prices in all areas consistently in one integrated framework. The capacity of relevant network elements in simulated market perimeter scope and the underlying CBCs allocation dynamics is, in market simulations, frequently overlooked. While the effects of market integration can dramatically modify the dynamics of electricity prices, there is a lack of a general modelling framework that could model this effect and analyse its impact on the electricity market (Lago et al., 2018). We, therefore, propose a new integrated simulation approach that appears to be a natural fit for applied market simulations in coupled electricity markets. CBCs allocation and electricity price determination is compliant with the social welfare maximisation algorithm (EUPHEMIA) used by the European power exchanges.

As discussed by Lijesen (2007), a spot market often represents just a small part of all system electricity trade. Therefore, market coupling simulations exclusively relying on a spot power exchange order book data could be influenced by the apparent lower market liquidity. In such an experimental setting, analysis of the overall market adaptation implied by the market coupling mechanism might be arguable. In contrast, power exchange order book data are typically publicly unavailable or in user-unfriendly formats – figures of aggregated curves. Therefore, we propose an alternative order book generation process based on the econometrically estimated aggregate supply price elasticity functions. Individual market order books are built upon the estimated measure of overall market responsiveness in quantity supplied to a change in price. The proposed day-ahead simulation framework, to calculate electricity prices across Europe, respecting the capacity of the relevant network elements, is to the best of our knowledge a new approach for applied simulations in coupled electricity markets.

The statistical VAR model encompasses the type of complex price dynamics that are characteristic of electrical networks (De Vany & Walls, 1999). In the analysed market scope, the model contemporaneously acknowledges the direct and indirect effects of a change in each network node electricity price. Electricity price shock transmission indicating market integration is therefore analysed with a VAR model and IRF functions. As far as we are aware, this is the earliest analysis of electricity price shock transmission for the same price observation under non-coupled and simulated market coupling regimes. Comparison of the electricity price shock transmission under both market regimes gives a statistical insight into the adjusted market dynamics implied by the market coupling mechanism.

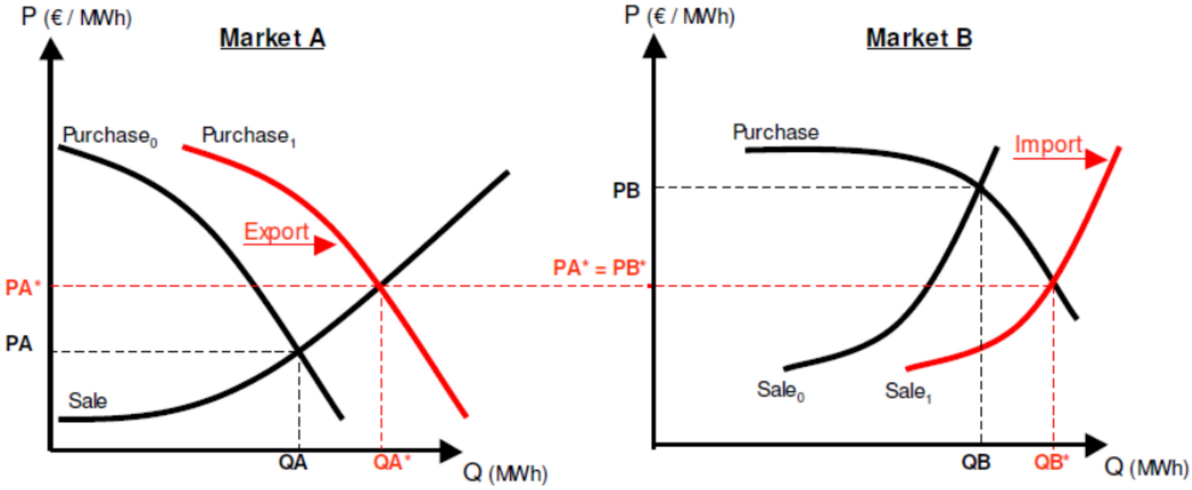
The remainder of this paper is organised as follows. The following section looks more closely into the market coupling and provides literature review on market coupling simulations and analysis. Section 2.3 outlines the methodology and its application. Data, data availability, and the underlying effects on the study design are summarised in Section 2.4. Section 2.5 reports and discusses the empirical results. Section 2.6 presents concluding remarks with summarised key research findings.

2.2 Day-ahead market coupling and pre-coupling inefficiencies at the crossroads of Europe

In the day-ahead auctions market, the clearing volume and market clearing electricity price is determined by the intersection of the supply and demand curves. However, in interconnected electricity markets, this traditional economic model of one demand curve and one supply curve has to be extended to incorporate for the possibility to "transport" electricity from one market area to the other (Kiesel & Kusterman, 2016). The possibility to "transport" electricity up to the interconnector capacity is recognised as a shift in supply and demand curves with respect to the underlying power exchange price elasticities. Market coupling process integrates energy and transmission market. Mandate to integrate energy and transmission market is given to a power exchange's social welfare maximising algorithm. This process is frequently recognized as the implicit CBC allocation. The core concept of the outlined market coupling principle is summarised in Figure 2.1.

The market coupling mechanism with the efficient use of CBC supports electricity price convergence in the EU. Please note that in interconnected non-coupled markets, the mandate to regulate electricity transport is given through explicit CBC auctions to market agents. As the electricity and CBC rights are traded at two different auctions, inefficiencies in their utilisation frequently occur (information asymmetry). Inefficient use of CBCs is typically a partial CBC utilisation in the case of a price spread between the market areas or CBC utilisation in an adverse direction (electricity export from higher price area to lower price area). These situations might be associated with the strategic behaviour of market agents or their inability to optimally act in non-coupled electricity markets. As a result, prices in non-coupled electricity markets diverge and provide an unreliable price signal to the market agents.

Figure 2.1:Price determination in coupled electricity markets



Source: JAO (2019), p.11.

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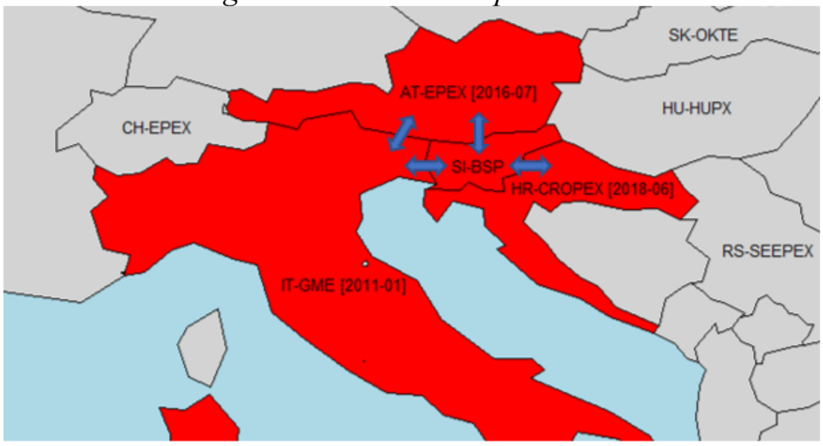
Regional scope of the simulation and geo-economic location is presented in Figure 2.2. The Slovenian electricity market is located at the power market crossroads of Europe. Through the Austrian interconnector it is connected to the mature Central Western Europe (CWE) power markets, through the Italian interconnector to the Italian-north region with traditionally high prices (Pellini, 2012), and through the Croatian interconnector to the evolving South Eastern Europe (SEE) markets that are characterised by high price volatility (Božić et al., 2020). The Slovenian day-ahead electricity market coupled on 1 January 2011 with the Italian market, and on 21 July 2016 with the Austrian market. The Croatian power exchange was established on 10 February 2016, whereas market coupling with the Slovenian power exchange was launched on 20 June 2018. On that date, Slovenia became fully coupled due to the fact that there are no existing CBCs with Hungary. With the available data on the ENTSOE-TP[3], we can simulate and analyse market effects of implicit CBC allocation on the Austrian-Slovenian (ATSI), Austrian-Italian (ATIT), and Croatian-Slovenian (HRSI) interconnectors.

[3] Transparency Platform (TP) operated by the European Network of Transmission System Operators for Electricity (ENTSO-E) was established in 2015. Therefore, data prior to 2015 is not available in the data set.

Figure 2.2: Simulation perimeter



Source: Own work.

Electricity is an essential commodity, and as such exhibits inelastic demand in the short-term (Cerjan et al., 2013). Demand in market simulations is typically assumed to be price inelastic since most consumers are inflexible and willing to pay high prices to ensure having the necessary power (Kiesel & Kusterman, 2016). The relationship between total peak demand and spot prices, i.e. demand price elasticity is empirically confirmed to be marginal by Lijesen (2007). In contrast, if producers sold electricity in the forward or futures market, they face a make-or-buy decision in the day-ahead market. This leads to price-sensitive demand in the auction, as producers are willing to buy back electricity and not to produce it in case of low market prices (Kiesel & Kusterman, 2016). Several authors discussed that strategic behaviour is different in implicit auctions as opposed to explicit auctions. Cross-border trade can induce price convergence across countries and thereby reallocate gains and losses correlated with market power as a result of two concomitant effects: a 'volume' effect, due to the mere increase/decrease of demand in each market, and a 'strategy or bid effect,' corresponding to the modifications of bid strategies induced by the increased/decreased number of despatched generators (Parisio & Bosco, 2008). If generators act strategically in oligopolistic markets, the integration of energy and transmission markets effectively induces demand elasticity because generators anticipate the impact of their bid on transmission. This should reduce the ability of strategic generators to exercise market power and should therefore reduce prices. However, if companies own generation facilities at several nodes, integration could also provide an incentive to increase the exercise of market power (Ehrenmann & Neuhoff, 2009).

The literature on empirical analysis and fundamental simulations of market coupling are rather scarce. De Vany & Walls (1999) analysed analysed day-ahead prices in five connected Central Western Europe markets. They conclude that due to improved liquidity, volatility, and extreme price situations are reduced in coupled markets. Kiesel & Kusterman (2016) discussed that in coupled markets it becomes crucial for risk and portfolio management to model electricity prices in all areas consistently in one integrated framework. There are papers exclusively researching electricity price forecasting in coupled electricity markets: electricity price forecasting with statistical models (Grossia et al., 2018; Hellwig et al., 2020; Parisio &

Pelagatti, 2014) or advanced computational intelligence models (Dagoumas et al., 2017; Lago et al., 2018). Dagoumas et al. (2017) proposed an integrated model for risk management in electricity trade with the goal to optimise CBCs trading on at the time non-coupled Greek and Italian border. They conclude that the proposed integrated model could potentially reduce risk in market operations in non-coupled interconnected electricity markets. Lago, et al. (2018) emphasise the importance of considering market integration in forecasting day-ahead electricity prices in Europe. They proposed a deep neural network approach with selected features on Belgium and French markets. Further, Abadie & Chamorro (2021) econometrically simulated the economics of interconnector between France and Spain with a policy recommendations for link expansion. The referenced econometric and computational intelligence studies typically only indirectly account for market interconnection and are too general for comprehensive CBC utilisation analysis. In comparison to the referenced studies our simulation framework directly models interconnection. Therefore, we can visualise CBC utilisation process and intuitively communicate benefits of the market coupling process. Pellini (2012) analysed the potential impact of market coupling in the Italian electricity market using the optimal dispatch model. The main finding is that high-priced areas such as Italy could greatly benefit from the introduction of this mechanism. The simulation was carried out by the production cost-based model under alternatives scenarios. The simulation perimeter is Italy with the interconnected markets where the ITSI interconnector is part of the simulation. The Slovenian electricity market is analysed by Predovnik & Švigelj (2017), where simulation of market coupling process on the ATSI interconnector based on a power exchange order book data for calendar year 2013 resulted in significant social welfare benefit improvement. In comparison to Predovnik & Švigelj (2017), the perimeter of market simulation is extended by the ATIT and HRSI interconnector. To simulate overall market addaptation, we utilise the estimated supply price elasticities instead of the power exchange order book data. In addition, visual comparison of CBC utilisation in non-coupled and simulated coupled markets for the same market time-unit is visually presented. Furthermore, simulation is enriched by the econometric analysis of electricity price shock transmisson under the non-coupled and simulated market coupling regimes.price convergence in the selected deregulated power markets in the USA by the estimated VAR model. They confirmed different price dynamics for different block-hours of the day. Gómez (2016) concluded that inefficient interconnector usage was eliminated and market integration improved with market coupling between France and Spain. Meeus (2011), based on the calculated performance indicator in transitional market phases on the interconnector between Denmark and Germany, concluded that price market coupling outperforms previous market settings. Huisman & Kiliç (2013) econometrically

2.3 Methodology

The analysis of the market coupling process is tackled by an interdisciplinary approach. The overall social-welfare maximising electricity prices and CBC allocations are determined by the EUPHEMIA algorithm. Simulation order books are generated based on the estimated aggregate supply price elasticities. Due to the possible reverse causality between the supplied quantity and equilibrium electricity prices, supply price elasticities are estimated by the method of instrumental variables. Electricity price dynamics in Slovenia and in interconnected neighbouring countries is further statistically analysed by the Vector Auto Regression (VAR) model. Data processing and computations are carried out in the R software environment.

2.3.1 Supply price elasticity estimation

Since renewable generation is supported by the feed-in tariffs, the purchased load in the electricity markets is reduced accordingly for the subsidised renewable generation (Keles et al., 2013). Renewable generation availability, therefore, has a negative impact on electricity prices, and this fact is recognised as a merit order effect (Martin de Lagarde & Lantz, 2018). Lower prices result from the fact that renewables bid into wholesale electricity markets at almost-zero prices and therefore shift the electricity supply curve accordingly (Keles et al., 2013). Residual load (RL) corresponds to the load reduced for the renewables' generation (Equation 2.1):

$$RL_h = Load_h - Wind_h - Solar_h \tag{2.1}$$

where index h indicates hourly observations.

The supply and demand in a particular electricity market always have to be balanced. Therefore, market equilibrium $Supply_h$, i.e. conventional generation (Equation 2.2), is calculated as a sum of market residual load and market net-export position (NX):

$$Supply_h = RL_h + NX_h \tag{2.2}$$

The basic form for the supply price elasticity estimation is a regression model defined by Equation 2.3. The Equation is known as the constant elasticity form as the elasticity of $Supply$ with respect to changes in $Price$ is $\beta = \frac{dSupply/Supply}{dPrice/Price} = \frac{dln\,(Supply)}{dln\,(Price)}$, which does not vary with other explanatory variables. A one percent change in $Price$, translates, on average, into an expected $Supply$ change by β percent.

The relationship between supply prices and equilibrium quantity may introduce a bias as a consequence of a possible reverse causality (Hellwig et al., 2020). Due to possible reverse causality, endogeneity is likely to be present in the base model form. Supply price elasticity (Equation 2.3) is thus estimated by the instrumental variables (IV) regression. We engage lagged values for $Price_{h-1}$ and RL_{h-1}, and daily average hydro production ($\overline{Hydro}_{d-1}$) variables as instruments (Equation 2.4). Using lagged values of the endogenous variable is an effective estimation strategy if the lagged values do not themselves belong to the respective estimating equation, and if they are sufficiently correlated with the simultaneously determined explanatory variable (Reed, 2015). Lagged electricity price values $Price_{h-1}$ are used as an adequate set of instruments in the econometric estimation of a real-time price elasticity of electricity by Lijesen (2007). Lagged residual load value RL_{h-1} is used as an instrument as it is correlated with $\widehat{Price}_h$ but does not directly effect $Supply_{h,m}$. Unavailable instrument variable data, the daily average hydro production in Croatia ($\overline{Hydro}_{HR}$), is substituted by the Slovenian hydro production ($\overline{Hydro}_{SI}$) variable. The Slovenian hydro electricity generation is intense on the Drava and Sava rivers, and both of them flow through Croatia (HSE, 2021). Unobserved Croatian hydro production is deemed to correlate on a daily average basis with the Slovenian hydro production. Therefore, we engage lagged daily average hydro production ($\overline{Hydro}_{d-1}$) as an additional instrument variable.

$$ln\ (Supply_{h,m}) = \alpha_m + \beta_m \times ln(\widehat{Price}_{h,m}) + \sum_{l_m=1}^{L_m} \vartheta_{m,l_m} \times CongestionDummy_{h,l_m} + \sum_{i=1}^{23} \gamma_i \times HourDummy_{h,m} + \varepsilon_{h,m} \quad (2.3)$$

$$ln(\widehat{Price}_{h,m}) = \alpha_m + \gamma_m \times ln(Price_{h-1,m}) + \delta_m \times ln(RL_{h-1,m}) + \eta_m \times ln\ (\overline{Hydro}_{d-1,m}) + \varepsilon_{h,m} \quad (2.4)$$

$$where\ m \in \{AT, IT, SI, HR\},$$
$$L_{AT} \in \{ATSI, SIAT, ATIT, ITAT\}, L_{HR} \in \{HRSI, SIHR\}, L_{IT} \in \{ITAT, ATIT, ITSI, SIIT\}, L_{SI} \in \{SIAT, ATSI, SIIT, ITSI, SIHR, HRSI\}.$$

In Equations 2.3 and 2.4 index m indicates the individual market included into the simulation scope and index l_m represents individual interconnector (line) connected to the market m. Index $h-1$ indicates lagged hourly observations.

Bollino & Madlener, (2016) analysed relationship between exercise of demand market power and renewable energy sources, in the Italian day ahead electricity market, using ex ante individual bids, in 2010–2011. They confirmed that in periods with high-RES generation and congested CBCs some generators exercise market power. To control for the potential exercise of market power in congested periods, we have included dummy variables $CongestionDummy_{h,l_m}$ in the supply price elasticity estimation (Equation 2.3). Dummy variables $CongestionDummy_{h,l_m}$ indicate CBC congestion in each border direction. Further, according to Longstaff & Wang (2004) electricity produced during a daily peak hour is quite different from that produced over night, in terms of the fundamental demand and supply functions, as well as the relative risk aversion of the market participants. Therefore, we included into the supply price elasticity estimation (Equation 2.3) a set of dummy variables $HourDummy_{h,m}$ indicating each individual hour of the day. Set of dummy variables $HourDummy_{h,m}$ controls in the supply price elasticity estimation fundamental differences described by Longstaff & Wang (2004).

As discussed by Halužan, Verbič & Zorić (2020), the majority of electricity price forecasting algorithms perform better with calibration on a smaller estimation sample size. Supply price elasticity functions are estimated by the selected 7-day rolling-window approach over the available data set. Therefore, each calibration dataset contains 168 data points for the model estimation. The selected window size is large enough for the unbiased supply price elasticity estimation and narrow enough to recognise for the temporary supply features. By the term "temporary supply features", we specifically address non-accounted variables such as hydrology situation, production availability, fuel prices, strategic behaviour, etc.

Simulation order books for each individual market are generated based on the estimated aggregate supply price elasticities functions according to the Equation 2.3. The joint effect of the estimated supply price elasticity (β) and included dummy variables (γ_i, $\vartheta_{,l_m}$) is considered in the orderbook generation process for each individual hour of the day. Realised market equilibrium electricity price ($Price_h$) and conventional generation ($Supply_h$) serve as a reference point in a calculation of orderbook's supply and demand orders. Unique supply price $p_{m,h,s,o}$ and quantity $q_{m,h,s,o}$ pairs are generated according to a 0.25 % price step increment from $Price_h$ and the estimated supply change from $Supply_h$, with the stopping criteria at the realised maximum $Supply_h$ value in past 7 days. In the power exchange order book, each price step increment is associated with a unique price $p_{m,h,s,o}$ and quantity $q_{m,h,s,o}$ pair. Index o indicates unique hourly order and index s classifies order type $s \in \{Supply|Demand\}$. Consumer demand in the simulation order books is assumed to be fixed, i.e. price inelastic. Therefore, price-sensitive demand in the orderbooks is associated with the producers' willingness to buy back electricity sold in forward or futures market and not to produce it in case of low market prices (Kiesel & Kusterman, 2016). Unique producers' demand order price $p_{m,h,s,o}$ and quantity $q_{m,h,s,o}$ pairs are generated according to a 0.25 % price step decrement from $Price_h$ and the estimated supply change from $Supply_h$, with the stopping criteria at the realised minimum $Supply_h$ value in past 7 days.

2.3.2 Market coupling algorithm

The electricity power exchange price is determined by the social welfare maximisation algorithm that maximises the consumer and producer surplus. The algorithm, used by the European power exchanges, is called EUPHEMIA (NEMO Committee, 2020a) and is a part of the Price Coupling of Regions[4] (PCR). EUPHEMIA[5] was developed to efficiently couple day-

[4] Price Coupling of Regions (PCR) is the project of European Power Exchanges to develop a single price coupling solution to be used to calculate electricity prices across Europe, respecting the capacity of the relevant network elements on a day-ahead basis.
[5] For a general algorithm description, please refer to a public description by NEMO Committee (2020a) and for a deeper technical discussion to a paper by Martin et al. (2014).

ahead markets and handle standard and more sophisticated order types with all their requirements (Gómez, 2016).

In an available transfer capacity (ATC) model, the bidding zones (markets) are linked by interconnectors (bidding zone lines) representing a given topology (NEMO Committee, 2020a). The energy from one bidding zone to its neighbouring zone can only flow through these lines and is limited by the available transfer capacity. Figure 2.2 presents a grid topology of the analysed market coupling area between Austria, Italy, Slovenia, and Croatia. The objective of the market coupling algorithm is to eliminate existing CBC utilisation inefficiencies at the time of simulation non-coupled borders. CBC utilisation adjustments at the time of simulation already coupled borders, result from energy redistribution associated with the inefficient CBCs utilisation on non-coupled borders. To handle energy redistribution effect appropriately, all neighbouring interconnected markets should be included in the simulation perimeter.

Implicit CBC allocation and market clearing prices based on newly generated order books and new flow limits are determined according to a mathematical optimisation model defined by Equations 2.5–2.7. In the objective function (Equation 2.5), $ACCEPT_{m,h,s,o}$ is a continuous variable assigning hourly order acceptance ($0 < ACCEPT_{m,h,s,o} \leq 1$) or order rejection ($ACCEPT_{m,h,s,o} = 0$). Supply order quantities have a positive sign, whereas demand order quantities have a negative sign ($q_{m,h,s,o}$). On each interconnector, the flow variable $Flow_l$ is limited according to the established available transmission capacity value ATC_l (Equation 2.6). ATC_l is the residual quantity that could be transmitted through the interconnector after the day-ahead CBCs nominations. A market clearing condition, i.e. the balance of domestic demand, domestic supply, and net-exports ($\sum_m Flow_{m,l}$) is imposed by the Equation 2.7. The last accepted order with the highest price determines the market clearing price. The optimisation objective function for aggregated hourly orders and optimisation constraints are defined by the following set of equations, adapted from EUPHEMIA's public description by NEMO (2020a):

$$-\sum_{m,h,s,o} ACCEPT_{m,h,s,o} \times q_{m,h,s,o} \times p_{m,h,s,o} \tag{2.5}$$

$s.t.$

$$Flow_l \leq ATC_l \tag{2.6}$$

$$\sum_m ACCEPT_{m,h,s,o} \times q_{m,h,s,o} - \sum_m Flow_{m,l} = 0 \tag{2.7}$$

where, $m \in \{AT, IT, SI, HR\}$, and $l \in \{ATIT, ITAT, ATSI, SIAT, SIIT, ITSI, SIHR, HRSI\}$.

The linear program defined by Equations 2.5–2.7 is written in the R programming environment with the *lpSolaveApi* package.

2.3.3 Vector Autoregression model

Vector autoregressive (VAR) models are a rational choice to study price dynamics in the interconnected neighbouring markets. VARs allow us to characterise the joint distribution of power prices in the studied electricity network perimeter. Furthermore, impulse-response functions are a convenient way to visualise the direct and indirect impact of an exogeneous shock at a particular network node on the time paths of prices at all nodes (De Vany & Walls, 1999).

VAR models are commonly written as $VAR(p)$, where p denotes the number of autoregressive terms in the model. In compact form notation, estimated $VAR(p)$ model is written as:

$$\begin{pmatrix} Price_{AT,t} \\ \vdots \\ Price_{m,t} \end{pmatrix} = \begin{bmatrix} a_{AT,1} & \cdots & a_{AT,4} \\ \vdots & \ddots & \vdots \\ a_{m,1} & \cdots & a_{m,4} \end{bmatrix} \begin{pmatrix} Price_{AT,t-p} \\ \vdots \\ Price_{m,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{AT,t} \\ \vdots \\ \varepsilon_{m,t} \end{pmatrix} \tag{2.8}$$

where $m \in \{AT, IT, SI, HR\}$.

VAR models are estimated on the realised day-ahead electricity price series and on the electricity price series generated by the market coupling simulation. For each model, the number of autoregressive terms p is determined by the Akaike Information Criterion (AIC). The VAR models require data to be stationary. A formal test for testing a stationary is the Dickey-Fuller test. The null of the test is "a unit root is present in the series", hence rejecting the null means having a stationary time series.

VAR modelling analysis enables Granger causality testing. The Granger causality test is a statistical test for determining whether a time series is useful in forecasting another time series. The Granger causality test is not a cause-and-effect relationship test, rather it is a test if lagged values of one variable can improve predictability of another variable i.e. reduce model residuals. Statistical testing is executed on the electricity price series before and after the market coupling simulation. If the null hypothesis is rejected, this means that the lags of a tested variable provide significant information about the future values of another variable.

2.3.4 Impact on the suppliers' and consumers' income

In the simulated market coupling environment change in the suppliers' income (ΔSI) for each individual market (*m*) is calculated according to the Equation 2.9:

$$\Delta SI_m = \sum Supply^*_{m,h} \times Price^*_{m,h} - \sum Supply_{m,h} \times Price_{m,h} \tag{2.9}$$

where:
$Supply^{*}_{m,h}$ is the simulated supply after the market-coupling simulation;
$Price^{*}_{m,h}$ is the simulated market clearing price after the market-coupling simulation.

Electricity demand is assumed to be inelastic, therefore we can calculate change in consumer's income (ΔCI) for each individual market (m) according to the Equation 2.10.

$$\Delta CI_m = \sum Load_{m,h} \times Price_{m,h} - \sum Load_{m,h} \times Price^{*}_{m,h} \tag{2.10}$$

Due to the publicly unavailable historical prices for CBCs in organised explicit auctions, we could not evaluate impact on transmission system operators' congestion rent income. Therefore, the overall market coupling impact on the suppliers' and consumers' income i.e. generated surplus ($\Delta Surplus$) is calculated for each individual market (m) as a joint income change according to the Equation 2.11.

$$\Delta Surplus_m = \Delta SI_m + \Delta CI_m \tag{2.11}$$

2.4 Data

Data availability and accessibility in a user-friendly format generally limits applied power market research (Hirth et al., 2018). Such conditions in Europe have changed in 2015 with the commencement of the Transparency Platform (TP) operated by the European Network of Transmission System Operators for Electricity (ENTSO-E). Simulation is based on a publicly available data source ENTSOE-TP. Data is available in the standardised format on the ENTSOE-TP from 1 January 2015 on. Due to data availability issue, we are limited to analyse and simulate market coupling on selected borders from 1 January 2015 on. The simulation cut-off date is 20 June 2018, as on that date the Slovenian market coupled with the Croatian market. As the ITSI border has been coupled since 1 January 2011, the implied simulation allocation changes on this border result from energy redistribution associated with inefficiencies on ATIT, ATSI, & SIHR borders.

According to ENTSO-E (2020) there are three channels of data collection, a graphical user interface (GUI), a restful application programming interface (API), and a file transfer protocol (FTP). Market coupling simulation is based on the following set of variables:

DA market clearing price: for every market time unit the day-ahead prices in bidding zone.
Actual load: actual total load per bidding zone per market time unit.
Actual hydro generation: actual aggregated run-of-river net generation output (MW) per market time unit.
Actual wind generation: actual aggregated wind net generation output (MW) per market time unit.

Actual solar generation: actual aggregated solar net generation output (MW) per market time unit.
Total nominated capacity: The value published for the day ahead time horizon consists of nominations from the following allocations: yearly, quarterly, monthly, weekly, and daily.
Forecasted Transfer Capacities: The forecasted NTC (MW) per direction between bidding zones, including technical profiles only in NTC allocation method, one value per market time unit. Please note that, the Available Transmission Capacity ATC, is the part of NTC that remains available, after each phase of the allocation procedure, for further commercial activity (ENTSOE, 2001).

In the supply price elasticity estimation (Equation 2.4), the missing instrument variable, the daily average hydro production in Croatia ($Hydro\_HR$), is substituted by the Slovenian hydro production ($Hydro\_SI$) variable. T

2.5 Results & discussion

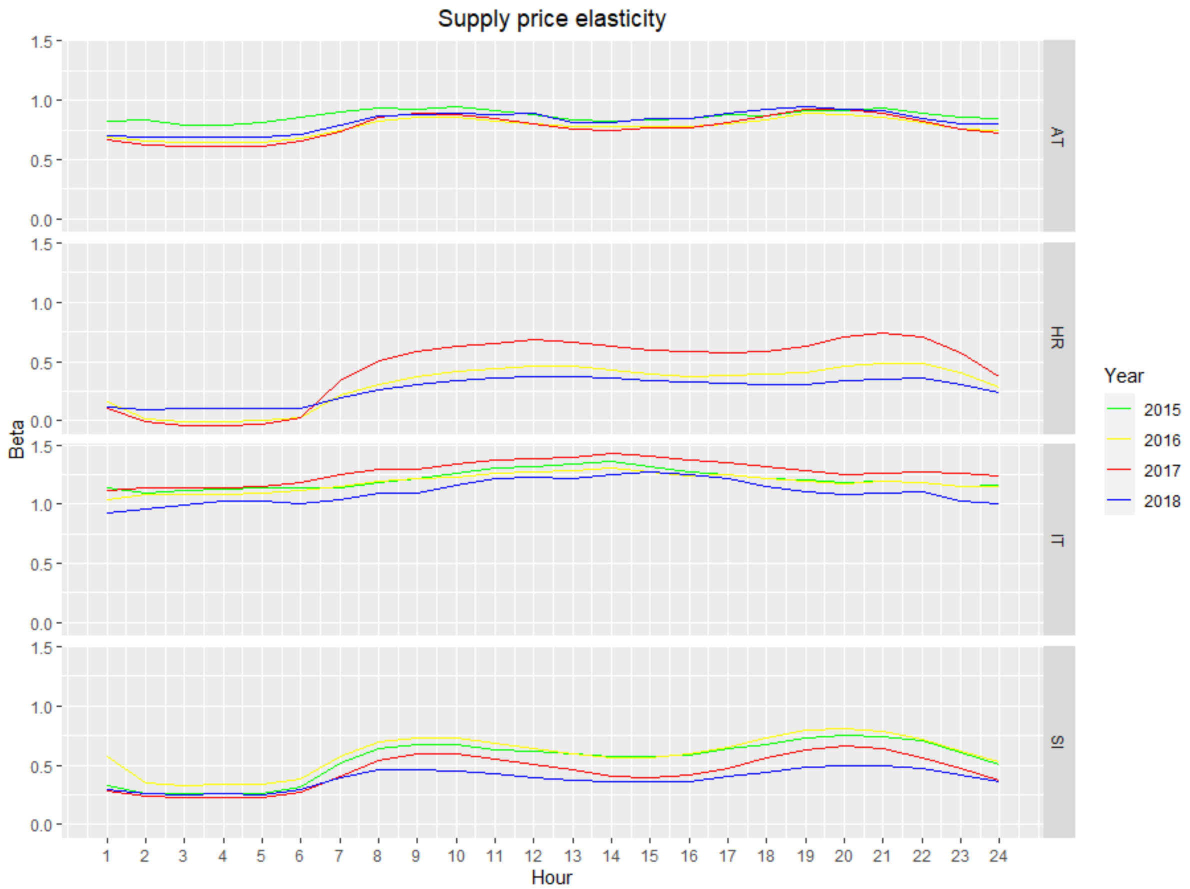
2.5.1 Market coupling simulation results

The supply price elasticity model is dynamically estimated for each simulation day by a rolling window approach. Table A5 in the Appendix represents the estimation summary with goodness-of-fit metrics. We can conclude that the most variation in dependent variable is explained if the explanatory variables are estimated by the 7-day rolling window. The Croatian power exchange has been operational since 10 February 2016. Therefore, there is a missing section in the estimated supply price elasticity curve before that date (CROPEX, 2016). According to the estimation results, the supply is relatively price inelastic in Slovenia and Croatia (Figure 2.3).

In Austria, the estimated price elasticity is higher compared to Slovenia and Croatia, whereas the supply in Italy can be described as price elastic (elasticity coefficients above one). The supply price elasticity during peak (9-20) hours is on average considerably higher compared to the off-peak (0-8 & 21-24) hours. A most notable hourly differentiation in supply price elasticity is observed in Croatian and Slovenian electricity markets. Estimation of the individual supply price elasticity functions for each individual hour of the day turned out to be justified. In terms of estimated supply price elasticities, electricity supplied during daily peak hours is more elastic from that supplied during off-peak hours. Analysis of this observation is beyond the scope of the article. Order book generation for the market coupling simulation with differentiated supply price elasticities on hourly basis is rationalised. In the analysed period ATSI cross-border interconnector transitioned from non-coupled to coupled market regime (integration of energy and transmission market). Based on the estimated supply price elasticities we do not recognize a pattern that would indicate changed market behaviour of generators in Austrian or Slovenian market after the integration (Figure 2.3). Estimation of the supply price elasticity by the rolling window approach recognises temporary supply features.

The estimated supply price elasticities are without a yearly trend, and this is most likely to be associated with the randomness of the available production capacity and hydrological situation. Detailed analysis of generators' market behaviour is beyond the scope of this article.

Figure 2.3:Estimated supply price elasticity (loglinear model)



Source: Own work.

Table 2.1 summarises realised electricity day-ahead prices and by the market coupling algorithm simulated prices. The Croatian power exchange was launched on 10 February 2016. Before that date, it was not part of the simulation perimeter. The most notable price and variance reductions are observed in Slovenia and Croatia. In Austria, where the realised day-ahead electricity prices are on average the lowest, simulated electricity prices rise on average by 0.22 €/MWh with a marginal increase in the standard deviation. On the Italian market, with the highest realised prices, simulated prices drop on average by 0.12 €/MWh with a minor decrease in the standard deviation. The Slovenian simulated price is on average lower by 0.24 €/MWh, whereas the Croatian price is lower by 1.19 €/MWh. The standard deviation fell on average in Slovenia by 10.01 €/MWh, and in Croatia by 42.77 €/MWh. The most notable declines are observed in simulation year 2017, where the Croatian price is reduced by more than 2 €/MWh and the standard deviation is reduced by 93 €/MWh. The market coupling simulation overall resulted in significantly improved price convergence.

The Appendix Table A6 reports changes in realised supply as a result of the market coupling simulation. In the market coupling simulation, demand is considered inelastic, subsequently all changes in CBC utilisation caused by the simulation are accounted as the supply changes. Simulation market clearing condition is respected (Equation 2.7) as the net sum of overall changes in CBC utilisation (sum of the supply shifts) equals 0. The simulated supply changes are proportional with respect to the country size in terms of total supply, however relative changes turned out to be rather small (on average less than 0.3 percent).

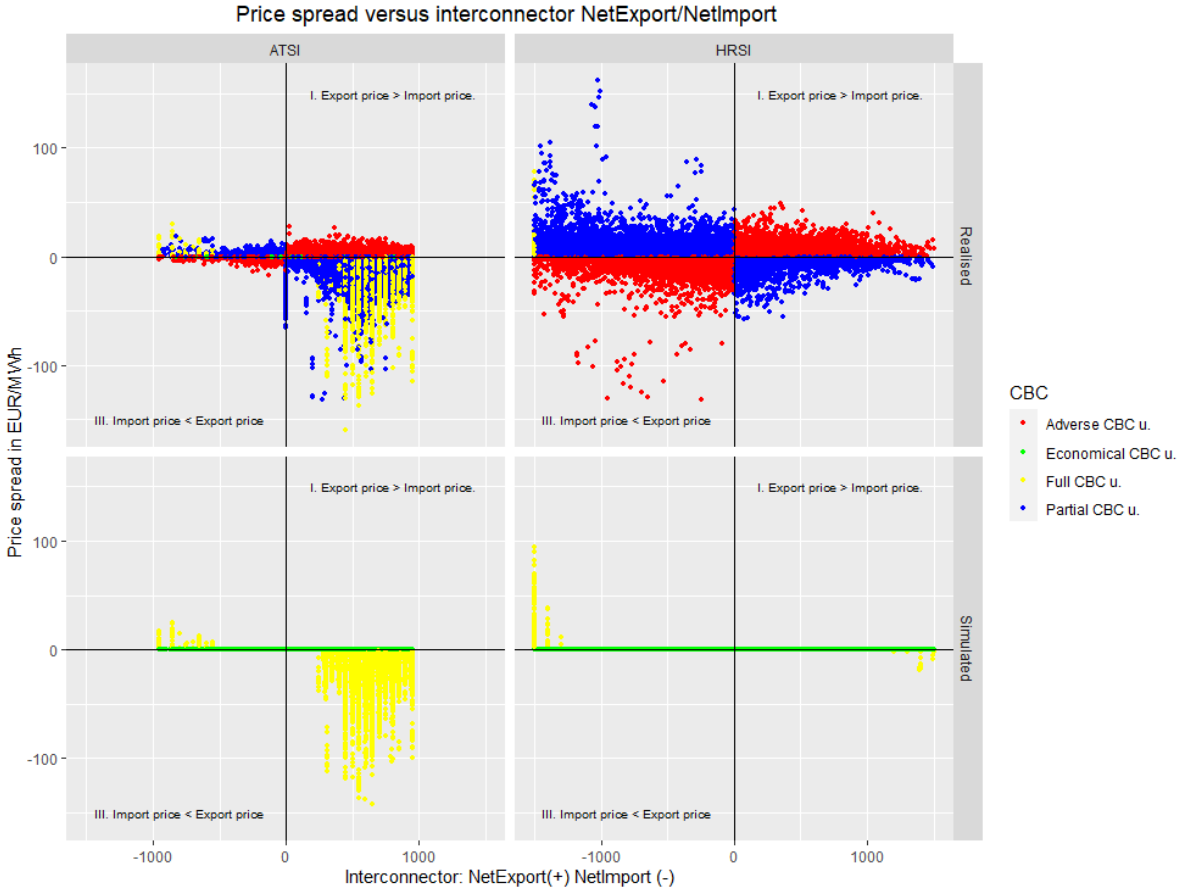
Table 2.1: Descriptive statistics for realised day-ahead prices and simulated prices.

		Realised Prices		Simulated Prices		Difference	
Year	Country	Mean	S.D.	Mean	S.D.	Mean	S.D.
2015	AT	31.76	158.41	32.03	161.32	0.27	2.91
2015	HR	NA	NA	NA	NA	NA	NA
2015	IT-Nord	52.76	200.72	52.64	198.55	-0.12	-2.17
2015	SI	41.48	266.73	41.20	248.63	-0.28	-18.10
2016	AT	28.93	156.32	29.08	158.38	0.15	2.06
2016	HR	34.68	164.50	34.68	157.78	0.00	-6.72
2016	IT-Nord	42.59	224.84	42.45	226.35	-0.14	1.51
2016	SI	35.53	180.28	35.24	170.36	-0.29	-9.92
2017	AT	34.23	310.80	34.49	312.44	0.26	1.64
2017	HR	51.82	576.44	49.76	483.15	-2.06	-93.29
2017	IT-Nord	54.46	339.79	54.36	332.09	-0.10	-7.70
2017	SI	49.58	468.44	49.28	450.25	-0.30	-18.19
2018-Q2	AT	35.55	234.98	35.76	234.03	0.21	-0.95
2018-Q2	HR	42.11	291.64	40.60	263.32	-1.51	-28.32
2018-Q2	IT-Nord	52.82	211.44	52.71	212.98	-0.11	1.54
2018-Q2	SI	40.66	281.45	40.56	287.61	-0.10	6.16

Source: Own work.

Figure 2.4 summarises cross-border transactions on the ATSI and HRSI interconnectors prior to market coupling implementation and simulated market coupling CBCs allocation. Instances with correct economic reasoning of energy exports from cheap to expensive markets are observed in the II. And IV. quadrants. Full CBC utilisation is an instance where the CBC is fully utilised, but, with insufficient capacity to ensure price convergence. Economical CBC utilisation is an instance where the CBC is sufficient and price convergence between price areas is achieved. These observations are marked by green colour and are located on horizontal axis (0 € price spread). The partial CBC utilisation (marked by blue colour) defines instances with the correct economic reasoning, however, by partial CBC utilisation and with an existing price spread. Adverse CBC utilisation instances (marked by red colour) are located in the I. and III. quadrants. These are instances with net energy exports from high-price area into a low-price area. Figure A3 in the Appendix further summarises cross-border transactions on the ATIT and ITSI borders. Please note that implicit allocation on ATIT border started on 24 February 2015 and on ITSI border on 1 January 2011, so we can observe evident CBC allocation corrections only on the ATIT border.

Figure 2.4: Realised and simulated flow on ATSI and HRSI interconnector.



Source: Own work.

The relative frequencies of cross-border capacity utilisation status before and after the market coupling simulation are reported in Table 2.2. The main outcome of the market coupling simulation is the elimination of the adverse and partial CBC utilisation category. On the ATIT border, implicit CBC allocation started on 24 February 2015. In Table 2.1, we can observe that the Austrian market is historically the cheapest, whereas Italy is the market with the highest prices. Due to the natural tendency of exports from the Austrian market to the Italian market and a short period under the explicit CBC allocation regime, there are no significant changes in the simulated market coupling CBC allocation on the ATIT border. The market coupling simulation on the ATSI border significantly improved CBC utilisation. Before the market coupling simulation, CBCs were adversely or partially utilised 27% of the time. These cases are altered in a market coupling simulation to full CBC utilisation category for 46% of the time or to the economic CBC utilisation category for 54% of the time. In the studied perimeter, the smallest price spread is observed between the Slovenian and Croatian markets. Most notable improvement is reported on the HRSI border where CBCs were adversely utilised 45% of the time and partially for 55% of the time. Under a simulated market coupling regime, economic CBC utilisation, i.e. price convergence, is reported for 99% of the time. On the ITSI border, implicit CBC allocation started on 1 January 2011. Simulation changes in CBC utilisation on the ITSI border are exclusively the result of energy redistribution, due to inefficiency elimination on the ATIT, ATSI, or HRSI borders. In the market coupling simulation, full capacity utilisation rises from 55% to 61% of the time.

Market coupling impact assessment on the suppliers' and consumers' income for the analysed period is reported in the Appendix Table A7. Please note, that Supply is realised supply in MWh (ENTSOE-TP data); Δ NX is a supply change induced by the market coupling simulation in MWh; Supply* is optimal supply according to market coupling simulation in MWh; Load in MWh (ENTSOE-TP data) and Average Price Δ is an average price change induced by the market coupling simulation in €/MWh. In the analysed period overall income improved for almost 16 million €. We observe that the most significant contribution to the generated surplus has the simulation of market coupling on HRSI interconnector. In the period when only HRSI interconnector operated in non-coupled market regime, the overall income in simulated market perimeter improved for more than 13 million €. This is in line with the observed frequent inefficient CBC utilization on HRSI interconnector (Table 2.2). Inefficient CBC utilization is less frequent on ATIT and ATSI interconnectors, subsequently market coupling simulation in that period has minor impact on the estimated overall suppliers' and consumers' income (563.789,00 €).

Table 2.2: Relative frequency table of cross-border capacity utilisation status.

Interconnector	CBC utilisation	Realised	Simulated
ATIT	Adverse CBC u.	1%	0%
ATIT	Economical CBC u.	2%	6%
ATIT	Full CBC u.	96%	94%
ATIT	Partial CBC u.	1%	0%
ATSI	Adverse CBC u.	10%	0%
ATSI	Economical CBC u.	28%	46%
ATSI	Full CBC u.	45%	54%
ATSI	Partial CBC u.	17%	0%
HRSI	Adverse CBC u.	45%	0%
HRSI	Economical CBC u.	0%	99%
HRSI	Full CBC u.	0%	1%
HRSI	Partial CBC u.	55%	0%
ITSI	Economical CBC u.	45%	39%
ITSI	Full CBC u.	55%	61%

Source: Own work.

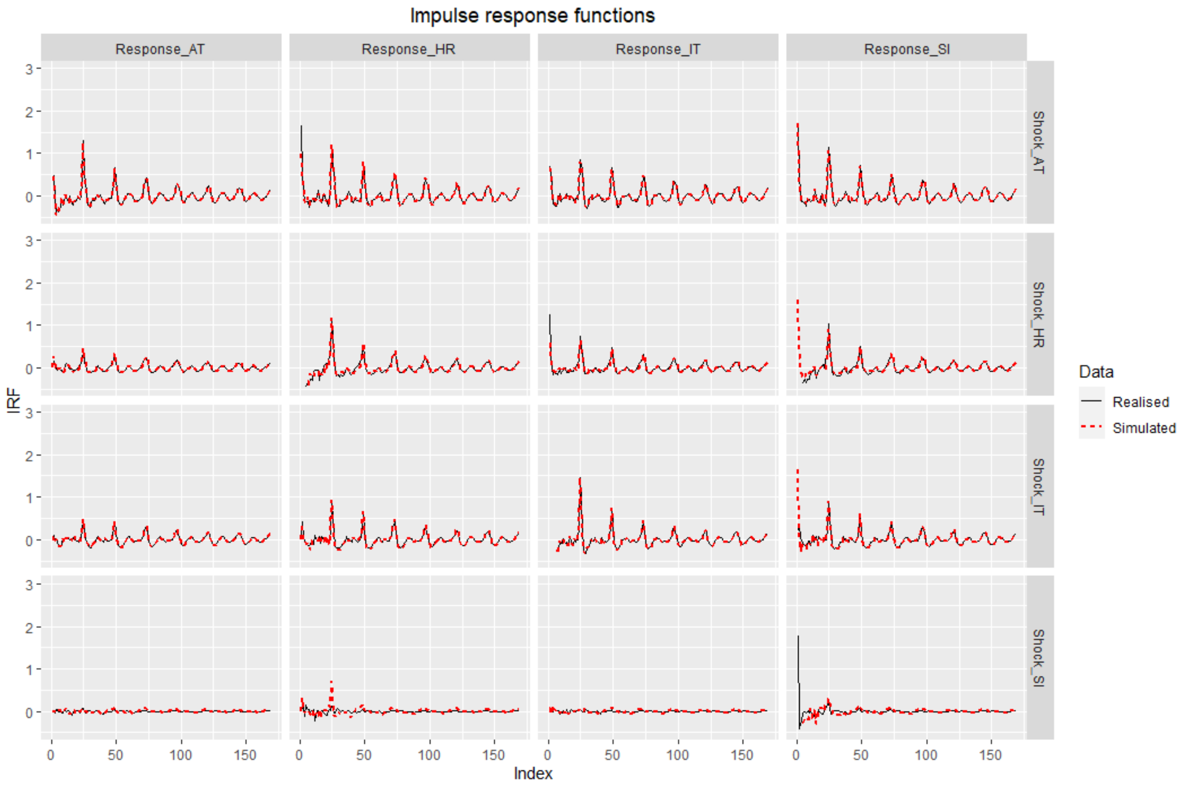
2.5.2 Price shock transmission

Impulse response functions are determined by the estimated VAR (24)[6] model on the realised and simulation generated electricity day-ahead price time series, for the period from 10 February 2016 to 20 June 2018. Selected time window coincides with the establishment of Croatian power exchange and observed severe inefficient CBCs usage on HRSI border. Executed Dickey-Fuller tests for testing a stationarity of price time series are rejected for all markets (Appendix Table A8). Test null hypothesis of having a non-stationary time series is

[6]For each model, the order of autoregression p is determined by the Akaike Information Criterion; in our case we employ a VAR(24) model.

tested. Tests are executed on the realised price time series and by the market coupling algorithm simulated price time series. Lags variable is the number of lagged variables included in the testing equation. Rejecting the null hypothesis means having a stationary price time series. Therefore, VAR models are estimated without any further time series transformations.

Figure 2.5: Impulse response functions (IRF) of estimated VAR models



Source: Own work.

In Figure 2.5, we can visualise the direct and indirect impact of an exogenous shock at a particular network node on the hourly time paths of prices at all nodes. All markets have in common that prices 24, 48, … and 168 hours past due exert a positively correlated influence on the current price in the studied markets. The previously mentioned influence diminishes over time. According to Figure 2.5, we can conclude that price shocks originating in the Slovenian and Croatian markets, characterised by the low supply price elasticity, are transmitted with low magnitude towards markets with relatively higher supply price elasticity (the Italian and Austrian markets). On the contrary, shocks originating in markets with higher supply price elasticity are transmitted with higher magnitude to markets with low supply price elasticity. In the simulated market coupling environment, price shock transmission dynamics amplifies towards the Slovenian market. Price shock transmission from Croatia and Italy to Slovenia is instantaneous and echoes above a 1.5 standard deviation. The most severe and frequent inefficient CBCs allocation occur on the HRSI border, therefore, instantaneous shock transmission from Croatia to Slovenia is in line with the market coupling theory and confirms improved market integrations in coupled electricity markets. The VAR model estimation results are reported in Table A9.

Price shock transmission with the characteristic 24-hour lag in the non-coupled market regime, indicates an incentive of market participants to readjust their strategies after the observed price shock in one of the neighbouring markets. The instantaneous and amplified price shock transmission from Italy and Croatia to Slovenia is most likely associated with the previously inefficient energy redistribution between the non-coupled Croatian and Slovenian markets. Market integration, indicated by the price shock transmission intensity and price shock transmission timing, improves in the simulated market coupling environment.

The null hypothesis in the Granger causality test is that the tested price time series does not Granger-cause other VAR model price time series. We have executed test for each VAR model price time series (AT, HR, SI, IT). Performed Granger causality test results are reported in the Appendix Table A10. By rejecting the null hypothesis, we confirm that the tested time series Granger causes at least one of the other time series. Tests executed on realised and simulated price time series are rejected at 0.00 p-value (Table A10 in the Appendix). Therefore, we infer that in the analysed perimeter, knowing the price value of a single market is valuable for forecasting future values of at least one of the other markets.

2.5.3 Discussion

Slovenia, positioned at the heart of the case study simulation perimeter, is connected to the Central Western Europe power markets, the Italian market, and South Eastern Europe markets, which substantially differ in terms of maturity and electricity price levels. Market coupling simulation at the power market crossroads of Europe makes it an interesting case to study the implications and benefits from market coupling with the neighbouring countries with respect to the CBC usage efficiency, electricity price convergence, price volatility, and price shock transmission.

Inefficient usage of CBC in non-coupled markets typically resulted in partial CBC utilisation in case of a price spread between the market areas or CBC utilisation in adverse direction (exports from high price area to low price area). As the electricity and CBC rights are traded at two different auctions, inefficient CBCs utilisation is frequently present. Price convergence in such a market set-up is rarely achieved. Partial or adverse CBC utilisation are less frequent on borders with pre-existing larger price spreads such as ATSI and ATIT, where CBCs are deemed to be fully utilised most of the time. In the studied perimeter, we can observe that most severe and frequent inefficiencies in CBCs utilisation occur on the HRSI border. The HRSI border connects markets with low supply price elasticity and sufficient CBC to eliminate price spread majority of the time. Due to the asymmetry in the electricity and CBC rights auction in non-coupled markets, the price convergence between the Slovenian and Croatian markets is not achieved. The market coupling algorithm eliminates all inefficiencies in CBCs utilisation, which is visualised in Figure 2.4. Further, we observe a pronounced price shock transmission with a characteristic 24-hour lag in non-coupled markets, indicating an incentive of market participants to readjust their strategies after the observed price shock in the neighbouring market. A strong incentive to readjust strategies after the observed price shock (Figure 2.5) and a considerable amount of unutilised CBCs on HRSI interconnector (Table 2.2), indicate the inability to optimally act in non-coupled electricity markets. Exercise of market power is typically associated with CBC congestions. Therefore, we conclude that the inability to optimally act in non-coupled electricity markets is associated with presented information asymmetry due to two different auctions. In simulated coupled markets, price shock transmission becomes instantaneous. Therefore, a given mandate to market agents to regulate electricity transport in non-coupled electricity markets is shown to be inefficient. Pellini (2012) concluded that high-priced areas, such as Italy, could greatly benefit from the introduction of the market coupling mechanism. According to our simulation results, we conclude that market coupling is beneficial for all involved counterparties.

Market coupling impact on the suppliers' and consumers' income is positive. In the analysed period the overall income improved for almost 16 million €. The most evident price change in the market coupling simulation is observed in the Croatian market with the price reduction on yearly average basis above 1 €/MWh. Price changes in other markets are considerably lower. Most severe and frequent instances of suboptimal CBC utilisation are registered on the HRSI border. Sufficient residual values of non-utilised CBCs on the HRSI border and low supply price elasticities in both markets resulted in a significantly improved price convergence between the Slovenian and Croatian markets. Due to low residual values of non-utilised CBCs on the ATIT, ATSI, and ITSI borders and relatively higher supply price elasticity on the Austrian and Italian markets, the price difference between the realised and simulated market is low. Price dynamics in markets with lower supply price elasticities marginally changes with the implementation of market coupling mechanism. The market coupling mechanism converts a residual value of the non-utilised CBCs in non-coupled markets into improved market liquidity. Significant price changes are achieved even by a marginal change in the CBC utilisation. We conclude similarly as Huisman and Kiliç (2013) that due to improved liquidity in coupled markets, volatility and extreme price situations are reduced. The risk related to the daily market operations is typically derived from high price volatility. This is especially valid for spot prices, where the volatility can be as high as 50% on a daily scale, i.e. over 10 times higher than for other energy products (natural gas and crude oil) (Weron & Misiorek, 2005). In non-coupled markets with low supply price elasticity and sufficient residual values of non-utilised CBCs, a reliable and fair price signal is essential. The market coupling mechanism guarantees a reliable and fair price signal to all market participants.

By the estimated VAR model and underlying impulse response functions, we have empirically confirmed that the magnitude of the price shock transmission in the coupled markets significantly amplifies and changes the overall price dynamics. In general, the price shock transmission amplifies from the markets with the most severe and frequent CBCs allocation inefficiencies. With the sufficient available cross-border capacity, price shocks are no longer locally absorbed. In the non-coupled market regime, the observed price shock transmission with a 24-hour lag indicates the incentive and opportunity of market participants to readjust their strategies after the observed price shock. The observed price shock transmission with the characteristic 24-hour lag in the non-coupled market regime is a result of asymmetry between the electricity and CBC rights auctions. Electricity price shock transmission materialise instantaneously i.e. without a lag in the simulated market coupling regime. With the improved price shock transmission, market integration in coupled markets significantly improves throughout the coupled market areas.

The applied simulation approach of order book generation and electricity price determination compliant to the social welfare maximisation algorithm used by the European power exchanges is a convincing choice for the applied market simulations in coupled day-ahead markets. Following from the mathematical optimisation model, we have confirmed that the market coupling mechanism ensures efficient transmission capacities utilisation with the power flow following economic logic. The proposed simulation framework provides invaluable and detailed insights in the price determination and CBCs allocation process that cannot be attained in the general statistical or computational intelligence modelling framework. An alternative order book generation process based on the econometrically estimated aggregate supply price elasticity functions closes a gap associated with power exchange order book data availability. Spot market often represents just a small part of the total electricity trade (2007). Apparent lower market liquidity in the real spot power exchange order book data is bridged by the econometrically estimated aggregate supply price elasticity functions. Estimation of the aggregated supply price elasticity by the rolling window is justified as it recognises unaccounted temporary supply features. The stylised fact that the supply price elasticity during daily peak hours is lower compared to off-peak hours is confirmed and accounted by the estimation on peak and off-peak hourly samples.

The proposed simulation framework could be modified for electricity price forecasting tasks. In an electricity price forecasting setting, applicable factors on the demand and supply sides can be incorporated in the order book generation mechanics, whereas network factors are accounted for in the binding network constraints. Insights in the price determination and CBCs allocation process could significantly improve price spike forecasting, as the CBC congestions are determined by the simulation. A price spike is characterised by a sudden departure of prices from the normal regime for a very short time interval (Grossi & Nan, 2019). Such a situation could be predominantly associated with electricity demand, generation outages, transmission congestion, market participant behaviours, etc. (Hong et al., 2016). In the future, we plan to extend our research to electricity price forecasting coupled European electricity markets, with the implementation of marginal costs and production availability in order book generation mechanics.

2.6 Conclusion

We have simulated market coupling at the power market crossroads of Europe, with a goal to eliminate the observed inefficient cross-border capacity (CBC) utilisation on Austrian-Italian, Austrian-Slovenian, and Croatian-Slovenian cross-border interconnectors. Empirical implications of regional market coupling on efficient cross-border capacity utilization and the underlying effect on market clearing prices have not been jointly researched yet.

Market coupling simulation results confirmed the efficient CBC usage, improved electricity price convergence, reduced price volatility, and improved price shock transmission in coupled electricity markets. Market integration, indicated by the price shock transmission intensity and price shock transmission timing, empirically improves in the market coupling environment. The market coupling mechanism ensures that the transmission capacities are always efficiently utilised with the power flow following economic logic. Spare capacity on cross-border interconnectors occurs only when all opportunities for arbitrage have been exploited and prices are equal, which follows from the mathematical optimisation model. In the studied regional scope of the simulation, the most severe and constant inefficiencies in CBCs utilisation occur on the interconnectors connecting the Slovenian and Croatian power markets. These markets are characterised by low supply price elasticity, but with a sufficient CBC to eliminate existing pre-coupling price spread. The estimated overall market coupling impact on the suppliers' and consumers' income i.e. generated surplus is significant, especially in period with simulated market coupling on the Croatian-Slovenian cross-border interconnectors.

Proposed simulation framework provides valuable and detailed insights in the electricity price determination and CBCs allocation process that cannot be attained in the general statistical or computational intelligence modelling framework. An alternative power exchange order book generation process, based on the publicly available ENTSOE-TP data, efficiently bridges concerns with the partially accounted system trade in real order books and public order book data availability. The proposed simulation framework, compliant with the social welfare maximisation algorithm (EUPHEMIA) is recognised as a convincing choice for the applied simulations in coupled electricity markets. With currently ongoing final steps in EU markets integration – referred as the Single Day-ahead Coupling project, the simulations results are of significant importance for EU policy makers, network operators, and market agents. Most important, exclusively relying on publicly available ENTSOE-TP data and flexible order book generation mechanics, the simulation framework can be adjusted for a specific application of the interested market participant.

3 THE CROWDING OUT OF CONVENTIONAL ELECTRICITY GENERATION BY RENEWABLE ENERGY SOURCES: IMPLICATIONS FROM GREEK, HUNGARIAN, AND ROMANIAN ELECTRICITY MARKETS

3.1 Introduction

Growth in electricity generation from renewable energy sources (RES) to achieve a less polluting and import-dependent energy sector in the EU member states has influenced electricity market dynamics. National promotion strategies triggered by the Directive (2001/77/EC) on renewable energies in the electricity sector have been the major driving force for this development. All EU member states have introduced policies to support the market introduction of RES (Ragwitz & Held, 2007). Guaranteed feed-in-tariffs have been most successful to stimulate investments in renewable energies, as investors receive their income on the basis of the set up renewable promotion scheme and not from the electricity sold on spot markets with highly volatile prices (Sensfuß et al., 2008). Consequently, increased renewable generation of electricity crowds out other high(er) marginal-cost technologies and results in lower electricity prices in the wholesale electricity market (Keles et al., 2013). The crowding out of generation from conventional (non-renewable) energy sources with higher marginal costs is recognised in the literature as a merit order effect (MOE). Lower prices result from the fact that renewables bid into wholesale electricity markets at almost-zero prices, and therefore shift the electricity supply curve to the right (Keles et al., 2013).

The novelties of this chapter are twofold. First, an empirical analysis is conducted in order to confirm and quantify merit order effect in yet unresearched Hungarian, Romanian and Greek electricity markets. Second, relying on data mining algorithms, we simulate electricity prices in the no-RES generation scenario and quantify changes in the conventional generation portfolio as a result of the excluded RES generation. The analysed electricity markets of Central and South East Europe given their characteristics qualify for a merit-order effect analysis. Greek and Romanian electricity markets have higher RES generation shares in their electricity generation mix, and clearly qualify as interesting case studies. In contrast, Hungary has a low share of renewable generation and serves as a control country. Due to its direct interconnection to the Romanian market, it could be considered as a natural price cap for the expected Romanian prices in the no-RES generation scenario simulation. We expect to confirm that the increase in RES generation crowds out conventional generation sources and in the short-run reduces the price of electricity. Further, based on the no-RES generation simulation results, we investigate the effect of RES generation on the electricity price levels, price volatility, and electricity net export.

The empirical MOE analysis is executed to supplement the existing literature focused on key EU energy areas in terms of installed renewable capacity and electricity market development.

Prior studies considering empirical confirmation and quantification of the MOE typically address the German (Benhmad & Percebois, 2018; Neubarth et al., 2006; Sensfuß et al., 2008; Weigt, 2009; Würzburg et al., 2013), Spanish (Figueiredo & Silva, 2019; Gelabert et al., 2011; Gil et al., 2012; Sáenz de Miera et al., 2008), and Danish (Jónsson et al., 2010; Unger et al., 2018) electricity markets. Based on the literature review, there is no similar study investigating the MOE in the EU member countries in Central and South East Europe regions.

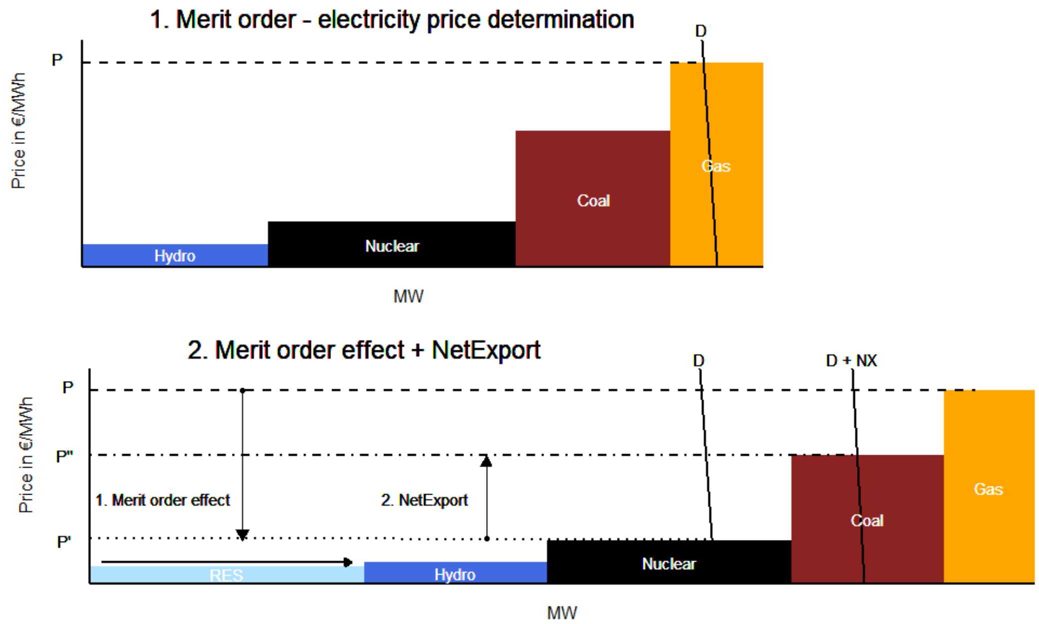
In this chapter, we empirically confirm and quantify MOE by a multivariate regression model similar to Würzburg et al. (2013) analysing the MOE in the German and Austrian electricity markets. For the preparation of simulated no-RES generation scenario, we have further estimated the influence of RES generation on the country electricity net-export and aggregated supply curves for different electricity generation technologies. Part of the domestic RES generation is typically exported to neighbouring countries. Therefore, only a domestically absorbed RES generation share causes MOE and reduces domestic electricity prices. The influence of RES generation on country electricity net export is quantified by a multivariate regression model. According to the economic theory, supply curve quantity and price pairs are determined by the short-run marginal costs of different electricity generation technologies. Aggregated supply curve for the individual generation technology is estimated based on the observed day-ahead electricity prices and reported electricity dispatch. Due to the prominent non-linear behaviour of the electricity price signals (Weron, 2014), we estimate aggregated supply curves by employing data mining algorithms. The estimated energy imbalance caused by the excluded renewable generation is compensated by the additional conventional generation dispatch. The required additional conventional generation dispatch to maintain energy balance is priced according to the estimated aggregated supply curves. Based on the no-RES generation simulation results, we can study the effect of RES generation on electricity price levels and volatility.

The chapter is structured as follows. Section 2 looks more closely into the MOE theory and provides literature review. Section 3 outlines the methodology and its application. Data, data availability, and country electricity generation mix features are summarised in Section 4. Section 5 reports and discusses the empirical results. Finally, Section 6 presents concluding remarks with summarised key research findings.

3.2 Merit order effect

Guaranteed feed-in-tariffs support for RES electricity generation has led to growth in the installed capacity of supported technologies. Throughout the chapter, wind and solar electricity generation are addressed by the RES electricity generation. Theoretical consideration introduced by Jensen and Skytte (2002) suggest that renewable electricity generation results in lower electricity prices. Electricity price is determined at the intersection of the aggregated demand and supply curves. According to Cerjan et al. (2013) electricity is an essential commodity, and as such, in the short-term exhibits inelastic demand (Cerjan et al., 2013). This is in Figure 3.1 indicated by a vertical line *D*. The profile of the supply curve is defined by the ranking of the generation units by their short-run marginal costs in increasing order, together with the dispatched energy, in a merit order (Sensfuß et al., 2008). In Figure 3.1, electricity price is determined at the price level *P* at the intersection with the gas power plant short-run marginal costs (Figure 3.1).

Figure 3.1: Merit order based on marginal costs, merit order electricity price setting & merit order effect.



Source: Own work.

The price reducing impact is called a 'merit-order effect' and can be explained with the right shift of the supply curve when RES generation with low variable costs is integrated into the supply curve (Figure 3.1). Assuming an inelastic demand, electricity price as an intersection between supply and demand will thus decrease to price *P'* associated with the short-run marginal costs of nuclear technology (Figure 3.1). The gradient of the supply curve depends mainly on technologies, efficiencies, fuel prices, start-up costs, and CO_2 price (Keles et al., 2013).

Electricity interconnections have become increasingly common as a means of integrating electricity markets (Macedo et al., 2021). In general, countries tend to (net) export greater amount of electricity if domestic RES generation increases (Croonenbroeck & Palm, 2020). In Figure 3.1 - 2, this is illustrated with the increase of electricity price from *P'* to *P''*. Price movement from *P'* to *P''* is induced by the foreign demand (*NX*) for cheaper electricity due to the MOE, which increases the final demand for electricity (*D* + *NX*). New electricity price *P''* is associated by the short-run marginal costs of coal electricity generation technology.

Table 3.1 summarises day-ahead electricity prices in the analysed period. The influence of German electricity prices on electricity prices across the other regions is confirmed in many studies (Bunn & Gianfreda, 2010; Lindström & Regland, 2012; Ziel et al., 2015). Table 3.1 confirms this stylized fact, as the electricity price levels of the analysed perimeter follow German price dynamics.

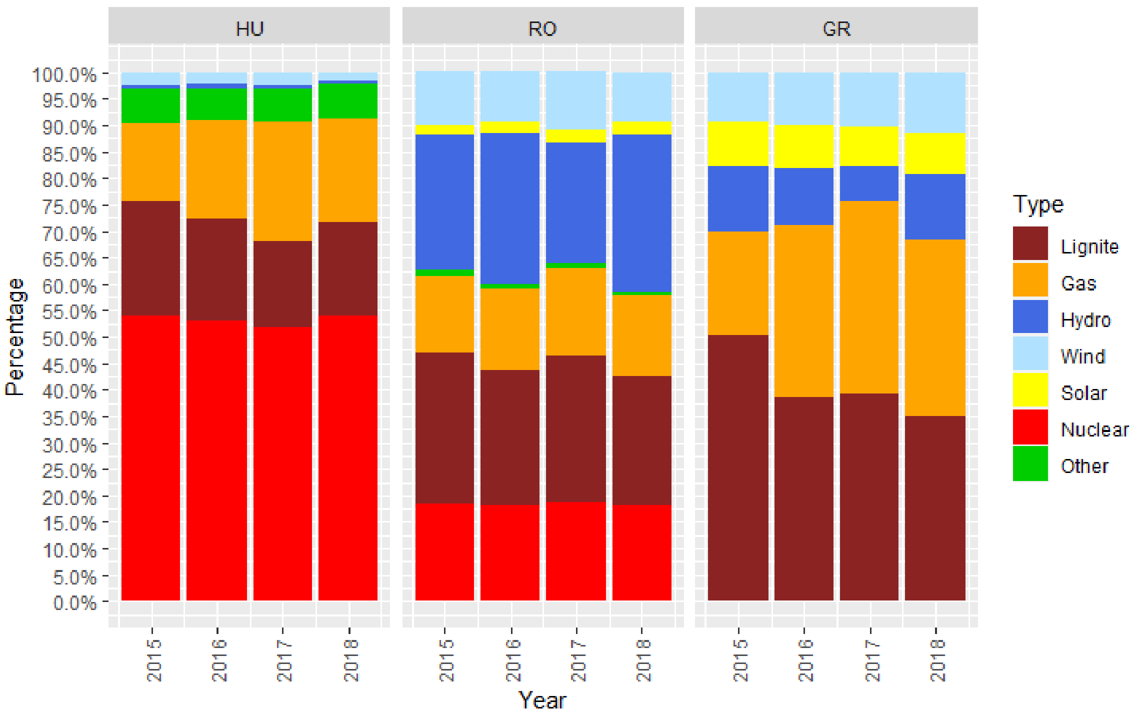
Table 3.1: Day-ahead electricity prices in €/MWh

Year	DE	HU	RO	GR
2015	31.8	40.6	36.4	51.9
2016	29.0	35.5	33.4	42.8
2017	34.2	50.4	48.2	54.7
2018	44,5	51.0	46,5	60,4

Source: ENTSO-E TP 2020.

Figure 3.2 presents electricity generation mixes of Hungarian, Romanian, and Greek power systems. RES have insignificant contribution to the Hungarian generation mix, as there is no solar generation, whereas wind accounts for less than 2.5% of total generation on a yearly basis. In the Romanian generation mix, on average, 10% of electricity is generated by the wind and 2.5% in solar power plants. In Greece, 10% and 7.5% of electricity is generated by the wind and solar power plants, respectively. Based on the observed wind and solar maximum generation outputs in the analysed power systems, we can conclude that the installed RES capacity remained relatively constant over the 2015–2018 period (Table A11 of the Appendix). Romania with 12.5% and Greece with 17.5% RES share in generation mix clearly qualify as good candidates for the MOE analysis.

Figure 3.2: Hungarian, Romanian and Greek electricity generation mixes in percentages.



Source: ENTSO-E TP 2020.

According to Würzburg et al. (2013), key MOE studies can be classified in simulation-based and empirical analysis studies. Simulation studies are based on the simulation models (e.g., unit commitment model) using real past or hypothetical data, whereas empirical studies are generally performed with econometrics models on real past data. Due to fundamental difference in approaches, drawing general conclusions and result comparison of different papers should be done with special care.

Important simulation-based studies typically rely on information rich and flexible simulation models used for power system or agent-based simulations. With an agent-based simulation platform, Sensfuss et al. (2008) analysed German electricity prices with and without RES generation. RES generation caused a price reduction by 1.7 to 7.8 €/MWh. Weber and Woll (2012) simulated the German electricity system by 34 generation technologies for electricity generation, fuel prices, and CO_2 prices. In the no-RES generation, scenario electricity prices are 4.04 €/MWh higher compared to the base scenario with wind generation. Fürsch et al. (2012) simulated merit-order effect for Germany based on the DIME Model (Dispatch and Investment Model for Electricity Markets in Europe). This model accounts for the international flows and dynamic adaptation of generation mix to increased RES generation. Due to the predicted RES generation growth, they predicted in years 2015, 2020, 2025, and 2030 a price reduction of 2 €/MW, 4 €/MWh, 5 €/MWh, and 10 €/MWh, respectively. Sáenz et al. (2008) in the Spanish market simulation analysis, between years 2005 and 2007, report a price reduction caused by the wind generation of 7.08€/MWh to 12.44 €/MWh.

With the increased market transparency and ex-post data availability number of published empirical studies quantifying the impact of RES generation on electricity prices significantly increased. Neuberth et al. (2006) estimated by the univariate econometric model the impact of wind generation on German electricity day-ahead prices in years 2004 and 2005. They find that the electricity price drops by 1.89 € for each additional GW of wind power generation. Using time series regression analysis, Cludius et al. (2014) estimated a price drop caused by RES generation in Germany by 6€/MWh in 2010, 10 €/MWh in 2012, and a projected price drop of 14-16 € in year 2016.

Macedo et al. (2021) using a SARMAX/GARCH time series econometric approach estimated the impact of RES generation and net export on Swedish day-ahead electricity prices from 2016 to 2020. They estimated model for each hour of the day individually and confirmed homogenous negative impact of RES generation on electricity price. A 1% increase in RES generation decreased the electricity price by 0.0609%. Macedo et al. (2020) expanded preceding study to the Portugal electricity market. They estimated that the 1% increase in RES generation on average decreased the Portuguese electricity price by 0.056%. Figueiredo and Pereira da Silva (2019) based on historical Spain and Portuguese (Iberian market) electricity power exchange data, quantified the MOE with the GARCH econometric model. For the period from 2013–2017, they confirmed a MOE of 13.11 €/MWh for wind generation and 8.79 €/MWh for solar generation.

Azofra et al. (2014) estimated the MOE in the Spanish electricity market using a data mining regression tree (M5P) algorithm. For year 2012, they have estimated a price drop between 7.42 and 10.94 €/MWh caused by the wind generation. Cló et al. (2015) estimated the MOE of wind and solar generation in the Italian power market. They have reported that in the years 2005–2013 for each additional GW of solar and wind generation the electricity prices on average dropped by 2.3 €/MWh and 4.2 €/MWh, respectively. Janda (2018) investigated the influence of solar generation on Slovak day-ahead electricity price in years 2011–2016. The estimated multivariate model indicates that, *ceteris paribus*, 1% increase in solar generation is associated with a spot price decrease from 0.016% to 0.067%. Given the literature review of the most important studies on MOE in European electricity markets, we aspire to close the gap of yet unresearched MOE in Central and South East European electricity markets.

3.3 Methodology

The presence of MOE in Hungary, Greece, and Romania is initially statistically verified by a multivariate regression model. Then, we simulate the adjustment of the realised electricity prices to the no-RES generation scenario. The applied no-RES generation simulation approach intuitively takes as an example the DIME model (Dispatch and Investment Model for Electricity Markets in Europe) used by Fürsch et al. (2012). The DIME model accounts for the international flows and dynamic adaptation of the generation mix to changes in RES generation.

3.3.1 Econometric merit order effect verification

To statistically verify the presence of the MOE, we estimate a multivariate regression model similar to Würzburg et al. (2013). Neubarth et al. (2006) found that with daily average values RES explanatory variables tend to be more relevant for the definition of day-ahead prices in the German market area. Therefore, to eliminate *ad hoc* anomalies and short-term noise, all model variables are calculated as the daily average values. In Equation 3.1, electricity price ($P_{elec,d}$) is the dependent variable, whereas the explanatory variables are the previous day electricity price ($P_{elec,d-1}$), realised German electricity price ($P_{DE,d}$), the demand for electricity ($Load_d$), wind and solar generation (RES_d), the net export of electricity (NX_d), and standard error term (ε_d). In Equation 3.1, Δ represents the first difference operator and d stands for daily observations:

$$\Delta P_{elec,d} = \beta_o + \beta_1 \Delta P_{elec,d-1} + \beta_2 \Delta P_{DE,d} + \beta_3 \Delta Load_d + \beta_4 \Delta RES_d + \varepsilon_d \quad (3.1)$$

According to Weron (2014), AR-type models provide the backbone of all time series electricity price models, therefore the autoregressive explanatory variable ($P_{elec,d-1}$) is used in the model. The German–Austrian market features an important renewable capacity that is obviously related to the strong renewable support scheme that has been in place for many years (Würzburg et al., 2013). Explanatory variable $P_{DE,d}$ is added into the models, as the influence of German electricity price on electricity prices across other regions is confirmed in other studies (Bunn & Gianfreda, 2010; Lindström & Regland, 2012; Ziel et al., 2015). According to Würzburg et al. (2013) Germany is a highly developed economy where the energy markets are linked either through substitution possibilities for consumers or through input factor influences (such as gas-fired power plants). For the studied perimeter, we could not find appropriate public coal and gas price indexes therefore, variable $P_{DE,d}$ is used as an indicator for the fuel and CO2 price levels in Greek, Hungarian, and Romanian markets. The electricity demand $Load_d$ is inelastic, but with high seasonality and sensitivity to weekly patterns of consumption. The MOE in Equation (3.1) is controlled by the variable RES_d measuring the daily wind and solar electricity generation.

3.3.2 Electricity price simulation in the no-RES generation scenario

In the no-RES generation simulation, we adjust observed hourly electricity prices by eliminating present merit order effect and adjusting net-export levels. Therefore, simulation requires estimation of the power plants merit order and electricity exports dependency on RES generation. In the no-RES generation scenario, an additional quantity that must be supplied from the conventional power plants is equal to the sum of realised RES-generation and net-export implied by the RES generation (foreign demand for cheaper energy). The power system characteristic is that the electricity supply and demand must always be balanced. Therefore, we can equate the required volume of additional conventional generation to secure the power system balance in the simulated no-RES generation scenario by Equation 3.2:

$$\Delta ConventionalSupply_h = \Delta Load_h + \Delta NX_h - \Delta RES_h \tag{3.2}$$

The electricity demand is deemed to be inelastic; therefore, we can reconstruct the realised intersection of the aggregated supply and demand curve as a function of the observed electricity day-ahead price and the estimated merit order of the system power plants. The simulated electricity price in the no-RES scenario corresponds to a shift of the supply and demand curve. The left shift of the supply curve is equal to the realised RES generation, whereas the demand shift is equal to the estimated change in the net export ($\Delta\widehat{NX}$) triggered by the RES generation. Therefore, estimated energy imbalance ($\widehat{EnergyImbalance}$) caused by the excluded RES generation is filled by the additional conventional generation supply, according to Equation 3.3:

$$Energy\widehat{Imbalance}_h = \Delta\widehat{NX}_h - \Delta RES_h \tag{3.3}$$

The estimated $Energy\widehat{Imbalance}_h$ is the required additional conventional supply that secures the power system balance and is priced according to the estimated system merit order. The simulated market clearing electricity price is equal to a price in the last price-quantity pair that fills estimated $Energy\widehat{Imbalance}$ quantity.

3.3.2.1 Impact of the RES generation on electricity net export

Traber & Kemfert (2009) confirmed that the neighbouring countries with lower RES generation in their generation mix (high CO_2 intensity) benefit by the electricity imports from countries with higher RES generation in the generation mix (low CO_2 intensity). The impact of RES generation on net export is estimated by the multivariate regression model (Equation 3.4). According to the economic theory, the electricity net export should be lower in no-RES generation scenarios. Therefore, it is crucial to quantify the impact of RES generation on electricity net export and account for it in the no-RES generation scenario. In Equation 24, electricity net export (NX_h) is the dependent variable, whereas the explanatory variables include the 24-hour-lagged electricity net export (NX_{h-24}) and the realised wind and solar generation (RES_h), whereas ε_h represents the standard disturbance term. In the multivariate regression model, defined by Equation 3.4, Δ represents the first difference operator and h stands for the hourly observations:

$$\Delta\widehat{NX}_h = \beta_o + \beta_1 \Delta NX_{h-24} + \beta_2 \Delta RES_h + \varepsilon_h \tag{3.4}$$

The influence of RES generation on net export, i.e. international trade, is controlled by the NX_h variable calculated as a sum of all country inflows and outflows (Equation 3.5):

$$NX_h = \sum_i^I (Inflow_i - Outflow_i) \quad where\ i \in \{Border_1, \dots, Border_I\} \tag{3.5}$$

The impact of RES generation on net export is estimated by the 7-day rolling-window approach over the available data set. Therefore, each model is estimated on 168 hourly data points.

3.3.2.2 Merit order estimation

The ranking of the generation units by their short-run marginal costs in the increasing order, together with the dispatched energy, can be efficiently simulated by the unit commitment models[7] that minimises the total dispatch costs of the power plant fleet (Schill et al., 2017). For the considered time-period and analysed country scope, we could not obtain the required data.[8] With our publicly available data source, we were limited to the reported aggregated hourly output for each type of power plants (presented in Figure 3.2) and hourly day-ahead power prices. Therefore, we model short-term economic dispatch of gas, lignite, nuclear, and other power plants on the aggregate level. Due to the low marginal costs of generation, the supply of the hydro and nuclear technology is predominantly defined by the hydrology levels and nuclear availability. The economic dispatch of the hydro and nuclear power plants in the no-RES generation scenario is due to the low marginal costs and technical characteristics of the generation deemed to be unchanged. The merit order of gas, lignite nuclear, and other power is modelled according to Equation 3.6, where $P_{elec,i,h}$ is the day-ahead electricity price, $OutputShare_{i,h}$ is the percentage output of the observed aggregate power plant capacity and $\varepsilon_{i,h}$ is the error term. According to the electricity market, economics observed day-ahead electricity price ($P_{elec,i,h}$) corresponds to the generation marginal costs of the most expensive power plant serving electricity to the market. In Equation 3.6, h stands for the hourly observations:

$$OutputShare_{i,h} = \beta_o + \beta_o P_{elec,i,h} + \varepsilon_{i,h} \quad where \ i \in \{Gas, Lignite, Other\} \tag{3.6}$$

Non-linear electricity price behaviour fundamentally results from the profile of the supply curve. Therefore, we estimate model defined by Equation 3.6 with predictive modelling approaches that can handle such non-linearities. We have estimated the merit order for the distinct types of power plants by three data mining algorithms: the k-nearest neighbours algorithm (KNN)[9], regression tree algorithm (M5P)[10], and the random forest algorithm (RFR)[11]. Merit order is estimated by the 7-day rolling-window approach over the entire data set. The selected window size is large enough for the unbiased estimation and narrow enough to recognise for the temporary supply features. By the term ‘temporary supply features,’ we specifically address non-accounted variables such as generation availability, fuel prices, CO_2 prices, start-up costs, strategic behaviour, etc.

3.4 Data

Data availability and accessibility historically limited applied power market research (Hirth et al., 2018). The situation in Europe has changed in 2015 with the commencement of the

[7] Troha and Hauser (Schill & Gerbaulet, 2015) used unit commitment model to evaluate the impact of start-up costs and grid operator on the UK power price equilibrium. Schill et al. investigated the impact of fluctuating RES generation on the start-up costs in Germany (Schill et al., 2017).
[8] Unit commitment models are reliable and efficient, but require exact set of data for each individual power plant (generation data, outages data, start-up cost, efficiency factor, fuel prices, CO_2 price, etc.).
[9] For a detailed description of the KNN algorithm please refer to (Mangalova & Agafonov, 2014).
[10] For a detailed description of the M5P algorithm please refer to (Wang & Witten, 1996).
[11] For a detailed description of the RFR algorithm please refer to (Breiman, 2001).

Transparency Platform (TP) (ENTSO-E TP, 2020) operated by the European Network of Transmission System Operators for Electricity (ENTSO-E). The Hungarian, Greek, and Romanian working data sets span from 1.1.2015 to 30.9.2018, resulting in a time series of 1,368 days or 32,832 hourly observations.

With the available ENTSO-E TP data, we were limited to the reported aggregated hourly output for each type of power plants, scheduled commercial exchanges (net export), and hourly day-ahead power prices. In the data collection phase, we noticed that there are missing data points and non-reported data types in the ENTSO-E TP data base. Therefore, the Romanian data set is a blend of ENTSO-E TP data and Romanian national transmission system operator's data source (Transelectrica, 2020) for the reported aggregated actual generation. With the blended data set, we can econometrically confirm the MOE and quantify the RES generation effect on the country's net exports. The no-RES generation simulation is structured upon the estimated merit order, as we could not find required data for solving unit commitment problem (historical power plant output, fuel prices, start-up costs, efficiency, etc.). Merit order estimation is performed with the family of data mining algorithms that can handle non-linearities associated with the profile of the supply curve and electricity prices. Due to the limited public data availability, the analysed countries can still be classified as less mature power markets.

3.5 Results & discussion

3.5.1 Econometric merit order effect verification and quantification

Multivariate regression models are estimated to econometrically confirm and quantify merit order effect in Hungary, Greece, and Romania in the period from 2015 to 2018-Q3. For each country, we have estimated eight model specifications to quantify and confirm MOE. Estimation results are reported in the Appendix Table A12. Model specifications 1–4 are estimated on the individual calendar year data samples. Model specification 5 is estimated on the whole data sample from year 2015 to 2018-Q3. Model specification 6 differentiates the impact of solar and wind generation on the observed day-ahead electricity prices. Models 7 & 8 differentiate the MOE of upper quarter of high-load days and the lower quarter of low-load days.

Estimation on the individual calendar year data samples is done to observe possible differences due to varying penetrations of renewable sources, and due to possible long-run adjustment of the electricity sector to merit-order effects (model specification 1–4). In Figure 3.2, we can observe that the electricity generation mix shares are varying in the analysed period. In all countries, we can observe a tendency towards less lignite generation share in the generation mixes. With such an analysis setting, we can detect the influence of generation shares in generation mixes on the price effects of renewable generation over the time.

Model specification 5 is estimated on the whole data sample from year 2015 to 2018-Q3. Table 3.2 summarises estimation results of model 5 and confirms MOE, i.e. negative impact of increased RES generation (Δ*Ren)* on electricity prices. Model specification 6 is estimated to differentiate the impact of solar and wind generation on the observed day-ahead electricity prices. This is done by the use of separate coefficients that intend to identify the different generation patterns of these technologies (Würzburg et al., 2013). Econometrically estimated quantitative MOE is interpreted as a price reduction in €/MWh for each additional GWh of renewable generation. Würzburg et al. (2013) reported that much higher price effects are reported for smaller power systems compared to larger power systems, as the 1 GWh of additional electricity generation presents much higher generation share in smaller systems. Models 7 & 8 are estimated on data samples of upper quarter of high-load days and the lower quarter of low-load days. This is done to verify economic theory, that due to the steep profile of merit order curve when the electricity system is close to full capacity, RES generation has much higher impact on the electricity price reduction. This phenomena is observed and confirmed in following reviewed papers: Gelabert et al. (2011), Jonsson et al. (2010), and Würzburg et al. (2013). Estimation results for different model specifications for the Greek electricity market are reported in Table A12, for the Hungarian electricity market in Table A13, and for the Romanian electricity market in Table A14 of the Appendix.

Table 3.2: OLS estimation of daily changes in electricity prices (2015-2018-Q3)

Model 5	GR	HU	RO
	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*
Δ*Pelec, t-1*	0.704 [0.00***]	0.582 [0.00***]	0.549 [0.00***]
Δ*DE, t*	0.160 [0.00***]	0.313 [0.00***]	0.283 [0.00***]
Δ*Load, t*	0.001 [0.00***]	0.006 [0.00***]	0.004 [0.00***]
Δ*Ren, t*	-0.004 [0.00***]	-0.013 [0.00***]	-0.007 [0.00***]
R^2	0.77	0.75	0.72
Adjusted R^2	0.77	0.75	0.72
F-test	1127.29	994.96	846.03
p-value (*F*)	0.00	0.00	0.00

Note: *** and ** indicating significance at 1% and 5 % levels, respectively; and p-values in [] brackets.

Source: Own work.

Model specification 5, estimated on the whole data sample, confirms the MOE presence in all three countries. The coefficients of renewable generation reported in Table 3.2 are negative and statistically significant. Greek day-ahead electricity price decreases ceteris paribus by 4 €/MWh for each additional GWh produced by the RES. Ceteris paribus, The Hungarian day-ahead electricity price would decrease by roughly 13 €/MWh, whereas the Romanian electricity price would decrease on average by 7 €/MWh for each additional GWh produced by the RES.

Model specifications 1–4, estimated for each individual year (2015–2018), confirm the general findings of the model 5. In the Greek electricity market, coefficients associated with the RES generation are always negative and indicate an average decrease of electricity price from 5–7

€/MWh for each additional GWh produced by the RES. In Figure 3.2, we can observe the highest share of gas generation in the year 2017. The gas price is only significant for the high-load days because of the additional requirements for fossil fuels so that peak-load plants can cope with the unusually high demand (Würzburg et al., 2013). Therefore, the electricity price was frequently set by the expensive gas generation technology. This coincides with the highest econometrically estimated MOE in 2017.

The coefficients associated with RES generation in Hungary are always negative and indicate an average decrease of the electricity price from 5–35 €/MWh for each additional GWh produced by the RES. In 2017, the high Hungarian electricity price coincided with the high share of gas generation in that year (Figure 3.2). The highest MOE is – similar to the Greek market – estimated by the model specification 3 for the calendar year 2017. The coefficients are statistically significant, except in the model estimated on data for 2018.

Generation shares in the Romanian generation mix are stable (Figure 3.2). RES generation coefficients for Romania are always negative and indicate an average decrease of electricity price from 6–11 €/MWh for each additional GWh produced by the RES. The highest MOE is estimated by the model specification 1 for the calendar year 2015. Therefore, the highest estimated MOE in the first year could be associated with the lagging adjustment of the electricity sector to merit-order effects.

Model specification 6 differentiates the MOE of wind and solar generation. According to Table A11 of the Appendix, the observed maximum solar penetration and wind penetration in Greece are 1.7 GW and 2.1 GW, respectively (ENTSO-E TP). The wind and solar generation coefficients in Greece are negative, similar in levels, and statistically significant. Ceteris paribus, additional GWh of wind generation decreases day-ahead electricity prices approximately by 4 €/MWh, whereas an additional GWh of solar generation reduces electricity prices by 3€/MWh. As there was no solar generation in Hungary in the analysed period, model specification 6 estimated to differentiate the MOE of wind and solar generation is equivalent to model specification 5. According to Table A11 of the Appendix, the observed maximum solar penetration and wind penetration in Romania are 2.8 GW and 0.9 GW, respectively (ENTSO-E TP). The wind generation coefficient in Romania is statistically significant and negative and, while solar generation coefficient is statistically significant and positive. Positive solar generation coefficient indicates higher electricity prices with solar penetration in the generation mix. This is not in line with the economic reasoning outlined in Section 2. Solar generation peaks in summer during day hours, where the electricity prices are due to naturally lower hydro generation availability and higher electricity consumption (air conditioning) typically higher. This positive correlation between the summer solar generation and electricity prices might have influenced model estimation. The inclusion of a dummy variable indicating a summer period did not improve the results.

For Greece, the comparison of the MOE on high- and low-load days confirms the findings of previous studies, wherein the MOE is more pronounced for high-load days. The difference between the high-load days (model specification 7) and low-load days (model specification 8) is approximately 2 €/MWh. The estimated coefficients are statistically significant in both model specifications. Similarly, the comparison of MOE on high and low load days in Hungary reveals an approximately 5 €/MWh difference in electricity price reduction. For Romania, the obtained results are not completely in line with previous studies, as the estimates indicate higher MOE on low load days, where the difference between the high- and low-load days is approximately 1 €/MWh.

3.5.2 Electricity price simulation in the no-RES generation scenario

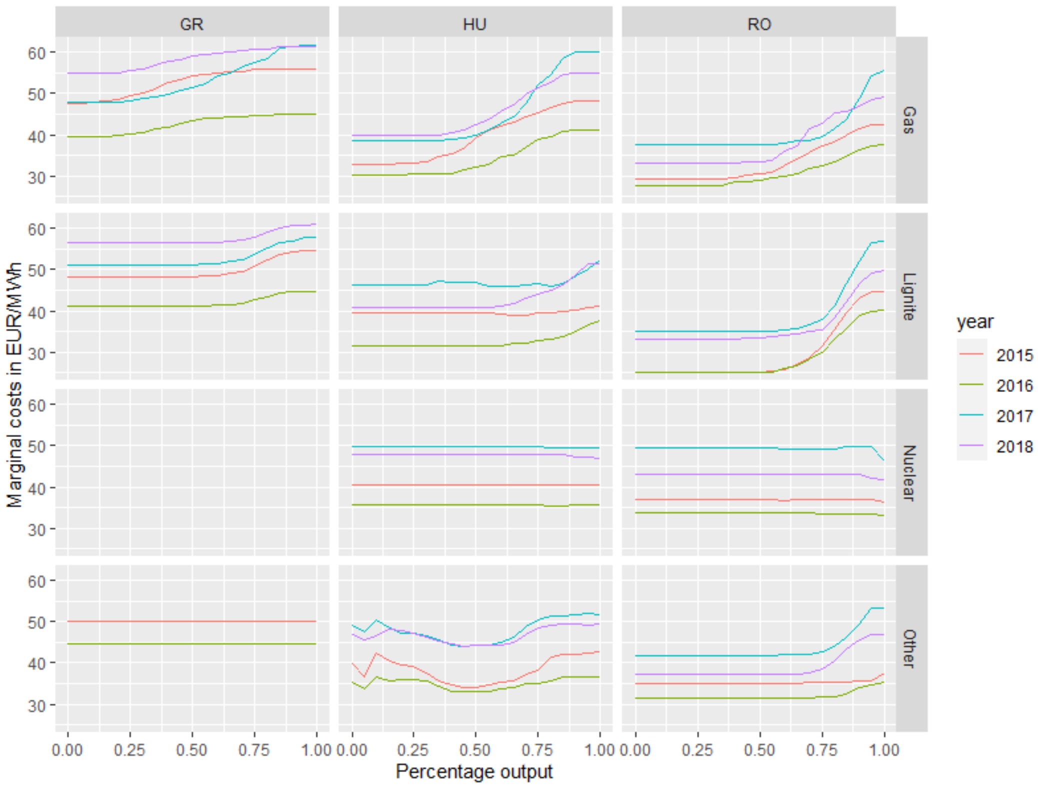
The adjustment of the realised day-ahead prices to the no-RES generation scenario requires several pieces of analysis. Firstly, it is crucial to quantify the impact of RES generation on the electricity net export. In the no-RES generation scenario, the electricity net export must be adjusted for the electricity net-export share associated with the RES generation. Secondly, merit order estimation is required for the determination of the aggregated demand and supply curve intersection (given the inelastic domestic demand assumption and observed day-ahead electricity price). Based on the estimated energy imbalance caused by the excluded RES generation (Equation 3.3), new no-RES generation electricity day-ahead price is determined with a left shift of the estimated merit order and demand shift that is equal to the estimated change in the net export.

Foreign demand for cheaper energy, i.e. the impact of RES generation on net export is estimated by the multivariate regression model (Equation 3.4). The model is estimated by the 7-day rolling-window approach over the available data set. The explanatory variable RES_t illustrates the impact of RES generation on net export. The estimation summary for the Greek electricity market results in statistically significant coefficients indicating that 4.5–5.5% of the Greek net export is RES generation dependent (Table A15). Yearly aggregation of the estimation results for the Hungarian electricity market is reported in Table A16 in the Appendix. The coefficient has a positive value between 0.43–0.85 and is statistically significant. Therefore, 43–85% of the Hungarian net export is RES generation dependent. Further, 46–53% of the Romanian net export is attributed to the RES generation (Table A17). The estimated explanatory coefficients are statistically positive and in line with previous research findings. A more detailed analysis of the RES generation impact on electricity net export is beyond the scope of this research. This is in line with the research findings of Traber & Kemfert (Traber & Kemfert, 2009), that the neighbouring countries with lower RES generation benefit by the electricity imports from countries with higher RES generation in the generation mix.

Merit order, i.e. ranking of the generation units by their short-run marginal costs in increasing order, together with the dispatched energy, is estimated by the family of data-mining algorithms. Different merit order estimation approaches are applied to assure and confirm simulation robustness. Merit order is estimated by the 7-day rolling-window approach over the entire data set. Figure 3.3 represents the aggregation of weekly merit order estimations by the regression tree algorithm (M5P). Estimated merit orders by the *k*-nearest neighbours (Figure A4) and random forest regression algorithms (Figure A5) have similar shapes compared to the M5P algorithm and are presented in the Appendix. Both algorithms serve as a robustness check and lead to similar results compared to the M5P algorithm. Supply curve shapes are defined by the technology short-run marginal costs. Estimated aggregated short-term economic dispatch of the marginal cost intensive technologies is in accord with the economic reasoning discussed in (Schröder et al., 2013).

Estimated supply curves of gas and lignite power plants have the steepest slope, which is expected due to the high fuel and CO_2 costs.[12] Conversely, the nuclear supply curve is very stable due to the low marginal costs and limited generation flexibility. The estimated supply curve of the nuclear technology is perfectly elastic at the approximate yearly average electricity price level. This confirms that the nuclear generation variation is especially low and estimating characteristic supply curve is unreasonable. Therefore, nuclear power plant generation is excluded from the merit order used in the no-RES generation scenario.

Figure 3.3: Estimated merit order by the M5P algorithms.



Source: Own work.

[12] For general review of generation costs for different electricity generation technologies please refer to Schröder et al. (2013).

Power plants classified under the category "Other" represent only a small generation share in the analysed scope (Figure 3.2). The estimated U-shaped Hungarian curve for other supply is a result of aggregating all other ENTSO-E TP generation types into this category (Biomass, Fossil Oil, Other, etc.) The estimated other supply curve for the Greek market is perfectly price elastic (Fossil Oil; ENTSO-E TP category), whereas for the Romanian market (Biomass; ENTSO-E TP category) it is price dependent. The merit order estimated by the *k*-nearest neighbours algorithm is graphically represented in Figure A4 of the Appendix.[13] Figure A5 of the Appendix is a graphical representation of the merit order estimated by the random forest algorithm.[14]

Merit orders estimated by all three algorithms are similar in shape and confirm discussed technology characteristics. The applied modelling approaches are suitable to cope with the non-linear electricity supply curve behaviour. Nuclear power plant generation is confirmed to be stable and does not vary. Due to the low marginal costs of generation, the supply of the hydro and nuclear technology is predominantly defined by the hydrology levels and nuclear availability. The slope of the merit order is defined by the technologies with significant short-term marginal costs of generation. Therefore, the adjusted electricity price in the no-RES generation simulation is determined by the estimated merit order of lignite, gas, and other technology.

Table 3.3: No-RES generation simulation results

			Realised Prices		Simulated Prices		Difference	
Year	Country	Model	Mean	S.D.	Mean	S.D.	Mean	S.D.
2015	HU	KNN	40.61	236.59	40.77	232.01	0.17	-4.58
2015	HU	M5P	40.61	236.59	40.66	234.85	0.05	-1.75
2015	HU	RFR	40.61	236.59	40.82	231.84	0.21	-4.75
2016	HU	KNN	35.49	171.09	35.52	170.50	0.03	-0.60
2016	HU	M5P	35.49	171.09	35.49	170.88	0.01	-0.22
2016	HU	RFR	35.49	171.09	35.54	170.19	0.05	-0.90
2017	HU	KNN	50.36	580.99	50.36	580.99	0.00	0.00
2017	HU	M5P	50.36	580.99	50.36	580.99	0.00	0.00
2017	HU	RFR	50.36	580.99	50.36	580.99	0.00	0.00
2018-Q2	HU	KNN	46.46	291.18	46.46	291.12	0.00	-0.07
2018-Q2	HU	M5P	46.46	291.18	46.46	291.13	0.00	-0.06
2018-Q2	HU	RFR	46.46	291.18	46.46	291.04	0.00	-0.14
2015	GR	KNN	51.93	121.42	52.75	105.21	0.82	-16.21
2015	GR	M5P	51.93	121.42	52.13	119.75	0.20	-1.67
2015	GR	RFR	51.93	121.42	52.89	104.76	0.96	-16.66
2016	GR	KNN	42.85	81.07	44.13	83.76	1.28	2.69
2016	GR	M5P	42.85	81.07	43.18	80.06	0.33	-1.00
2016	GR	RFR	42.85	81.07	44.43	82.89	1.58	1.83

[13] A free parameter applicable to this specific model application, "*k*" (number of nearest neighbours), is set to 20. For detailed algorithm description please refer to Mangalova & Agafonov (2014).

[14] A free parameter applicable to this specific model application, "number of trees," is set to 20. For a detailed RFR algorithm description, please refer to Breiman (2001).

			Realised Prices		Simulated Prices		Difference	
Year	Country	Model	Mean	S.D.	Mean	S.D.	Mean	S.D.
2017	GR	KNN	54.68	292.08	57.56	322.83	2.88	30.75
2017	GR	M5P	54.68	292.08	55.53	297.71	0.85	5.63
2017	GR	RFR	54.68	292.08	57.94	332.23	3.26	40.15
2018-Q2	GR	KNN	56.94	103.94	58.96	76.84	2.02	-27.10
2018-Q2	GR	M5P	56.94	103.94	57.55	94.59	0.61	-9.36
2018-Q2	GR	RFR	56.94	103.94	59.35	72.48	2.41	-31.46
2015	RO	KNN	36.43	204.84	37.66	197.59	1.23	-7.25
2015	RO	M5P	36.43	204.84	36.85	204.64	0.42	-0.20
2015	RO	RFR	36.43	204.84	38.03	195.57	1.60	-9.27
2016	RO	KNN	33.37	163.77	34.63	160.33	1.25	-3.44
2016	RO	M5P	33.37	163.77	33.76	164.20	0.39	0.43
2016	RO	RFR	33.37	163.77	35.01	156.80	1.63	-6.97
2017	RO	KNN	48.19	575.54	50.34	564.07	2.15	-11.47
2017	RO	M5P	48.19	575.54	48.88	572.86	0.69	-2.69
2017	RO	RFR	48.19	575.54	50.91	563.52	2.72	-12.02
2018-Q2	RO	KNN	41.19	356.62	42.91	343.25	1.72	-13.37
2018-Q2	RO	M5P	41.19	356.62	41.63	353.76	0.44	-2.86
2018-Q2	RO	RFR	41.19	356.62	43.26	346.44	2.07	-10.18

Source: Source: Own work..

Table 3.3 summarises the results of the no-RES scenario simulation based on the previously analysed impact of RES generation on net export and estimated merit order. The Hungarian realised day-ahead price adjusted to the no-RES generation scenario on average changed insignificantly (Table 3.3). In year 2015, simulated electricity prices would rise between 0.05–0.21 €/MWh, whereas the standard deviation is reduced. Analogous results are established for the year 2016. The reduced standard deviation in the no-RES generation scenario, registered in all simulation years, is a result of eliminated volatile RES generation. Similar to Dong et al. (Dong et al., 2019), we confirm that RES generation amplifies electricity price volatility. In contrast, according to the simulation results in years 2017 and 2018, the effect of RES generation on the electricity prices is insignificant. Due to lower RES generation share in the Hungarian generation mix (Figure 3.2) and high electricity exports associated with the RES generation (Table A15 of the Appendix), simulation results correspond to the MOE reasoning. Simulation robustness is proved, as the general conclusions do not depend on the selected merit order forecasting algorithm.

The Greek realised day-ahead price adjusted to the no-RES generation scenario on average changed between 0.2–3.26 €/MWh. Estimated energy imbalance covered by the conventional generation technologies had the highest impact on the electricity prices in simulation years 2017 and 2018. However, in the analysed period, the Greek RES generation share remained steady. Therefore, simulated electricity price peaks in years 2017 and 2018 coincide with the changed estimated merit order profile of gas generation. In years 2017 and 2018, the estimated merit order profiles become much more explicit and with notable slope changes near the full capacity utilisation (Figure 3.3). After year 2016, German electricity prices significantly increased. Therefore, changed estimated merit order profiles slope is most likely associated with the structural change in the short-term marginal costs structure. The highest electricity price increase between 0.85–3.26 €/MWh is simulated in year 2017. Price volatility is on average reduced, though in 2017 simulation results indicate increased price volatility. The lowest hydro generation is reported in year 2017 (Figure 3.2), whereas RES generation share remained steady. As a result, market clearing price occurred more frequently at the steepest profile of the supply curve. Low hydrology was compensated by the increased lignite and gas generation (Figure 3.2). Therefore, realised RES generation had to some extent stabilizing effect on the electricity prices as the simulated standard deviation in no-RES scenario increased. Due to higher RES generation share in the Greek generation mix (Figure 3.2) and low electricity exports associated with the RES generation, simulation results correspond to the MOE reasoning.

The Romanian realised day-ahead price adjusted to the no-RES generation scenario on average amounted between 0.39–2.72 €/MWh (Table 3.3). The estimated energy imbalance covered by the conventional generation technologies had the highest impact on the electricity prices in simulation years 2017 and 2018. In the analysed period, the Romanian RES generation share remained steady. Therefore, the simulated electricity price peaks in years 2017 and 2018 coincide with the changed estimated merit order profile of the gas and lignite generation. The estimated merit order profiles in these years become much more explicit and with notable slope changes near the full capacity utilisation (Figure 3.3). The simulation results confirm reduced price volatility with excluded RES generation. With the simulation results, we can confirm that the RES generation has much higher impact on the electricity price reduction if the electricity price setting occurs at the steep profile of the merit order. The highest electricity price increase between 2.15–2.72 €/MWh is simulated in year 2017. The highest electricity price increase coincides with the lowest reported hydro generation in Romania and structural change in the German electricity price. The German electricity price was on average 5 €/MWh higher in year 2017 compared to the year 2016 (Table 3.1). In year 2018, the German electricity price rose an additional 7 €/MWh. The change in the estimated Romanian gas & lignite supply curves profiles coincides with a rise of German electricity prices. Therefore, we conclude that the rise in Romanian electricity prices is associated with higher short-term marginal costs of electricity generation. Further analysis is beyond the scope of this chapter.

The simulated electricity price and standard deviation are on average reduced in all three countries. Due to the lower RES generation share in the Hungarian generation mix (Figure 3.2), simulation results indicate minor price changes and standard deviation reductions. Therefore, simulation results are more representative in the Greek and Romanian electricity markets, as the price increments are in the range 0.2–3.26 €/MWh, and with notably reduced standard deviations. The overall simulation robustness is provided, as the general conclusions do not depend on the selected merit order forecasting algorithm.

3.5.3 Discussion

Würzburg et al. (2013) classify MOE studies in the simulation-based and empirical analysis studies. In our study, the initial empirical confirmation and ceteris paribus quantification of the MOE is performed by the frequently practiced econometric approach. The adjustment of the realised day-ahead prices to the no-RES generation scenario is simulated according to the estimated power plant merit order. Simulation-based studies typically rely on solving information rich and flexible simulation models used for power system or agent-based simulations (Schill et al., 2017; Troha & Hauser, 2015). Due to the limited public data availability in the analysed country scope discussed in the previous sections, assembly of such simulation-based studies was not feasible. Therefore, modern statistical methods are used to bridge this gap in the preparation of the no-RES generation simulation. A family of data mining algorithms is used to estimate the power plants merit order. The estimated energy imbalance caused by the excluded RES generation is compensated by the additional conventional generation dispatch according to the estimated power plant merit order that sets a new electricity price.

Due to the fundamental difference in electricity generation mixes, interconnection properties, and approaches to the analysis, the comparison of obtained results from different studies could be misleading and should be done with special care. Therefore, we limit discussion section to the MOE econometric confirmation, as the ceteris paribus quantification of the MOE is a characteristic of the individual electricity market. In the existing literature focused on the key EU energy markets, MOE is econometrically confirmed by the negative sign and statistical significance of the explanatory variable indicating the effect of RES generation on electricity prices. Based on the estimated econometric models, we confirmed MOE in Hungarian, Romanian, & Greek electricity markets. In Greece, we could not find significant difference between the coefficients for solar and wind generation, and therefore the price effects seem to be very similar. Conversely, the Romanian solar generation coefficient turned out to be positive. The positive correlation between the pronounced summer solar generation peak and high electricity prices might have influenced model estimation. Wind is the only reported RES source in the Hungarian electricity system, therefore the distinction between the effect of solar and wind generation on electricity prices in not applicable.

The estimated MOE in Hungary and Greece is higher on the high-load days compared to the low load days. A similar effect is reported by Würzburg et al. (2013), Sensfuß et al. (2008), Weight (2009), and Wo et al. (2009). In contrast, the estimated MOE in Romanian electricity market is higher on low load days. One possible explanation for this contradicting phenomenon is a steeper profile of the lignite supply curve. The estimated lignite supply curve has a steeper profile already in the lower-quantity area, compared to the estimated Hungarian and Greek lignite supply curves (Figure 3.3). The electricity price setting on low-load days occurs in the lower-quantity area, therefore a pronounced MOE could be justified by the steep merit order profile in the price setting area. The econometric findings are in accord to the estimated merit order profiles. Therefore, estimation of the power plant merit order by the modern statistical methods turned out to provide invaluable reasoning insights to the econometrically estimated results.

The simulation results of the no-RES generation scenario on average suggest insignificant changes of the Hungarian realised day-ahead price adjusted to the no-RES generation scenario. The Greek and Romanian electricity markets, with higher RES generation shares in their electricity generation mix, empirically qualify as more interesting case studies. In line with the economic theory, the simulation results indicate significant price increments in the no-RES generation scenario in both countries. Additionally, reduced price volatility is found due to eliminated intermittent RES generation.

Simulation robustness of our no-RES generation simulation is proved as the general conclusions do not depend on the selected merit order forecasting algorithm. On average, we confirm higher electricity prices and lower price volatility. Further, impact of RES generation is more profound with higher electricity prices, i.e. higher short-term marginal costs of production. Supply side dynamics associated with profit optimisation is due to the limited public data availability approximated with modern statistical methods and requires special attention in future research. The simulation approach, with the direct control of the short-term electricity production marginal costs, would provide additional valuable insights into the merit order data generation process.

3.6 Conclusion

With the empirical analysis and no-RES generation simulation, we confirm economic theory predictions that an increase in RES generation in the short-run reduces the electricity price in the Hungarian, Greek, and Romanian electricity markets. National promotion strategies triggered by the Directive (2001/77/EC) on renewable energies in the electricity sector are considered as the main reason for this development. All EU member states have introduced policies to support the market introduction of RES generation. Therefore, this chapter supplements and verifies existing literature findings focused on the investigation of the effects of installed renewable capacity on electricity market development.

Econometric models confirmed statistically significant MOE in all analysed countries. The RES generation effect on the electricity price levels primarily depends on the individual power system characteristics. Econometrically estimated MOE is quantitatively interpreted as a price reduction in €/MWh for each additional GWh of renewable generation. Therefore, the estimated merit order effect is much larger in the smaller Hungarian power system, compared to the bigger Greek and Romanian power systems. The estimated MOE is stable throughout different model variations and in line with the reviewed literature findings. In the Romanian electricity market, we found an exception, as the solar generation turned out to be positively correlated with electricity prices. The positive correlation between the pronounced summer solar generation peak and high electricity prices might have influenced model estimation with differentiated RES sources. In the Hungarian and Greek electricity markets, we found a pronounced MOE on high-load days, whereas in Romania the effect is more pronounced on low-load days. The estimated supply curves for each generation technology provided valuable insights to assist the reasoning behind the estimated econometric coefficients.

Simulation of the no-RES generation scenario accounts for the international flow dynamics and adaptation of the conventional generation dispatch to the omitted RES generation. The estimated energy imbalance in the no-RES generation scenario, caused by the excluded RES generation, is compensated by the additional conventional generation dispatch according to the estimated power plant merit order. A family of data mining algorithms applied for the merit order estimation suitably handled non-linear behaviour of the electricity price signals and bridged gap in limited data availability. The impact of RES generation on country net export is estimated by the multivariate regression model and empirically reveals that RES generation stimulates foreign demand. We confirmed price increments due to the excluded RES generation in all three countries. In addition, the reduced standard deviation in the no-RES generation scenario is a result of omitted volatile RES generation. Simulation robustness is proved as the general conclusions do not depend on the selected merit order estimation algorithm. Econometric MOE confirmation and supporting simulation framework turned out to be successful combination, as the estimated power system merit order profiles support results from econometric models.

CONCLUDING REMARKS

This doctoral dissertation aims to provide insights into electricity price forecasting and the roll of new developments in electricity markets. It provides answers to several research questions pertaining to the following three research topics: performance of alternative electricity price forecasting methods with findings from the Greek & Hungarian power exchanges; an integrated model for electricity market coupling with evidence from the European power market crossroad; and the crowding out of conventional electricity generation by renewable energy sources in Greek, Hungarian, and Romanian electricity markets. A summary of the findings and an assessment of the contribution to the field of knowledge is provided in the form of answers to the research questions identified in the beginning of the dissertation. Leading numbers indicate a chapter connection with a research question.

- *Research question 1.1: Do, in electricity price forecasting, modern statistical approaches (data mining and machine learning) perform better compared to the econometric time series model?*

Electricity price forecasting is a relatively young interdisciplinary research field, which started expanding with the power market liberalisation, when the first studies on the determinants of electricity prices in liberalised market emerged, and accelerated in Europe with the increased renewable generation after 2010. In the beginning, sophisticated statistical techniques were proposed to achieve satisfactory short-run predictions. With the increased renewable generation and implied increased electricity price volatility the field has moved towards the application of data mining and machine learning forecasting algorithms. Statistical models are criticized for linearity bias i.e., the inability to model rapid changes in the price signal. Systematic benchmarking of forecasting performance of the selected k-nearest, regression tree, random forest regression, support vector machine, artificial neural net, and long short-term memory algorithm against the econometric time series model, revealed that the support vector machine algorithm overcomes the linearity bias in the ordinary least squares estimator. This is confirmed by the lower forecasting accuracy metrics and a statistically significant Diebold-Mariano. A random forest, regression tree, and k-nearest neighbour algorithm have higher forecasting accuracy compared to the benchmark econometric model, however, with the statistically insignificant Diebold-Mariano test.

- *Research question 1.2: What is the effect of training data set size on the forecasting performance?*

With the electricity price forecasting shift towards the application of data mining and machine learning algorithms new research questions have emerged. Data mining and machine learning algorithms typically have a set of "free parameters" that can influence forecasting performance. Lago, De Ridder, & De Schutter (2018) presented to date the largest benchmark of electricity price forecasting algorithms with an open research question on optimal learning sample size. By relying on a large number of experiments for each individual model, we have extensively analysed the effect of training data set size on forecasting performance. The forecasting performance of the individual methods depends on the selected market, and so our findings cannot be used to formulate general statements about a method's optimal training sample size. However, our findings suggest that the sample size is positively correlated with the electricity price forecasting accuracy and models have a turning point after which the relationship is converted. Artificial neural network-based models achieve higher accuracy if trained on considerably larger training samples compared to the other proposed alternative models.

- *Research question 1.3: Does model training on hourly clustered data samples enhance electricity price forecasting performance?*

In one of the earliest electricity price forecasting publications by Crespo Cuaresma, Hlouskova, Kossmeier, & Obersteiner (2004), a univariate time series ARMA model was used to forecast Germany's day-ahead price. To fully extract the individual hour predictive information, they trained an ARMA model for each single hour i.e., model training on hourly clustered samples. The hourly clustered training regime has a consequence of having an individual model for each hour of the day. They reported better forecasting performance for models calibrated on the hourly clustered data samples. Scholars typically train a single model that is used to forecast all day hours. A consequence of the hourly clustered training regime is a reduction of training samples by the factor 24. Such a training regime could be a specific challenge for models that achieve higher forecasting accuracy if trained on considerably larger training samples. Our models trained on the Greek data set performed better with training on the hourly non-clustered data samples. However, training on hourly clustered Hungarian data samples on average resulted in higher forecasting accuracy. Therefore, training on hourly clustered data samples could in a specific electricity market enhance electricity price forecasting performance.

- *Research question 1.4*: Does the demand-supply ratio (DSR) explanatory variable enhance electricity price forecasting performance in extreme price situations?

An extreme price situation is characterised by a sudden departure of prices from the normal regime for a very short time interval. The DSR explanatory variable indicates the share of the available installed generation capacity to cover the electricity demand. High DSR index values indicate low availability of free generation capacities and tight market conditions (Alexander & Dominique, 2007). In tight market conditions, so-called 'price spikes' may occur. Conversely, in loose market conditions negative electricity prices may occur. In the Greek market, models reach better forecasting performance with the additional DSR ratio explanatory variable. And yet, in Hungary only the artificial neural network (ANN) model has the highest accuracy with added DSR ratio explanatory variable. However, under both data sets accuracy improvement is trivial, which is especially true considering the extreme price forecasting accuracy. Closely studying the forecasting behaviour on the 50 highest and 50 lowest observed prices in each market, revealed that the DSR explanatory variable has an insignificant impact on forecasting accuracy. Alexander & Dominique (2007) reported similar findings.

- *Research question 2.1:* How should market simulations be designed in coupled electricity markets?

One of the major changes in the European electricity markets is the fact that previously independent market areas have become connected through market-coupling auctions. Day-ahead market auctions are no longer organised separately for cross-border capacities (CBCs) and electricity. Instead, in coupled electricity markets the overall social-welfare maximising electricity prices and CBC allocations are determined jointly by the EUPHEMIA algorithm. Kiesel & Kusterman (2016) discussed that in coupled markets that it becomes crucial to model electricity prices in all areas consistently in one integrated framework. Further, Lago, et al. (2018) once again explained that there is a lack of a general modelling framework to model electricity market coupling and analyse its impact on the electricity market. Therefore, we propose an integrated simulation framework where the CBC's allocations and electricity prices are determined by the solution of a single mathematical optimisation problem, i.e., the

EUPHEMIA algorithm. An orderbook for each market area is generated based on the econometrically estimated aggregate supply price elasticities. With the proposed simulation framework, we can jointly analyse the impact of electricity market coupling on capacity allocation and its implications on electricity price determination process. Statistical models or advanced computational intelligence models are too general for such a detailed analysis.

- *Research question 2.2:* Does electricity market coupling ensure efficient cross-border capacity allocation and electricity price convergence?

To study the effect of electricity market coupling on efficient cross-border capacity allocation and electricity price convergence, the dissertation simulates market coupling at the power market crossroads of Europe. The simulation goal is to eliminate the observed inefficient CBCs utilisation at the time of the simulation non-coupled interconnectors, and to adjust market clearing prices in Austria, Italy, Slovenia, and Croatia, accordingly. The market coupling mechanism ensures that the transmission capacities are always efficiently utilised with the power flow following economic logic. Spare capacity on cross-border interconnectors occurs only when all opportunities for arbitrage have been exploited and prices are equal, which follows from the mathematical optimisation model. In the studied perimeter, we can observe that most severe and frequent inefficiencies in CBCs utilisation occur on the HRSI border. The HRSI border connects markets with low supply price elasticity and sufficient CBC to eliminate observed price spread majority of the time. Due to the asymmetry in the electricity and CBC rights auction in non-coupled markets, the price convergence between the Slovenian and Croatian markets is not achieved. A given mandate to market agents to regulate electricity transport in non-coupled markets is shown to be inefficient. Based on the simulation results, we confirm that the market coupling algorithm eliminates all inefficiencies in CBCs utilisation and enhances electricity price convergence. We can empirically confirm Meeus' (2011) research findings, that electricity market coupling outperforms previous market settings.

- *Research question 2.3:* What is the impact of market coupling on electricity price volatility?

As shown in the answers to Research questions 2.1 and 2.2, the dissertation that is based on the simulation results studies the implications and benefits from electricity market coupling on different market features. According to Lago, et al. (2018) effects of market integration, i.e., electricity market coupling can dramatically modify the dynamics of electricity prices. With the market coupling simulation results, we can empirically confirm reduced electricity price volatility in the simulated electricity market perimeter. The simulation results therefore confirm the findings of Huisman and Kiliç (2013), who econometrically analysed day-ahead prices in five connected Central Western Europe markets, and concluded that due to improved liquidity, volatility and extreme price situations are reduced in coupled electricity markets.

- *Research question 2.4:* Does market coupling improve electricity price shock transmission?

As shown in the answers to Research questions 2.1, 2.2 and 2.3, based on the simulation results the dissertation studies the implications and benefits from electricity market coupling on various market features. De Vany & Walls (1999) discussed that the statistical Vector Autoregression (VAR) model encompasses the type of complex price dynamics that are characteristic of electrical networks. Therefore, the dissertation analyses electricity price shock transmission indicating market integration with estimated VAR models and impulse response functions (IRF). As far as we are aware, this is the earliest analysis of electricity price shock transmission for the same price observation under realised non-coupled and simulated market coupling regimes. The comparison of estimated impulse response function representing electricity price shock transmission under both market regimes reveals modified electricity price dynamics in coupled electricity markets.

The observed price shock transmission with the characteristic 24-hour lag in the non-coupled market regime, indicates an incentive of market participants to readjust their strategies after the observed price shock in one of the neighbouring markets. Price shock transmission in the simulated market coupling regime is instantaneous and amplified. Market integration, indicated by the price shock transmission intensity and price shock transmission timing, empirically improves in the simulated market coupling environment.

- *Research question 3.1:* Does crowding out of conventional electricity generation sources by renewable energy generation lead to lower electricity prices on the Southeast Europe (SEE) electricity markets?

National promotion strategies, triggered by the Directive (2001/77/EC), to support renewable energy sources (RES) and achieve a less polluting and (foreign) dependent energy sector have many consequences. Among them, an increased renewable production of electricity crowds out other high(er) marginal-cost generation technologies and results in lower electricity prices in the wholesale electricity market (Würzburg et al., 2013). The crowding out of conventional electricity generation sources by renewable energy generation is recognised by scholars as the so-called ‘merit order effect’ (MOE). With the estimated econometric models on Hungarian, Romanian and Greek electricity market data, the dissertation statistically confirms the significant presence of MOE in the developing Southeast Europe (SEE) electricity markets. Executed econometric MOE analysis supplements existing research findings focused on key EU energy areas in terms of installed renewable capacity and electricity market development. Also, the dissertation adjusts observed hourly electricity prices to the simulated no-RES generation scenario by eliminating the observed merit order effect and adjusting net-export levels, accordingly. The estimated energy imbalance caused by the excluded RES generation is filled by the additional conventional generation supply. The required additional conventional generation dispatch to maintain energy balance is priced according to the estimated conventional generation supply curves. Hence, the simulated market clearing electricity price is equal to a price in the last price-quantity pair, supplied by the conventional generation that fills the estimated energy imbalance quantity. The simulation results indicate a significant price increment in countries with pronounced RES generation (Greece and Romania). Therefore, simulated significant price increments affirm econometric findings that RES generation leads to lower electricity prices on the Southeast Europe electricity markets.

- *Research question 3.2:* Can modern statistical approaches bridge the gap in data availability and efficiently simulate electricity prices in the no-RES generation scenario?

As illustrated in the answer to Research questions 3.1, the dissertation in the simulated no-RES generation scenario adjusts observed electricity prices accordingly. The applied no-RES generation simulation approach intuitively takes as an example DIME model (Dispatch and Investment Model for Electricity Markets in Europe) applied by Fürsch, Malischek, & Lindenberger (2012). The DIME model accounts for the international flows and dynamic adaptation of the generation mix to changes in RES generation. Dynamic adaptation of the generation mix can be efficiently simulated by the unit commitment model that minimises the total dispatch costs of the power plant fleet. Due to the limited publicly data availability, the unit commitment models used in the power system or agent-based simulations cannot be applied in analysed markets. Therefore, the dissertation relies on a family of data mining algorithms to rank generation units by their short-run marginal costs in the increasing order together with the dispatched energy. Due to the prominent non-linear behaviour of the electricity price signals (Weron, 2014), we estimate aggregated supply curves by the modern statistical approaches that can handle such non-linearities. The proposed simulation framework is intuitively close to power system or agent-based simulations. Therefore, the application of modern statistical approaches can bridge the gap in the limited public data availability to efficiently simulate electricity prices in the no-RES generation scenario.

- *Research question 3.3:* Does renewable energy source (RES) generation enhance electricity price volatility in Southeast Europe (SEE) electricity markets?

As shown in the answer to Research question 3.1, the dissertation in the simulated no-RES generation scenario adjusts observed hourly electricity prices accordingly. Therefore, the dissertation can analyse simulated electricity prices and observed electricity prices for the same time-periods. Electricity price volatility in the no-RES generation scenario is on average reduced compared to the observed price volatility. Reduced electricity price volatility is a result of omitted volatile RES generation. Therefore, renewable energy generation enhances electricity price volatility in the Southeast Europe (SEE) electricity markets. The research findings are consistent with the results found by Dong et al., (2019).

Hirth, Mühlenpfordt, & Bulkeley (2018) discussed that data availability and accessibility historically limited applied power market research. However, the situation in Europe changed in 2015 with the commencement of the Transparency Platform (TP) operated by the European Network of Transmission System Operators for Electricity (ENTSO-E). Applied electricity market research is data-intensive and requires hourly data resolution. The dissertation' quantitative work objective is to rely on a single data source and avoid common data blending approach, which limits fast and easy research reproducibility. Therefore, we collected data from ENTSOE-TP through a restful application programming interface (API) program in R environment. Downloaded data sets from ENTSO-E TP revealed specific data type unavailability and missing data observations. Due to missing reported outages data type, we could not have included the Romanian power market in the scope of the first chapter. Furthermore, the dissertation approximated missing hydro generation data in Croatia by Slovenian data in the second chapter. Lastly, due to the missing Romanian actual generation data on ENTSO-E TP, we could not avoid data blending in the third chapter. Data blending is clearly time-consuming as it requires development of additional data gathering procedures and data manipulation. We conclude that the data availability and quality is an ongoing issue still limiting applied electricity market research.

Even though the dissertation provides several new findings regarding the electricity price modelling and the role of new developments in electricity markets, several limitations exist. First, the dissertation offers a systematic quantitative overview of the forecasting performance of six contemporary forecasting algorithms only on Greek and Hungarian electricity market data. Therefore, it cannot be used to formulate general statements about a method's efficiency. Further, analysis is limited to a six fundamental contemporary forecasting algorithms and results cannot be generalised to other existing alternative algorithms. Second, analysis of the market coupling effect on electricity prices and cross-border capacities utilisation would greatly benefit from the inclusion of all EU electricity markets in the simulation scope. An extended simulation scope would as well enrich the vector autoregression analysis of the electricity price shock transmission. In addition, the orderbook generation process based on the econometrically estimated supply price elasticity function could be supplemented with other modern statistical methods. Third, electricity price simulation in the no-RES generation scenario is due to unavailable public data in the analysed countries limited to the execution with modern statistical methods. However, it would be valuable to simulate no-RES generation scenario with the agent-based unit commitment models and benchmark obtained results.

Despite the discussed limitations, which could stimulate much needed future research, the dissertation addresses certain unanswered research questions and showcases the practical application of modern statistical approaches in the electricity markets. First, with the first systematic overviews of the statistically evaluated forecasting performance of the contemporary algorithms with respect to the applicative limitations in the day-ahead market operations, the dissertation provides reliable information to the interested electricity market participants and research community. Further, the dissertation thoroughly analyses the impact of training sample size on algorithms forecasting performance and provides insights to this yet unaddressed research question. Second, with ongoing final steps in EU electricity markets integration, the dissertation proposes a solution for applied simulations in coupled day-ahead electricity markets. Scholars discuss that there is a lack of a general modelling framework to model electricity market coupling and analyse its impact on the electricity market. Moreover, the dissertation has empirical simulations that provide answers to the research questions on improved electricity price convergence, reduced price volatility, and improved price shock transmission in coupled electricity markets. Third, by researching the merit order effect in the developing SEE electricity markets, the dissertation supplements existing literature focused on key EU energy areas in terms of installed renewable capacity and electricity market development. Fourth, the electricity market research is data-intensive and typically requires hourly data resolution. Data availability and accessibility historically limits applied power market research. The dissertation is built upon a publicly available data source ENTSO-E TP, and avoids data source blending as much as possible. This ensures fast and easy study reproducibility and could hopefully promote future research.

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APPENDICES

Appendix 1: Chapter 1

Table A1: Greek price index descriptive statistics

Hour	Maximum	Minimum	Mean	Median	Standard deviation	Variance
1	82.00	0.00	49.22	49.59	8.49	72.11
2	82.00	1.00	47.96	48.98	8.94	79.96
3	76.53	0.00	46.07	47.25	9.90	98.01
4	76.51	0.00	44.79	46.40	10.54	111.09
5	76.11	2.00	45.34	46.83	10.10	101.92
6	79.00	0.00	47.15	48.41	9.15	83.67
7	145.56	5.00	49.94	50.15	9.97	99.39
8	145.56	0.00	52.41	51.29	12.25	150.00
9	150.25	0.00	53.38	51.80	13.64	186.13
10	150.27	0.00	53.07	51.41	13.55	183.67
11	150.32	0.00	52.19	50.95	13.23	175.05
12	150.32	0.00	51.36	50.64	12.93	167.16
13	150.30	0.00	50.92	50.49	12.80	163.92
14	141.61	0.00	48.99	50.00	12.67	160.54
15	150.27	0.00	49.80	50.14	13.92	193.73
16	150.27	0.00	51.11	50.56	14.23	202.45
17	150.27	0.00	53.06	51.09	14.90	221.98
18	299.00	7.70	55.95	52.30	18.37	337.46
19	299.00	26.52	57.73	53.00	19.99	399.47
20	299.00	32.00	58.10	53.66	19.05	362.87
21	149.00	36.91	56.21	53.23	13.78	189.94
22	145.05	25.00	52.71	51.65	9.01	81.18
23	111.11	2.00	51.34	51.20	7.88	62.12
24	83.50	0.00	50.75	51.10	10.12	102.51

Source: Own work.

Appendix 2: Chapter 1

Table A2: Hungarian price index descriptive statistics

Hour	Maximum	Minimum	Mean	Median	Standard deviation	Variance
1	83.64	0.02	33.22	32.10	11.49	132.06
2	79.03	0.00	29.81	29.30	10.53	110.81
3	64.49	0.00	27.24	26.89	9.99	99.79
4	60.25	–0.02	26.07	26.13	9.84	96.83
5	70.18	–17.44	26.97	26.80	9.98	99.60
6	88.74	–25.97	30.72	30.47	11.30	127.58
7	133.11	–6.00	38.42	38.55	14.67	215.18
8	195.15	0.02	46.87	46.81	18.26	333.45
9	250.04	0.08	50.18	49.10	19.24	370.09
10	250.09	0.11	50.40	48.47	19.03	362.30
11	250.05	0.21	49.28	46.96	18.83	354.55
12	250.07	0.21	49.27	46.57	19.20	368.47
13	190.35	0.21	48.50	45.66	19.39	375.88
14	150.03	0.05	46.34	44.07	19.01	361.31
15	200.07	0.01	45.36	43.02	19.41	376.59
16	250.02	0.10	46.21	43.92	19.99	399.48
17	250.06	0.25	48.32	45.84	20.46	418.52
18	300.10	2.15	51.39	49.01	21.25	451.50
19	200.07	11.06	53.40	50.76	19.35	374.61
20	150.06	15.99	55.06	52.18	18.16	329.73
21	144.43	10.30	53.49	51.00	16.55	273.88
22	133.39	6.44	46.85	44.01	14.34	205.61
23	113.04	0.78	42.48	40.60	12.56	157.67
24	93.23	0.02	36.17	34.50	11.36	129.13

Source: Own work.

Appendix 3: Chapter 1

Table A3: Working days EPF models performance – ascending sMAPE ordering

Country	Method	RL/DSR	Data sample	Test input	Window	MAE	RMSE	SMAPE	MAPE	DM test p-value
GR	SVM	DSR	Non-clustered	Actual	56	3.99	8.23	7.70%	13.20%	0.96
GR	SVM	DSR	Non-clustered	Forecast	56	3.98	8.22	7.70%	13.20%	0.89
GR	RFR	DSR	Non-clustered	Actual	28	4.33	8.59	8.20%	13.50%	1.00
GR	RFR	DSR	Non-clustered	Forecast	28	4.27	8.47	8.10%	13.50%	0.99
GR	M5P	DSR	Non-clustered	Actual	112	4.38	8.76	8.30%	13.30%	/
GR	M5P	DSR	Non-clustered	Forecast	112	4.36	8.67	8.30%	13.30%	/
GR	ARX	DSR	Non-clustered	Actual	28	4.54	8.26	8.70%	14.10%	1.00
GR	ARX	DSR	Non-clustered	Forecast	28	4.56	8.29	8.80%	14.20%	1.00
GR	KNN	DSR	Non-clustered	Actual	28	4.69	9.35	8.80%	13.90%	1.00
GR	KNN	DSR	Non-clustered	Forecast	28	4.65	9.25	8.70%	14.00%	1.00
GR	ANN	DSR	Non-clustered	Actual	140	4.80	8.80	9.20%	14.50%	1.00
GR	ANN	DSR	Non-clustered	Forecast	140	4.75	8.63	9.10%	14.50%	1.00
GR	LSTM	RL	Non-clustered	Actual	336	5.32	8.93	10.20%	15.40%	1.00
GR	LSTM	RL	Non-clustered	Forecast	336	5.33	8.94	10.10%	15.60%	1.00
HU	SVM	RL	Clustered	Actual	28	6.39	10.23	14.70%	18.90%	0.03
HU	SVM	RL	Clustered	Forecast	28	6.68	10.54	15.50%	19.00%	0.32
HU	ARX	RL	Clustered	Actual	112	6.73	10.81	15.20%	18.60%	/
HU	ARX	RL	Clustered	Forecast	112	7.10	11.24	16.30%	18.70%	/
HU	LSTM	RL	Clustered	Actual	112	6.73	10.81	15.20%	18.60%	0.59
HU	LSTM	RL	Clustered	Forecast	112	7.10	11.24	16.30%	18.70%	0.18
HU	RFR	DSR	Clustered	Actual	28	6.68	10.22	15.30%	19.40%	0.03
HU	RFR	DSR	Clustered	Forecast	28	6.68	10.23	15.40%	19.10%	0.33
HU	ANN	DSR	Non-clustered	Actual	224	7.06	11.57	15.80%	20.50%	0.97
HU	ANN	DSR	Non-clustered	Forecast	224	7.14	11.61	16.00%	20.80%	0.57
HU	M5P	RL	Non-clustered	Actual	28	7.08	10.83	16.10%	20.70%	0.52
HU	M5P	RL	Non-clustered	Forecast	28	7.22	11.01	16.70%	20.30%	0.61
HU	KNN	RL	Clustered	Actual	28	7.34	11.49	16.30%	22.30%	0.67
HU	KNN	RL	Clustered	Forecast	28	7.30	11.32	16.50%	21.90%	0.39

Source: Own work.

Appendix 4: Chapter 1

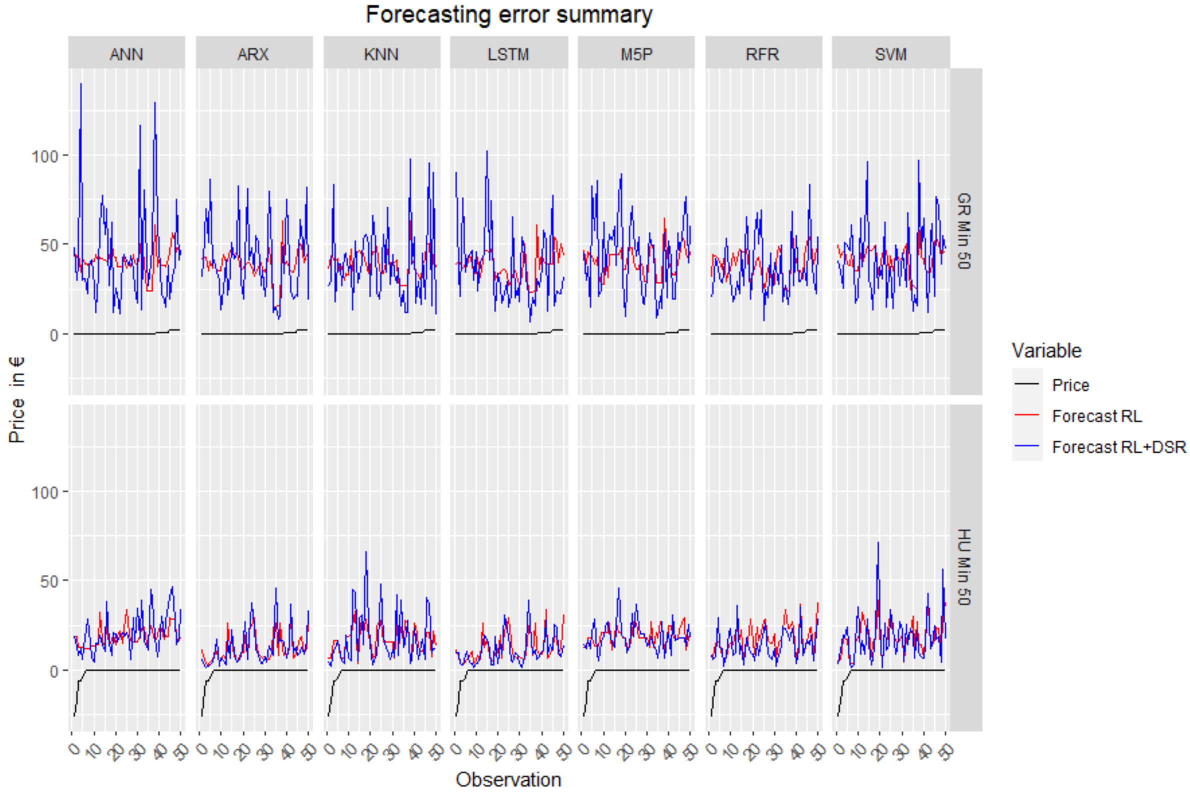
Table A4: Weekends EPF models performance – ascending sMAPE ordering

Country	Method	RL/DSR	Data sample	Test input	Window	MAE	RMSE	SMAPE	MAPE	DM test p-value
GR	SVM	DSR	Non-clustered	Actual	56	4.24	7.79	10.00%	26.40%	0.00
GR	SVM	DSR	Non-clustered	Forecast	56	4.27	7.92	10.10%	26.70%	0.00
GR	RFR	DSR	Non-clustered	Actual	140	4.45	7.33	10.50%	25.30%	0.00
GR	RFR	DSR	Non-clustered	Forecast	140	4.47	7.45	10.50%	25.30%	0.00
GR	M5P	RL	Non-clustered	Actual	196	4.54	7.59	10.50%	26.60%	0.00
GR	M5P	RL	Non-clustered	Forecast	196	4.59	7.69	10.60%	26.80%	0.00
GR	KNN	DSR	Non-clustered	Actual	28	4.70	8.27	10.80%	26.30%	0.06
GR	KNN	DSR	Non-clustered	Forecast	28	4.70	8.39	10.80%	26.30%	0.11
GR	LSTM	DSR	Non-clustered	Actual	336	4.95	7.74	11.40%	24.80%	0.00
GR	LSTM	DSR	Non-clustered	Forecast	336	4.90	7.76	11.20%	25.10%	0.00
GR	ANN	RL	Non-clustered	Actual	336	5.12	8.31	11.60%	27.80%	0.99
GR	ANN	RL	Non-clustered	Forecast	336	5.07	8.41	11.50%	27.10%	0.71
GR	ARX	DSR	Non-clustered	Actual	56	5.11	8.18	11.80%	26.70%	/
GR	ARX	DSR	Non-clustered	Forecast	56	5.10	8.25	11.80%	26.90%	/
HU	SVM	RL	Clustered	Actual	56	6.44	9.04	20.60%	35.60%	0.98
HU	SVM	RL	Clustered	Forecast	56	6.64	9.25	21.40%	35.50%	0.71
HU	ARX	RL	Clustered	Actual	112	6.58	8.93	21.30%	30.50%	/
HU	ARX	RL	Clustered	Forecast	112	6.99	9.34	23.10%	30.20%	/
HU	LSTM	RL	Clustered	Actual	112	6.58	8.93	21.30%	30.50%	1.00
HU	LSTM	RL	Clustered	Forecast	112	6.99	9.34	23.10%	30.20%	1.00
HU	RFR	RL	Clustered	Actual	56	6.71	9.29	21.50%	35.10%	1.00
HU	RFR	RL	Clustered	Forecast	56	6.87	9.48	22.10%	34.70%	1.00
HU	ANN	RL	Non-clustered	Actual	252	7.16	9.71	22.30%	35.60%	1.00
HU	ANN	RL	Non-clustered	Forecast	252	7.22	9.78	22.40%	35.90%	1.00
HU	M5P	DSR	Non-clustered	Actual	112	7.26	9.91	22.50%	37.40%	1.00
HU	M5P	DSR	Non-clustered	Forecast	112	7.34	10.08	22.90%	36.70%	1.00
HU	KNN	RL	Non-clustered	Actual	28	7.26	9.84	23.20%	37.80%	1.00
HU	KNN	RL	Non-clustered	Forecast	28	7.81	10.57	25.20%	37.10%	1.00

Source: Own work.

Appendix 5: Chapter 1

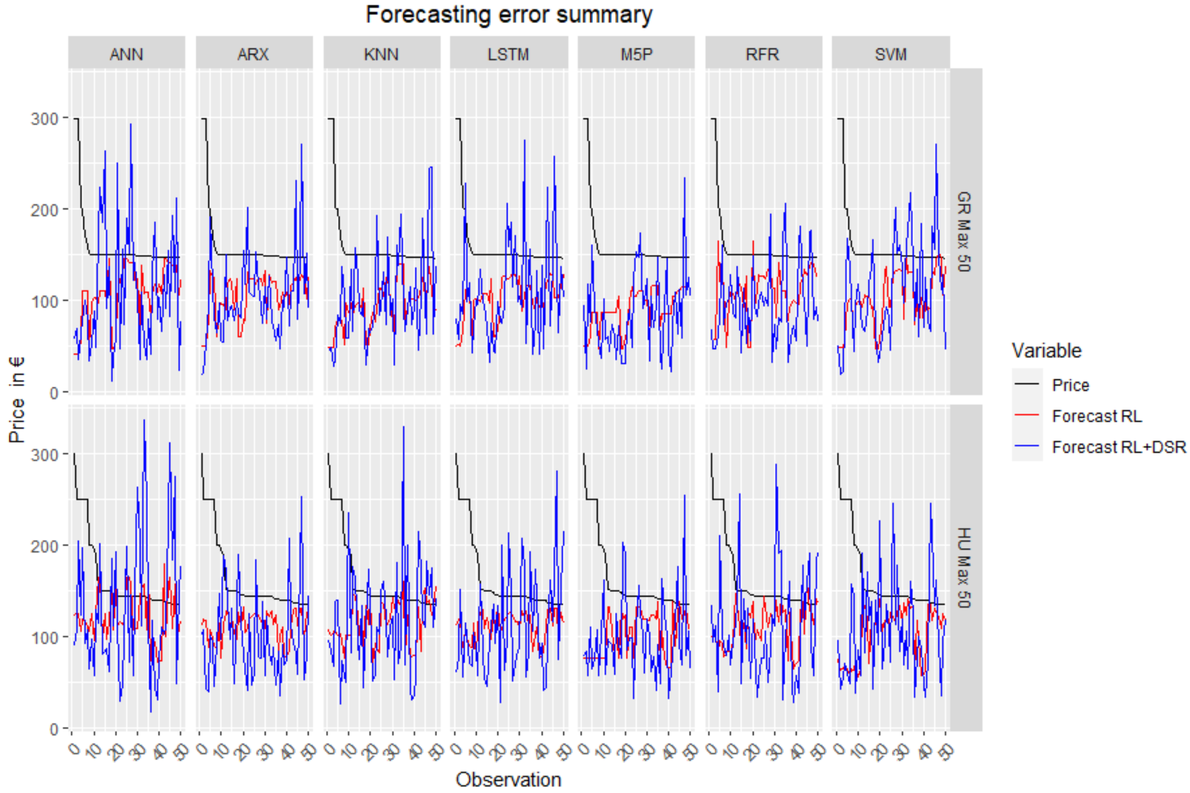
Figure A1: Extreme minimum price forecasting – 50 lowest price observations



Source: Own work.

Appendix 6: Chapter 1

Figure A2: Extreme maximum price forecasting – 50 highest price observations



Source: Own work.

Appendix 7: Chapter 2

Table A5: Average price elasticity of generation – loglinear model, estimated by the rolling window approach

Country	Product	Window (days)	Beta (%)	p-value	R^2
AT	OFF-PL	7	0.89	0.00	0.59
AT	OFF-PL	14	0.77	0.00	0.51
AT	OFF-PL	21	0.70	0.00	0.46
AT	OFF-PL	28	0.66	0.00	0.43
AT	PL	7	0.89	0.00	0.67
AT	PL	14	0.80	0.00	0.61
AT	PL	21	0.75	0.00	0.57
AT	PL	28	0.71	0.00	0.54
HR	OFF-PL	7	0.63	0.02	0.31
HR	OFF-PL	14	0.55	0.03	0.24
HR	OFF-PL	21	0.50	0.02	0.22
HR	OFF-PL	28	0.47	0.01	0.20
HR	PL	7	0.23	0.08	0.20
HR	PL	14	0.21	0.07	0.15
HR	PL	21	0.20	0.08	0.13
HR	PL	28	0.19	0.07	0.11
IT	OFF-PL	7	1.36	0.00	0.68
IT	OFF-PL	14	1.27	0.00	0.65
IT	OFF-PL	21	1.22	0.00	0.63
IT	OFF-PL	28	1.18	0.00	0.62
IT	PL	7	1.26	0.00	0.62
IT	PL	14	1.17	0.00	0.60
IT	PL	21	1.12	0.00	0.59
IT	PL	28	1.08	0.00	0.59
SI	OFF-PL	7	0.58	0.01	0.38
SI	OFF-PL	14	0.49	0.00	0.31
SI	OFF-PL	21	0.43	0.00	0.26
SI	OFF-PL	28	0.39	0.01	0.24
SI	PL	7	0.40	0.03	0.34
SI	PL	14	0.36	0.03	0.29
SI	PL	21	0.33	0.02	0.26
SI	PL	28	0.32	0.02	0.24

Source: Own work.

Appendix 8: Chapter 2

Table A6: Realised supply in MWh (ENTSOE-TP data) and supply changes induced by the market coupling simulation

Year	Country	Realised supply	Supply change	Relative supply change
2015	AT	37,909,618	124,484	0.33%
2015	HR	9,361,044	0	0.00%
2015	IT-Nord	109,012,866	-104,493	-0.10%
2015	SI	11,921,937	-19,991	-0.17%
2015	**∑**	**168,205,464**	**0**	**/**
2016	AT	44,030,736	158,939	0.36%
2016	HR	10,588,367	24,038	0.23%
2016	IT-Nord	115,557,100	-135,293	-0.12%
2016	SI	13,359,509	-47,685	-0.36%
2016	**∑**	**183,535,711**	**0**	**/**
2017	AT	42,058,191	187,941	0.45%
2017	HR	10,490,766	-138,717	-1.32%
2017	IT-Nord	114,851,058	-40,991	-0.04%
2017	SI	13,215,258	-8,233	-0.06%
2017	**∑**	**180,615,272**	**0**	**/**
2018-Q2	AT	21,991,988	64,132	0.29%
2018-Q2	HR	6,489,009	-30,697	-0.47%
2018-Q2	IT-Nord	59,894,443	-33,919	-0.06%
2018-Q2	SI	6,265,449	484	0.01%
2018-Q2	**∑**	**94,640,889**	**0**	**/**

Source: Own work.

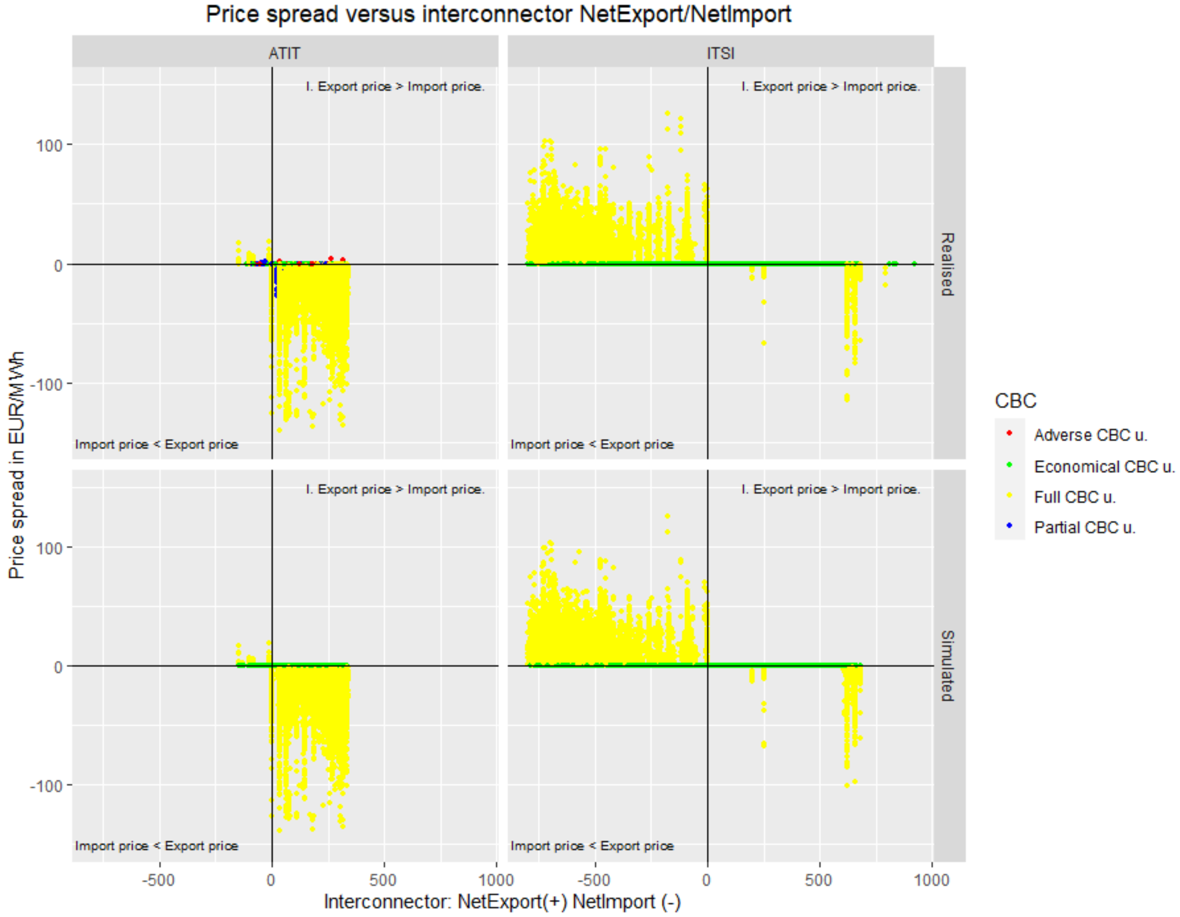
Appendix 9: Chapter 2

Table A7. Estimated impact on the suppliers' income in € (Δ SI), estimated impact on consumers' income in € (Δ CI) and the combined income effect in € (Δ Surplus)

Period	NonCoupled CBCs	Country	Supply	Δ NX	Supply*	Load	Average Price Δ	Δ SI	Δ CI	Δ Surplus
1.1.2015-23.2.2015	ATSI_ATIT	AT	5,353,812	8,052	5,361,864	8,880,343	0.29	2,053,473	-2,672,647	-619,174
1.1.2015-23.2.2015	ATSI_ATIT	HR	1,557,442	NA	NA	2,515,751	NA	NA	NA	NA
1.1.2015-23.2.2015	ATSI_ATIT	IT-Nord	14,874,713	-13,927	14,860,786	23,079,203	-0.10	-1,512,727	2,333,696	820,969
1.1.2015-23.2.2015	ATSI_ATIT	SI	1,774,269	5,876	1,780,144	1,870,143	0.04	814,667	-975,270	-160,603
1.1.2015-23.2.2015	**ATSI_ATIT**	**∑**	**23,560,237**	**0**	**22,002,794**	**36,345,440**	**/**	**1,355,413**	**-1,314,221**	**41,192**
24.2.2015-9.2.2016	ATSI	AT	36,556,185	69,607	36,625,793	57,967,437	0.26	5,148,410	-12,592,746	-7,444,335
24.2.2015-9.2.2016	ATSI	HR	7,803,599	NA	NA	16,127,095	NA	NA	NA	NA
24.2.2015-9.2.2016	ATSI	IT-Nord	106,315,506	-94,631	106,220,875	154,884,558	-0.13	-19,768,282	26,305,674	6,537,392
24.2.2015-9.2.2016	ATSI	SI	11,548,216	25,023	11,573,240	11,957,944	-0.32	-2,458,911	3,888,451	1,429,540
24.2.2015-9.2.2016	**ATSI**	**∑**	**162,223,506**	**0**	**154,419,908**	**240,937,034**	**/**	**-17,078,782**	**17,601,379**	**522,597**
10.2.2016-20.7.2016	ATSI_HRSI	AT	16,121,613	87,247	16,208,860	22,209,701	0.22	6,006,987	-4,859,499	1,147,488
10.2.2016-20.7.2016	ATSI_HRSI	HR	4,528,609	-20,507	4,508,102	6,472,817	-0.70	-2,588,502	4,364,983	1,776,481
10.2.2016-20.7.2016	ATSI_HRSI	IT-Nord	36,641,352	-75,291	36,566,061	54,958,053	-0.20	-8,456,914	8,307,833	-149,082
10.2.2016-20.7.2016	ATSI_HRSI	SI	4,920,005	8,551	4,928,555	4,453,536	-0.20	-1,599,945	1,087,710	-512,234
10.2.2016-20.7.2016	**ATSI_HRSI**	**∑**	**62,211,579**	**0**	**62,211,578**	**88,094,107**	**/**	**-6,638,374**	**8,901,027**	**2,262,653**
21.7.2016-20.6.2018	HRSI	AT	87,958,922	307,709	88,266,631	126,757,486	0.20	27,944,779	-25,325,319	2,619,460
21.7.2016-20.6.2018	HRSI	HR	23,039,533	-180,772	22,858,761	36,797,061	-1.27	-37,538,847	47,937,901	10,399,054
21.7.2016-20.6.2018	HRSI	IT-Nord	241,483,896	-108,220	241,375,676	324,805,533	-0.11	-31,336,333	33,016,178	1,679,845
21.7.2016-20.6.2018	HRSI	SI	26,519,663	-18,716	26,500,947	26,245,551	-0.27	-8,201,565	6,658,031	-1,543,534
21.7.2016-20.6.2018	**HRSI**	**∑**	**379,002,014**	**0**	**379,002,015**	**514,605,631**	**/**	**-49,131,967**	**62,286,791**	**13,154,825**

Appendix 10: Chapter 2

Figure A3: Realised and simulated flow on ATIT (from 1 January 2015 to 20 June 2018) and the HRSI (from 10 February 2016 to 20 June 2018) interconnector



Source: Own work.

Appendix 11: Chapter 2

Table A8: Dickey-Fuller test results

	Realised			Simmulated		
Country	Dickey-Fuller	Lags	p-value	Dickey-Fuller	Lags	p-value
AT	-16.619	26	0.01	-16.491	26	0.01
HR	-12.486	26	0.01	-12.01	26	0.01
IT	-12.13	26	0.01	-10.006	26	0.01
SI	-10.126	26	0.01	-11.813	26	0.01

Source: Own work.

Appendix 12: Chapter 2

Table A9: Vector Autoregression estimates – realised day ahead price time series & market coupling simulation day ahead price time series

Variable	Realised day-ahead prices				Simulatated day-ahead prices			
	AT	HR	IT	SI	AT	HR	IT	SI
AT(-1)	0.10 [0.00***]	0.15 [0.00***]	0.13 [0.00***]	0.15 [0.00***]	0.11 [0.00***]	0.16 [0.00***]	0.14 [0.00***]	0.16 [0.00***]
AT(-2)	-0.03 [0.00***]	0.07 [0.00***]	0.02 [0.00***]	0.05 [0.00***]	-0.03 [0.00***]	0.08 [0.00***]	0.04 [0.00***]	0.08 [0.00***]
AT(-3)	-0.12 [0.00***]	0.01 [0.53]	-0.01 [0.12]	0.03 [0.03**]	-0.11 [0.00***]	0.05 [0.00***]	-0.01 [0.43]	0.04 [0.00***]
AT(-4)	-0.06 [0.00***]	0.03 [0.01***]	0.01 [0.23]	0.06 [0.00***]	-0.05 [0.00***]	0.05 [0.00***]	0.00 [0.54]	0.05 [0.00***]
AT(-5)	-0.08 [0.00***]	0.05 [0.00***]	-0.01 [0.16]	0.04 [0.00***]	-0.08 [0.00***]	0.05 [0.00***]	-0.01 [0.23]	0.04 [0.00***]
AT(-6)	-0.06 [0.00***]	0.01 [0.33]	0.00 [0.67]	0.03 [0.02**]	-0.05 [0.00***]	0.02 [0.04**]	0.00 [0.83]	0.02 [0.02**]
AT(-7)	-0.01 [0.07]	0.05 [0.00***]	0.03 [0.00***]	0.06 [0.00***]	-0.01 [0.12]	0.05 [0.00***]	0.03 [0.00***]	0.06 [0.00***]
AT(-8)	-0.07 [0.00***]	0.03 [0.00***]	0.02 [0.02**]	0.03 [0.01**]	-0.06 [0.00***]	0.03 [0.01***]	0.02 [0.00***]	0.03 [0.00***]
AT(-9)	-0.04 [0.00***]	0.03 [0.00***]	-0.02 [0.04**]	0.03 [0.01***]	-0.03 [0.00***]	0.05 [0.00***]	-0.02 [0.06]	0.04 [0.00***]
AT(-10)	-0.01 [0.10]	0.02 [0.03**]	0.00 [0.72]	0.01 [0.26]	-0.01 [0.11]	0.02 [0.04**]	0.00 [0.73]	0.02 [0.05]
AT(-11)	-0.04 [0.00***]	0.02 [0.10]	0.00 [0.63]	0.01 [0.32]	-0.05 [0.00***]	0.02 [0.15]	0.00 [0.78]	0.02 [0.09]
AT(-12)	-0.06 [0.00***]	0.01 [0.62]	-0.01 [0.39]	0.02 [0.13]	-0.05 [0.00***]	0.03 [0.00***]	-0.01 [0.47]	0.03 [0.00***]
AT(-13)	-0.01 [0.32]	0.05 [0.00***]	0.03 [0.00***]	0.08 [0.00***]	-0.01 [0.33]	0.07 [0.00***]	0.03 [0.00***]	0.07 [0.00***]
AT(-14)	-0.05 [0.00***]	0.05 [0.00***]	0.01 [0.18]	0.04 [0.00***]	-0.05 [0.00***]	0.05 [0.00***]	0.01 [0.21]	0.04 [0.00***]
AT(-15)	-0.06 [0.00***]	0.01 [0.43]	0.02 [0.02**]	0.04 [0.00***]	-0.05 [0.00***]	0.02 [0.08]	0.02 [0.00***]	0.02 [0.05]
AT(-16)	-0.06 [0.00***]	0.01 [0.33]	0.00 [0.61]	0.02 [0.13]	-0.06 [0.00***]	0.02 [0.17]	0.00 [0.77]	0.01 [0.30]
AT(-17)	-0.04 [0.00***]	0.04 [0.00***]	0.03 [0.00***]	0.00 [0.88]	-0.04 [0.00***]	0.02 [0.03**]	0.02 [0.00***]	0.02 [0.14]
AT(-18)	-0.05 [0.00***]	0.04 [0.00***]	0.00 [0.99]	0.03 [0.02**]	-0.05 [0.00***]	0.05 [0.00***]	0.00 [0.56]	0.04 [0.00***]
AT(-19)	-0.03 [0.00***]	0.00 [0.95]	-0.02 [0.03**]	0.00 [0.77]	-0.03 [0.00***]	0.00 [0.94]	-0.01 [0.09]	0.00 [0.92]
AT(-20)	-0.03 [0.00***]	0.02 [0.13]	0.00 [0.81]	0.00 [0.80]	-0.03 [0.00***]	0.00 [0.86]	0.00 [0.70]	0.00 [0.81]
AT(-21)	-0.04 [0.00***]	-0.03 [0.01***]	0.00 [0.94]	-0.05 [0.00***]	-0.04 [0.00***]	-0.04 [0.00***]	0.00 [0.72]	-0.04 [0.00***]
AT(-22)	-0.03 [0.00***]	-0.02 [0.05**]	-0.01 [0.14]	-0.02 [0.06]	-0.03 [0.00***]	-0.02 [0.05**]	-0.02 [0.05]	-0.03 [0.01***]
AT(-23)	0.04 [0.00***]	0.06 [0.00***]	0.02 [0.04**]	0.04 [0.00***]	0.04 [0.00***]	0.05 [0.00***]	0.02 [0.01***]	0.05 [0.00***]
AT(-24)	0.23 [0.00***]	0.15 [0.00***]	0.09 [0.00***]	0.14 [0.00***]	0.23 [0.00***]	0.14 [0.00***]	0.10 [0.00***]	0.15 [0.00***]
HR(-1)	0.04 [0.00***]	-0.09 [0.00***]	0.07 [0.00***]	0.14 [0.00***]	0.02 [0.25]	-0.20 [0.00***]	0.05 [0.00***]	0.09 [0.00***]
HR(-2)	0.01 [0.01***]	-0.13 [0.00***]	0.03 [0.00***]	0.09 [0.00***]	0.03 [0.07]	-0.27 [0.00***]	0.01 [0.38]	0.05 [0.02**]
HR(-3)	0.00 [0.51]	-0.11 [0.00***]	0.01 [0.01***]	0.06 [0.00***]	-0.02 [0.14]	-0.17 [0.00***]	0.02 [0.36]	0.06 [0.01***]
HR(-4)	0.00 [0.76]	-0.14 [0.00***]	0.02 [0.00***]	0.04 [0.00***]	-0.02 [0.22]	-0.26 [0.00***]	0.00 [0.88]	0.01 [0.54]
HR(-5)	0.01 [0.05]	-0.12 [0.00***]	0.02 [0.00***]	0.05 [0.00***]	0.01 [0.73]	-0.21 [0.00***]	0.00 [0.99]	0.01 [0.61]
HR(-6)	0.01 [0.29]	-0.10 [0.00***]	0.01 [0.14]	0.03 [0.00***]	0.01 [0.72]	-0.24 [0.00***]	-0.02 [0.33]	0.00 [0.89]
HR(-7)	0.00 [0.58]	-0.08 [0.00***]	0.03 [0.00***]	0.02 [0.01**]	0.01 [0.42]	-0.21 [0.00***]	-0.01 [0.47]	-0.02 [0.33]
HR(-8)	-0.01 [0.01***]	-0.09 [0.00***]	0.02 [0.00***]	0.02 [0.02**]	0.00 [0.97]	-0.24 [0.00***]	0.00 [0.80]	-0.06 [0.01***]
HR(-9)	-0.01 [0.04**]	-0.08 [0.00***]	0.01 [0.10]	0.02 [0.01**]	-0.03 [0.11]	-0.25 [0.00***]	-0.01 [0.72]	-0.07 [0.01***]
HR(-10)	0.01 [0.18]	-0.08 [0.00***]	0.01 [0.32]	0.01 [0.14]	0.00 [0.80]	-0.25 [0.00***]	0.02 [0.32]	-0.07 [0.00***]

Variable	Realised day-ahead prices				Simulatated day-ahead prices			
	AT	HR	IT	SI	AT	HR	IT	SI
HR(-11)	0.00 [0.53]	-0.07 [0.00***]	0.02 [0.00***]	0.01 [0.37]	0.01 [0.45]	-0.12 [0.00***]	-0.01 [0.68]	-0.01 [0.56]
HR(-12)	0.01 [0.12]	-0.06 [0.00***]	0.02 [0.00***]	0.03 [0.00***]	-0.02 [0.18]	-0.18 [0.00***]	0.02 [0.34]	0.00 [0.89]
HR(-13)	0.01 [0.24]	-0.07 [0.00***]	0.01 [0.01**]	0.01 [0.36]	-0.01 [0.52]	-0.17 [0.00***]	-0.03 [0.12]	-0.03 [0.17]
HR(-14)	0.00 [0.65]	-0.09 [0.00***]	0.01 [0.32]	-0.01 [0.31]	0.00 [0.91]	-0.22 [0.00***]	0.00 [0.90]	-0.03 [0.16]
HR(-15)	0.01 [0.02**]	-0.07 [0.00***]	0.01 [0.05]	0.00 [0.69]	0.04 [0.02**]	-0.17 [0.00***]	0.02 [0.34]	0.00 [0.85]
HR(-16)	-0.01 [0.07]	-0.08 [0.00***]	0.00 [0.57]	0.00 [0.57]	-0.01 [0.66]	-0.22 [0.00***]	0.00 [0.91]	-0.06 [0.02**]
HR(-17)	0.00 [0.52]	-0.09 [0.00***]	0.00 [0.62]	0.00 [0.93]	0.00 [0.96]	-0.21 [0.00***]	-0.02 [0.23]	-0.02 [0.31]
HR(-18)	-0.01 [0.04**]	-0.09 [0.00***]	0.00 [0.71]	0.01 [0.17]	-0.01 [0.40]	-0.18 [0.00***]	-0.01 [0.52]	0.01 [0.58]
HR(-19)	-0.01 [0.09]	-0.05 [0.00***]	0.01 [0.14]	0.01 [0.32]	0.00 [0.92]	-0.12 [0.00***]	-0.01 [0.61]	0.04 [0.07]
HR(-20)	-0.01 [0.24]	-0.07 [0.00***]	0.00 [0.93]	0.01 [0.21]	0.00 [0.96]	-0.11 [0.00***]	-0.01 [0.76]	0.01 [0.71]
HR(-21)	0.01 [0.08]	-0.07 [0.00***]	-0.01 [0.01**]	-0.01 [0.48]	0.02 [0.27]	-0.10 [0.00***]	-0.02 [0.32]	0.03 [0.25]
HR(-22)	0.01 [0.22]	-0.03 [0.00***]	-0.01 [0.24]	0.01 [0.18]	0.01 [0.69]	-0.09 [0.00***]	-0.02 [0.27]	-0.01 [0.79]
HR(-23)	0.01 [0.11]	0.01 [0.08]	0.01 [0.04**]	0.02 [0.03**]	0.00 [0.78]	-0.04 [0.05**]	-0.03 [0.06]	-0.04 [0.08]
HR(-24)	0.05 [0.00***]	0.11 [0.00***]	0.06 [0.00***]	0.11 [0.00***]	0.01 [0.70]	0.02 [0.30]	0.01 [0.61]	-0.01 [0.75]
IT(-1)	0.01 [0.03**]	0.07 [0.00***]	-0.01 [0.23]	0.11 [0.00***]	0.02 [0.00***]	0.10 [0.00***]	0.00 [0.77]	0.11 [0.00***]
IT(-2)	-0.01 [0.12]	-0.01 [0.16]	-0.17 [0.00***]	0.02 [0.06]	-0.01 [0.08]	0.02 [0.04**]	-0.17 [0.00***]	0.02 [0.01**]
IT(-3)	0.00 [0.68]	0.01 [0.13]	-0.14 [0.00***]	0.06 [0.00***]	0.00 [0.69]	0.04 [0.00***]	-0.15 [0.00***]	0.04 [0.00***]
IT(-4)	-0.01 [0.43]	-0.01 [0.26]	-0.16 [0.00***]	0.02 [0.17]	0.00 [0.64]	0.01 [0.21]	-0.16 [0.00***]	0.02 [0.06]
IT(-5)	-0.03 [0.00***]	-0.02 [0.11]	-0.11 [0.00***]	0.02 [0.12]	-0.03 [0.00***]	0.00 [0.92]	-0.12 [0.00***]	0.00 [0.92]
IT(-6)	-0.04 [0.00***]	-0.02 [0.07]	-0.12 [0.00***]	0.00 [0.88]	-0.03 [0.00***]	-0.01 [0.49]	-0.13 [0.00***]	-0.01 [0.55]
IT(-7)	-0.02 [0.01***]	-0.05 [0.00***]	-0.12 [0.00***]	0.02 [0.10]	-0.02 [0.00***]	0.00 [0.71]	-0.13 [0.00***]	0.00 [0.67]
IT(-8)	-0.01 [0.33]	-0.03 [0.01***]	-0.08 [0.00***]	0.00 [0.83]	-0.01 [0.25]	-0.01 [0.57]	-0.08 [0.00***]	0.00 [0.82]
IT(-9)	-0.03 [0.00***]	-0.01 [0.26]	-0.10 [0.00***]	0.01 [0.51]	-0.03 [0.00***]	-0.01 [0.47]	-0.11 [0.00***]	-0.01 [0.58]
IT(-10)	-0.01 [0.04**]	-0.01 [0.15]	-0.09 [0.00***]	-0.03 [0.01**]	-0.01 [0.06]	-0.03 [0.01***]	-0.09 [0.00***]	-0.03 [0.00***]
IT(-11)	-0.01 [0.16]	-0.01 [0.51]	-0.07 [0.00***]	0.04 [0.00***]	-0.01 [0.27]	0.02 [0.04**]	-0.07 [0.00***]	0.02 [0.02**]
IT(-12)	-0.02 [0.04**]	-0.02 [0.02**]	-0.09 [0.00***]	-0.01 [0.24]	-0.02 [0.01**]	-0.02 [0.04**]	-0.09 [0.00***]	-0.02 [0.04**]
IT(-13)	-0.02 [0.01***]	-0.03 [0.01***]	-0.07 [0.00***]	0.00 [0.77]	-0.02 [0.02**]	0.00 [0.67]	-0.08 [0.00***]	0.00 [0.82]
IT(-14)	-0.01 [0.32]	0.01 [0.21]	-0.09 [0.00***]	0.03 [0.01**]	-0.01 [0.33]	0.01 [0.45]	-0.09 [0.00***]	0.01 [0.22]
IT(-15)	-0.02 [0.02**]	-0.01 [0.46]	-0.09 [0.00***]	-0.01 [0.37]	-0.02 [0.02**]	-0.02 [0.10]	-0.09 [0.00***]	-0.02 [0.12]
IT(-16)	0.00 [0.49]	0.02 [0.10]	-0.05 [0.00***]	0.02 [0.07]	0.01 [0.40]	0.02 [0.10]	-0.05 [0.00***]	0.02 [0.05]
IT(-17)	0.01 [0.46]	0.01 [0.61]	-0.09 [0.00***]	0.01 [0.37]	0.00 [0.49]	0.01 [0.54]	-0.09 [0.00***]	0.00 [0.95]
IT(-18)	-0.01 [0.05**]	0.01 [0.35]	-0.10 [0.00***]	-0.01 [0.57]	-0.02 [0.03**]	0.00 [0.96]	-0.10 [0.00***]	0.00 [0.91]
IT(-19)	-0.01 [0.14]	-0.02 [0.03**]	-0.06 [0.00***]	0.01 [0.51]	-0.01 [0.05]	-0.01 [0.60]	-0.06 [0.00***]	0.00 [0.85]
IT(-20)	-0.02 [0.03**]	0.01 [0.40]	-0.08 [0.00***]	-0.01 [0.58]	-0.02 [0.01**]	-0.01 [0.62]	-0.08 [0.00***]	-0.01 [0.38]
IT(-21)	-0.02 [0.02**]	0.00 [0.98]	-0.07 [0.00***]	0.00 [0.92]	-0.01 [0.04**]	-0.01 [0.53]	-0.07 [0.00***]	-0.01 [0.47]
IT(-22)	0.00 [0.96]	-0.04 [0.00***]	-0.06 [0.00***]	-0.01 [0.40]	0.00 [0.75]	-0.01 [0.18]	-0.07 [0.00***]	-0.01 [0.32]
IT(-23)	0.02 [0.00***]	0.05 [0.00***]	0.01 [0.13]	0.06 [0.00***]	0.03 [0.00***]	0.05 [0.00***]	0.01 [0.04**]	0.05 [0.00***]
IT(-24)	0.08 [0.00***]	0.14 [0.00***]	0.28 [0.00***]	0.18 [0.00***]	0.09 [0.00***]	0.18 [0.00***]	0.29 [0.00***]	0.18 [0.00***]

Variable	Realised day-ahead prices				Simulatated day-ahead prices			
	AT	HR	IT	SI	AT	HR	IT	SI
SI(-1)	0.00 [0.39]	0.05 [0.00***]	0.02 [0.00***]	-0.25 [0.00***]	0.01 [0.51]	0.06 [0.01***]	0.01 [0.61]	-0.24 [0.00***]
SI(-2)	0.00 [0.33]	0.03 [0.00***]	0.03 [0.00***]	-0.25 [0.00***]	-0.02 [0.17]	0.09 [0.00***]	0.03 [0.09]	-0.23 [0.00***]
SI(-3)	0.01 [0.31]	0.02 [0.04**]	0.01 [0.06]	-0.21 [0.00***]	0.02 [0.13]	0.00 [0.99]	0.01 [0.65]	-0.23 [0.00***]
SI(-4)	0.01 [0.20]	0.02 [0.00***]	0.03 [0.00***]	-0.17 [0.00***]	0.02 [0.21]	0.12 [0.00***]	0.05 [0.01**]	-0.15 [0.00***]
SI(-5)	0.01 [0.07]	0.03 [0.00***]	0.01 [0.02**]	-0.16 [0.00***]	0.01 [0.73]	0.09 [0.00***]	0.03 [0.14]	-0.13 [0.00***]
SI(-6)	0.01 [0.25]	0.02 [0.03**]	0.00 [0.41]	-0.15 [0.00***]	0.00 [0.99]	0.11 [0.00***]	0.04 [0.05]	-0.13 [0.00***]
SI(-7)	0.00 [0.79]	0.01 [0.23]	0.01 [0.37]	-0.15 [0.00***]	-0.01 [0.43]	0.09 [0.00***]	0.04 [0.02**]	-0.10 [0.00***]
SI(-8)	0.00 [0.84]	0.00 [0.74]	0.01 [0.20]	-0.14 [0.00***]	-0.01 [0.43]	0.12 [0.00***]	0.01 [0.50]	-0.07 [0.01***]
SI(-9)	0.01 [0.06]	-0.01 [0.21]	0.00 [0.83]	-0.13 [0.00***]	0.02 [0.20]	0.11 [0.00***]	0.01 [0.46]	-0.06 [0.01***]
SI(-10)	0.02 [0.00***]	0.01 [0.28]	0.01 [0.09]	-0.09 [0.00***]	0.02 [0.20]	0.15 [0.00***]	0.00 [0.87]	-0.03 [0.28]
SI(-11)	0.01 [0.02**]	-0.02 [0.04**]	0.00 [0.57]	-0.12 [0.00***]	0.00 [0.91]	0.00 [0.88]	0.01 [0.51]	-0.10 [0.00***]
SI(-12)	0.00 [0.89]	-0.01 [0.51]	0.00 [0.93]	-0.12 [0.00***]	0.03 [0.11]	0.08 [0.00***]	0.00 [0.85]	-0.11 [0.00***]
SI(-13)	0.00 [0.66]	0.00 [0.58]	-0.01 [0.04**]	-0.09 [0.00***]	0.01 [0.41]	0.07 [0.01**]	0.03 [0.18]	-0.07 [0.01***]
SI(-14)	0.00 [0.41]	-0.03 [0.00***]	-0.01 [0.29]	-0.14 [0.00***]	0.00 [0.91]	0.07 [0.01***]	-0.01 [0.73]	-0.11 [0.00***]
SI(-15)	-0.01 [0.15]	-0.03 [0.00***]	-0.01 [0.06]	-0.12 [0.00***]	-0.04 [0.01**]	0.05 [0.08]	-0.03 [0.15]	-0.12 [0.00***]
SI(-16)	0.00 [0.78]	-0.02 [0.04**]	0.00 [0.85]	-0.10 [0.00***]	0.00 [0.89]	0.10 [0.00***]	-0.01 [0.77]	-0.06 [0.02**]
SI(-17)	-0.01 [0.25]	-0.02 [0.01***]	-0.01 [0.08]	-0.09 [0.00***]	-0.01 [0.48]	0.09 [0.00***]	0.01 [0.48]	-0.08 [0.00***]
SI(-18)	0.00 [0.55]	-0.01 [0.22]	0.00 [0.64]	-0.07 [0.00***]	0.00 [0.80]	0.08 [0.00***]	0.00 [0.85]	-0.10 [0.00***]
SI(-19)	0.01 [0.31]	-0.02 [0.04**]	0.00 [0.40]	-0.07 [0.00***]	0.00 [0.81]	0.03 [0.20]	0.00 [0.87]	-0.12 [0.00***]
SI(-20)	0.00 [0.82]	-0.01 [0.10]	0.00 [0.75]	-0.07 [0.00***]	-0.01 [0.67]	0.02 [0.51]	0.00 [0.98]	-0.09 [0.00***]
SI(-21)	0.00 [0.93]	0.01 [0.14]	0.01 [0.02**]	-0.04 [0.00***]	-0.02 [0.35]	0.04 [0.08]	0.03 [0.16]	-0.07 [0.00***]
SI(-22)	0.00 [0.38]	0.01 [0.08]	0.01 [0.03**]	-0.03 [0.00***]	0.01 [0.62]	0.07 [0.01***]	0.03 [0.10]	-0.01 [0.54]
SI(-23)	0.01 [0.01***]	0.01 [0.12]	0.00 [0.50]	-0.01 [0.20]	0.02 [0.17]	0.04 [0.13]	0.03 [0.04**]	0.04 [0.10]
SI(-24)	0.01 [0.00***]	0.12 [0.00***]	0.01 [0.04**]	0.03 [0.00***]	0.04 [0.01***]	0.10 [0.00***]	0.03 [0.05**]	0.12 [0.00***]
R^2	0.3953	0.3767	0.464	0.2997	0.3937	0.3298	0.4597	0.3323
Adjusted R^2	0.3924	0.3738	0.4614	0.2964	0.3908	0.3266	0.4571	0.3291
F-test	137.3	126.9	181.8	89.86	136.4	103.3	178.7	104.5
p-value(F)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Log-likelihood	-240,423.0				-216,040.5			

Source: Own work.

Appendix 13: Chapter 2

Table A10: Granger causality test results

	Realised		Simulated	
Country	F-Test	p-value	F-Test	p-value
AT	30.581	0.00	32.797	0.00
HR	27.34	0.00	7.6089	0.00
IT	14.967	0.00	13.307	0.00
SI	5.6263	0.00	4.1955	0.00

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Table A11: Observed maximum generation mix penetrations in MW

Country	Type	2015	2016	2017	2018-Q3
GR	Gas	3,733	3,492	3,850	4,310
GR	Hydro	1,979	2,080	1,961	2,260
GR	Lignite	4,110	3,808	5,150	3,651
GR	Other	2	2	0	0
GR	Solar	2,062	1,923	1,847	1,933
GR	Wind	1,412	1,330	1,702	1,695
HU	Gas	854.25	800.75	770.5	763
HU	Hydro	26.5	27	26	26.25
HU	Lignite	1,502.25	1,651.25	1,948.75	1,681.50
HU	Nuclear	1,941.00	1,937.75	1,939.00	1,939.00
HU	Other	458.25	464.75	432.75	164
HU	Wind	304.75	306	301	298.25
RO	Gas	3,466	3,635	3,523	3,007
RO	Hydro	4,330	4,691	3,985	4,416
RO	Lignite	2,283	2,390	2,441	2,147
RO	Nuclear	1,426	1,420	1,433	1,415
RO	Other	78	74	70	64
RO	Solar	774	807	847	864
RO	Wind	2,686	2,795	2,756	2,750

Source: ENTSO-E TP 2020.

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Table A12: OLS estimation of daily changes in Greek electricity prices.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Year 2015	Year 2016	Year 2017	Year 2018	All Years	All Years Ren split	All Years High load	All Years Low load
	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*
Δ*Pelec, d-1*	0.382 [0.00***]	0.390 [0.00***]	0.645 [0.00***]	0.672 [0.00***]	0.704 [0.00***]	0.707 [0.00***]	0.677 [0.00***]	0.578 [0.00***]
Δ*DE, d*	0.065 [0.01***]	0.107 [0.00***]	0.199 [0.00***]	0.156 [0.00***]	0.160 [0.00***]	0.161 [0.00***]	0.226 [0.00***]	0.107 [0.00***]
Δ*Load, d*	0.003 [0.00***]	0.002 [0.00***]	0.002 [0.00***]	0.001 [0.07]	0.001 [0.00***]	0.001 [0.00***]	0.002 [0.00***]	0.003 [0.00***]
Δ*Ren, d*	-0.005 [0.00***]	-0.005 [0.00***]	-0.006 [0.00***]	-0.005 [0.00***]	-0.004 [0.00***]	/	-0.005 [0.00***]	-0.003 [0.00***]
Δ*Wind, d*	/	/	/	/	/	-0.004 [0.00***]	/	/
Δ*Solar, d*	/	/	/	/	/	-0.003 [0.00***]	/	/
R^2	0.59	0.50	0.76	0.78	0.77	0.77	0.80	0.57
Adjusted R^2	0.59	0.49	0.76	0.78	0.77	0.77	0.80	0.57
F-test	130.80	88.34	291.30	233.72	1127.29	903.12	330.65	112.90
p-value (F)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***

Note: "***" and "**" indicating significance at 1% and 5 % levels respectively and P-values in [] brackets.

Source: Own work.

Appendix 16: Chapter 3

Table A13: OLS estimation of daily changes in Hungarian electricity prices

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Year 2015	Year 2016	Year 2017	Year 2018	All Years	All Years Ren split	All Years High load	All Years Low load
	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*
Δ*Pelec, d-1*	0.469 [0.00***]	0.549 [0.00***]	0.501 [0.00***]	0.424 [0.00***]	0.582 [0.00***]	0.582 [0.00***]	0.689 [0.00***]	0.563 [0.00***]
Δ*DE, d*	0.207 [0.00***]	0.305 [0.00***]	0.228 [0.00***]	0.531 [0.00***]	0.313 [0.00***]	0.313 [0.00***]	0.258 [0.00***]	0.262 [0.00***]
Δ*Load, d*	0.008 [0.00***]	0.004 [0.00***]	0.013 [0.00***]	0.003 [0.00***]	0.006 [0.00***]	0.006 [0.00***]	0.008 [0.00***]	0.005 [0.00***]
Δ*Ren, d*	-0.015 [0.00***]	-0.009 [0.05]	-0.035 [0.00***]	-0.005 [0.47]	-0.013 [0.00***]	/	-0.014 [0.07]	-0.009 [0.08]
Δ*Wind, d*	/	/	/	/	/	-0.013 [0.00***]	/	/
Δ*Solar, d*	/	/	/	/	/	/	/	/
R^2	0.63	0.71	0.74	0.82	0.75	0.75	0.74	0.70
Adjusted R^2	0.63	0.71	0.73	0.81	0.75	0.75	0.74	0.70
F-test	152.8	218.78	248.39	294.11	994.96	994.96	235.97	194.62
p-value (*F*)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***

Note: "***" and "**" indicating significance at 1% and 5 % levels respectively and P-values in [] brackets.

Source: Own work.

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Table A14: OLS estimation of daily changes in Romanian electricity prices

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Year	Year	Year	Year		All Years	All Years	All Years
	2015	2016	2017	2018	All Years	Ren split	High load	Low load
	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*	Δ*Pelec, t*
Δ*Pelec, d-1*	0.362 [0.00***]	0.414 [0.00***]	0.433 [0.00***]	0.497 [0.00***]	0.549 [0.00***]	0.545 [0.00***]	0.633 [0.00***]	0.452 [0.00***]
Δ*DE, d*	0.243 [0.00***]	0.209 [0.00***]	0.294 [0.00***]	0.386 [0.00***]	0.283 [0.00***]	0.254 [0.00***]	0.251 [0.00***]	0.262 [0.00***]
Δ*Load, d*	0.004 [0.00***]	0.005 [0.00***]	0.008 [0.00***]	0.003 [0.00***]	0.004 [0.00***]	0.006 [0.00***]	0.005 [0.00***]	0.007 [0.00***]
Δ*Ren, d*	-0.008 [0.00***]	-0.006 [0.00***]	-0.011 [0.00***]	-0.008 [0.00***]	-0.007 [0.00***]	/	-0.007 [0.00***]	-0.008 [0.00***]
Δ*Wind, d*	/	/	/	/	/	-0.007 [0.00***]	/	/
Δ*Solar, d*	/	/	/	/	/	0.015 [0.00***]	/	/
R^2	0.68	0.68	0.73	0.73	0.72	0.73	0.72	0.71
Adjusted R^2	0.67	0.67	0.72	0.73	0.72	0.73	0.72	0.7
F-test	186.68	185.74	226.84	178.19	846.03	708.57	210.61	197.77
p-value (F)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***

Note: "***" and "**" indicating significance at 1% and 5 % levels respectively and P-values in [] brackets.

Source: Own work.

Appendix 18: Chapter 3

Table A15: OLS estimation of net export in Greece

	Year 2015	Year 2016	Year 2017	Year 2018
	NX, t	*NX, t*	*NX, t*	*NX, t*
NX, t-24	0.750 [0.00***]	0.811 [0.00***]	0.796 [0.00***]	0.759 [0.00***]
RES, t	0.048 [0.00***]	0.052 [0.00***]	0.055 [0.00***]	0.045 [0.00***]
R^2	0.59	0.66	0.66	0.59
Adjusted R^2	0.59	0.66	0.66	0.59
F-test	2814.29	7426.11	8053.16	4659.02
p-value (F)	0.00	0.00	0.00	0.00

Note: "***" and "**" indicating significance at 1% and 5 % levels respectively and P-values in [] brackets.

Source: Own work.

Appendix 19: Chapter 3

Table A16: OLS estimation of net export in Hungary

	Year 2015	Year 2016	Year 2017	Year 2018
	NX, t	*NX, t*	*NX, t*	*NX, t*
NX, t-24	0.860 [0.00***]	0.860 [0.00***]	0.847 [0.00***]	0.886 [0.00***]
RES, t	0.427 [0.00***]	0.626 [0.00***]	0.849 [0.00***]	0.695 [0.00***]
R^2	0.75	0.75	0.74	0.78
Adjusted R^2	0.75	0.75	0.74	0.78
F-test	13091.44	12891.61	12407.85	12122.70
p-value (F)	0.00	0.00	0.00	0.00

Note: "***" and "**" indicating significance at 1% and 5 % levels respectively and P-values in [] brackets.

Source: Own work.

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Table A17: OLS estimation of net export in Romania

	Year 2015	Year 2016	Year 2017	Year 2018
	NX, t	*NX, t*	*NX, t*	*NX, t*
NX, t-24	0.458 [0.00***]	0.528 [0.00***]	0.363 [0.00***]	0.446 [0.00***]
RES, t	0.330 [0.00***]	0.424 [0.00***]	0.513 [0.00***]	0.393 [0.00***]
R^2	0.55	0.58	0.57	0.48
Adjusted R^2	0.55	0.58	0.57	0.48
F-test	5208.98	6010.65	5664.70	3118.52
p-value (F)	0.00	0.00	0.00	0.00

Note: "***" and "**" indicating significance at 1% and 5 % levels respectively and P-values in [] brackets.

Source: Own work.

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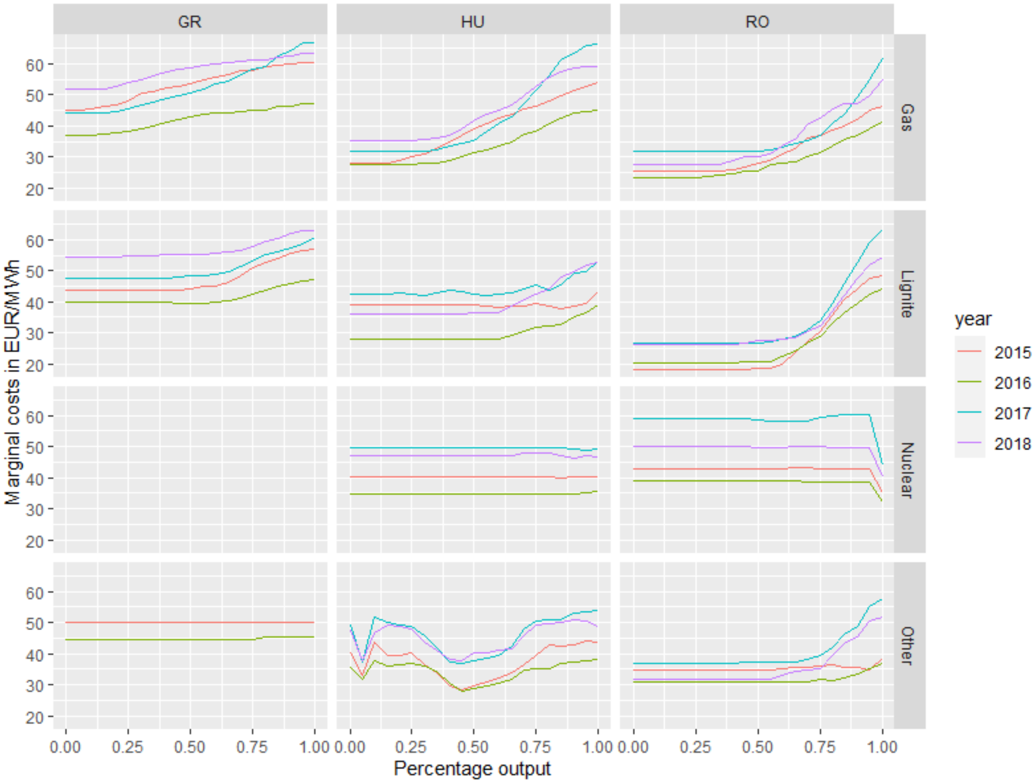
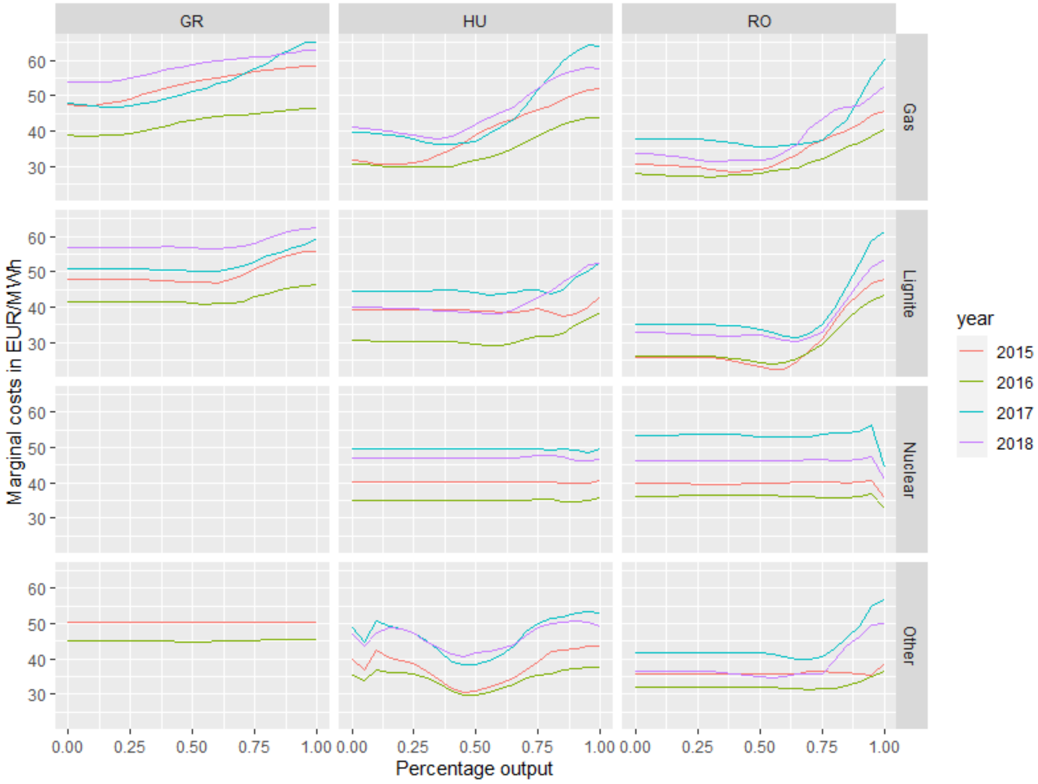
Figure A4: Estimated merit order by the *k*-nearest neighbour algorithm (yearly aggregation of weekly estimates)



Source: Own work.

Appendix 22: Chapter 3

Figure A5: Estimated merit order by the random forest algorithm (yearly aggregation of weekly estimates)



Source: Own work.

Appendix 23: Razširjeni povzetek disertacije v slovenskem jeziku

V zadnjih letih so evropske države prestrukturirale trge z električno energijo iz vertikalno integrirane strukture v konkurenčne liberalizirane trge. Trg z električno energijo za dan vnaprej je veleprodajni trg, kjer se trguje s standardiziranimi urnimi pogodbami s fizično dobavo za dan vnaprej. Borzna cena električne energije je določena s presečiščem tržne funkcije ponudbe in povpraševanja. Glavne značilnosti, ki pomembno vplivajo na oblikovanje cen električne energije na konkurenčnem trgu, so: nezmožnost skladiščenja, zahtevano ravnovesje proizvodnje in potrošnje v realnem času, nujna in homogena dobrina, nizka elastičnost povpraševanja, razlikovanje fizičnih in pogodbenih tokov. Kot posledica nezmožnosti ekonomičnega skladiščenja in zahtevanega ravnovesja proizvodnje in porabe v realnem času se lahko oblikujejo negativne cene električne energije, ki niso značilne za trge ostalih surovin. Disertacija temeljito razišče uporabnost sodobnih algoritmov za napovedovanje cen električne energije in vpliv novih dejavnikov na trge električne energije. Pod krovnim izrazom »vpliv novih dejavnikov na trge električne energije« ločeno raziščemo tržni vpliv subvencionirane proizvodnje iz obnovljivih virov energije in proces spajanja trgov z električno energijo. Omenjena trenda poglavitno vplivata na delovanje trga in sta predmet številnih raziskav. Doktorsko delo temelji na javno dostopnem podatkovnem viru ENTSOE-TP in se ob tem izogiba mešanju virov. Na ta način zagotovimo enostavno in hitro ponovljivost izvedenih podatkovnih simulacij.

Z doktorsko disertacijo želimo odgovoriti na naslednja raziskovalna vprašanja, ki jih lahko razvrstimo vzdolž treh raziskovalnih dimenzij. Prva dimenzija naslovi naslednja raziskovalna vprašanja: Ali so sodobni statistični pristopi (podatkovno rudarjenje in strojno učenje) pri napovedovanju cen električne energije uspešnejši v primerjavi z linearnim ekonometričnim modelom časovnih vrst; Kako vpliva velikost množice podatkov za učenje modelov na uspešnost napovedovanja; Ali učenje posamičnih modelov za vsako uro v dnevu posebej izboljša učinkovitost napovedovanja cen električne energije; Ali pojasnjevalna spremenljivka, ki opisuje razmerje med povpraševanjem in ponudbo, izboljša učinkovitost napovedovanja cene električne energije v robnih pogojih?

Z drugo dimenzijo raziščemo naslednja raziskovalna vprašanja: Kako oblikovati tržne simulacije na spojenih trgih električne energije; Ali spajanje trgov električne energije zagotavlja učinkovito dodeljevanje čezmejnih prenosnih zmogljivosti in konvergenco cen električne energije; Kakšen je vpliv spajanja trgov električne energije na volatilnost cen električne energije; Ali spajanje trgov električne energije pozitivno vpliva na prenos cenovnih šokov?

Tretja raziskovalna dimenzija odgovori na naslednja znastvena vprašanja: Ali izrivanje konvencionalnih virov proizvodnje električne energije z obnovljivimi viri energije znižuje cene električne energije na trgih jugovzhodne Evrope; Ali lahko sodobni statistični pristopi premostijo vrzel v razpoložljivosti podatkov in učinkovito simulirajo cene električne energije v scenariju brez proizvodnje iz obnovljivih virov energije; Ali proizvodnja iz obnovljivih virov energije povečuje volatilnost cen električne energije na trgih jugovzhodne Evrope; Ali razpoložljivost podatkov omejuje raziskovalno delo s področja trgov električne energije?

Vsaka dimenzija raziskovalnih vprašanj tvori eno od naslednjih treh raziskovalnih tem: Kratkoročno napovedovanje cen električne energije s sodobnimi statističnimi pristopi; Simulacije spojenih trgov električne energije; Izrivanje konvencionalnih virov električne energije na veleprodajnem trgu z obnovljivimi. V doktorski disertaciji so omenjene raziskovalne teme predstavljene v obliki treh samostojnih poglavij, in sicer: (1) Učinkovitost sodobnih metod za napovedovanje cene električne energije: ugotovitve iz grškega in madžarskega trga; (2) Integrirani model za simulacije spojenih trgov električne energije: opažanja na stičišču evropskih trgov električne energije; (3) Izrivanje konvencionalne proizvodnje električne energije z obnovljivimi viri energije: izid na grškem, madžarskem in romunskem trgu električne energije.

Vsi trije sklopi tvorijo splet ekonomske teorije s področja trga električne energije in aplikacije sodobnih statističnih pristopov za empirično raziskavo izhodiščnih raziskovalnih vprašanj. Odgovore vzdolž prve raziskovalne dimenzije smo pridobili s primerjavo učinkovitosti napovedovalnih tehnik s področja ekonometrije, podatkovnega rudarjenja in strojnega učenja. Učinkovitost napovedovalnih tehnik smo primerjali z merami natančnosti in na podlagi izvedenega statističnega Diebold-Marianovega testa. V drugem sklopu smo pri oceni agregirane elastičnosti ponudbe zaradi potencialnih pristranskosti, ki bi lahko vplivale na oceno z metodo najmanjših kvadratov, instrumentirali cene električne energije in s tem kontrolirali modelsko endogenost. Borzne cene in čezmejne pretoke na območju spojenih trgov električne energije smo določili na podlagi tehnične specifikacije borznega algoritma tj. linearnega programiranja. Z oceno vektorsko avtoregresijskega modela smo dodatno analizirali prenos cenovnih šokov v nespojenem režimu delovanja trgov in v simuliranem okolju spojenih trgov električne energije. V zadnjem sklopu ekonometrično ocenimo vpliv izrivanja konvencionalnih virov energije (angl. *merit order effect*) in vpliv proizvodnje iz obnovljivih virov energije na izvoz električne energije. Simulacija cen brez proizvodnje iz obnovljivih virov energije je izvedena s pomočjo algoritmov iz družine podatkovnega rudarjenja, in sicer za oceno ponudbene funkcije konvencionalne proizvodnje električne energije.

Učinkovitost sodobnih metod za napovedovanje cene električne energije: ugotovitve z grškega in madžarskega trga

V prvem poglavju obravnavamo temo, ki ji raziskovalci s področja trga z elektročino energijo posvečajo največ pozornosti. Napovedovanje cen je z liberalizacijo trga in rastjo nestanovitne proizvodnje iz obnovljivih virov energije postalo interdisciplinarno področje, ki privlači različne strokovnjake (ekonomiste, inženirje, matematike in statistike). Zaradi tveganosti tržnih operacij v opisanem dinamičnem okolju je napovedovanje cen električne energije postala prednostna naloga proizvajalcev in odjemalcev električne energije (García-Martos, Rodríguez

& Sánchez, 2012). Za grški in madžarski trg smo pridobili podatke iz javno dostopne podatkovne baze ENTSOE-TP in jih uporabili za izvedbo primerjalne analize učinkovitosti sodobnih metod za napovedovanje cen električne energije .

Napovedovanje cen električne energije je razmeroma mlado interdisciplinarno raziskovalno področje, ki je ob nastanku temeljilo na uporabi statističnih in ekonometričnih pristopov za doseganje zadovoljivih kratkoročnih napovedi. S povečano proizvodnjo iz obnovljivih virov energije in posledično povečano nestanovitnostjo cen električne energije sta se znanost in stroka zatekli k uporabi naprednih algoritmov s področja podatkovnega rudarjenja in strojnega učenja. Statistični in ekonometrični modeli so kritizirani zaradi linearnosti oz. slabe napovedovalne učinkovitosti, ki je povezana z nezmožnostjo učinkovitega modeliranja hitrih sprememb cenovnega signala. Izvedena sistematična primerjalna analiza uspešnosti napovedovanja ekonometričnega modela časovnih vrst z izbranimi metodami s področja rudarjenja podatkov in strojnega učenja pokaže, da je metoda podpornih vektorjev statistično natančnejša. To potrdi nižja metrika natančnosti napovedi in statistično značilen Diebold-Marianov test. Preostali napovedovalni algoritmi so; regresijska drevesa, naključni gozd, metoda najbližjih sosedov in nevronske mreže, ki so glede na metriko natančnosti uspešnejše v primerjavi z referenčnim ekonometričnim modelom, vendar imajo statistično neznačilen Diebold-Marianov test.

Z uporabo algoritmov podatkovnega rudarjenja in strojnega učenja za napovedovanje cen električne energije so se pojavila nova raziskovalna vprašanja. Algoritmi za rudarjenje podatkov in strojno učenje imajo običajno nabor "prostih parametrov", ki lahko vplivajo na uspešnost napovedovanja. Lago, De Ridder in De Schutter (2018) zaključijo študijo o učinkovitosti osrednjih metod za napovedovanje cen električne energije z odprtim raziskovalnim vprašanjem o optimalni velikosti vzorca za učenje algoritmov. Z velikim številom simuliranih nastavitev za vsak posamezen model smo statistično raziskali omenjen učinek na uspešnost napovedovanja cen električne energije. Ugotovili smo, da je učinkovitost napovedovanja cen električne energije posameznih metod odvisna od izbranega trga in velikosti učnega vzorca. Zato omenjenih zaključkov ni mogoče uporabiti za oblikovanje splošnih trditev o optimalni velikosti vzorca za učenje določene metode. Kljub temu smo ugotovili, da je velikost učnega vzorca pozitivno povezana z natančnostjo napovedovanja cen električne energije in da imajo modeli prelomno točko, kjer se razmerje obrne. Modeli, ki temeljijo na nevronskih mrežah, ob bistveno večjih vzorcih za učenje v splošnem dosegajo večjo natančnost v primerjavi z drugimi izbranimi metodami.

V eni zgodnejših publikacij so Crespo Cuaresma, Hlouskova, Kossmeier in Obersteiner (2004) uporabili ARMA model časovnih vrst za napovedovanje cen električne energije v Nemčiji za dan vnaprej. Da bi v celoti izluščili informacije posamezne ure, so za vsako uro v dnevu ocenili ARMA model, ki so ga učili na grupiranih urnih podatkih. Poročali so o boljši učinkovitosti v primerjavi s pristopom, ki se ga v raziskavah najpogosteje uporablja in temelji na uporabi enega splošnega modela za napovedovanje vseh ur v dnevu. Posledica učenja na grupiranih urnih podatkih je zmanjšanje velikosti učnega vzorca za faktor števila 24 (število ur v dnevu) v primerjavi z učnim vzorcem, uporabljenim pri tradicionalnem pristopu. Takšen režim učenja bi lahko bil problematičen za modele, ki dosegajo boljšo napovedovalno uspešnost šele pri bistveno večjih učnih vzorcih. V primerjavi z uporabo enega splošnega modela za napovedovanje cen električne energije madžarskega trga so modeli, uporabljeni v naši raziskavi, uspešnejši, ker za učenje uporabijo grupirane urne podatke. Pri napovedovanju cen na grškem trgu so enaki modeli manj uspešni. Zato zaključimo, da lahko na določenih trgih učenje modelov na grupiranih urnih podatkih izboljša uspešnost napovedovanja cen električne energije.

V modele za napovedovanje cen električne energije smo vključili dodatno pojasnjevalno spremenljivko DSR (angl. *demand-supply ratio*), ki označuje delež razpoložljive inštalirane proizvodne zmogljivosti za pokrivanje povpraševanja po električni energiji. Visoke vrednosti pojasnjevalne spremenljivke DSR kažejo na nizko razpoložljivost prostih proizvodnih zmogljivosti in tesne tržne razmere (Alexander & Dominique, 2007). V zaostrenih tržnih razmerah lahko pride do t. i. cenovnih skokov, v ohlapnih razmerah pa do negativnih cen električne energije. Za cenovne skoke (angl. *price spike*) je značilen zelo kratek nenaden odmik cen EE od običajnega režima. Z dodatno vključeno pojasnjevalno spremenljivko DSR vsi modeli na grškem trgu dosežejo boljše napovedovalne rezultate. Medtem ko na madžarskem trgu doseže višjo natančnost samo model nevronske mreže, ki ima dodano pojasnjevalno spremenljivko DSR. Podrobna analiza uspešnosti napovedovanja cen električne energije na obeh trgih razkrije, da pojasnjevalna spremenljivka DSR nepomembno vpliva na natančnost napovedovanja cen električne energije v 50. najvišjih in 50. najnižjih primerih cen električne energije. Alexander in Dominique (2007) poročata o podobnih ugotovitvah, zato zaključimo, da v zaostrenih tržnih razmerah dodatna pojasnjevalna spremenljivka DSR ne izboljša uspešnosti napovedovanja cen električne energije.

Integrirani model za simulacije spojenih trgov električne energije: učinki na stičišču evropskih trgov električne energije

V drugem poglavju podrobno preučimo spajanje trgov električne energije v EU in predlagamo metodološko rešitev za tržne simulacije na spojenih trgih električne energije . Prav tako odgovorimo na pomembna vprašanja, povezana z učinkovito alokacijo čezmejnih prenosnih kapacitet, konvergenco cen električne energije in prenosom cenovnih šokov med trgi. Odgovore na raziskovalna vprašanja pridobimo empirično, z izvedeno simulacijo spajanja avstrijskega, italijanskega, slovenskega in hrvaškega trga z električno energijo. Slovenski trg, ki je osrednji trg simulacije, je preko avstrijskega daljnovoda povezan z razvitimi trgi električne energije srednjezahodne Evrope, ob tem je povezan s severno regijo Italije s tradicionalno visokimi cenami (Pellini, 2012) in preko hrvaškega daljnovoda z jugovzhodnimi evropskimi trgi v razvoju, za katere je značilna visoka volatilnost cen (Božić et al., 2020). Empirične ugotovitve s stičišča evropskih trgov električne energije so vsebinsko izredno relevantne in pridobljene na podlagi podatkov javno dostopne podatkovne baze ENTSOE-TP.

V povezavi z energetskimi trgi je eden izmed glavnih ciljev EU vzpostavitev energetske unije in posledično konvergence cen električne energije. Zaradi tehničnih omejitev prenosnega omrežja in različnih proizvodnih mešanic električne energije je konvergenca cen znotraj EU težko dosegljiva. Eden izmed ukrepov, ki bistveno pripomore k doseganju tega cilja, je spajanje trgov (angl. *market coupling*). Ti omogočajo optimalno izkoriščenost čezmejnih prenosnih zmogljivosti med trgi. Dražbe za čezmejne prenosne kapacitete in električno energijo na trgu za dan v naprej niso več organizirane ločeno. Namesto tega se na celotnem spojenem območju trgov z borznim algoritmom EUPHEMIA, ki maksimira socialno blaginjo vseh udeležencev na trgu, določita cena in alokacija čezmejnih prenosnih kapacitet . Kiesel in Kusterman (2016) sta ugotovila, da je na spojenih trgih električne energije ključnega pomena hkratno modeliranje cen na vseh področjih z enim simulacijskim modelom. Lago et al. (2018) podobno izpostavijo, da primanjkuje metodologija za empirične simulacije na spojenih trgih z električno energijo. Zato v drugem poglavju predlagamo simulacijski pristop, kjer se alokacija čezmejnih prenosnih kapacitet in cena EE določita hkrati z rešitvijo matematičnega optimizacijskega problema – algoritem EUPHEMIA. Vhodni podatek za matematično optimizacijo je knjiga oddanih naročil, ki jo za posamezno tržno območje pridobimo na podlagi ekonometrično ocenjene cenovne elastičnosti ponudbe. S predlaganim simulacijskim pristopom lahko tako hkrati analiziramo vpliv spajanja trga na dodeljevanje čezmejnih prenosnih kapacitet in na proces določitve cene električne energije. Statistični modeli ali napredni modeli s področja podatkovnega rudarjenja in strojnega učenja so splošni in ne omogočajo izvedbe takšne empirične analize.

Cilj izvedene simulacije spajanja avstrijskega, italijanskega, slovenskega in hrvaškega trga je odpraviti ugotovljeno neučinkovito rabo čezmejnih prenosnih kapacitet med takrat še nespojenimi trgi in temu ustrezno prilagoditi tržne cene električne energije v Avstriji, Italiji, Sloveniji in na Hrvaškem. Mehanizem spajanja trgov zagotavlja, da so čezmejne prenosne kapacitete vedno učinkovito izkoriščene z ekonomsko razlago pretokov energije proti trgom z višjo tržno ceno električne energije. Proste čezmejne prenosne kapacitete se pojavijo šele, ko so izkoriščene vse možnosti za arbitražo in so cene med trgi enake, kar izhaja iz specifikacije matematičnega optimizacijskega modela. V proučevanem obdobju lahko opazimo, da se izrazito neučinkovita raba čezmejnih prenosnih kapacitet pojavlja na meji med Hrvaško in Slovenijo (HRSI). Omenjena meja povezuje trga z ocenjeno nizko cenovno elastičnostjo ponudbe in zadostno količino čezmejnih prenosnih kapacitet za odpravo cenovnih razlik. Zaradi časovne razlike med dražbo za čezmejne prenosne kapacitete in električno energijo prihaja do informacijske asimetrije na nespojenih trgih, zato je konvergenca med slovenskim in hrvaškim trgom redko dosežena. Izkaže se, da je dano pooblastilo tržnim agentom za regulacijo prenosa električne energije na nespojenih trgih neučinkovito. Na podlagi simulacijskih rezultatov potrjujemo, da algoritem za spajanje trga odpravlja vse neučinkovitosti pri izkoriščanju čezmejnih prenosnih kapacitet in poveča konvergenco cen. Z izvedeno simulacijo empirično potrdimo, da je spojitev trgov z električno energijo učinkovitejše od prejšnjega tržnega mehanizma.

Po mnenju Laga et al. (2018) lahko učinki spajanja trgov izrazito spremenijo dinamiko oblikovanja cen električne energije. Z empiričnimi rezultati simulacije spajanja trgov lahko potrdimo zmanjšano volatilnost cen na simuliranem območju. Prav tako ti rezultati potrjujejo ugotovitve Huismana in Kiliça (2013), ki sta ekonometrično analizirala cene na petih spojenih trgih srednje in zahodne Evrope. Ugotovila sta, da se zaradi izboljšane likvidnosti cenovna volatilnost zmanjša, ob enem pa se zmanjša tudi število ekstremnih cenovnih situacij na spojenih trgih električne energije.

De Vany in Walls (1999) zaključita, da je ekonometrični model vektorske avtoregresije (VAR) izrazito primeren za modeliranje kompleksne dinamike cen električne energije, ki je značilen za povezane trge s čezmejnimi prenosnimi kapacitetami. Zato v poglavju z ocenjenimi VAR modeli raziščemo prenos cenovnih šokov, ki so dober indikator integriranosti trgov v EU. Na podlagi pregledane literature zaključimo, da gre za prvo analizo prenosov cenovnih šokov na realiziranih podatkih nespojenih trgov in na podlagi podatkov simulacije spojenih trgov. Primerjava ocenjenih funkcij impulznega odziva (angl. *impulse respone functions*), ki v VAR modelu predstavljajo prenos cenovnih šokov, razkriva spremenjeno tržno dinamiko cen na spojenih trgih električne energije. Statistično značilen prenos cenovnih šokov na nespojenih trgih s 24-urnim zamikom kaže na iniciativo tržnih udeležencev, da ob opaženem cenovnem šoku na enem od sosednjih trgov prilagodijo svoje strategije z enodnevnim zamikom. Prenos cenovnih šokov električne energije v simuliranem spojenem tržnem režimu je glede na rezultate ocenjenega modela takojšen in okrepljen. Glede na podatke empirične simulacije se integriranost trga z električno energijo v EU izboljša z uvajanjem spajanja trgov, kar potrjuje odpravljen časovni zamik in okrepljena intenzivnost prenosov cenovnih šokov s trgi, ki so povezani s čezmejnimi prenosnimi kapacitetami.

Izrivanje konvencionalne proizvodnje električne energije z obnovljivimi viri energije na grškem, madžarskem in romunskem trgu električne energije

V zadnjem poglavju analiziramo vpliv proizvodnje električne energije iz obnovljivih virov energije na trg. Nacionalne podporne sheme, ki jih je sprožila direktiva (2001/77/ES) za podporo obnovljivim virom energije s ciljem zmanjšanja izpusta toplogrednih plinov in tuje energetske odvisnosti, izrazito vplivajo na oblikovanje tržnih cen. Proizvodnja električne energije iz obnovljivih virov energije je brez stroškov goriva in se poplača iz omenjenih podpornih shem. Posledično proizvodnje iz obnovljivih virov energije na trgu izrivajo konvencionalne proizvodne tehnologije z višjimi mejnimi stroški proizvodnje, kar privede do nižjih tržnih cen (Würzburg et al., 2013). Izrivanje konvencionalnih virov proizvodnje električne energije s proizvodnjo iz obnovljivih virov energije raziskovalci poimenujejo kot t. i. učinek izrivanja konvencionalnih virov (angl. *merit order effect*). Cilj poglavja je ekonometrično potrditi prisotnost izrivanja konvencionalnih virov in simulacijsko prilagoditi realizirane tržne cene električne energije na scenarij brez proizvodnje iz obnovljivih virov energije na grškem, madžarskem in romunskem trgu.

Zaradi manjkajočih romunskih podatkov o proizvodnji na javno dostopni podatkovni bazi ENTSOE-TP se v raziskavi nismo mogli izogniti mešanju podatkovnih virov. Mešanje podatkovnih virov je zamudno, saj zahteva razvoj dodatnih programov za zbiranje podatkov in njihovo nadaljnjo obdelavo. Razpoložljivost in kakovost podatkov še vedno omejujeta raziskave s področja trgov z električno energijo.

Z ocenjenimi ekonometričnimi modeli statistično potrdimo prisotnost t. i. učinka izrivanja konvencionalnih virov električne energije na evropskih trgih v razvoju. Za vsako državo smo ocenili osem različnih modelov za potrditev omenjenega učinka. Razlikujemo med modeli, ki so ocenjeni na podatkih za posamezno koledarsko leto, in modeli, ki so ocenjeni na urnih podatkih med letoma 2015 in 2018. S prvo skupino modelov lahko zaznamo možne dolgoročne prilagoditve tržnih udeležencev na povečano proizvodnjo iz obnovljivih virov energije, z drugo skupino modelov pa lahko razlikujemo med učinkom vetrne in solarne proizvodnje na izrivanje konvencionalne proizvodnje električne energije. Izvedena ekonometrična analiza dopolnjuje obstoječe raziskave, ki so osredotočene na ključna energetska področja EU glede na inštalirano moč obnovljivih virov energije in razvitost trga z električno energijo.

Za dodatno potrditev negativnega vpliva obnovljivih virov energije proizvodnje na cene električne energije in z namenom ocene vpliva obnovljivih virov energije proizvodnje na volatilnost cen, realizirane tržne cene električne energije simulacijsko prilagodimo na scenarij brez proizvodnje iz obnovljivih virov energije. Uporabljen simulacijski pristop intuitivno sledi modelu DIME (Dispatch and Investment Model for Electricity Markets in Europe), ki so ga v podobni študiji uporabili Fürsch, Malischek in Lindenberger (2012). Model DIME upošteva vpliv proizvodnje iz obnovljivih virov energije na mednarodne pretoke električne nergije in dinamično prilagajanje konvencionalnih virov proizvodnje glede na spremembe proizvodnje iz obnovljivih virov energije. Proizvodnjo električne energije je mogoče učinkovito simulirati z optimizacijskimi modeli proizvodnje (angl. *unit commitment models*), ki minimizirajo skupne stroške proizvodnje elektrarn. Zaradi omejene dostopnosti javnih podatkov za razvoj optimizacijskega modela proizvodnje s pomočjo algoritmov podatkovnega rudarjenja ocenimo ponudbo konvencionalnih elektrarn, razvrščeno glede na kratkoročne mejne stroške proizvodnje v naraščajočem vrstnem redu skupaj s količino proizvedene energije (angl. *merit order*). Omenjeni pristop učinkovito opravi z nelinearnostjo cenovnih signalov električne energije (Weron, 2014) in premosti vrzel manjkajočih podatkov za implementacijo optimizacijskega modela proizvodnje, s katerim lahko opravimo učinkovito simulacijo tržnih cen električne energije v scenariju brez proizvodnje iz obnovljivih virov energije.

Vpliv proizvodnje iz obnovljivih virov energije na mednarodne pretoke električne energije smo ocenili z ekonometričnim modelom. Ocenjene vrednosti pojasnjevalnih spremenljivk so statistično značilne in v skladu s predhodnimi raziskavami (Traber & Kemfert, 2009), ki potrjujejo, da proizvodnja iz obnovljivih virov energije zmanjšuje uvoz električne energije. Rezultate ekonometričnega modela smo za izračun scenarija brez proizvodnje iz obnovljivih virov energije integrirali v simulacijsko okolje. Rezultati simulacije kažejo na znaten porast cen v državah z izrazito proizvodnjo električne energije iz obnovljivih virov energije (Grčija in Romunija). Izračunana volatilnost cen električne energije se v scenariju brez proizvodnje iz obnovljivih virov energije v povprečju zmanjša. Zmanjšana volatilnost cen električne energije je posledica izključene nestanovitne proizvodnje iz obnovljivih virov energije. S simulacijo potrdimo, da na trgih jugovzhodne Evrope proizvodnja energije iz obnovljivih virov niža cene električne energije in povečuje cenovno volatilnost. Simulacijski rezultati se ujemajo z raziskovalnimi spoznanji iz danskega in švedskega trga z električno energijo (Dong et al., 2019).

Čeprav disertacija ponuja več novih spoznanj glede modeliranja cen in vpliva novih dejavnikov na trge električne energije, ima določene omejitve. Prvič, disertacija je s sistematičnim kvantitativnim pregledom napovedovalne uspešnosti šestih sodobnih napovedovalnih algoritmov omejena na ugotovitve z grškega in madžarskega trga električne energije, zato oblikovanje splošnih trditev o učinkovitosti metod ni možno. Poleg tega je analiza omejena na šest temeljnih sodobnih napovedovalnih algoritmov, zato rezultatov ni mogoče posplošiti na druge obstoječe alternativne napovedovalne algoritme. Drugič, analiza učinka spajanja trgov električne energije trgov na cene in izkoriščenost čezmejnih prenosnih zmogljivosti bi bila z vključitvijo vseh evropskih trgov z električno energijo v izvedeno simulacijo metodološko ustreznejša. Razširjen obseg simulacije bi dodatno obogatil vektorsko avtoregresijsko analizo prenosa šoka cene električne energije, saj bi lahko preučili omenjen vpliv na vseh evropskih trgih. Uporabljen postopek izdelave knjige borznih naročil, ki temelji na ekonometrično ocenjeni funkciji elastičnosti ponudbene cene, bi lahko dopolnili tudi z uporabo sodobnih statističnih metod. Tretjič, simulacija cene električne energije v scenariju proizvodnje brez obnovljivih virov energije je zaradi nedostopnih javnih podatkov v analiziranih državah omejena zgolj na izvedbo s sodobnimi statističnimi metodami. Izvedba dodatne simulacije scenarija proizvodnje brez obnovljivih virov energije z optimizacijskimi modeli, ki temeljijo na teoriji agentov, in primerjava dobljenih rezultatov bi dodatno doprinesla k vrednosti študije.

Disertacija s prvim sistematičnim pregledom natančnosti sodobnih napovedovalnih metod, ki upošteva omejitve delovanja trga z električno energijo za dan vnaprej, poda raziskovalcem in tudi udeležencem trga z električno energijo statistično ovrednoteno informacijo. S statistično analizo prinaša tudi nove odgovore na aktualno raziskovalno vprašanje o vplivu velikosti podatkovne množice za učenje natančnosti napovedovalnih metod. Raziskovalci pogosto razpravljajo o pomanjkanju učinkovitega metodološkega pristopa za modeliranje spojenih trgov z električno energijo. Disertacija zaradi aktualne problematike na področju raziskovanja spojenih trgov v EU predlaga metodološki pristop, ki omogoča robustno izvedbo tržnih simulacij na spojenih trgih. Z izvedenimi empiričnimi simulacijami odgovori tudi na aktualna raziskovalna vprašanja o konvergenci in volatilnosti cen ter prenosu cenovnih šokov na spojenih trgih električne energije. Raziskovalno delo z analizo izrivanja konvencionalnih virov proizvodnje električne energije z obnovljivimi viri energije na trgih jugovzhodne Evrope dopolni obstoječo literaturo, ki je osredotočena le na razvita energetska področja EU. Znanstveno raziskovalno delo s področja trgov z električno energijo je podatkovno intenzivno in je bilo v preteklosti zaradi nerazpoložljivosti in javne nedostopnosti podatkov oteženo. Disertacija temelji na javno dostopni podatkovni bazi ENTSOE-TP in se v največji možni meri izogiba mešanju virov podatkov. To zagotavlja enostavno ponovljivost študije in bi lahko skupaj z izpostavljenimi omejitvami spodbudilo nadaljnje raziskovalno delo na področju trgov z električno energijo.