Data-driven Approach for Analyzing and Correlating Energy Market Products: Case Studies of Denmark and Croatia

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***Abstract*—Electricity price forecasting plays a vital role in the strategy decision making for almost all power market participants. This article investigates statistical background and potential relations between different power market products (e.g. day-ahead prices, intraday prices, etc.). Danish and Croatian power markets are used for the purpose of the case study to present the methods used in this article. First, Danish and Croatian power market structures are shortly explained to clarify the context of the problem. The data collection and preprocessing methods are described, followed by the core focus of the study: statistical analysis. In addition to the presented histograms of respective power market components, we examine interrelationships through statistical analysis, demonstrating significant correlations both numerically and graphically. Furthermore, price spreads are investigated as a logical next step of the noticed correlations. Our comparative analysis of Danish and Croatian market peculiarities reveals three key findings: i) statistically significant relationships between specific market components, ii) distinct behavioral patterns among observed factors, and iii) an open-access analytical tool with accompanying dataset for future research. Finally, the findings of this article present to market participants an efficient tool to adjust business strategies and increase profit.**

***Index Terms*—Day-ahead, distribution, intraday, prices, spread, statistical analysis.**

I. Introduction

In the past, national electricity systems were, by definition, big monopolies. From the mid-nineties, the EU Electricity Act introduced a step-wise opening of markets for all the EU member states [1]. Nowadays, every EU member state is obligated to have liberalized and deregulated electricity markets [2], [3]. Mentioned processes and regulatory changes are leading towards bigger competition and participation of privately owned companies in the electricity business [4]. Various markets offer diverse conditions and present different possibilities and downsides to its participants. Operational planning for any power system entity is subject to uncertainties. Inadequate forecasting and strategic bidding based on those uncertainties can significantly reduce its profit [5]. This paper closely observes operational planning dependent on trends in the electricity markets. To state it more precisely, this paper delivers, primarily, an extensive analysis of possible mutual influence of different markets based on their prices. Denmark and Croatia have been picked as reference cases, since their their geographical locations, climatic conditions and consumption profiles are different. Hence, it is interesting to observe how those characteristics affect market prices.

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A. Literature Review

1) Price Forecasting

Nowadays, price forecasting is rather a necessity than an optional feature. Currently, there are numerous articles in the academic community tackling the price forecasting topic. In [6], Ellatar *et al*. argued that their hybrid local general regression neural network and harmony search algorithm (LGRNN-HSA) significantly improve forecasting accuracy compared to other methods, whereas Toubeau *et al*. [7] focused on forecasting of distributional local marginal prices (DLMPs) using a new spatio-temporal framework for day-ahead probabilistic forecasting. In [8] the authors proposed a hybrid forecasting model. To obtain the optimal model, it combines the advantages of i) adaptive parameter-based variational mode decomposition, ii) Kernel-based extreme learning machine, iii) Chaotic sine cosine algorithm, iv) leave-one-out optimization strategy, and v) the selection strategy proposed in their article.

It should be noted the model currently has a limitation of focusing only on a single-variable forecasting issue. Hybrid approach was also used in [9], where Osorio *et al*. proposed a hybrid probabilistic forecasting model for short-term electricity market prices combining wavelet transforms, hybrid particle swarm optimization, adaptive neuro-fuzzy inference system, and Monte Carlo simulation. Bento *et al*. [10] are combining recent/similar day selection (best input features selection), wavelet transform, neural networks, bat and scaled conjugate gradient algorithms in an optimized arrangement, with a claim that the proposed approach can be applied to different electricity markets without loss of performance.

It is interesting to note that most recent articles observe the problem mainly for short term price forecasting. In that manner Banitalebi *et al*. [11] used the double and triple exponential smoothing technique to forecast electricity price volatility; Zhang *et al*. [12] proposed a deep neural network-based hybrid approach for short-term electricity price forecasting, while results in [13] point that deep learning-based Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN)-LSTM and CNN-Fully-Connected-Network outperform the supervised learning-based Recurrent Neural Network. Chang *et al*. [14] further elaborated and proposed a new hybrid model based on wavelet transform and Adam optimized LSTM neural network. On the other hand, Marjasz *et al*. [15] have shown that long-term seasonal components may also be included. Moreover, incorporating nonlinear autoregressive neural network models with identical input variables to the Seasonal Auto-Regressive models may yield superior performance metrics.

Early research in forecasting predominantly employed time series modeling approaches. Contreras *et al*. [16] developed a day-ahead electricity price forecasting method using ARIMA models, while [17] enhanced this approach by incorporating wavelet transform for decomposing non-stationary price series. Nogales *et al*. in [18] proposed a time-series based model, namely dynamic regression and transfer function models presenting more accurate predictions than articles that used ARIMA models. Reference [19] demonstrates that the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methodology achieves comparable average forecast accuracy to ARIMA models (approximately 9% error), while exhibiting significantly superior performance during periods of market volatility and price spikes.

2) Spread Forecasting

Price forecasting represents only one aspect of research interest; the analysis of price spreads constitutes an equally significant area of investigation. In that manner, Dialo *et al*. [20] focused on forecasting the spread between HUPX and EEX DAM prices cost benefit analysis. Fundamentally, these forecasts are underpinned by complex interrelationships between multiple facets of power markets, and more broadly, by connections between electricity markets and external contributing factors from other domains (e.g. oil prices [21], weather forecasts [22], geopolitical situations [23], . . .). Hence, it is of great value to detect most influential factors on price formation process and their mutual relations. Some examples of well-known relations are load-price relations [24] or relations between prices in different markets [25]. This topic is well researched and some of the research done will be tackled in the following paragraphs. Aghaie [26] conducted statistical analysis of the German electricity market in the presence of renewable energy sources. Results have shown that the correlation between price and residual load is much higher than correlation between price and RES generation. In [27], the authors argued that both demand and price dynamics exhibit scale and time dependent structures with annual cycle, thus, refuting the random walk claim [28] and encouraging efforts for this and many more articles. Maciejowska *et al*. in [25] argued that the price spread sign can be successfully predicted and used for an adequate market positioning of small RES units. Kremer *et al*. [29] focused on intraday electricity pricing of 15-minute contracts during night hours (in German market) and argued the price information of neighboring contracts, trading volumes, and intraday wind power forecasts play a significant role for electricity prices of night contracts. Srestha investigated in [30] which statistical distributions describe Singapore electricity market prices in the most precise manner. Normal, Log-normal and Weibull distributions were identified as possible candidates, and Log-normal distribution fitted observed data.

Besides the statistical analysis between different factors considering power markets, researchers have dedicated their efforts to investigate possible relationships between different energy markets. In that manner, Bencivenga *et al*. have published a book [31] investigating the relationship between crude oil, natural gas and electricity price. They argued that gas, oil and electricity markets are integrated. Wang *et al*. [32], who investigated four major energy futures markets (electricity, coal, natural gas and crude oil) argued the connectedness among the four energy markets is much stronger in short term than in longer time horizons.

The conducted literature survey presented various statistical techniques and methodologies used in price forecasting. Research studies encompass analyses of relationships between prices in different markets and future price (and load) forecasting. However, there is a gap in research articles concerned solely with deep statistical analysis and descriptive explanations about different occurrences in power markets. This article, hence, thoroughly analyzes the relationships between various electricity market components in two different regions (Denmark and Croatia). In addition to observed patterns in Denmark and Croatia, difference between those two regions are also pointed out and possible reasons are discussed.

B. Paper Positioning and Contribution

Contributions of this paper are multi-fold. First of all, the paper brings a concise explanation of the Danish (and consequently Croatian) power market structure and a glimpse into data acquisition and preprocessing of power data. The paper's main contributions can be summarized as the following aspects: 1) An (novel) approach of observing DA and ID power market segment characteristics for speculative strategies other than pure price hedging; 2) DA-ID price spread analysis including investigation of what are the main drivers for price differences and its disposition depending on specific categories (time of day, season); 3) Discussion of differences between price patterns in Denmark and Croatia.

To facilitate future research on market price correlations and their underlying determinants, the authors have made all datasets and analytical tools openly accessible to the research community. The rest of the paper is structured as follows: Section II explains the electricity power market with emphasis on Denmark and remarks regarding Croatia, considering primarily nordic power exchange - Nord Pool (day-ahead and intraday trading), balancing and reserve markets. Section III explains data acquiring and preprocessing steps. Section IV provides step-by-step in-depth analysis of Danish and Croatian power market. Section V provides relevant conclusions and guidelines for future work.

II. MARKETS

A. Denmark - General

The Danish market is split into two areas: 1) The West Denmark area, covers the Jutland peninsula, Fyn island, and the rest of the islands west of the Great Belt; 2) East Denmark area covers the islands to the East of Fyn.

The West Denmark area is connected to the European continental grid, and the East Denmark area is connected to the Nordic grid. Since autumn of 2010, the two areas have been connected through a 600 MW DC connection across the Great Belt [33]. The Transmission System Operator (TSO) in Denmark is "Energinet", while Denmark's physical market is part of the Nord Pool, a company which offers day-ahead and intraday trading, clearing and settlement. Nord Pool operates electricity markets across multiple European regions, encompassing the Nordic and Baltic areas, Denmark, Germany, France, the Netherlands, Belgium, Austria, and the United Kingdom. It is owned by TSOs from Sweden, Norway, Finland, Denmark and Baltic TSOs.

B. Nord Pool

Nord Pool provides two markets for physical trade; day-ahead market (Elspot) and intraday market (Elbas). It uses the concept of implicit auction, meaning the transfer capacity is allocated concurrently with electricity being traded. Thus, all bidding between different bidding areas must go through Nord Pool.

1) Day-ahead Market

Elspot market is a common name for the day-ahead market on Nord Pool. Its participants are able to trade power contracts for next day physical delivery with a trading horizon from 12 to 36 hours ahead.

Every day by 10:00, it is known how much transfer capacity between bidding areas is guaranteed by the Nordic TSOs. Trading closes at 12:00 CET each day, when all bids (sale or purchase) are collected. Bids are aggregated into a supply and demand curve; consequently, hourly prices for the following day are calculated and published not before 12:42 CET. A limit has been set to negative price of -500 €/MWh and positive price of 3000 €/MWh. The unified price ceiling applies to all participating countries within the single day-ahead coupling framework [34]. In the absence of inter-zonal transmission congestion, this mechanism ensures uniform pricing across all bidding zones. However, congestion typically results in price divergence between zones.

2) Intraday Market

The Electricity Balance Adjustment System (Elbas) operates as a continuous intraday market, permitting power trading until one hour before physical delivery. This market functions on a price-time priority basis, where participants submit binding bids specifying both quantity (MWh) and price.

C. Energinet

1) Balancing Markets

Some refer to it as real-time market because it presents the last market opportunity to balance production and consumption prior to delivery. In terms of the balancing market, important factors are Balance Responsible Parties (BRPs). Their primary goal is to avoid any possible imbalances and they are financially responsible to settle all imbalances with the respective TSO. BRPs are divided into load balance responsible (LBR) and production balance responsible (PBR). PBRs are usually a power generation company or cluster of more power generators joined together. Their responsibility is to precisely plan production for the upcoming day. LBRs are in most of the cases electricity trading companies. Their main task is to plan consumption for the upcoming day. As they pool consumers, they can bid on various electricity markets. To settle imbalances, BRPs are active in the balancing market. The balancing market is divided into a regulating and balancing power market [35].

a) Regulating Power Market: According to bids for upward and downward regulation submitted to the Energinet by players, Energinet buys/sells (regulating) power from/to them in the delivery hour. Players have two options on how to participate in the regulating power market. 1) A player can conclude an agreement with Energinet on keeping manual reserves available. This commits the player to enter regulating-power bids for a specified volume over a specified period of time. In addition to the energy payment, the player also receives an availability payment. 2) While market participants may submit uncommitted bids for regulating power, such offers become ineligible for capacity availability payments and only qualify for energy delivery compensation. One of the prerequisites to participate in the regulating power market is the ability to fully activate a given bid in a maximum of 15 minutes from receipt of the activation order. Furthermore, bids can range from 5 MW to a maximum of 50 MW, with the following pricing restrictions: i) For the upward regulation, minimum price is the spot price for the respective hour and maximum price cannot be more than 5,000 €/MWh. ii) Speaking of downward regulation, maximum price is the spot price for the respective hour. Assuming no bottlenecks and no extraordinary situations, the common price is determined by the highest activated regulating power bid. If bottlenecks occur, regulating power market splits into different regions with their own prices.

b) Balancing Power Market: Balancing power market allows Energinet to buy/sell (balancing) power from/to the players in order to neutralize imbalances incurred by them. Settlement calculations for these transactions are performed post-delivery, following the availability of all metered data and final determination of system imbalances. Energinet uses both the one-price model and two price model. The first one is used for settlement of balancing power from the perspective of consumption and trade, whilst the other model considers pricing of production imbalances. In one-price system, imbalances are settled at the regulating power price (see Table I) in contrast to the two-price system model where imbalances which consequently contribute to the system's imbalance, are settled at the regulating power price, while opposite imbalances which unintentionally help the system are settled at spot price (see Table II). Through this way, the pricing system does not allow PBR to make a profit from their imbalances.

TABLE I
ONE-PRICE SYSTEM

Situation in the system	LBR consumed more than planned	LBR consumed less than planned
Upward regulation needed	Pays regulating power price	Receives regulating power price
Downward regulation needed	Pays regulating power price	Pays regulating power price

TABLE II
TWO-PRICE SYSTEM

Situation in the system	PBR produced more than planned	PBR produced less than planned
Upward regulation needed	Receives spot price	Pays regulating power price
Downward regulation needed	Receives regulating power price	Pays spot price

2) Ancillary Services

The West Denmark area distinguishes following ancillary services: 1) Primary reserve, FCR; 2) Secondary reserve, aFRR; 3) Manual (tertiary) reserve, mFRR.

a) FCR: Frequency containment reserve (FCR) is an automatic regulation which, after some disturbance, has the task to stabilize frequency deviation close to 50 Hz. The first half of the activated reserve must be supplied within 15 seconds. The rest of the reserve must be supplied within 30 seconds. Allowed frequency deviation is +/- 200 mHz relative to system frequency of 50 Hz. Once activated, it must be possible to maintain the regulation for a minimum of 15 minutes, when other ancillary services are intended to take its place. After no longer than 15 minutes of idle time, the reserve must be reestablished. It consists of upward and downward regulation. The West Denmark area was obliged to supply +/- 20 MW in 2017 [36], while for 2020 the requirement increased to +/- 21 MW [37]. An auction is being held once a day for the next day of operation which is divided into six four-hour blocks. Market participants must submit their bids by 15:00 for day-ahead delivery. All the accepted bids for the upward regulation receive an availability payment in the amount of the highest accepted bid. The same principle is applied for downward regulation. Pricing of supplied energy is settled like ordinary imbalances.

b) aFRR: Automatic frequency restoration is the secondary reserve. If a major system disturbance occurs, its task is to restore system frequency to 50 Hz. The primary reserve constitutes the frequency containment resource, activated immediately following system disturbances. The secondary reserve serves dual functions: i) relieving the committed primary reserve capacity, and ii) restoring scheduled power exchanges on interconnectors. Secondary reserve must be fully in service no later than fifteen minutes upon receipt of the activation signal. The regulation must be possible to maintain continuously. Same as the FCR, aFRR consists of upward and downward regulation. Players submit their bid (from min 1 MW to max 50 MW) indicating the price for the offered volume throughout the respective period. All the accepted bids receive payment according to the price they submitted (pay-as-bid system) for offered capacities. Actually provided energy is paid in the following manner: i) Upward regulation: spot price per MWh + DKK 100/MWh, based, at least, on the regulating power price for upward regulation; ii) Downward regulation: spot price – DKK 100/MWh, but not exceeding the regulating power price for downward regulation.

3) mFRR - Regulating Power Market

Manual frequency restoration, considered also as tertiary reserve, is manually activated ordering upward and downward regulation from relevant suppliers. In addition to supplementing and replacing the secondary reserve for minor imbalances, this reserve tier maintains system equilibrium during disturbances affecting both generation assets and interconnectors. With activation requirements identical to secondary reserves, full deployment must be achieved within 15 minutes of activation notice. Two types of manual reserve are to be distinguished – upward and downward regulation power. As mFRR is in fact energy traded on the Regulating power market, all the characteristics are already mentioned, but for the sake of completeness it will be also briefly mentioned here. Once a day an auction is held for each of the hours of the upcoming day. On the day before the delivery, Energinet announces expected reserve requirements for the upcoming day latest at 9:00 and bids must be sent no later than 9:30 of the same day. Bids should state hour-by-hour volume (from 5 MW to 50 MW) and price. All accepted bids for upward regulation receive the same availability payment which is equal to the highest accepted bid. The same principle of pricing is applied for downward regulation. Delivered energy volumes are based upon balancing market rules (prices for regulating power). Replacement Reserves (RR) are currently not used in the Nordic synchronous area [38].

D. Croatia

Croatian power market is not as highly developed as the one described in Denmark, but the tendency is to develop it in the same direction. Hence, here we mention only the most important facts about Croatian power market as the focus of this paper is mainly on day-ahead and intraday markets which are the same in both countries. Unlike Denmark's two-region configuration, Croatia operates as a single bidding zone in its electricity market structure. Day-ahead and intraday markets are organized on Croatian Power Exchange (CROPEX) [39]. Furthermore, unlike Denmark's fully liberalized ancillary services market, Croatia maintains partial market restrictions on these services. FCR provision is obligatory (and without compensation) for all thermal power plants over 30 MW and hydro power plants over 10 MW. The aFRR payments consist of reserved capacity and procured energy reimbursement. The prices are determined by Croatian authorities, meaning that the pricing system is not the same as in Denmark. Provided energy price is calculated in regards to the stock indices

HUPX and BSP multiplied with following coefficients: 1.4 for upward regulation and 0.6 for downward regulation. It is important to mention a potential problem lies in the fact that, currently, only hydro power plants are included in the aFRR, hence availability is strongly weather dependent [40]. The mFRR for system security refers to regulation block Bosnia and Herzegovina, Croatia and Slovenia. An auction for capacity reservation is conducted on a weekly basis. The generation facility may offer both reserved capacity and energy services, or only bid for energy services. Balancing market prices are calculated with regards to the pondered upward and downward regulation prices, day-ahead prices and total amount of activated upward and downward energy volume from reserved capacity.

E. Market Structure Overview

Previous sections have described market structure in Denmark (in a detailed manner) and in Croatia (in a short version). To emphasize key characteristics in both countries, Table III presents the most important features of the observed market components.

TABLE III
BASIC MARKET CHARACTERISTICS

Description	Denmark	Croatia
DA	NordPool	CROPEX
ID	NordPool	CROPEX
FCR	Auction for capacity; Provided energy settlement as ordinary imbalance	No reimbursement
aFRR	Capacity - pay as bid; Provided energy settlement depending on the spot price	Prices for capacity and provided energy determined by authorities
mFRR	Auction for capacity; Provided energy settlement as ordinary imbalance	Capacity auction on weekly basis; Provided energy settlement price determined by authorities
BM	One- and two-price system	One-price system

F. Imbalance - Motivation

Nowadays, we are facing fast penetration of highly intermittent energy sources such as wind farms and solar panels. These trends raise the importance of high quality forecasts from renewable energy resources as they create challenges for system operators when predictions are off by a big margin. Various studies have been conducted to determine the value of forecasts. First, by examining the economic impact of price forecast inaccuracies on forecast users, Zareipour *et al.* [41] have come to the conclusion that importance of forecast errors highly depends on the type of the forecast user. Wang *et al.* [42] investigated the cost of day-ahead solar forecasting errors in the United States for solar power plants participating in real-time markets or combination of day-ahead and real-time markets. They argued that the average costs of forecasting errors at solar plants were no more than 1\$/MWh in all of the observed years except 2016 when it rose to 1.5\$/MWh using a publicly available meteorological forecast model. Having the cost of inaccuracies in mind, Stratigakos *et al.* [43] incorporated minimization of trading costs as a consequence of erroneous forecasts in their forecasting model.

In general, forecasts can be divided into two main categories: short-term and long-term forecasting. Long-term forecasting is used by system operators for system planning and by interested stakeholders for siting and sizing of potential renewable power plants. On the other hand, short-term forecasting is important for system stability from the system operator viewpoint and trading from the market players viewpoint [44]. For the purpose of this article, we are interested primarily in short-term forecasting and to have a better understanding of the order magnitude of forecast errors, a few methods and the recorded error metrics are listed. For instance, [45] used SARIMA based models to predict solar radiation and wind speed in Los Angeles and Chicago in order to determine and investigate a reasonable sizing for a hybrid renewable energy system powering a data center. The absolute mean error (MAE) for solar radiation was 7.03% in Los Angeles and 15.6% in Chicago, whereas for wind speed 29.83% in Los Angeles and 12.54% in Chicago. Zhang *et al.* [46] have developed a two-stage wind speed forecasting model that combines the advantages of the VMD technique, IMODA, error correction and the nonlinear ensemble approach lowering MAE under 5%. There are also other articles with similar errors for wind power prediction such as [47], [48]. Speaking about PV generation forecasts, [49] claimed their forecasting method based on Artificial Neural Networks (ANN) exhibits MAE of 6%, while [50] also used ANN and recorded average annually Root Mean Square Error (NRMSE) of 11.12. Furthermore, as we are using official data from Danish and Croatian markets, it is interesting to mention the Croatian Energy Market Operator reported MAE of 4.78% for wind energy, whereas for solar energy MAE of 1.85% in 2020 [51]. The forecast errors of the Danish TSO are not publicly available, however available data suggests over-forecast errors with MAE no higher than 5% [52], [53]. It is quite obvious that such magnitude of errors in systems with high share of RES may cause technical and economic difficulties.

To reduce stress on the system and additional financial burden for market players, forecasting methods are constantly being developed. Consequently, strategies to balance supply and demand in close to real-time trading markets, such as intraday in the EU context, are continuously improved. In those situations, when DA forecasts/schedules diverge from actual generation (in the intraday framework) market players have a choice to either pay the imbalance by the imbalance settlement price or they can use the intraday market to reschedule their market position according to the most recent forecasts. Intraday is the last resort before the ex-post imbalance settlement and it is traditionally used to hedge against costly penalties in the ex-post balancing markets [54], [55]. In the intraday market, trade is realized if a match between bid and ask price is found, meaning the trade is conducted when both parties are satisfied with the price; otherwise a match is not found. On the other hand, ex-post imbalance settlement forces player whose errors in prediction caused the imbalance to pay balancing prices (penalties) that are often very high and, most importantly, non-negotiable. The intention of this article is to show that besides hedging, which is a very useful strategy, intraday market may also be used for other speculative strategies, such as arbitrage, with the main goal of increasing profits. To be able to conduct price arbitrage, difference between prices in those two markets should be investigated. Furthermore, one of the main ideas of the integrated EU power market is that prices reflect the real situation in the system. This principle is called scarcity pricing and it is possible only when a price floor is low enough and price cap high enough [56], [57]. In that manner, extra low prices express abundance of energy compared to demand, whereas high prices express the situation when there is a lack of energy compared to demand. The expanding price spread between declining floor prices and rising price ceilings enhances the relevance of our analysis, as it reflects increased market volatility and creates broader arbitrage opportunities.

III. Data Collection and Preprocessing

Regardless which market is investigated, acquiring data is the first and necessary step for any further analysis. According to Statista.com, the amount of data/information produced in 2010 was about 2 zettabytes and the predicted amount for 2024 reaches 149 zettabytes [58]. In only fourteen years, the predicted increase is more than seventy times. Without any doubt, such vast amount of data presents quite a challenge for data scientists to efficiently store and preprocess in order to solve respective tasks in an optimal manner. While this article provides a concise overview of the methodology, its principal contribution lies in publishing comprehensively processed EU market datasets in an accessible format, enabling replication studies and further analysis by researchers.

A. Data Collection

For this research, the primary data collection focused on historical price series from key electricity market segments, including day-ahead market, intraday market, balancing market (activated energy), and ancillary services (capacity) prices.

Primarily, the most important datasets are day-ahead and intraday market prices, while others were also considered helpful. In previous years it was quite a problem to gather data across all EU markets. Nowadays, there is a tendency to make publicly available all of relevant data as TSOs around Europe prepare to be part of projects such as PICASSO [59], TERRE [60] or MARI [61] and FCR cooperation [62]. While the emerging practice of commercializing historical data by major platforms like EPEX presents accessibility challenges, our analysis incorporates additional critical data categories whose availability varies significantly across markets: wind power forecasts, gross electricity consumption, generation forecasts, load predictions, total scheduled cross-border flows, and solar PV production forecasts.

As far as the Danish market is concerned, their TSO has a specialized web-site [63] which provides numerous publicly available data including wholesale market and ancillary services. Combined with Nord Pool's website [64], it is fairly easy to locate all needed data. Regarding data for other EU countries, ENTSO-e Transparency Platform [65] is a good starting point (especially for historical DA prices), but often there is a need to find local web-sites in order to find specific data (e.g.price information about ancillary services). Fortunately, current trend is to centralize EU databases with all relevant market data. Day-ahead and intraday prices for Croatia may be found on the CROPEX website [39].

B. Data Preprocessing

Following data acquisition, the preprocessing phase transforms raw datasets into analyzable formats through two systematic procedures, i.e. finding and fixing errors; fine tuning.

It is often the case that fetched data may have some inconsistencies, gaps and smaller or bigger mistakes that need to be detected and corrected. For example, one of the problems encountered was different ways of dealing with daylight-saving time and because of that, the data from various sources were out of sync. On the other hand, although data may be perfectly in order, to be in line with requirements of further analysis, sometimes fine tuning is necessary. Such tailor-made modifications depend from case to case, thus publicly available data should be error-prone, and individual users then further modify the data for their respective purposes.

IV. Statistical Analysis

This chapter is dedicated to thorough statistical analysis of the publicly available data for the observed power markets. In the following subsections, sequential step-by-step in-depth analysis is presented.

A. Evolution of the DA, ID and Their Spread Values

The main data used in the remainder of this paper consists of DA prices, ID prices and the price difference between the DA and the ID (price spread). Hence, before any further detailed analysis of different characteristics these data sets exhibit, it is interesting to perceive the evolution of respective curves throughout the whole observed period (Jan 2018 – Jan 2021). Fig. 1 depicts daily mean DA prices for three consecutive years. Following the same principle, Fig. 2 presents the ID price curve evolution, while Fig. 3 presents the spread curve. Although these graphs bring vague information until more detailed analyses are made, it is interesting to note

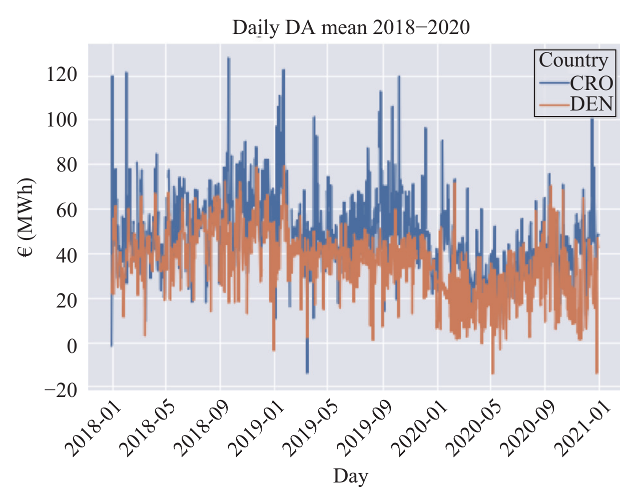

Fig. 1. DEN and CRO: DA price curve.

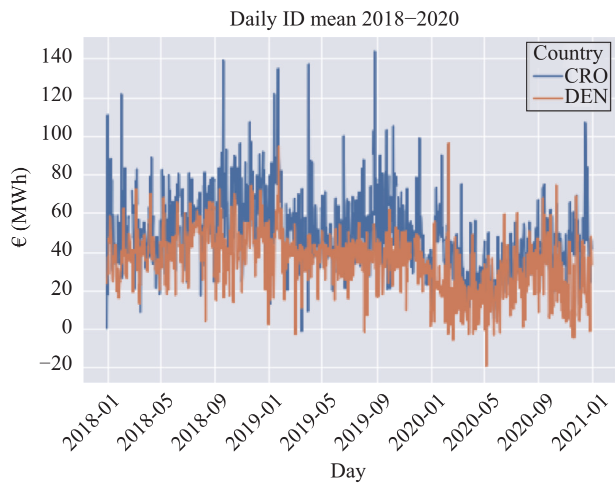

Fig. 2. DEN and CRO: ID price curve.

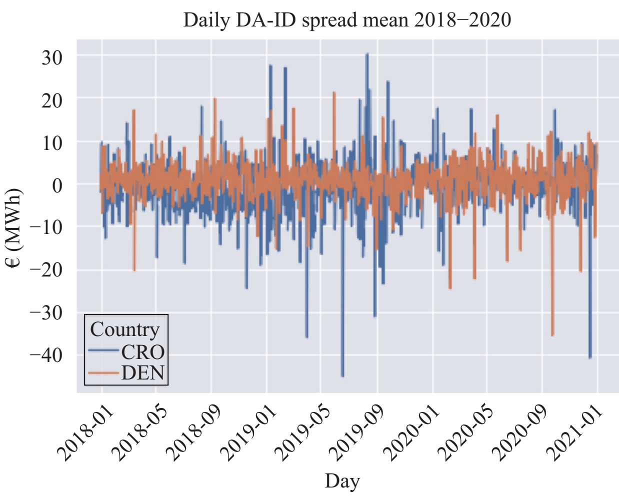

Fig. 3. DEN and CRO: Spread value curve.

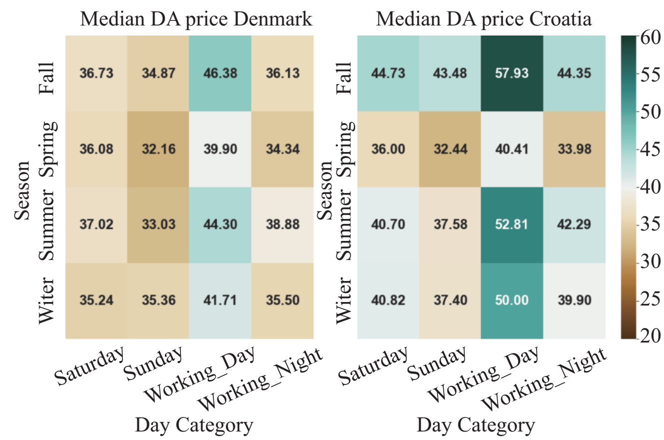

Fig. 4. Median day-ahead prices per season per day category (€/MWh).

that generally, both DA and ID prices are somewhat higher in Croatia compared to Denmark, while following the same trends.

Moreover, as in the following paragraphs price spreads are analyzed in great detail, the authors find it important to bring the relationship between price levels and their spreads closer to the reader. Hence, Fig. 4 depicts median day-ahead prices per season per day category, while later in the text, the price spreads are analyzed. In that manner, price spread order of magnitude compared to prices themselves, are presented to the interested reader. Similar representation for ID prices is not included due to redundancy and brevity of the article. It is fairly easy to assume median ID prices knowing median DA prices and their spreads.

B. Distribution of DA and ID Prices

The application of most statistical methods requires prior knowledge of the underlying data distribution. Furthermore, the selection of appropriate analytical techniques should be guided by the identified distributional characteristics.

Figure 5 presents a histogram of spot prices for different seasons (Autumn, Winter, Spring, Summer) and different categories of a day (Sunday, Saturday, Working Night, Working Day) both in Denmark and Croatia. Light blue color depicts Denmark's day-ahead price distribution, while the orange color is reserved for Croatia. To have a fair amount of data in each of the categories, including "Sundays", we have merged real holidays and Sundays into one category ("Sunday") as they exhibit similar patterns.

Distribution on the histogram resembles Gaussian distribution, but it is not perfect. Closer observation may show in the Danish day-ahead prices histogram, left and right side are not symmetrical. The distribution's left tail exhibits a secondary frequency maximum, though with significantly lower density than the central tendency. This asymmetry indicates higher probability mass for below-median price realizations compared to above-median outcomes. Depending on the season and day category, the Danish distribution exhibits either positive skewness or symmetrical distribution. Kurtosis is somewhat bigger than in normal distribution, hence extreme outliers are more common. As for the day-ahead price distribution in Croatia, negative skew is easily observed, while the kurtosis is smaller than in the Danish case. Further statistical tests have been made to check if resemblance is good-enough to consider it as a bell-curve. In the perfect scenario, the mode, mean and median should be the same. But, as Table IV shows, this is not the case.

Nevertheless, quantile-quantile plot (for Denmark), shown on Fig. 6 even better demonstrates that spot prices share resemblance with Gaussian distribution, but with deviations on both sides of the extremes.

In case of perfect bell-curved distribution, the blue line would follow the red one - a straight line with angle to the x-axis of 45 degrees. As they indeed deviate a bit, the strongest claim for the given dataset, as already stated above, may be that it resembles the bell-curved distribution. Fortunately, this is good enough for research purposes of this article, as methods used in the remainder of this article do not require perfectly shaped Gaussian distribution.

The same distribution analysis was conducted for intraday prices too. By observing Fig. 7, one could also notice a Gaussian-like shape. But, it is categorized by more noticeable tails, meaning that intraday prices exhibit somewhat wider

Fig. 5. DEN and CRO: Spot prices distribution.

TABLE IV
DA PRICES - MEAN, MODE, MEDIAN, MAX AND MIN

Time		Mean		Mode		Median		Max		Min	
		CRO	DEN	CRO	DEN	CRO	DEN	CRO	DEN	CRO	DEN
Saturday	Fall	46.33	34.04	35	37	44.73	36.73	108.16	86.11	8.20	-6.79
	Winter	44.04	34.13	36	31	40.82	35.24	126.00	76.06	1.35	-11.86
	Spring	36.84	33.68	37;42	40	36.00	36.08	114.10	85.96	1.35	-3.46
	Summer	44.58	38.57	32	28;35	40.7	37.02	138.18	114.00	4.70	2.34
Sunday	Fall	44.48	32.96	40	32	43.48	34.87	110.13	79.72	1.05	-7.98
	Winter	37.38	31.30	41	37	37.40	35.36	94.43	77.98	-20.23	-33.58
	Spring	33.69	29.87	15	36	32.44	32.17	100.01	82.12	-23.48	-15.04
	Summer	40.08	32.92	30	44	37.58	33.03	115.09	79.96	1.57	-58.80
Working Day	Fall	60.01	44.89	70	44;46	57.93	46.38	172.07	128.26	0	-35.75
	Winter	53.64	41.83	40	42	50.00	41.71	155.06	110.56	-0.48	0.09
	Spring	41.92	37.29	45	40	40.41	39.90	136.03	87.12	-4.93	-49.97
	Summer	54.50	43.51	40	50	52.82	44.30	180.05	144.33	7.25	-8.96
Working Night	Fall	46.90	34.76	37	36	44.35	36.13	151.00	200.04	-10.79	-12.55
	Winter	41.62	33.37	34;40	41	39.90	35.50	150.02	96.70	-5.98	-48.29
	Spring	35.96	32.82	30	34	33.98	34.34	140.10	93.43	-14.91	-15.08
	Summer	45.27	38.68	40	38	42.29	38.89	163.06	189.25	8.67	-15.05

Probability Density Function (PDF). The skewness in both Danish and Croatian cases is similar to the Gaussian distribution. In the Croatian case, a slight positive skew may be observed in a few of the Season-Day Category combinations. On the other hand, in Danish case some Season-Day Category combinations exhibit already mentioned thicker left tails.

C. Correlations

After establishing the most basic statistical properties of the day-ahead and intraday markets (chosen as the two most common type of power markets), further steps raise the question how are (if at all) their prices mutually connected. Analysis is done in two directions: 1) investigate correlation between DAM and other prices occurring in power system and 2) investigate correlation between DAM price and physical values occurring in power system. We acknowledge that other prices can also be correlated to physical values but to maintain brevity of the article such correlations research is left for future research. Moreover, emphasis has been put on the relationship between DAM and IDM prices. To estimate coefficients of the correlation, the Spearman method was used. The formula for Spearman's correlation is [66]:

$$\rho_{\mathrm{rank}_x,\mathrm{rank}_y} = \frac{\mathrm{cov}(\mathrm{rank}_x,\mathrm{rank}_y)}{\sigma_{\mathrm{rank}_x}\sigma_{\mathrm{rank}_y}} \tag{1}$$

The coefficient can be between -1, which means that two variables are in perfect negative correlation, and 1, which means that two variables are in perfect positive correlation.

TABLE V
ID PRICES - MEAN, MODE, MEDIAN, MAX AND MIN

Time		Mean		Mode		Median		Max		Min	
		CRO	DEN	CRO	DEN	CRO	DEN	CRO	DEN	CRO	DEN
Saturday	Fall	46.65	33.51	40	46	44.00	35.60	120.00	82.79	7.58	−8.44
	Winter	45.64	33.72	36	50	42.2	35.00	150.00	76.17	1.50	−13.74
	Spring	38.41	32.89	40	39	37.09	35.81	140.00	88.33	0.87	−28.14
	Summer	45.43	38.11	25	28;33	40.33	36.49	150.00	106.70	5.40	−0.28
Sunday	Fall	44.54	32.03	39	30	42.96	33.21	112.90	81.15	3.01	−44.31
	Winter	37.79	29.98	30	40	36.98	33.07	87.00	87.61	−3.00	−40.31
	Spring	33.46	28.40	30;38	37	33.00	30.60	100.36	96.32	−2.13	−29.99
	Summer	39.96	31.92	33;36	34	36.00	32.78	115.00	75.37	7.18	−31.43
Working Day	Fall	61.95	44.23	45	50	59.15	45.80	200.00	172.91	1.00	−51.07
	Winter	55.44	41.02	50	44	50.87	40.88	214.83	262.65	1.81	−1.92
	Spring	43.13	36.78	30	39	40.69	38.89	137.08	143.69	−12.15	−73.53
	Summer	56.25	42.70	50	36	53.89	42.93	171.50	102.22	8.16	−54.74
Working Night	Fall	47.03	34.23	37;40	34	43.32	35.58	147.06	130.37	0.23	−19.10
	Winter	42.46	32.98	40	38	40.00	34.68	145.09	138.63	−1.57	−48.51
	Spring	36.38	31.89	30	38	33.59	33.80	133.20	92.72	−12.57	−15.66
	Summer	46.39	38.28	32	343	42.07	38.24	168.73	182.43	3.00	−18.28

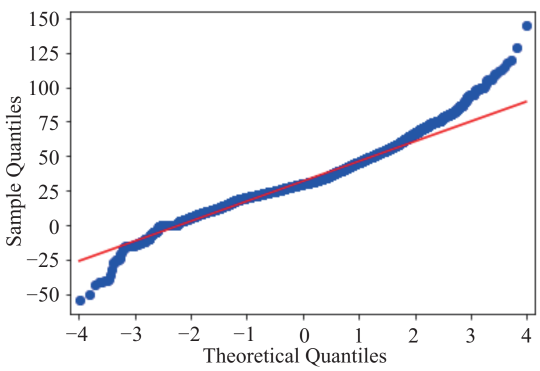

Fig. 6. Quantile-quantile distribution.

Zero stands for no correlation. The Spearman coefficient was used because observed datasets do not form ideal normal distribution and Spearman method is more robust to such deviations. The mentioned correlation/statistical investigation is presented in Figs. 8 and 9. Only the Danish datasets were used due to limited availability of required data in Croatia and also due to higher level market development in Denmark. The first one refers to prices of different sub-markets and second refers to spot prices and various data concerning energy volumes

Figure 8 shows correlation coefficients between all Denmark's power submarkets. For the observed period (2015-01-01 to 2018-12-31), mFRR downward service was not traded and therefore it is omitted from the heatmap on Fig. 8. Heatmap very precisely illustrates exceptionally strong connections between some of the submarkets with day-ahead market prices. Prices of the Elbas (AVG_ID) have very high correlation coefficient of 0.93 with prices of the day ahead market (DAM), and the same applies for the balancing market. Furthermore, prices for activation of secondary reserve (aFRR) are almost completely correlated with DAM price because the aFRR activation price is calculated as spot price + fixed amount (see section II-C2b). The analysis reveals fundamentally different correlation patterns: FCR capacity payments show no significant correlation with energy prices (DAM, IDM, BM) since they compensate availability rather than stochastic activations. Conversely, mFRR capacity payments exhibit moderate positive correlation with energy markets, reflecting their structural similarity to day-ahead trading and participants' strategic bidding behavior when anticipating higher returns than DAM markets. General conclusion would be that reserve activation prices are usually more correlated with the DAM, as opposed to correlation between DAM and reserve payments. The mFRR differs from this rule due to the chronological clearing schedule similarity with the DAM. On the other hand, Fig. 9 illustrates that some correlations between day-ahead prices and various energy volumes do exist, but not strong enough to draw any further conclusions. Publicly available data include gross consumption (GrossCon), consumption prognosis (cons_progn), production prognosis (prod_progn), and wind production prognosis (wind_prod_progn). Sum (Sum) refers to the difference between consumption and wind production prognosis. Import (Imp) refers to total volume of imported energy. Export (Exp) refers to total volume of exported energy. Sum 2 (Sum2) is the sum of the previous mentioned Sum, Import and Export.

D. Significant Findings

The previous chapter demonstrated correlations between different submarkets. This chapter presents a thorough analysis of the most important findings. Each property is introduced in its own dedicated sub-chapter with a short description, corresponding illustrations and short conclusions the observed characteristic may help profit-oriented players. Moreover, practical implementation methodologies are proposed.

1) Median Spread Through Year (Season and Day Category)

Among others, day-ahead and intraday market have a very strong correlation coefficient. Thus, one can with great certainty conclude by knowing price behaviour on the day-ahead market. It is possible to model price behaviour on the intraday market (and vice-versa). To gain even better insight, further analysis deals with the spread between the day-ahead and intraday market prices. The possible spread would present market participants a possibility to make extra profit

Fig. 7. DEN and CRO intraday prices distribution.

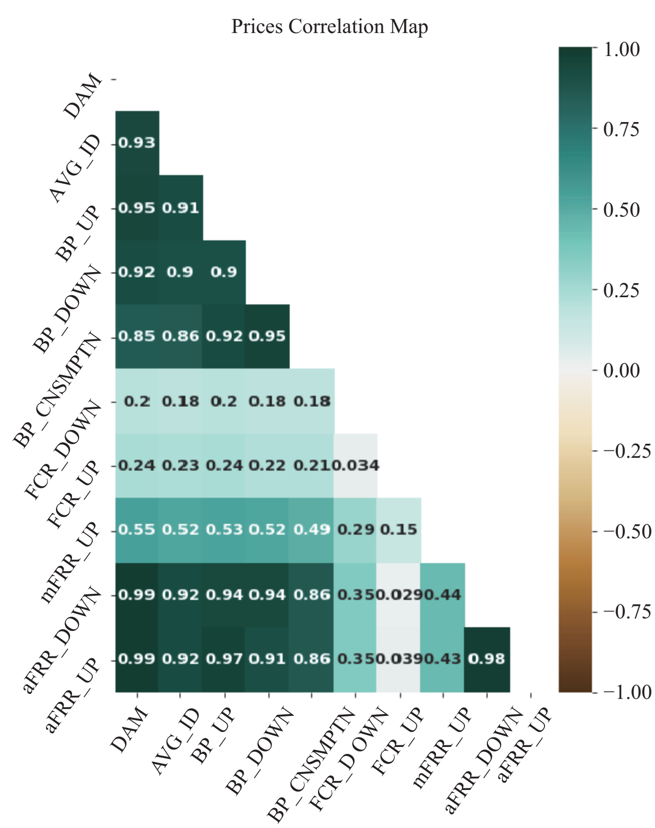

Fig. 8. Correlation heatmap (prices).

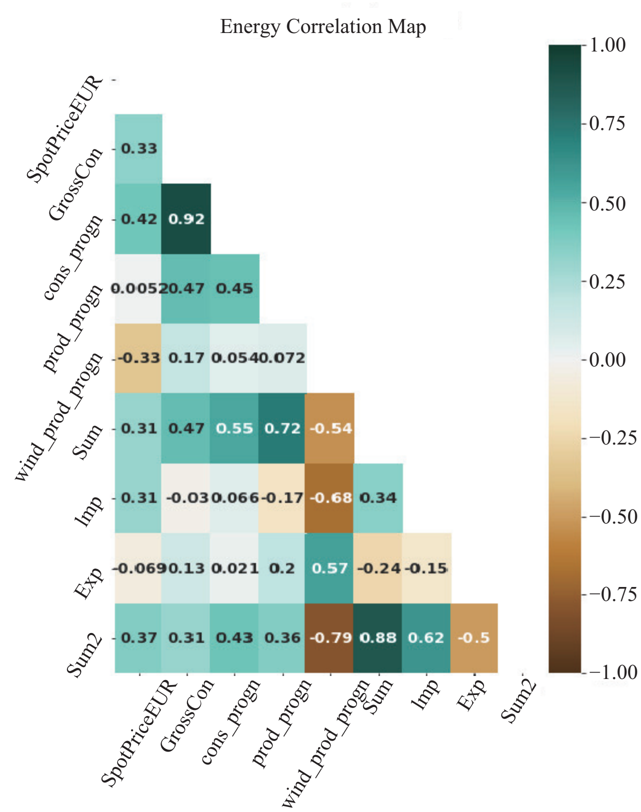

Fig. 9. Correlation heatmap (energy volumes).

by optimizing on which exact submarket, and in what capacity, to participate.

Figure 10 presents the DA-ID price spreads dependent on season and day category. Analysis has been conducted both for Denmark and Croatia, so it could be easy to compare peculiarities in the two observed countries. In Denmark, DA

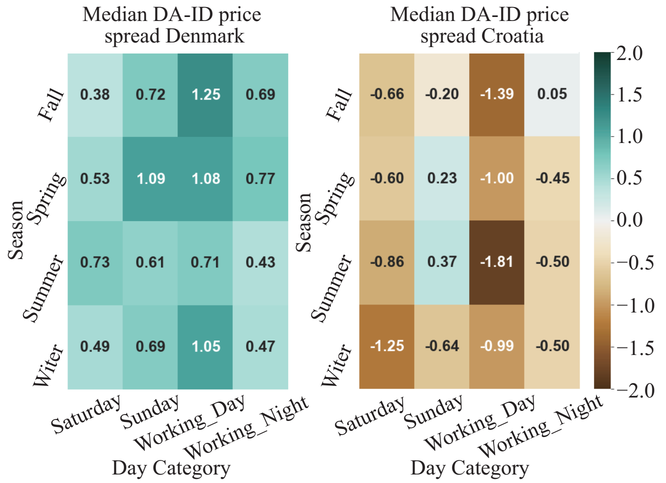

Fig. 10. Median DA-ID price spreads per season per day category (€/MWh).

prices are usually higher than ID prices, while in Croatia the situation is just the opposite. Observing the situation in Denmark, during work hours the highest median spread value is recorded, and Spring stands out as the season with the most consistency in higher spreads. When observing seasonality and day category, Croatia also experiences the highest (negative) price spreads during work hours, while Winter brings the most consistent state of relatively high (negative) spreads. The analysis reveals distinct cross-market patterns: Croatian day-ahead and intraday prices exhibit near-zero spreads during nighttime workweek hours, contrasting sharply with Danish market dynamics. This divergence creates opposing optimal trading strategies - Danish participants benefit from intraday price advantages, while Croatian market conditions favor day-ahead procurement with subsequent intraday resale. Particularly in Croatia, these characteristics enable innovative prosumer strategies capitalizing on the unique DA-ID market coupling. This kind of information about relationship between market knowledge could then be incorporated in bidding strategies such as proposed for an aggregator in [67], where the authors proposed a method for producing optimal bidding curves for an aggregator participating in day-ahead and intraday markets.

As noticed, Denmark and Croatia exhibit opposite DA-ID price patterns. To examine what may cause those differences, it was necessary to examine characteristics of both countries.

a) Energy Mix: First, the energy mix in Denmark is not the same as in Croatia. Scandinavian representative relies mostly on wind energy (56%), bio-energy (18%) and coal (15%). While the rest is equally divided between solar energy, gas and remaining fossil fuels according to data from the year 2020 [68]. On the other hand, hydro-power (44%), gas (26%), wind energy (12%), coal (10%) and bio-energy (7%) are dominant energy resources in Croatia. While other sources such as solar plants, geothermal energy, etc., are not so relevant [69].

b) Market Maturity: Furthermore, it is important to emphasize that in Croatia most of conventional generation units are owned by a state-owned company that was in charge of all processes in Croatian power system while the system was vertically integrated. Although in the meantime the system was unbundled and liberalized, the state-owned company still remained as the most dominant player in the Croatian power system having more than 85% of the total market share, now as a horizontally integrated group with separate legal entities. Hence, generation units of their portfolio usually do not trade in wholesale markets, but bilaterally settle within their own separated entities (supply and generation). On the other hand, the Danish market is more mature with a more competitive market and smaller market shares per stakeholder.

When speaking about renewable energy sources, namely solar power plants and wind energy, in Croatia they are part of the ECO Balance Group and still mostly under the feed-in tariffs regime. ECO Balance Group consists of energy producers entitled to fixed selling prices (i.e. wind and solar power plants) [70]. Moreover, energy suppliers are obliged to secure at least 40% from ECO Balance Group, the rest of the energy produced under the ECO Balance Group is sold via auctions organized on a year or half-year basis and DAM [51]. Denmark also did not completely phase out subsidy schemes, especially for off shore wind farms. Nevertheless, market prices are already very attractive which can be seen from the 1 GW Thor offshore wind farm project, where bidders offered to develop the project for the minimum price of 0.01 øre/kWh (0.0001 Danish crowns) and full capacity under the contract for difference (CfD) scheme [71].

c) Climate Peculiarities: Denmark is called “Country of Winds” as it has the highest proportion of wind power in the world (relatively strong and constant), whereas Croatia has much more intermittent wind regime [72], but higher solar irradiance.

d) Different DAM-IDM Price Relations: It is a difficult task to precisely identify the main reason why DAM prices in Denmark are on average higher than IDM prices, and why the situation in Croatia is the opposite. Nevertheless, we have identified many peculiarities that distinguish the two observed countries and consequently affect price formation and general market behaviour, both motivation and strategies to participate in DAM and IDM. Furthermore to elaborate on DAM-IDM price relationship in Denmark, Karanfil and Li [55] argued that wind and conventional generation forecast errors are the fundamental factors that drive intraday prices apart from day-ahead values both in Denmark West and East, and relative intraday prices decrease with the level of wind forecast errors.

2) Median Spread Through Day

Figure 11, in addition to season and day-category analysis, introduces one more angle to observe the DA-ID price relationship. It presents median price spreads between DA and ID prices throughout the whole day for the four different observed day categories. Analyzing individually, price spreads in Denmark are almost always positive (DA prices higher than the ID prices) with highest values in afternoon hours, regardless if it is Saturday, Sunday (holiday) or normal night during the work week. The lowest median price spreads are recorded in the period between midnight and 07:00 AM, with the curiosity that for the day category Saturday, median price spreads are negative. On the other hand, DA-ID price spreads in Croatia are dominantly negative, i.e. ID prices are usually

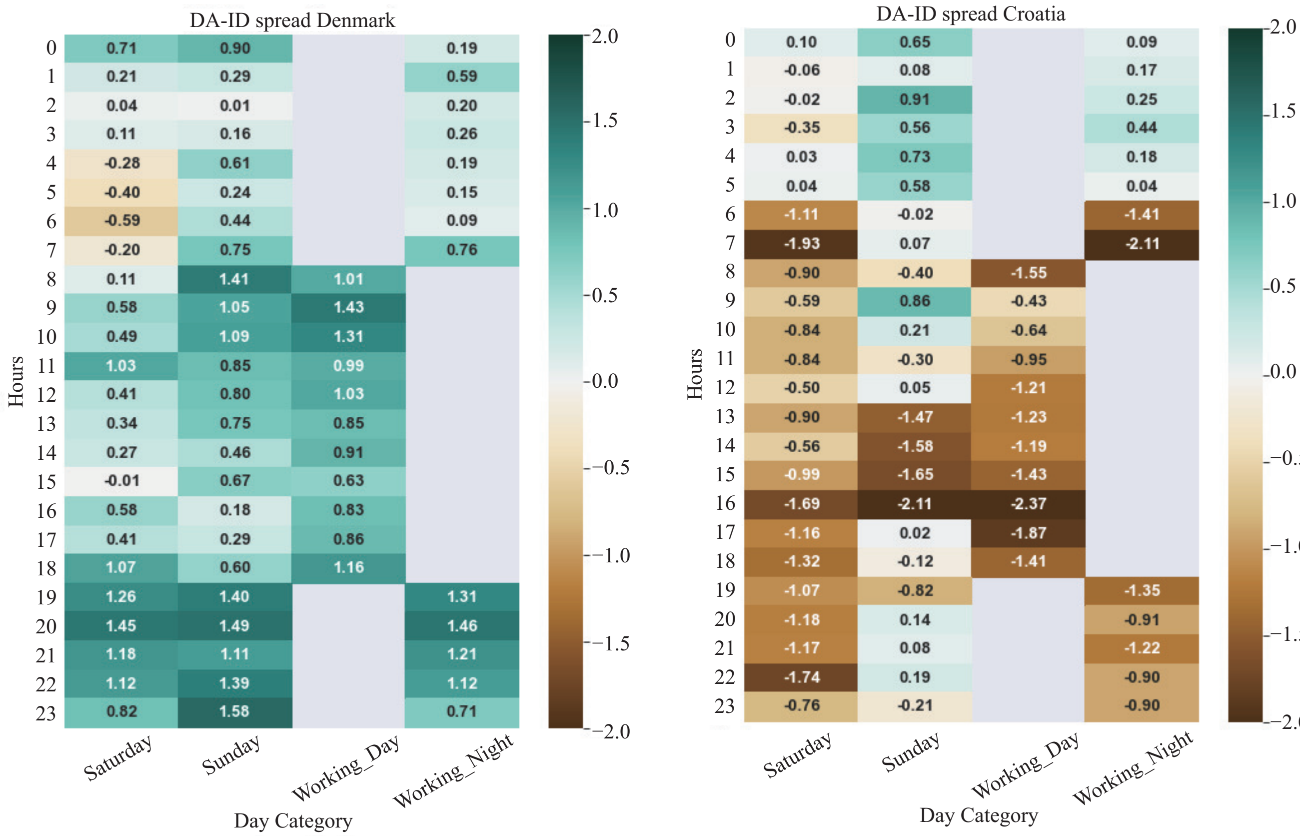

Fig. 11. Median spread between day-ahead and intraday prices (€/MWh).

higher than prices in the DA market. The most extreme median value has been recorded for a work day at 04:00 PM. The median price spread between DA and prices at that moment was 2.37 €/MWh. Other day categories at that time also exhibit high (negative) price difference between the DA and ID market prices. Mornings are characterized mostly by positive price spreads without extreme values. Exception are Saturday mornings where price spreads are very close to zero, or slightly negative. Both countries exhibit a steady, although mutually opposite when comparing them together, relationship between the two observed markets. This gives interested stakeholders a valuable insight for developing optimized arbitrage strategies in order to take advantage of possible price spreads in an optimal manner.

It can be concluded that in Denmark, market players can take the most from day-ahead intraday arbitrage if they are cross-trading in evening hours or morning workday peak hours. In Croatia, profit-oriented players will benefit most from cross-trading during evening hours on Saturdays, early afternoon hours during holidays and Sundays and during working hours. The big difference when compared to Denmark is the direction of trades, as DA-ID spread in Denmark is positive, while in Croatia negative.

3) Extreme Values

The identification of consistent price spreads, regardless of magnitude, can confer substantial competitive advantages in strategic business planning and market positioning. Moreover, it is interesting to examine the maximum spreads that have occurred in the observed period. Fig. 12 shows the highest negative values that have been reported both for Denmark and Croatia. Notably, both countries exhibited their most extreme negative prices within the same market segment: Denmark reached -157.25 €/MWh while Croatia recorded -134.83 €/MWh, with both occurrences transpiring during winter weekdays. Fig. 13 illustrates extreme values in the opposite direction - the maximum positive difference between the DA and ID prices. They did not go above 70 €/MWh, as opposed to the negative extremes that went even over 100 €/MWh 3 times in Denmark and 2 times in Croatia

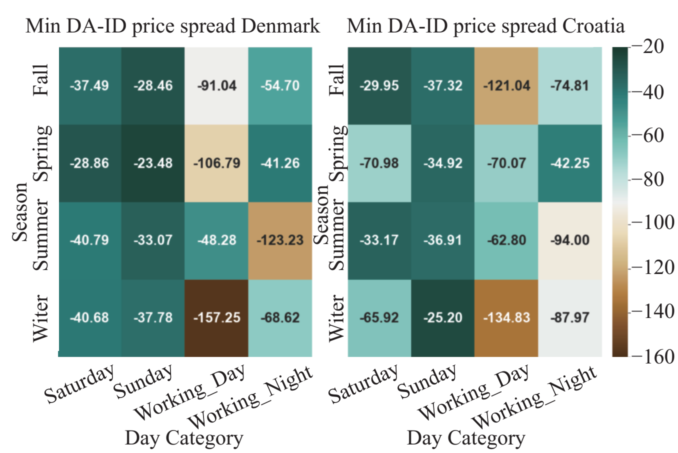

Fig. 12. Max. negative spread between DA and ID prices (€/MWh).

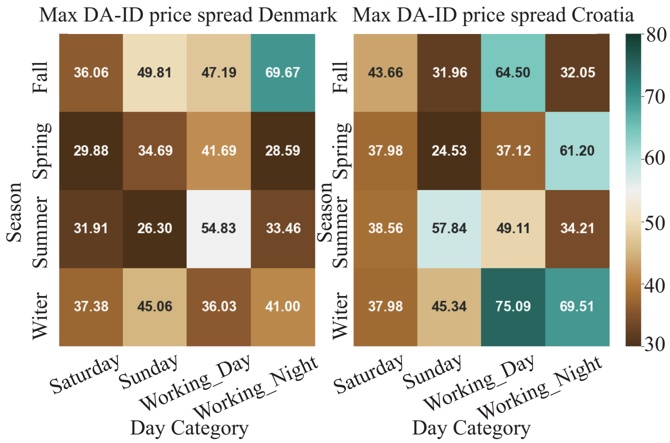

Fig. 13. Max. positive spread between DA and ID prices (€/MWh).

(Fig. 12). Fig. 13 discovers that positive extreme values are fairly equal across different day categories and seasons. The analysis demonstrates that price spreads can reach extreme values, where optimal timing may yield substantial profits or cost savings, while ill-timed transactions could impose significant financial penalties.

4) Spread Histogram and Box-plot

To achieve even better insight into how spread values are distributed, Fig. 14 presents a histogram of recorded spread values in the observed period. The Gaussian like curve is noticeable with tails longer on the left side and most of the recorded price spread values located around zero. Fig. 15 clearly illustrates, for both the Danish and Croatian cases, that while spread values are predominantly concentrated around zero, they also exhibit significant extremes. Regardless of spread direction, both of these illustrations present good motivation to further investigate if relatively higher spreads are occurring frequently enough to focus on them, or do they occur no more than once or twice a year due to some unpredictable situations. Furthermore, it is interesting to analyse how far does the dataset differ from the ideally shaped Gaussian curve and what can we conclude when talking about standard deviation for Danish and Croatian DA-ID spread values. In the Danish case, standard deviation for the whole observed period is 7.3 €/MWh, that means that over 30% of all values would in an ideally shaped bell curve, have a spread bigger than 7.3 €/MWh. The observed period consists of 23,585 values, so around 7,075 observed moments would provide an opportunity to take advantage of the spread bigger than 7.3 €/MWh. Although, as already stated, spread distribution does not ideally follow the bell curve, this is still a valid motivation to investigate further occurrence of the spread between spot and intraday prices. To support this claim, it is worth mentioning that spread bigger than 7.3 €/MWh was noted more than 6,100 times in the real dataset, which is less than the theoretical value of an ideally bell-shaped curve (around 7,075). In other words, around 26% of all values have absolute spreads greater than 7.3 €/MWh, while theoretically in an ideally shaped bell curve this percentage should be above 30%. For the case in Croatia, calculated standard deviation is 8.79 €/MWh. The volume of recorded values is somewhat lower than the Danish case, more precisely - the dataset consists of 14,856 records of DA-ID price spread values. Meaning, in an ideally shaped bell curve more than 4,457 values should mark an absolute spread higher than 8.79 €/MWh The real situation is: 2902, which is around 20% of the entire dataset. So it is easy to conclude that the

Fig. 14. Histogram of the spread between spot and intraday prices in Denmark and Croatia.

Croatian data-set deviates from the ideally shaped bell-curve characteristics more than the Danish dataset. Lower number of records within the dataset might also be one of the reasons why deviation is bigger. Nevertheless, results are encouraging for energy traders to use price spreads and these findings as their advantage when planning a market strategy. Generally speaking for both countries, it is fair to conclude that although most price-spread values are close to zero, the presence of non-negligible outliers can be leveraged to generate higher profits or achieve greater cost savings.

5) Outliers

To deepen research a little bit more, it is interesting to find out when does the spread bigger than one standard deviation (7.3 for Denmark and 8.79 for Croatia) really occur. Fig. 16 presents relative count of positive and negative spreads for Denmark and Croatia compared to the total of recorded DA-ID spread values per each category, respectively. It is fairly obvious to conclude that in most of seasons, working day

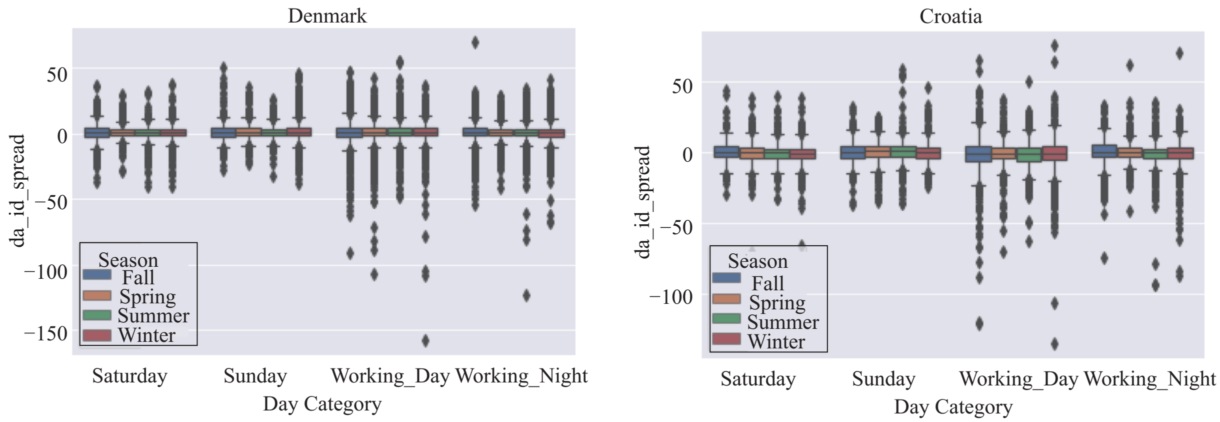

Fig. 15. Spread values in Denmark and in Croatia.

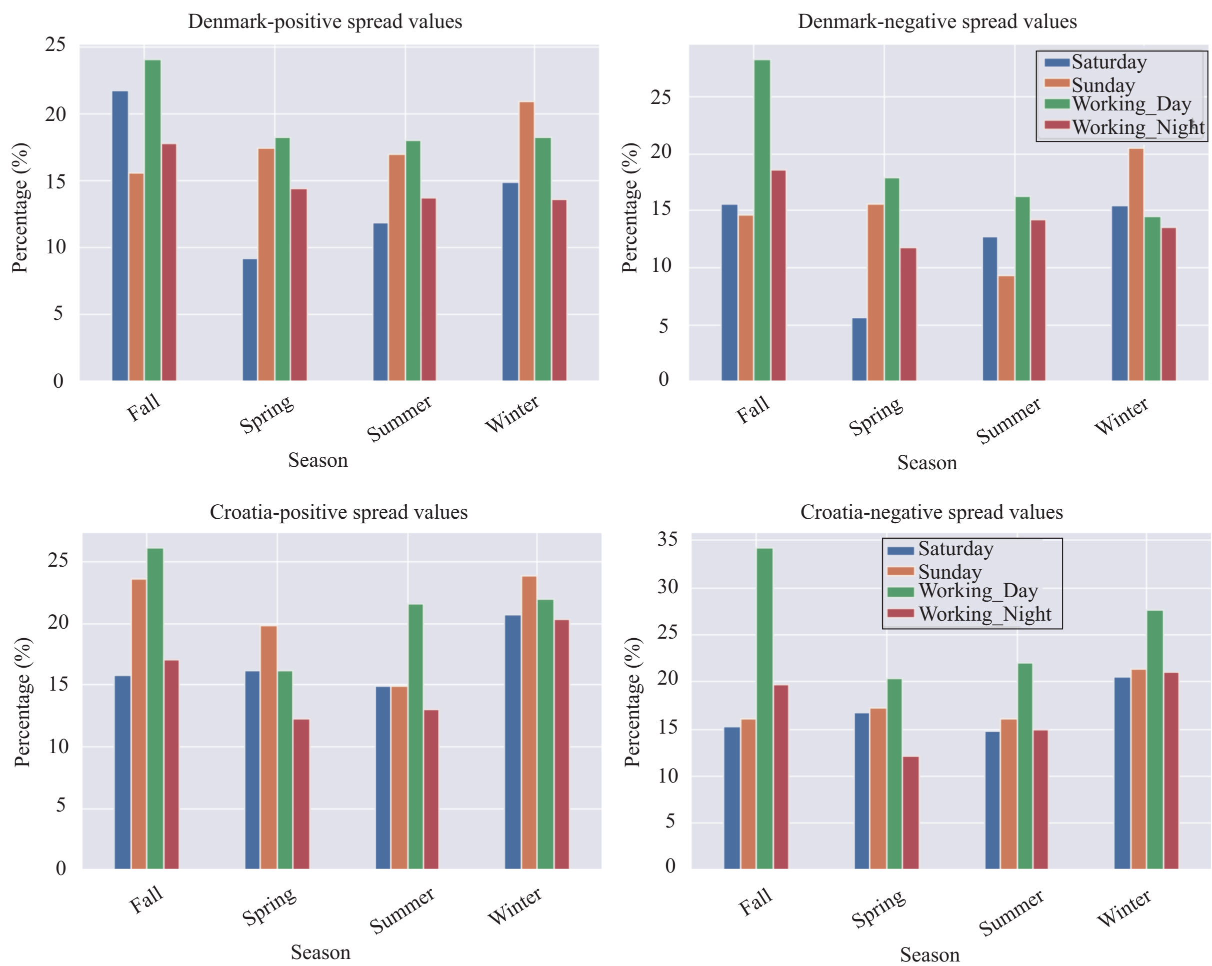

Fig. 16. Relative DA-ID spread count compared to the total of recorded spreads of each category.

usually exhibits highest price difference between the DA and ID markets. A bar graph displaying the ratio of high spreads to total spreads—categorized by season and time of day—was selected to eliminate the misleading effect caused by solely reporting raw counts of high-spread occurrences. Hence, regardless of the fact that working day consists of more values than Sunday, both are mutually comparable due to relative value expression. This figure suggests that there are no significant seasonal variations, indicating that profit-driven market participants can develop strategies on an annual basis rather than adjusting for seasonal fluctuations.

6) Intertemporal Correlation

In Section IV-C, a small glimpse about correlations between different prices and quantities has been given. It is interesting to extend analysis even further, while focusing on various peculiarities and possibly interesting points. For instance, investigating inter-temporal correlations within the datasets could yield interesting insights—such as how prices in hour x related with prices in the hour $x-1, x+1, \ldots$ etc. In such manner, Fig. 17 presents inter-temporal comparison between spot prices and spread (spot-intraday) correlation for the Danish case. In the correlation matrix, day-ahead inter-temporal correlations appear in the upper-right diagonal, with spread inter-temporal correlations shown in the lower-left diagonal. Without even investigating exact correlation coefficients, heat map colors clearly distinguish highly correlated inter-temporal relations between spot prices from almost uncorrelated spread values between different hours of the day. For the sake of clarification, it is useful to mention the scale on Fig. 17 goes from 0 (no correlation) to 1 (perfect positive correlation) and the brighter the color, the higher the correlation coefficient for the observed variable pair. Having in mind that both day-ahead prices and intraday prices exhibit high correlation coefficients not only mutually (Fig. 8), but also considering values of each set between different hours of the day (DA: upper diagonal Fig. 17), the temporal patterns of these spread values exhibit asymmetric behavior, as evidenced by the differing correlation structures in the lower diagonal of Fig. 17. It is worth to mention, although the graph is not included, that intertemporal correlations between intraday prices are very vague. Only the closest neighbors exhibit correlation coefficients greater than 0.6. In Fig. 18 the upper-right diagonal represents a relative spread with regards to spot price correlation coefficients, while the lower-left diagonal is analogue but with regards to intraday prices. It is interesting how relative value of the spread to the spot price value shows high correlation coefficients during neighboring afternoon hours, while relative value of the spread to the intraday price values does not exhibit such noteworthy coefficients. According to these results, it is fair to conclude in both cases spread prediction based on previous hours is only viable for immediately adjacent time periods, and even then, the reliability remains insufficient for practical application.

V. Conclusion

In liberalized and deregulated electricity markets, profit-driven participants must continuously refine their strategies to maintain competitive advantage and maximize returns. This requires in-depth understanding of price formation mechanisms and market dynamics. In such manner, this article conducted thorough statistical analysis of power market structures in two EU countries, Denmark and Croatia. The two countries have been chosen as representative examples to demonstrate methods which can then be applied to other markets. Having in mind different energy mix, consumption profile and geopolitical characteristics, they fit the purpose of examining how such diverse power markets have different characteristics and peculiarities but at the same time, the same approach may be utilized to discover how to enhance strategy of the respective profit-oriented player. We believe that regardless of each country's peculiarities, the general idea remains the same

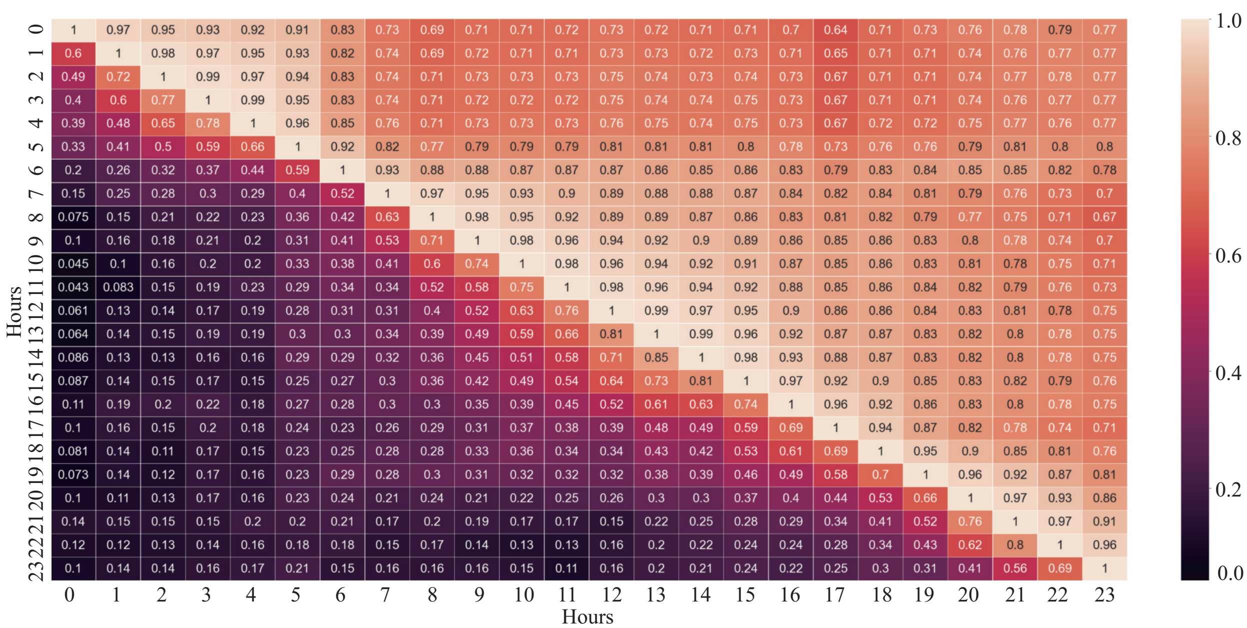

Fig. 17. Comparison of correlation matrix of spread during different hours and spot prices.

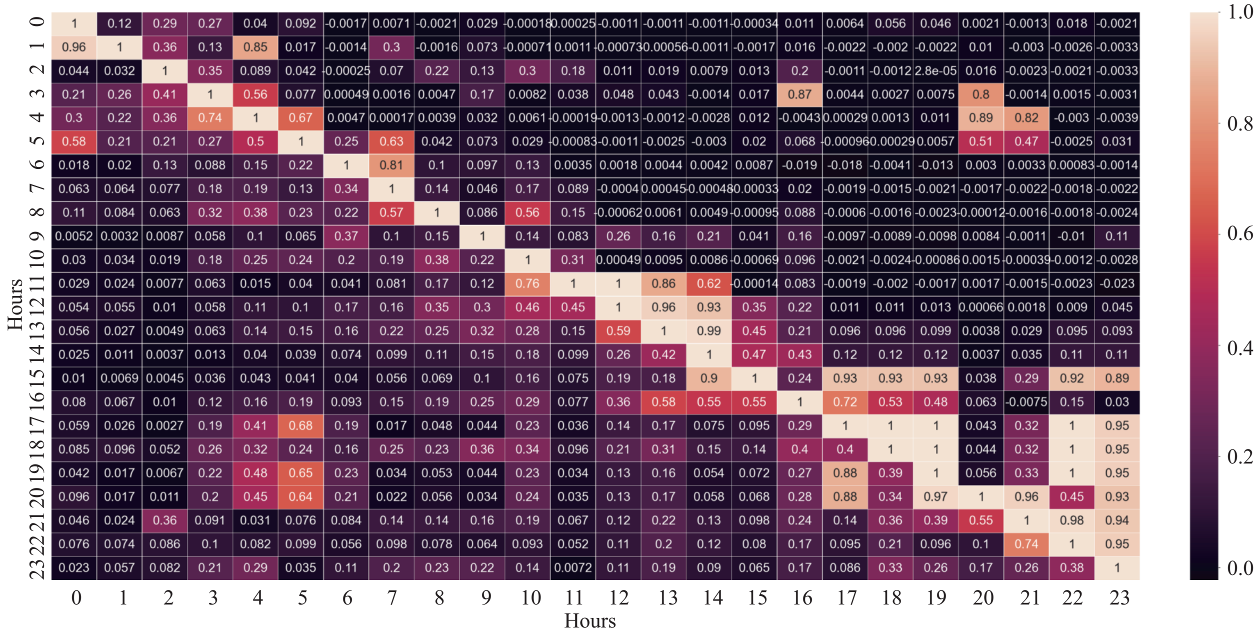

Fig. 18. Comparison of correlation matrix of relative spread with regards to spot and intraday prices during different hours.

and can be applied to further research each country or market arbitrage potential. When speaking about data availability, although the tendency is to make power market data publicly available, the reality is different and still some data is harder or impossible to obtain. One must always have in mind to proof-check acquired data as more often than rare is the case to encounter some mistakes (different time indexes, wrong inputs, etc.).

Although a developed tool should be applicable to various markets, to ensure brevity, this paper has focused on day-ahead and intraday market. Future research should deal also with other markets. The conducted analyses have shown Gaussian-like distribution of the intraday and day-ahead prices. Furthermore, multiple graphs and numerical results indicated high levels of correlation between intraday, balancing, activated aFRR and day-ahead prices. This phenomenon stems from multiple factors, ranging from fundamental price interdependencies to more complex drivers including market participant behavior, weather conditions, and other exogenous variables. Energy volumes have not shown such high correlation factors with day-ahead prices, but further research shall also investigate this relation in a deeper manner. This paper also provides an interesting insight into spread between day-ahead and intraday prices. It has been shown that spreads present an interesting opportunity to gain extra profit. Furthermore, the paper detects regularities which can be exploited when creating optimal bidding strategies. In a more detailed manner, it is important to say that different countries experience different price spreads. In terms of countries observed in this paper, DA prices in Denmark are usually higher than intraday prices, while the situation in Croatia is just the opposite. The analysis has shown that the frequency of extreme value occurrences is non-negligible and right timing may result with high profits for involved stakeholders. Furthermore, spreads are present throughout the year, but the analysis shows that specific periods of the day usually exhibit much higher price deviations creating a playground for cross-trading and other market strategies. Furthermore, it is interesting to note that inter-temporal correlations are pretty vague (except) from DA prices, and thus they are not of much help to the profit-oriented player. To conclude, further research should expand analysis to other aspects of the power market. According to results of this article, there is great potential of exploiting well processed results of the power market factor analysis. Moreover, motivated by results from this article, following analysis will employ canonical correlation analysis to examine how combinations of different factors may be mutually interrelated.

Finally, this study's findings reveal distinct market-specific characteristics that can be captured through a universal statistical framework. These insights provide market participants with a robust analytical tool to adapt their business strategies to regional market dynamics.

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