

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

**SYNTHETIC NET IMBALANCE VOLUME GENERATION IN BALANCING
MARKET WITH MARKOV CHAIN APPROACH**



M.Sc. THESIS

Bilge Dilara İSKEÇELİ

Department of Energy Science and Technology

Energy Science and Technology Programme

JULY 2021

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**MARKOV ZİNCİR YAKLAŞIMI İLE Dengeleme Güç Piyasasında
Sentetik Net Dengesizlik Hacmi Üretimi**

YÜKSEK LİSANS TEZİ

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To my family,



FOREWORD

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ABBREVIATIONS

AIC	: Akaike Information Criterion
ANN	: Artificial Neural Network
AR	: Autoregressive
ARIMA	: Autoregressive Integrated Moving Average
ARMA	: Autoregressive Moving Average
ARX	: Autoregressive Exogeneous Explanatory Variables Model
BIST	: Istanbul Stock Exchange (Borsa İstanbul Anonim Şirketi)
EAK	: Available Capacity (Emre Amade Kapasite)
EMRA	: Energy Market Regulatory Authority (Enerji Piyasası Düzenleme Kurumu)
EPIAŞ	: Energy Markets Operation Corporation (Enerji Piyasaları İşletme Anonim Şirketi)
ETKB	: Energy and Natural Resources Ministry (Enerji ve Tabii Kaynaklar Bakanlığı)
EÜAŞ	: Electricity Generation Corporation (Elektrik Üretim Anonim Şirketi)
EV	: Electric Vehicle
EXIST	: Energy Exchange Istanbul
GAMLSS	: Generalized Additive Models for Location Scale and Shape
GRU	: Gated Recurrent Units
KGUP	: Definite Daily Generation Program (Kesinleşmiş Günlük Üretim/Tüketim Programı)
KNN	: K-Nearest Neighbours
LASSO	: Least Absolute Shrinkage and Selection Operator
LOLP	: Loss of Load Probability
LSTM	: Long Short-Term Memory
M5P	: Regression Tree
MA	: Moving Average
MBE	: Mean Bias Error
MCP	: Market Clearing Prices
NLPC	: National Load Dispatch Center
NMBE	: Normalized Mean Bias Error
NRMSE	: Normalized Root-Mean-Square Error

PV	: Photovoltaic
QRA	: Quantile Regression Averaging
R²	: Coefficient of determination
RFR	: Random Forest Regression
RMSE	: Root-Mean-Square Error
RNN	: Recurrent Neural Network
SARIMA	: Seasonal Auto Regressive Integrated Moving Average
SMP	: System Marginal Price
std	: Standard deviation
SVM	: Support Vector Machine
TEAŞ	: Turkish Electricity Generation-Transmission Corporation (Türkiye Elektrik Üretim-İletim Anonim Şirketi)
TEDAŞ	: Turkish Electricity Distribution Corporation (Türkiye Elektrik Dağıtım Anonim Şirketi)
TEİAŞ	: Turkish Electricity Transmission Corporation (Türkiye Elektrik İletim Anonim Şirketi)
TEK	: Turkish Electricity Administration (Türkiye Elektrik Kurumu)
TETAŞ	: Turkish Electricity Trade Corporation (Türkiye Elektrik Ticaret ve Taahhüt Anonim Şirketi)
XGBoost	: Extreme Gradient Boosted Trees
YEKA	: Renewable Resource Areas (Yenilenebilir Enerji Kaynak Alanları)
YEKDEM	: Renewable Energy Resources Support Mechanism (Yenilenebilir Enerji Kaynakları Destekleme Mekanizması)

SYMBOLS

$a_1, \dots, a_p$	: AR parameters
c	: Constant
d	: Degree of differencing
$m, \dots, m_q$	: MA parameters
p	: Order of AR
P	: Transition matrix
p_{ij}	: Conditional probability
q	: Order of MA
S	: State space
t	: Time (discrete parameter)
T	: Set of time points
t_n	: Time (continuous parameter)
u_t	: White noise
$X(t)$	: The observation made at time t (discrete parameter)
$X(t_n)$	: The observation made at time t_n (continuous parameter)
X	: Random variable
x_n	: A real number
X_t	: Current state
X_{t+1}	: Next state
y_t	: Predicted value at time t
μ	: Expectation of y_t



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SYNTHETIC NET IMBALANCE VOLUME GENERATION IN BALANCING MARKET WITH MARKOV CHAIN APPROACH

SUMMARY

In the conventional grid, there is a need for a controlling agency to prevent the grid from blackouts since electricity should be consumed at the time of production, and the consumption and production processes should be simultaneous. The transmission system operator coordinates balancing generation and consumption of the system across the transmission grid. Large generation capacity should meet high electricity demand occurring in short peak periods. This represents the challenge of stabilizing the electricity grid for system operators, especially with the growing share of intermittent renewable energy sources feed into the grid. That is why different market mechanisms are needed such as day ahead, intraday, real time balancing markets.

Day-ahead planning of generation and consumption sets the market price but not meeting the promised actions and causing imbalance has consequences. The imbalance is penalized by the system operator. A chance to rearrange the placed bid is possible by participating in the intraday market where bids for two hours later can be made. But whether to participate in the intraday market or accept the penalty to optimize the income depends on the system marginal price occurring in the balancing market.

To decide this action, a prediction on system marginal price is needed. However, the latest system marginal price announcement is the value of 5 hours previous, and the closest intraday market action is for 2 hours later. On the other hand, instruction volume announcement is made after the end of each hour. Considering the high instruction volume and price relation in the market, predicting the instruction volume which has a closer forecast date is more beneficial and would give more accurate results. That is why in this paper a stochastic Markov Chain method to predict the instruction volume is proposed.

In the methodology, to generate future values of the net imbalance volume a stochastic method was presented. By using transition matrix of the Markov chain method, hourly net imbalance volume data was simulated. To be able to simulate all possible states the net imbalance time series was divided into various states depending on maximum and minimum occurrence in the year of 2020. Once the transition matrix has been formed with the corresponding probabilities, synthetic series were generated on desired lengths.

The aim of the model was not to point forecast at a certain time but to realistically represent a possible chain of events of synthetic net imbalance volume values. Historical data of imbalance volume were used to generate synthetic series while preserving the autocorrelation and statistical parameters.

First order Markov chain was used to generate a few hours forward net imbalance volume data and repeats its action with the addition of new inputs. To be able to compare the results, ARIMA model was applied by using the same input and window

shift method. Proposed method in this study has a low computational requirements and cost, easy to implement and is able to represent the autocorrelation function of recorded data. Unlike other studies that point forecast the system marginal price which has a longer prediction window due to late announcement of price data, this study proposes to generate net imbalance volume data with the ability to obtain more input before the closest market action hour. After generating the net imbalance volume with a closer prediction time, system marginal price then can be calculated using the high correlation between net imbalance volume and system balancing price which was not a part of the study but a suggestion for the further studies. For the purpose of using net imbalance volume data as a preview for market actions, Markov chain approach was applied and ARIMA model applied for comparison of result accuracies, since ARIMA is a widely used data-driven model.

Data distribution graphs has showed that both methods produced close results to the observed data. Although showing more deviation than ARIMA model in the histograms, the presented method was able to preserve the general characteristics of the observed data. Autocorrelation function exhibits that the proposed model was also able to preserve the daily oscillatory behavior similar to the observed one. On the statistical metrics, results are close between Markov chain and ARIMA models where ARIMA results has slightly higher accuracy in general. In each model the accuracy gets lower as data generated for further from latest observation time. On the other hand, MBE, NMBE, RMSE, NRMSE values are low which can be noted as a satisfactory accordance between the observed and the generated net imbalance volume data. Mean values were also close to the observed one considering the state range was 500 MW.

In general, ARIMA method showed slightly better performance than Markov chain approach in most of the metrics. Markov chain has closer mean value to the observed data in all three Saturday results. In the 2 and 3 hours forward predictions, Markov chain had similar or better results than ARIMA method during Saturday and Sunday predictions in terms of coefficient of determination, RMSE and NRMSE. Additionally, Markov chain has closer MBE, NMBE and mean values to the observed data in all three Saturday values. In the day of week comparison, the highest coefficient of determination values occurred on Saturday, followed closely by weekdays and lowest values occurred on Saturday in both models. This was interpreted as the cause of highest and lowest value difference occurring depending on the day of week, which is highest on Sunday, followed closely by weekday and lowest on Saturday. And the reason for having smaller differences between the metric results of ARIMA and Markov chain approach on weekday can be having less weekend input compared to weekday input.

To further improve the results, a smaller bin range can be used like 200 MW. Higher order transition can also be considered in future research. State range can be changed dynamically with each window shift and can be between maximum and minimum occurrences of the input time series to improve the performance. As stated before, synthetic net imbalance volume values may be utilized as the input for balancing market price forecasts and power plant operation optimization models.

MARKOV ZİNCİR YAKLAŞIMI İLE Dengeleme Güç Piyasasında Sentetik Net Dengesizlik Hacmi Üretimi

ÖZET

Geleneksel elektrik şebekesinde elektriğin üretim ve tüketim süreçlerinin eşzamanlı olması gerektiğinden, şebekede elektrik kesintilerini önlemek için bir kontrol kurumuna ihtiyaç vardır. Bu sebeple iletim şebekesi boyunca sistemin talebini karşılamak için üretim gönderimi iletim sistemi işletmecisi tarafından koordine edilir. Mevcut üretim kapasitesi ile kısa dönemlerde ortaya çıkan yüksek elektrik talebini karşılamalıdır.

Son 20 yıllık dönemde, Türkiye enerji piyasası büyük değişimler geçirmiş ve bu sayede önemli ölçüde büyüme sergilemiştir. Piyasanın serbestleşmesi, özelleştirmeler, yenilenebilir enerji teknolojilerinin devreye girmesinin yanı sıra yapılan düzenlemeler ve çıkarılan kanunlar ile toplam kurulu güçte sürekli artışlar gözlenmiştir. Özellikle şebekeye beslenen kesintili yenilenebilir enerji kaynaklarının artan payıyla birlikte, sistem operatörlerinin elektrik şebekesini dengeleme işleminde kullanılmak üzere gün öncesi, gün içi ve gerçek zamanlı dengeleme piyasaları gibi farklı piyasa mekanizmalarına ihtiyaç duyulmaktadır.

Üretim ve tüketimin gün öncesi planlaması piyasa fiyatını belirler ancak vaat edilen eylemlerin karşılanmaması sistemde dengesizliğe neden olmaktadır. Gerçek zamanlı dengeleme, dengeleme güç piyasası ve yan hizmetlerden oluşur. Bu piyasa, gerçek zamanlı dengeleme için sistem işletmecisine hızlıca devreye girebilecek yedek kapasiteyi sağlarken, yan hizmetler aracılığı ile de talep kontrolü ve frekans kontrolü sağlanır. Dengeleme güç piyasasında gerçek zamanlı arz ve talep dengelenmesi için, on beş dakika içerisinde devreye girebilecek çıkış gücündeki değişim ile elde edilen yedek kapasitenin alım-satımı gerçekleştirilir.

Gün öncesi piyasası ile sistem işletmecisine üretim ve tüketim miktarı bakımından dengelenen bir piyasa sunulmuş olmasına karşın gerçek zamanda sapmalar olmaktadır. Böyle durumlarda sistem işletmecisi, sistem dengesini dengeleme güç piyasasına sunulmuş teklifleri kullanarak sağlarken dengesizliğe sebep olan piyasa katılımcılarına da sebep oldukları maliyetten ötürü bir yaptırım uygulanır.

Dengesizliğe sebep olan piyasa katılımcılarına, gün öncesi piyasasında oluşan piyasa takas fiyatı ile dengeleme güç piyasasında oluşan sistem marjinal fiyatı arasında alım yönünde yüksek ve satış yönünde düşük olan fiyata %3'lik sapma cezası uygulanır. Dengesizliğe düşme durumu söz konusu olan piyasa katılımcılarının, iki saat sonrası için tekliflerin verilebileceği gün içi piyasasına katılarak verilen teklifi yeniden düzenleme şansı da mümkündür. Ancak cezadan kaçınmak için gün içi piyasasına katılmak veya kazancı maksimize etmek için cezayı kabul etmek, dengeleme piyasasında oluşan sistem marjinal fiyatına bağlıdır.

Bu eyleme karar vermek için, sistem marjinal fiyatı hakkında bir öngöründe bulunmak gerekir. Ancak, son açıklanan sistem marjinal fiyatı 5 saat öncesinin değeridir ve en yakın gün içi piyasa eylemi 2 saat sonrası için yapılabilir. Öte yandan her saat sonunda

talimat hacmi duyurusu yapılmaktadır. Piyasadaki yüksek talimat hacmi ve fiyat ilişkisi düşünüldüğünde, tahmin tarihi daha yakın olan talimat hacmi hakkında bir öngöründe bulunmak daha faydalı ve daha doğru sonuçlar verebileceğinden, bu çalışmada talimat hacmini tahmin etmek için stokastik bir Markov Zinciri yöntemi önerilmiştir.

Metodolojide, net dengesizlik hacminin gelecekteki değerlerini oluşturmak için stokastik bir metot sunulmuştur. Saatlik net dengesizlik hacmi verileri, Markov zincir yönteminin geçiş matrisi yaklaşımı kullanılarak simüle edilmiştir. Bu amaçla net dengesizlik zaman serileri, 2020 yılında gerçekleşen maksimum ve minimum değerlere bağlı olarak çeşitli durumlara bölünmüştür. Her bir duruma karşılık gelen olasılıklar ile geçiş matrisi oluşturulduktan sonra, istenilen uzunluklarda sentetik seriler üretilmiştir.

Modelin amacı ileri bir zamanda gerçekleşecek net sistem dengesizliklerini noktasal olarak tahmin etmekten ziyade, gerçek durumu temsil edebilecek şekilde sentetik net dengesizlik hacmi değerlerinin oluşturulmasıdır. Dengesizlik hacminin geçmiş verileri, istatistiksel parametreler ve otokorelasyonu korurken sentetik seriler oluşturmak için kullanılmıştır.

Birinci dereceden Markov zinciri, birkaç saat ilerisi için net dengesizlik hacmi verisi oluşturmak için kullanılmıştır ve yeni girdilerin eklenmesiyle işlem tekrarlanmıştır. Sonuçların karşılaştırılması için aynı girdi ve pencere kaydırma yöntemi kullanılarak ARIMA modeli uygulanmıştır.

Bu çalışmada önerilen yöntemin hesaplama gereksinimleri ve maliyeti düşüktür, uygulaması kolaydır ve gözlemlenen verilerin otokorelasyon fonksiyonunu temsil edebilir. Fiyat verilerinin geç açıklanması nedeniyle daha uzun bir tahmin aralığına sahip olan sistem marjinal fiyatını tahmin eden diğer çalışmalardan farklı olarak, bu çalışma en yakın piyasa işlem saatinden önce daha fazla girdi elde etme yeteneği ile net dengesizlik hacim verisi üretmeyi önermektedir. Daha yakın bir tahmin süresi ile net dengesizlik hacmi oluşturulduktan sonra, sistem marjinal fiyatı, net dengesizlik hacmi ile sistem dengeleme fiyatı arasındaki yüksek korelasyon kullanılarak hesaplanabilir. Bu, hazırlanan çalışmanın bir parçası olmamakla beraber ileriki çalışmalarda kullanılmak üzere verilen bir öneridir. Net dengesizlik hacmi verilerinin piyasa hareketlerinin bir ön izlemesi olarak kullanılması amacıyla Markov zincir yaklaşımı uygulanmış ve yaygın olarak kullanılan veriye dayalı bir model olduğundan, sonuç doğruluklarının karşılaştırılması için ARIMA modeli uygulanmıştır.

Gün içi piyasasında yapılabilecek en yakın işlemin 2 saat sonrası için olduğu ve açıklanan en güncel gerçekleşen alış ve satış yönlü işlem hacimleri de bir saat öncesinin değerleri olduğu düşünüldüğünde, açıklanan değerden 3 saat sonrasının net işlem hacmi verisi öngörülmelidir. Bu sebeple model 1, 2 ve 3 saat ilerisine ait sentetik net dengesizlik hacmi verisi oluşturmak için kullanılmıştır. Veri oluşturma işlemi bir aylık süre ile devam ettirilerek oluşturulan veri setlerinin doğrulanabilmesi için zaman serileri elde edilmiştir. Sonrasında, oluşturulan zaman serileri, gözlemlenen net dengesizlik hacim zaman serisinin istatistiksel özelliklerini koruma becerilerini belirlemek için incelenmiştir.

Veri dağılım grafikleri, yöntemin gözlemlenen verilere yakın sonuçlar ürettiğini göstermiştir. Histogramlarda ARIMA modelinden daha fazla sapma göstermesine rağmen, sunulan yöntem gözlemlenen verilerin genel özelliklerini koruyabilmiştir. Otokorelasyon fonksiyonu, modelin günlük salınım davranışını da gözlemlenene benzer şekilde koruyabildiğini göstermiştir. İstatistiksel ölçümlerde, ARIMA

sonuçları genel olarak biraz daha yüksek doğruluğa sahip olsa da Markov zinciri ve ARIMA modellerinin sonuçları oldukça yakındır.

İstatistiksel ölçütlerde, belirleme katsayısı yüksek değildir ve en son gözlem zamanından daha ileri bir tarih için veri oluşturuldukça bu değer daha da düşmektedir. Bununla birlikte, MBE, NMBE, RMSE ve NRMSE değerleri de düşüktür ve bu, gözlemlenen ve üretilen net dengesizlik hacmi verileri arasında tatmin edici bir uyum olarak not edilebilir. Durum aralığının 500 MW olduğu düşünüldüğünde, ortalama değerler de gözlemlenen değere yakındır.

Genel olarak, ARIMA yöntemi, metriklerin çoğunda Markov zincir yaklaşımından daha iyi performans göstermiştir. Markov zinciri, her üç Cumartesi sonucunda da gözlemlenen verilere daha yakın bir ortalama değere sahiptir. 2 ve 3 saat ileri tahminlerde Markov zinciri, Cumartesi ve Pazar tahminlerinde belirleme katsayısı, RMSE ve NRMSE açısından ARIMA yöntemine eş veya daha iyi sonuçlar vermiştir. Ek olarak, Markov zinciri, her üç Cumartesi değerinde de gözlemlenen verilere daha yakın MBE, NMBE ve ortalama değerlere sahiptir. Haftanın günü karşılaştırmasında, her iki modelde de en yüksek belirleme katsayısı değerleri Cumartesi günü meydana gelmiştir, bunu hafta içi günler yakından takip ederken ve en düşük değerler Cumartesi günü gerçekleşmiştir. Bu durum, haftanın gününe bağlı olarak meydana gelen en yüksek ve en düşük değer farkının en yüksek Pazar günü, daha sonra hafta içi ve en düşük ise Cumartesi günü gerçekleşmesi olarak yorumlanmıştır. Ayrıca hafta içi ARIMA ve Markov zincir yaklaşımının metrik sonuçları arasında farkların daha küçük olmasının nedeninin, hafta içi girdi sayısına kıyasla hafta sonu girdisinin daha az olmasından kaynaklanmasına bağlanmıştır.

Sonuçları daha da iyileştirmek için 200 MW gibi daha küçük bir durum aralığı kullanılabilir. Daha yüksek dereceli geçiş de ileriki araştırmalarda kullanılabilir. Performansı arttırmak için durum aralığı küçültülüp, geçiş matrisi 1 ay uzunluğundaki girdi setinin maksimum ve minimum değerleri arasında oluşturulabilir ve bu değerler girdi seti her güncellenişinde dinamik olarak değiştirilebilir. Daha önce belirtildiği gibi, sentetik net dengesizlik hacim değerleri, dengeleme güç piyasası fiyat tahminlerinin ve santral işletme optimizasyon modellerinin girdisi olarak kullanılabilir.



1. INTRODUCTION

Electrical energy is one of the most convenient therefore the most used energy forms in the world. Its ability to be converted into any other form of energy with ease to be and be transported efficiently and safely over long distances makes it preferable compared to other energy source in daily use. It powers home appliances, computers, vehicles, motors and energizes the lighting in homes and cities. For our daily needs, electricity is provided from its generation to the customers through the electrical grid. From small local designs, the system has grown to thousands of kilometers and connect millions of consumers today. The grid is an intrigued system and consists of many complex interconnections, yet its three main sections are electricity generation, transmission, and distribution.

In the conventional grid, electricity should be consumed at the time of production, and the consumption and production processes should be at the same time or else it affects the frequency and may lead to blackouts (Gaudard and Madani, 2019; Jeon and Mo, 2018). Therefore, there is a need for a transmission system operator as a controlling agency, to coordinate the balancing generation and consumption of the system across the transmission grid. Large generation capacity should meet high electricity demand occurring in short peak periods. This represents to one of the major challenge for system operators; stabilizing the electricity grid, especially with the growing share of intermittent renewable energy sources feed into the grid (Fleer et al., 2017).

In the last decades, the electricity generation industry developed a great interest in integrating renewable energy sources into existing power systems as the world is facing serious challenges emerging from the continuing consumption of fossil fuels and the worsening global environment (Kou et al., 2015). However, as the growth in the share of renewable, non-dispatchable and intermittent generation continues, its integration in power systems becomes more and more challenging. Potential solutions on enabling the integration of renewable generation considered as further increases in demand flexibility, additional investments in grid infrastructures and storage systems (Metz and Saraiva, 2018). System operators must ensure the ability to maintain

continuous service in the case of rapid and large swings in supply or demand. This is a challenging task, considering the electricity generation fluctuations in a grid with high renewables penetration. The system can be operated at low cost and high reliability with scheduling and dispatching generation resources (Wang et al., 2019).

Since electricity cannot be stored, or storage techniques are rather expensive, it must be used when it is generated. Generation and consumption must match so grid frequency will not be affected. However, the consumption side still cannot be managed at a desirable level. Facilities and factories with great consumption may be directed with tariff adjustment but consumption of households is not able to control in today's condition in Turkey. Generation side however is more flexible in that respect. Natural gas plants as example can take orders on operate or not. Although control level drops as the penetration of renewables such as wind increase in the grid mixture. And that is why different market mechanisms are needed like day-ahead, intraday, real-time balancing markets.

Day-ahead planning of generation and consumption sets the market price but not meeting the promised actions and causing imbalance has consequences. The imbalance is penalized by the system operator. A chance to rearrange the placed bid is possible by participating in the intraday market where bids for two hours later can be made. But whether to participate in the intraday market or accept the penalty to optimize the income depends on the system marginal price (SMP) occurring in the balancing market. To decide the action, a prediction on SMP is needed. However, the latest system marginal price announcement is the value of 5 hours previous, and the closest intraday market action is for 2 hours later. On the other hand, instruction volume announcement is made after the end of each hour. Considering the high instruction volume and price relation in the market, predicting the instruction volume which has a closer forecast date is more beneficial and would give more accurate results. That is why in this paper a stochastic Markov Chain method to predict the instruction volume is proposed.

In the first section literature on the market structure, alternative approaches and penalty deviation methods are presented, in the second section Turkish electricity market history, structure and current situation is shown with past data. On the third section presented method is explained, and finally in the last section results and conclusion is given.

2. LITERATURE REVIEW

2.1 Electricity Market Studies

In the past for many years, government agencies or utility commissions determined electricity prices as the electricity sector was under monopolistic and state-owned structures. However, currently prices of wholesale electricity are mostly determined by demand and supply dynamics.

On the demand side, many studies focused on demand side management to minimize the cost. Electricity is a major production resource in many sectors. Wholesale market is a way to purchase electricity, albeit it is prone to high price fluctuations. For this reason, most of the consumers choose to purchase electricity from retailers or make medium-term contracts with higher but known price rates. Habibian et al. (2020) proposed a load scheduling model for demand response of large manufacturers who purchase electricity from a co-optimized energy and reserve market, while taking into account the influence of their actions on the prices of energy and reserve. The proposed method for strategic electricity consumption scheduling reduced the cost 18% compared to the fixed consumption policy. It showed that the time horizon of the scheduling, more flexibility in the consumption level can be taken advantage which further reduces the total cost. Compared to daily scheduling, weekly scheduling saved 2% for the same total consumption over the week. It also showed that the consumption behavior of a major consumer who has flexible load and purchases electricity from the wholesale market can both reduce its own cost and benefit the smaller consumers by lowering the spot price of electricity.

Scheduling the production can be considered as a more common case compared to incorporating the residential loads into market. On the other hand, grid operations and market research are always looking for more flexibility options. As the technology enhanced, the term prosumer is made into the literature as individuals that both a consumer and producer. Houses with battery storage integrated wind and solar generation is becoming a more common case as the prices for those technologies

comes down. With the term of prosumer coming to life, participation of residential loads to market became a topic.

A modular optimization framework examining an aggregator of residential customers presented in the study of Schwabeneder et al. (2021), which optimizes a portfolio of flexible electricity production, consumption and storage technologies on the day-ahead, intraday and balancing markets. It concluded with the assumption of the worst-case scenario in the objective function and neglecting the risk of additional cost caused by unforeseen balancing activities both give suboptimal results. Therefore, a more detailed risk measure on the optimization model suggested to use. Also, taking the intraday market to react on balancing market activations into account lets offering significantly more balancing markets reserves.

Technology enhancement allowed more penetration of renewable sources into the system. Nevertheless, those renewable resources are intermitted and mostly cannot be scheduled. As a result of their intermittent nature, renewable energy sources effect the electricity price formation as they lower the base price level in the merit-order and challenges the profitability of conventional plants, changes the electricity price volatility, and increases the short-term demand for flexibility.

Variable renewable energy generation technologies are changing the supply curve. They are shifting the conventional plant with high marginal cost such as natural gas and coal power plants to the later end of the merit order and forcing them to out of production in the day-ahead market. Consequently, price volatility increases in intraday and balancing markets as the share of variable energy sources increased in the grid mix and power delivery Furthermore, due to the problem of intermittency and forecasting errors, imbalance costs are increasing.

Sirin and Yilmaz (2021) analyzed the impact of intermittent renewable energy generation on electricity markets, specifically intraday and imbalance markets. By means of variable renewable sources, they considered wind and run-off river power plants. The results confirmed the effect of renewable generation in the Turkish electricity market. It showed the different effects of variable renewable generation on day-ahead and balancing market where an increase in real-time variable energy generation affects prices mostly at night, and deviations in their generation affects balancing market at almost all hours. The direction analysis of imbalance was

examined, and it was found that while positive imbalance was rather stable while negative imbalance has declined which is concluded to cause by increasing renewable generation. They also proposed suggestions to improve the market design. First was changing the pricing mechanism of a single zone which does not reflect the regional supply and demand characteristics and applies uniform market price. Second was reviewing the EXIST (Energy Exchange Istanbul) optimization algorithm where grid-constraints in determining day ahead market-clearing price does not included. Both situations result in increasing balancing and operation costs. And lastly, they took attention to the low liquidity of the intraday market.

On another study, Goodarzi et al. (2019) investigated the impact of wind and solar generation forecast errors on imbalance volume and subsequent spot electricity prices. The results showed the negative significant effects of both wind and PV production forecast errors on imbalance volume which means surplus in electricity generation causes a negative imbalance. For most of the time, wind forecast errors have a stronger effect compared to solar. Solar mostly occurs during the non-peak time while wind errors are distributed across the day including the evening peak where imbalances are generally higher in Germany.

The more variable prices mean more opportunities for controllable electricity producers who provide up/down-ramping flexibility to increase their revenues while the variable renewable energy sources with high degrees of randomness tend to pay for this flexibility in the electricity spot market to reduce their imbalance exposure. Thus, as stated in the study of Pape (2018), the intraday market gains importance as the effort increases to balance intraday deviation from day-ahead schedules and for market value of different technologies. In the article, considering self-curtailment during over-supply in the system and adjusting the factor metric of market value suggested.

Chaves-Ávila and Fernandes (2015) too investigated the intraday market and its ability to balance the renewable generation in Spain. They pointed out that Spanish intraday market has a high trading volume compared to other European intraday markets and said it was because of different market regulations where participation in the Spanish intraday market is incentivized. Some of these market regulations are the mechanism of dual imbalance pricing where energy imbalances are strongly penalized, the balance responsibility allocation to all market parties including all renewable producers, and

unit scheduling in place of the portfolio balancing which means imbalances cannot be matched among different renewable technologies. The analysis showed that the balancing of renewable sources is favored in the Spanish intraday market. In these short-term markets intermittent energy sources have more flexibility to bid and they bid on these markets to maximize economic profits.

As another flexibility option for the grid, different uses of storage systems proposed in many other studies. Terlouw et al. (2019) studied energy arbitrage and peak shaving optimization in community energy storage systems from aggregator and distribution system operator perspective while Tian et al. (2018) studied the technical benefits and stacked revenue of a grid-connected energy storage system by modelling a small grid while considering battery and transmission line constraints.

Nikolakakis and Fthenakis (2018) worked on compressed air storage models for energy arbitrage and ancillary services, Gaudard and Madani (2019) compared its benefits with pumped-storage. Metz and Saraiva (2018) described a price arbitrage operation optimizing model considering 15- and the 60-minutes auctions in Germany intraday market.

Aside from aggregator and system operator perspective for energy arbitrage, peak shaving and ancillary service usage, energy storage systems also used coupled with renewable energy generation systems to manage forecast deviations. In order to mitigate their deviation penalties suppliers may choose to invest on storage technologies. Also, to increase the profitability of the system, storage can be used to participate in intraday and ancillary services which was forbidden before for non-dispatchable technologies (Heredia et al., 2018).

Similarly, Trovato and Kantharaj (2020) studied different cases where a system uses an energy storage unit with a large-scale wind power generator to manage imbalance of the wind farm, carry out energy arbitrage and help the grid during demand peaks. However, they studied a rather unique situation. Apart from other studies, they considered a different approach to imbalance case. In many precious works the local imbalance only treated as a cost which should be minimized without considering wider system-level conditions which can be the imbalance prices. The presented algorithm in their study reverses this process of minimizing the imbalance. It aims to intentionally take advantage of the imbalance position by measuring the net imbalance

volume through the imbalance price and by creating imbalance if profitable. In the results, it was found that compared to other strategies the net imbalance volume chasing case ended up with higher revenues and a quite low number of charging/discharging cycles. They also warned the systems operator to be aware of the opportunities and measures of the net imbalance chasing and in which conditions it can be dangerous, like intentionally and nearly at the same time changing the operation to perform net imbalance chasing with large quantities of assets.

Similar to wind power systems, in solar generation plants the imbalances occurring during weather changes, system limits or failure conditions, storage technologies can be used, as in the study of Bordin et al. (2017) where battery integration with solar generation studied. Looking from a different perspective, O'Shaughnessy et al. (2018) worked on the prosumer side of action and reviewed the end-user economic of load control in residential buildings and solar PV integration with storage.

Storage systems are a practical solution however they are still an expensive solution. On the other hand, enhancing forecasting methods is an option which does not requires high acquisition cost for reducing penalties. Not by physically controlling the generation but with a better bidding result. There are studies for wind generation forecasts both for long term and short term. Climate variability greatly effects electricity generation, demand and maintenance activities in the energy as stated by In Lledó et al. (2019). Thus, in their study, they proposed a methodology to produce seasonal capacity factor predictions for a range of turbine classes.

The stochastic character of wind power generation puts limitations to the increased shares of wind energy in electricity systems and challenges market integration of wind power, mostly since more dynamic pricing mechanisms which new wind plants are set to deal with. Thus short term forecasts are necessary and many different artificial intelligence methods used for wind generation such as neural network and support vector as in the study of Zafirakis et al. (2019) or hybrid models as in Camelo et al. (2018) based on different prediction horizons. In some studies instead of direct wind generation forecasts, wind speed forecasts made as in Memarzadeh and Keynia (2020) where the method is based on fine-tuned LSTM (Long Short-Term Memory) neural network and optimal input sets.

Some studies combine statistical methods with machine learning algorithms. In Korprasertsak and Leephakpreeda (2019) an autoregressive moving average model, an artificial neural network model, and a grey prediction model predictions comparatively examined, then a weighting method applied systematically to put together the predicted values of the predictive models based on performance of their forecasting results.

Not only generation but load can also be forecasted with artificial intelligence methods. Producing reliable and accurate electricity demand forecasting is crucial for all electricity markets on different levels as stated by Citroen et al. (2016). In their study wavelet neural networks method used in long term forecasting of electricity demand. Xie et al. (2019) combined Elman neural network with particle swarm optimization for short-term load forecasting. Similar to wind generation forecasts, solar generation also forecasted with machine learning methods. Leo et al. (2014) forecasted both load and solar generation by using reinforcement learning method for optimal energy management of a solar microgrid.

As mentioned before the intraday market gains importance as the effort increases to balance intraday deviation, the physical control of those imbalances occurs at balancing market. Balancing market is where the imbalance in the grid is compensated where mostly plant whose power outcome can be controlled at desired amounts and react at desired times are participates. As expected, those plants are mostly conventional power plants. However, considering the new technological advancements, such as lower costs of energy storage, achievement of higher availability ratios on the renewable sources, enhancement the accuracy of forecast results, conventional power plants are not the only alternative anymore.

Small-scale electricity generation units such as variable renewable energy resources, wind turbines, solar generation plants, storage and demand response connected to the distribution network are named as distributed energy resources. As their cost decrease and availability increase, an interest is raised on finding different ways of their participation to the electricity market. On the other hand, not only the source of generation but the quantity of output is affecting the participation of the power plants in the balancing market. On that front, Poplavskaya and de Vries (2019) examined three European balancing markets cases, the Netherlands, Austria and Germany. They conclude that contribution of distributed sources to balancing market heavily depends

on auction configuration and market access criteria. They also think the minimum bid sizes between 1 and 5 MW quite restrictive for aggregation and recommend increasing the bidding frequency, a higher product resolution and pool-based prequalification.

Parallel with these recommendations, there are studies where changing the bidding frequency is examined. Facchini et al. (2019) looked at the case of reducing the gate-closing time from 3.5 hours to 1 hour in the past by analyzing the complex dynamics of the UK half-hourly spot price both studying the spectral properties of the price time series and the temporal recurrence dynamics. They stated that occurring dynamic price regime shift was linked to the gate closure change since shorter gate closure intervals leads to shorter forecasting on electricity demand and better reliability on the supply side. Hence, closer gate-closing to real time was associated to reduced price fluctuations in the wholesale market.

Similarly, Wu et al. (2020) proposed an agent-based modelling combined with multiple criteria decision analysis model to analyze different margins of tolerance, program time units and imbalance pricing mechanisms of imbalance settlement design. They found that a program time unit 1 hour can ensure balancing operation with a relatively low renewable share but with the increase of renewable share and further development in spot market, it suggested to be gradually shortened to 30-15 minutes to divide the imbalance responsibilities more precisely and encourage efficiency and justice in the balancing market.

Likewise, Petit et al. (2019), gate closure time impact on the balancing efficiency in self-dispatch electric power systems studied. They proposed a quantitative evaluation of postponing the closure of the balancing gate time from 1 hour to 15 minutes ahead of the imbalance settlement period based on a multi-level simulation tool with a realistic short-term power system operation modelling. On the other hand, they found that the overall variable cost was 0.08%–0.43% higher in the 15-minutes before gate-closing than 1-hour before gate-closing time depending on the simulation scenario. They concluded that the cost difference is primarily caused by a better available resource coordination by the central decision maker than by decentralized power companies.

For balancing market mechanism Viehmann et al. (2021) focused on competitive electricity balancing market auction design. They pointed the ongoing debate between

uniform price auctions where successful bids receive the marginal clearing price and discriminatory price auctions where successful bids are paid their bidding price. In Europe, some countries use one of those designs for most of their balancing capacities while both auction types are used in some countries for different types of balancing capacities. By using an agent-based Q-learning model to compare the results of these designs, they simulated the strategic bidding behavior under different market conditions. They found that uniform price auctions lead to higher prices in all analyzed market settings which is mostly because of engagement of players in bid shading more aggressively. Furthermore, they stated that small players benefit from the price setting of large players and earn higher profits per unit of capacity in uniform price auctions, while they are disadvantaged in discriminatory price auctions.

In the case of Germany, Koch and Hirth (2019) quantitatively examined the situation of declining short-term balancing reserve coincided with increasing wind and solar generation share. They pointed the reason for reduced balancing need is as the increased and improved short-term wholesale electricity trading on the intraday market where around the clock trading and quarter-hour base rather than full-hour base contracts are done. They found that shift to quarter-hourly is responsible of 17% decrease in energy balancing.

Pool intermediaries of distributed renewable generation can be needed to provide market access, since it is complicated by the excessively high transaction costs in power markets, and manage risks caused by ambiguity in quantities and prices. It called virtual power plants by Wozabal and Rameseder (2020) where they proposed a model for optimal bidding of these virtual power plants in day ahead market and intraday market for electricity.

There is a great interest in wind power forecasting both in the literature and among producers who participate in electricity market. Nevertheless, since forecast of wind power inherently contain a portion of ambiguity, there will always be deviation penalty induced by forecasting errors. By Pinson et al. (2007) a general methodology for deriving optimal bidding strategies based on probabilistic forecasts of wind generation, and on modeling regulation costs sensitivity of a wind power producer formulated. In the methodology introduced suitable in the event of wind power producer participation in day-ahead electricity market, it showed that an uncertainty information integrated in the process of decision-making could significantly increase the wind power

forecasts market value. In the study, it assumed that regulation unit cost trends on an annual or quarterly basis may be estimated and left the possibility to model and forecast the regulation penalties to further studies.

Khalid et al. (2018) too stated that additional income can be earned from predicting variability trends in market price and increase the profit of the operation. A model which uses wind power prediction and market price prediction as inputs proposed both to enhance the operation of wind power plant coupled with battery energy storage system and, to determine the optimal battery storage capacity necessary for the overall income maximization together with the operational profit. However, the predictions used for wind power generation and market price in the study obtained by adding 10% error to the actual data. It added that the forecasting information utilization for wind power and market pricing in order to take full optimization outcomes for renewable power plant sizing and operation still demands contribution.

Solar PV (photovoltaic) power trading is majorly based on committing to sell the forecasted solar generation. However, there can be other business opportunities for solar power producers. Sánchez de la Nieta et al. (2020), proposed two stochastic methods for scheduling and re-scheduling for energy trade of solar generation in day-ahead and intraday markets while considering risk-hedging. They considered the risk-hedging by co-optimizing expected profit with the metric of conditional value at risk.

Reserve market has participation rules where participants asked to bid both price and volume, and there is a requirement of minimum volume, as mentioned before, which is a discussed constraint both in European and the US markets. Another study on aggregated participation of small-scale electricity generation units to the reserve market studied in Romero et al. (2021) which focused the case of electric vehicles (EV). In the paper an EV aggregator optimization problem considered to trade the EV fleet charging by participate in both day ahead and reserve markets which can also be adapted to include imbalance settling in the balancing markets or trading at the intra-day market. In the scenario-based model, the regulation price, market capacity price, the proportion of a program time unit when reserves are deployed and day ahead market prices taken from 2016 and 2017 historical market data. Several state-of-the-art methods proposed, and results compared.

Forecast inaccuracy causes imbalance yet it is not the only factor effecting the imbalance cost. Imbalance cost is determined in the market, and it is specifically related to balancing market electricity price volatility. In order to reduce the imbalance cost Dinler (2021) presented a method which first casts reducing imbalance cost problem, then extracts information from the market data to find the higher price between day-ahead price and imbalance price at a given hour of the next day. After that, based on this information, supporting algorithms changes the existing production forecasts and avoid abrupt rises in the imbalance cost which occur when the prediction accuracy is low, and the marginal price and day-ahead price difference is high. It stated that the proposed framework does not require the day-ahead price and balancing market price predictions and can be used by any wind power forecasting system. In the study, testing period of a year showed that the strategy performs quite well, and it provided a decrease in the balancing cost between 6.258% and 11.195% for four tested wind power plants.

2.2 Electricity Market Price Studies

In the previous part of this section general studies on electricity market was examined to emphasize the supply and demand dynamics determining the wholesale electricity prices. As can be seen, many studies focused on offering structural changes for market to design whether the price formation, gate closure time or tariff calculations while some other searched the ways of enhancing the forecasting techniques. Forecasting is done both for supply which is generation from conventional sources or from renewable sources such as wind, solar, and run-of-river and demand which can be scheduling the consumption of price maker manufacturers or demand side management and so on. Many other combined their forecast with optimization methods to define best operation scheduling. In the optimization studies, the main purpose is either to maximize the profit of the plant or minimize the deviation from promised bids. We can thus say price is one of the key factors in all of the electricity markets and price occurs where system is balanced.

To begin with the literature on electricity market price forecast studies, Weron (2014) suggested a categorization of models based on a comprehensive review of hundreds of relevant articles and journals as shown in Figure 2.1. In the review, instead of providing accurate hourly price forecasts the main intention of reduced-form

(quantitative, stochastic) models explained as to replicate the main daily electricity price characteristics such as future marginal distributions, commodity price correlations and price dynamics.

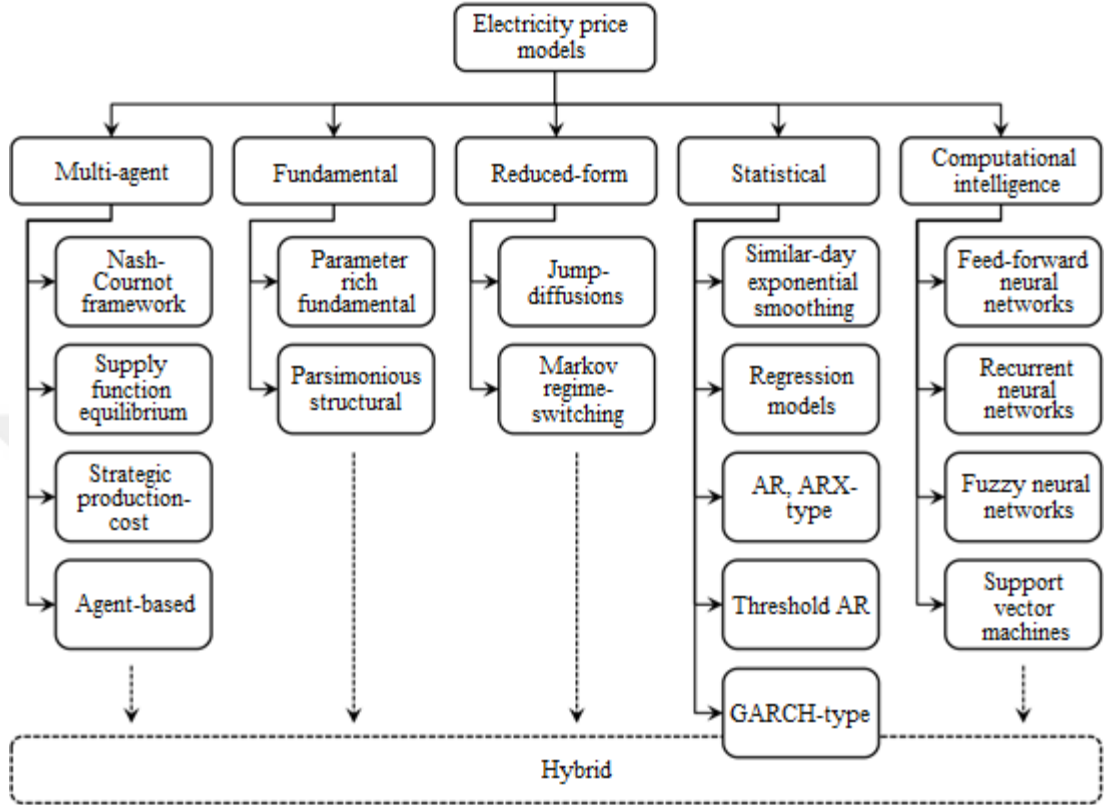


Figure 2.1 : Electricity price modelling approaches taxonomy based on Weron (2014).

Similar to the previous study, Nowotarski and Weron (2018) continued with the review of probabilistic electricity price forecasting methods, measures and tests. Computational intelligence is a popular method in price forecast studies. Halužan et al. (2020) used various computational intelligence and statistical methods such as autoregressive exogenous explanatory variables model (ARX), Support vector machine (SVM), K-nearest Neighbours (KNN), Random forest regression (RFR), Regression tree (M5P), Long short-term memory model (LSTM) and Artificial neural network (ANN) to evaluate their performance on forecasting day-ahead market price with using variables like day-ahead market clearing price (MCP), actual and forecasted load, wind and solar generation data. They also analyzed the impact of training sample size and using hourly clustering training sample.

A hybrid model for a very short-term day-ahead price forecasting using extreme gradient boosted trees (XGBoost), RFR, Bayesian Linear Regression, bootstrap aggregation of stacked generalization methods proposed by Bhatia et al. (2021) but used variables were not only renewable energy parameters but also meteorological parameters which affects the renewable energy generation. The proposed model also compared with various existing models.

Combination of another two popular methods, agent-based modeling and machine learning, proposed in the study of Fraunholz et al. (2021). An hourly long-term forecasting from 2020 to 2050 covering ten interconnected European countries made as a case study and the statistical significance and superiority of the results against a simpler linear regression mode evaluated by using Diebold–Mariano hypothesis tests.

Limitation of widely used data processing in complex time series forecasting and data decomposition which use future information in the data preprocessing stage mentioned in Yang et al. (2020) and a multi-step probabilistic interval forecasting system that successfully improve the performance of deterministic forecasting in management practice with no requirement of future information in the modeling process developed.

Sparking interest on Quantile Regression Averaging (QRA) in electricity price forecasting community happened after the variations of the method were used by the top two winning teams in the price track in the Global Energy Forecasting Competition 2014. Spotting the vulnerability of the method to low quality predictors when the set of regressors is larger than just a few in other studies, Uniejewski and Weron (2021) proposed a regularized version of QRA by using Least Absolute Shrinkage and Selection Operator (LASSO) to automatically choose the relevant regressors. Thus, a tool which can boost the energy trading profitability, help with day-ahead market bidding actions, and improve management of risk in the power sector proposed.

The literature on the electricity price forecast in the intraday markets is not as wide as day-ahead market or other intraday market studies as stated in Narajewski and Ziel (2020) where they proposed a probabilistic intraday electricity price forecasting to allow more efficient redispatch and trading on intraday market via simulating trajectories in every trading window to receive a realistic ensemble. The generalized additive models for location scale and shape (GAMLSS) mixed with and logit-lasso

estimation methods was used for modelling and forecasting of the trajectories and efficient decision-making.

The focus of intraday market studies also mentioned in Oksuz and Ugurlu (2019) as on the features and descriptive statistics and with motivation of this lack of study, they compared a variety of methods, statistical methods such as LASSO, linear regression, and the machine learning methods such as LSTM, Gated Recurrent Units (GRU) and ANN compared in order to predict market prices of electricity in intraday market of Turkey and statistical significance of the results evaluated with Diebold-Mariano tests. The results showed that neural network methods performed a better estimation of prices compared to linear regression and LASSO models while Recurrent Neural Network (RNN) models performed better than the ANN methods. Finally, it stated that among RNN methods GTU outperformed LSTM.

For the real-time market price forecast studies, Olsson and Söder, (2008) presented a model for simulating prices in order to construct scenario trees representing possible stochastic price realization on balancing market. Discrete Markov processes and Seasonal auto regressive integrated moving average (SARIMA) combined with the purpose of generating price series with periods without the need of demand for balancing power. A whole year data used in the case study for parameter estimation which result in a model acting in accordance with yearly mean prices of that year.

Considering the flexible operation of enterprises with high electricity consumption who can participate in spot market or offering ancillary services on demand, Schäfer et al. (2019) proposed an optimization of the bidding strategy for balancing power as a mixed-integer nonlinear program which considers both ancillary service market price forecasts and hourly varying spot market prices. Participation of an industrial aluminum electrolysis process in the German primary balancing market considered and solved by a two-stage approach, decomposing into a mixed-integer linear scheduling problem and a nonlinear bidding problem. The results showed saving up to more than 20% in specific weeks and an optimal balancing market participation can offer considerably higher profits than that can be made on spot markets, precisely almost doubling the savings in some of the considered weeks.

Another very-short term forecast applied this time in balancing market. Bottieau et al. (2020) proposed a deep-learning encoder-decoder model to generate improved probabilistic imbalance signal forecasts and then the predicted quantiles used to quantify the risk and optimize the real-time participation of market participants who act as price-makers in the imbalance market.

The behavior of companies to estimate the extremes of prices or revenues for opportunity and risk management, assets assignment in an optimal way also stated in Lucas et al. (2020) too. With a different approach, five Loss of Load Probability (LOLP) variables with different time-ahead estimations and other quasi-deterministic variables including system load, base production, wind and solar generation, day-ahead market price, imbalance volume and seasonality used to explain the price behavior and three machine-learning algorithms which are gradient boosting, random forest and XGBoost applied to for performance test. In the results, the highest performance given by XGBoost and Net Imbalance Volume was the variable that contribute the most to the model. It was also stated that the net imbalance volume used in most models however it cannot be a direct input to as it cannot be accurately forecasted.

Another study mentioning the lack of search on balancing market price forecast, Bunn et al. (2021) investigated the role of market transparency to improve predictability. A non-linear model approach results showed that system imbalance price reflects a regime-switching behavior, driven demand, wind and solar forecast errors, scarcity variables, lagged imbalance volumes and lagged prices. A significant lagged autoregressive effect also stated which adds to the predictability, therefore strong confirmation of fundamental predictability was found.

3. METHODOLOGY

In the methodology, to generate future values of the net imbalance volume a stochastic method was presented. By using transition matrix of the Markov chain method, hourly net imbalance volume data was simulated. To be able to simulate all possible states the net imbalance time series was divided into various states depending on maximum and minimum occurrence in the past few years. Once the transition matrix has been formed with the corresponding probabilities, synthetic series were generated on desired lengths.

The aim of the model was not to point forecast at a certain time but to realistically represent a possible chain of events of synthetic net imbalance volume values. Historical data of imbalance volume were used to generate synthetic series while preserving the autocorrelation and statistical parameters. In this section, data characteristics are examined, Markov chain and its basic properties are defined, and methodology is explained.

3.1 Autoregressive Integrated Moving Average

Data-driven models has been achieved significant accuracy levels and that is why they are widely used in energy forecasting studies. For time-series forecasting applications one of the widely used method, Autoregressive Integrated Moving Average (ARIMA), has a simple approach. Two types of linear regressions which are the Autoregressive (AR) and the Moving Average (MA) are used in the model (Al-Musaylh et al., 2018). The AR model is given in equation 3.5 below.

$$y_t = c + a_1 y_{t-1} + \dots + a_p y_{t-p} + u_t \quad (3.5)$$

Here, c denotes a constant, $a_1, \dots, a_p$ denotes the AR parameters, p the order of the AR, and u_t denotes the white noise. Similarly, the MA model is given in the equation 3.6

$$y_t = \mu + u_t + m_1 u_{t-1} + \dots + m_q u_{t-q} \quad (3.6)$$

where μ is the expectation of y_t , q is the order of MA, $m, \dots, m_q$ are the MA parameters, and $u_t, u_{t-1}, \dots, u_{t-q}$ are the white noise (error) terms. Autoregressive Moving Average (ARMA) model [ARMA (p,q)] is formed by using the same training data with linear combination of the predictors of the two models, as given in equation 3.7.

$$y_t = c + a_1 y_{t-1} + \dots + a_p y_{t-p} + u_t + m_1 u_{t-1} + \dots + m_q u_{t-q} \quad (3.7)$$

where p and q represent the autoregressive and moving average terms, respectively (Al-Musaylh et al., 2018).

The model premise that the time-series data statistically stationary which means measured statistical properties, such as the variance, autocorrelation and mean remain constant over time. In case of the data is non-stationary, the model requires differencing to transform it to stationary and this is denoted as ARIMA (p,d,q) where d is the degree of differencing (Al-Musaylh et al., 2018).

3.2 Markov Chain

Markov chain is a commonly used stochastic process. Stochastic processes provide a method of quantitative explanation and management of business operations and take a major part in business management science and operational research. To provide an insight about stochastic processes, a time series is a chronologically arranged set of observations which is denoted as $\{X(t): t \in T\}$, where T is a set of time points that measurements are made and $X(t)$ is the observation made at time t , while similarly, in a stochastic process, $X(t)$ is an observed value of a random variable. A random variable X is a real-valued quantity, a variable whose values are taken randomly according to a probability distribution function.

Thus by the definition, a stochastic process is a collection of random variables, $\{X(t): t \in T\}$, and characterized by an empirical process, the progress of which in time is ruled by probabilistic laws. The parameter T is the index set of the process and t describes time, can be discrete or continuous. When the set of possible values of T is finite or countable, $T = \{0, \pm 1, \pm 2, \dots\}$ or $T = \{0, 1, 2, \dots\}$, the process said to be

discrete and when the index set T is formed by an interval of real line, $T = \{t: -\infty < t < \infty\}$ or $\{t: \geq 0\}$, the process is called a continuous process (Parzen, 2015, Chapter 1).

As mentioned before, Markov process is a stochastic process and according to the formal definition, if the conditional distribution of $X(t_n)$ for any set of time points $t_1 < t_2 < \dots < t_n$ in the index set of the process of a discrete parameter stochastic process, $\{X(t), t = 0, 1, 2\}$, or a continuous parameter stochastic process, $\{X(t), t \geq 0\}$, for given values of $X(t_1), \dots, X(t_{n-1})$ depends only on the previous value $X(t_{n-1})$, the process is called a Markov process. For any real numbers $x_1, \dots, x_n$

$$\begin{aligned} P[X(t_n) \leq x_n | X(t_1) = x_1, \dots, X(t_{n-1}) = x_{n-1}] \\ = P[X(t_n) \leq x_n | X(t_{n-1}) = x_{n-1}] \end{aligned} \quad (3.1)$$

equation 3.1 means that the conditional probability of any future state, given the present and past states, is independent of the past states and depends only on the present state.

The nature of the index set and the nature of the state space defines the class of the Markov processes. If a time t exists in the index set of T where the probability $P[x - h < X(t) < x + h]$ is positive for every $h > 0$, the real number x is said to be a possible value, a state, of a stochastic process $\{X(t) : t \in T\}$. The set of all possible values of a stochastic process that the random variable $X(t)$ can take is represents its state space, S . In the discrete case, the state space can be finite or infinite and the case which is not discrete is called continuous. Figure 3.1 describes the classification of Markov processes. And finally, as seen in the figure below, a Markov process with a discrete state space is called a Markov chain.

		State space	
		Discrete	Continuous
Nature of parameter	Discrete	Discrete parameter Markov chain	Discrete parameter Markov process
	Continuous	Continuous parameter Markov chain	Continuous parameter Markov process

Figure 3.1 : Markov process classification.

A transition probability function is what describes a Markov process. It is the conditional probability of the state that the system will be at time t (Parzen, 2015, Chapter 6). In the case of this study, Markov chain method is used to generate next values of net instruction volume. The net balancing instructions are observed at a discrete set of time where $X_0, X_1, X_2, \dots, X_t$ are successive observations, X_t is a random variable which represents the state of the system at time n . Since there are only finite number of states, the sequence $\{X_t\}$ is called a chain. Thus, the Markov property expressed as in equation 3.2 for any real value of $x_0, x_1, \dots, x_n$.

$$P[X_t \leq x_t | X_0 = x_0, \dots, X_{t-1} = x_{t-1}] = P[X_t \leq t | X_{t-1} = x_{t-1}] \quad (3.2)$$

The Markov property states that the current states only affected by the latest state and whatever happens before that have no effect. Similarly, only the current state affects what happens on the next state. Each transition between states has a possibility and the matrix containing all transition possibilities is called a transition matrix. The transition probabilities of matrix of Markov chain is shown in the equation 3.3 where $\{X_0, X_1, X_2, \dots\}$ is a Markov chain with state space S , where S has size N .

$$p_{ij} = P(X_{t+1} = j | X_t = i) \text{ for } i, j \in S, t = 0, 1, 2, \dots \quad (3.3)$$

In the transition matrix p_{ij} is conditional probability, i is current and j is next state where it represents the probability of going from state i to state j . $P = (p_{ij})$ shows the transition matrix, the rows represent current state, or from (X_t) and columns represents next state, or to (X_{t+1}). The transition matrix is an $N \times N$ square matrix since both X_{t+1} and X_t takes N values in the same state space. Thus, all the possible states in the state space is given in the transition matrix and the sum of conditional probabilities in each row added up to 1 as shown in Figure 3.2 below.

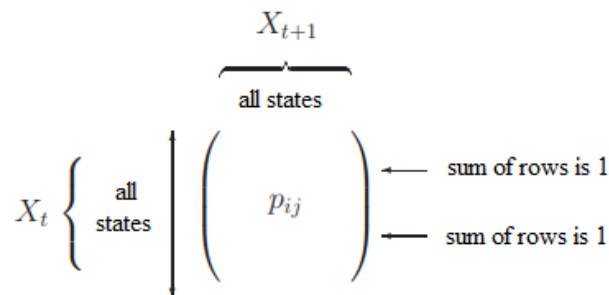


Figure 3.2 : Transition probability matrix representation.

On a mathematical notation, sum of all values in each rows should sum to 1 as shown in equation 3.4.

$$\sum_{j=0}^N p_{ij} = \sum_{j=0}^N P(X_{t+1} = j \mid X_t = i) = \sum_{j=0}^N P_{\{X_t=i\}}(X_{t+1} = j) = 1 \quad (3.4)$$

There is also order in Markov processes. All Markov process models are determined by the transitional probability matrices of various time steps. In first order Markov chain, each state depends only on the state just before the current state while in second or higher order Markov chains are the processes in which the next state depends on two or more preceding states. Due to the statistical parameter and first-order autocorrelation coefficient preservation in the synthetic sequences, the first-order Markov chain is the most commonly used version (Sahin and Sen, 2001).

3.3 Synthetic Data Generation

Data which are not obtained by direct measurement but obtained by a production method and are applicable to a given situation is called synthetic data. Synthetic data generator algorithms preserve the statistical characteristics of observed data while producing entirely new data points. In cases that real data does not exist, but general features are known, a random sample of any distribution can be generated and can be used to conduct various processes. As well as the data can be drawn from a distribution, agent-base and deep learning models can be used. Data utility is improved by feeding models with more data in deep learning models. In agent-base modelling created model explains observed behavior then reproduce random data. It also shows the effects of agent interactions on the system. In this study, Markov chain model was used for synthetic data generation method due to its statistical parameter and first-order autocorrelation coefficient preservation ability



4. OVERVIEW OF TURKISH ELECTRICITY MARKET

4.1 Electricity Market

Electricity market is a system enabling purchases with bids to buy and sales with offers to sell, short-term trading, mostly as financial or obligation swaps. Offers and bids are used to determine demand and supply and set the price. There are also long-term trades carried out with contracts like power purchase agreements and generally considers private bilateral transactions which carried out between counterparties. Market operator generally clear and settle the wholesale transactions like bids and offers and the market operator in Turkey is Energy Markets Operation Corporation (EPIAŞ, Enerji Piyasaları İşletme Anonim Şirketi) which established in March 2015 and also named as EXIST after it was launched in 2018. Meanwhile the transmission system operator which is responsible from physical delivery of electricity is Turkish Electricity Transmission Corporation (TEİAŞ, Türkiye Elektrik İletim Anonim Şirketi).

4.1.1 History of electricity market in Turkey

The first electricity generation in Turkey was started with a 2 kW hydroelectric power plant in 1902 in Tarsus and the first large power plant was a thermal power plant established in 1914 in Istanbul Silahtarağa (Arslan, 2017). Energy and Natural Resources Ministry (ETKB, Enerji ve Tabii Kaynaklar Bakanlığı) which is responsible for Turkey's energy policy was established in 1963. Few years after the establishment of the Ministry, in 1970, Turkish Electricity Administration (TEK, Türkiye Elektrik Kurumu) was established which was a state monopoly. TEK was the government agency responsible for the generation, transmission and distribution of electricity in the country from 1970 to 1994 (Ministry of Energy and Natural Resources, n.d.). In 1993, with the Council of Ministers Decision, TEK was divided into two separate state-owned enterprises: Turkish Electricity Distribution Corporation (TEDAŞ, Türkiye Elektrik Dağıtım Anonim Şirketi) and Turkish Electricity Generation-Transmission Corporation (TEAŞ, Türkiye Elektrik Üretim-İletim Anonim Şirketi).

After this decision, in 1994, both structures were acquired legal entity status (Turkish Electricity Distribution Corporation, 2017). Parallel with the increasing demand, the installed capacity was also increased from 28 GW in 2001 to 96 GW at the end of 2020 (TEİAŞ, *Santral Kurulu Güç Raporları (Power Plant Installed Capacity Reports)*, 2021). With the enactment of the Electricity Market Law No. 4628, the Electricity Market Regulatory Authority was established. Then in the same year, the name was changed to Energy Market Regulatory Authority (EMRA, Enerji Piyasası Düzenleme Kurumu) which is the institution responsible for regulation and supervision in the energy market (Energy Market Regulatory Authority, n.d.). Moreover, in 2001, TEAŞ unbundled into three separate state economic enterprises: Electricity Generation Corporation (EÜAŞ, Elektrik Üretim Anonim Şirketi) responsible for generation, Turkish Electricity Transmission Corporation (TEİAŞ) responsible for transmission, and Turkish Electricity Trade and Contracting Corporation (TETAŞ, Türkiye Elektrik Ticaret ve Taahhüt Anonim Şirketi) responsible for trade (Turkish Electricity Transmission Corporation, n.d.).

With the Law No. 5346 on the Use of Renewable Energy Resources for the Purpose of Generating Electrical Energy, which entered into force in 2005, was paved the way for investment in renewable energy resources (Law on Utilization of Renewable Energy Sources for the Purpose of Generating Electrical Energy, 2005). Based upon this law, with the relevant regulation in 2011, the Renewable Energy Resources Support Mechanism (YEKDEM, Yenilenebilir Enerji Kaynakları Destekleme Mekanizması) was put into effect and the foundation was laid for the incentive mechanism for renewable energy sources. With the mechanism that offers a fixed purchase guarantee to wind, solar, geothermal, biomass, run-off-river and some hydroelectric power plants, an increase in installed capacity of domestic and renewable energy resource was aimed. With YEKDEM, it is aimed to apply the prices determined in the relevant regulation for 10 years to the facilities that have been put into operation until the end of 2015 with the effective date of the YEK Law. Later on, the activation date was extended until 2020 for power plants that want to benefit from this mechanism (Inal et al., 2011).

The steps towards liberalization were continued in 2004 with the decision to privatize distribution, and distribution privatizations were completed in 2013. Today, distribution activities are carried out by private companies with distribution licenses

in 21 distribution regions. Another step taken towards the goal of altering the electricity market from a monopoly to a free and competitive electricity market model was the Balancing and Settlement Regulation which was issued in 2006. At first, Temporary Balancing and Settlement Regulation was published in 2004 than 1st Phase of Balancing Power Market Mechanism was came into effect. Settlement of imbalances at day, peak and night periods was started in 2006. With this regulation the Intraday Market was targeted, but the Day Ahead Planning system was operated between the years of 2009-2011 instead, because the markets were not yet ready for this change.

The day ahead market system, which currently is in use, was established in the last month of 2011. Also, in October 2011, electricity commodities were started to be traded on the Derivatives Exchange, then together with all other stock exchanges in Turkey, it was gathered under the new Istanbul Stock Exchange (BIST, Borsa İstanbul Anonim Şirketi). EPIAŞ was officially established in 2013, subject to the provisions of the Electricity Market Law No. 6446, and the registration process was completed in 2015. Again in 2015, the Intraday Market was started its operations. In 2015 for the participants and public to access data related with electricity market, Transparency Platform was released and few years after that EXIST was launched in 2018. Also (Çelikkol and Köse, 2015; Energy Exchange Istanbul (EXIST), n.d.).

In 2016, a regulation announcement was made by the ETKB on Renewable Resource Areas, also known as YEKA (Yenilenebilir Enerji Kaynak Alanları). With this regulation the effective and efficient use of renewable energy resources by creating large-scale renewable energy resource areas, the rapid investment by allocating these areas to investors, and the production of advanced technology components used in electrical energy production facilities required to be locally manufactured products, depending on the case either through manufacture by the applicant itself or through supply from other local manufacturers and contribution to the provision of technology transfer was aimed (Boden Law, 2019)

With another structural change in the electricity market in Turkey, EÜAŞ and TETAŞ was gathered by one roof in 2018 (Bakırcı et al., 2018). In addition, the Ancillary Services Market Regulation and Capacity Mechanism Regulation were put into effect in the same year (Arseven et al., 2018; Erdem and Erdem, 2018).

In the current situation, the basic institutions in the market considered as; ETKB, EMRA, TEİAŞ, Electricity Generation Company and EPIAŞ. Within the context of market operation activities, day ahead market and intraday market are operated by EPIAŞ. In accordance with submitted orders by market participants to day-ahead market, demand and supply volumes are announced together with the market clearing prices while in the Intraday Market there are matches with continuous trading method. Besides the operations in day ahead, ancillary services and balancing markets, intraday market gives almost real-time trading and portfolio balancing opportunities to market participants in short term. Thus, intraday market acts as a bridge between the day ahead market and the balancing market, hereby it essentially contributes to electricity market balancing and sustainability.

4.1.2 Electricity trade

Electricity trade in Turkey is basically carried out in two different ways, financial and physical. The two markets differ in terms of the necessity to deliver electricity. There is no physical delivery requirement in the financial contracts. On the other hand, physical trade option requires physical delivery of electricity. Physical electricity trading has different options compared to financial trading. Trade options in Turkey are as shown in Figure 4.1 below (Yazıtış, 2018).

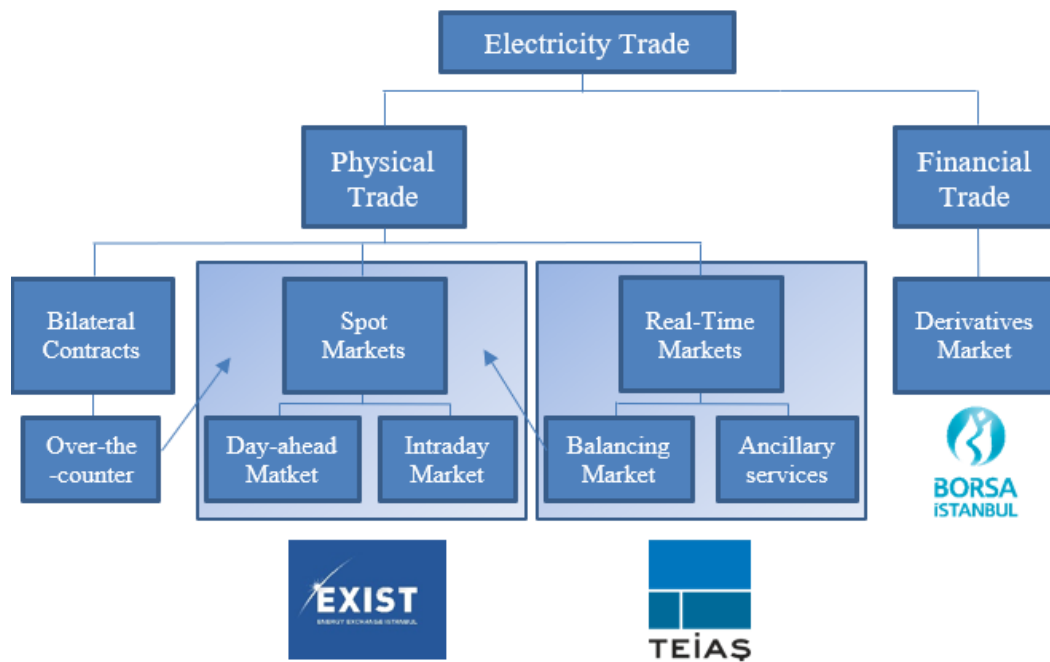


Figure 4.1 : Turkish electricity market options.

As can be seen from Figure 4.1, the market has 3 sub-markets with physical delivery obligation. Over-the-counter market is partly under EPIAŞ in terms of data entry and conciliation, and balancing market in terms of software support and conciliation.

Bilateral contracts are generally referred to trade agreements made for long terms. Bilateral contracts can be made between two market participants without any intermediaries or by brokers in between. Participants who bid in the over-the-counter markets in terms of buying and selling are matched under more flexible terms. In these matches, the parties do not know each other, and transactions are made through brokers. Brokers, who collect the needs of buyers and sellers, carry out the trade for a certain commission.

In Turkey, over-the-counter market is also fall within the scope of bilateral contracts (İlter and Narin, 2018). Agreements between the two parties are made independently of EPIAŞ. However, this situation resulted with some arise of conflicts in the past years. And as a result of these conflicts, electricity futures market was introduced in February by the Energy Market Regulatory Authority (EPIAŞ, 2020). Since the electricity future market is an electricity trading option with physical delivery obligations, it is expected to attract over-the-counter transactions to an organized market and create greater market depth, price transparency as well as more predictability.

Another electricity trading sub-market with physical electricity delivery is the spot markets. Spot markets consists of day-ahead market and intraday market. The day ahead market is a market, where buying and selling bids are made a day before. This market is mainly aimed at establishing a reference price in the electricity market, solving imbalances day ahead and offering trade opportunities to participants in addition to bilateral agreements. Transactions in day ahead market are performed daily on hourly basis, and volumes and prices applied for clearing of the market at daily basis are determined for each hour. In the day ahead market, every day, a supply and demand curve are created for each hour of the day.

The supply curve is obtained with a method called merit order where the supplier offers are ranked according to increasing marginal cost. The day ahead market price, in other words, the market clearing price, is the price at which demand and supply curves are intersect. Marginal cost is calculated by considering only the fuel cost. Thus, plants

with low marginal cost offer lower bids per unit volume. The price of the relevant hour is determined at the point where the demand is met, and all power plants sell at the determined price. Likewise, participants who submit a request offer also buy at the determined price. Consumers who make a purchase bid below the market price cannot make a purchase, while the suppliers, which makes a sale offer above the market price, cannot make a sale. At hours which renewable generation is high, a low price occurs since renewable sources such as wind and solar plants works with very little marginal cost.

The other spot market under EPIAŞ is the intraday market. In the intraday market, hourly transactions are executed every day. In the event of a new order match with an existing offer on the order book, the price of the existing offer will be the exchange price. Settlement prices applied over the intraday market are defined by taking all offers and transactions made within the context of the Intraday Market into account for each settlement period and matching.

In the intraday market, participants are given the opportunity of trading and balancing their portfolios in short term, almost real-time. This characteristic mainly contributes to the balancing and the sustainability of the electricity market and the intraday market act as a bridge between the day-ahead market and the balancing market. Under unexpected circumstances which leads to imbalance such as power fluctuations from renewable generation, participants are allowed to minimize or balance their positive/negative imbalances which they may experience during the day.

Until an hour before the physical delivery, orders can be given, updated, cancelled, or marked as inactive. Trading actions on intraday market is performed on hourly basis where a day starts at 12:00 am and finishes at 12:00 am the following day. The orders which are made for the following day can only be given after the opening time of the market which is 06:00 pm. System requirements will be monitored twice a day before the intraday market opens and trading take place. Different from the day-ahead market, which is a single session tender, instantaneous order interpretation and offer match is carried out in the intraday market. Also, for a particular period participants can place hourly or block orders.

The last market under the physical electricity trade is the real-time markets. Although a balanced production and consumption amounts is presented to the system operator

with the day-ahead market and the intraday market, deviations occur in real time. In such cases, National Load Dispatch Center (NLPC) tries to sustain system balance by the real-time market. The real-time market consists of ancillary services and balancing market. Ancillary services provide frequency and demand control which involves keeping three interconnected capacity quantities in the system as primary, secondary, and tertiary control. The balancing power market provides spare capacity to the system operator for real-time balancing which can be activated within 15 minutes at the most. In Figure 4.2 relation of balancing power market and ancillary services is shown.

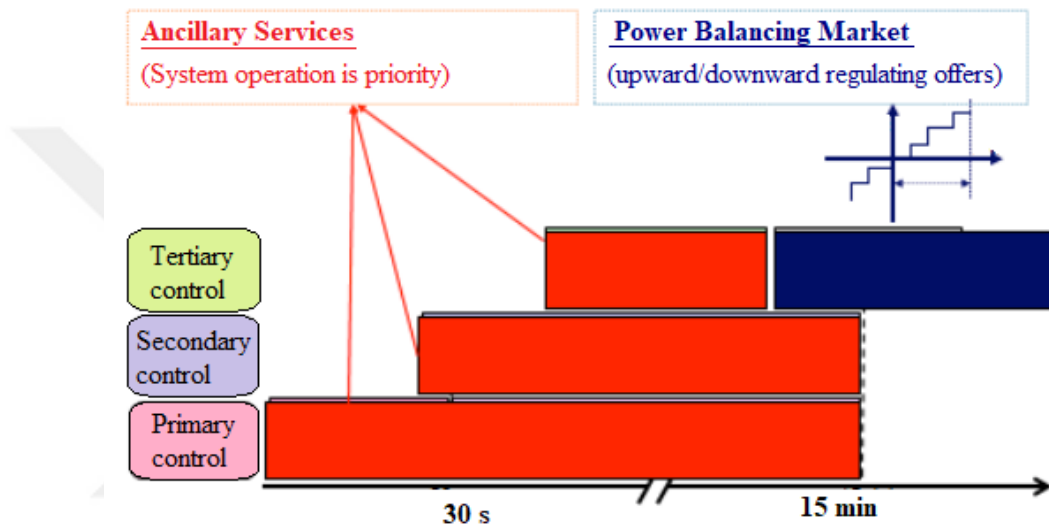


Figure 4.2 : Balancing power market and ancillary services relation.

Primary control starts within a few seconds following the frequency deviation and reaches its maximum value without exceeding 30 seconds. This value must be maintained for at least 15 minutes. Secondary control starts in 30 seconds and continues for 15 minutes. Tertiary control reserve is the part that is taken into service manually when needed after the secondary control reserve is activated and is selected in a way to enable the secondary reserve to be released against the danger of another frequency deviation. Tertiary frequency control is provided by the balancing units through upward and downward instructions given within the scope of balancing power market.

Balancing power market primarily mediates the creation of tertiary capacity and indirectly secondary capacity. Market participants make hourly offers containing price and quantity information in the direction of buying or selling. Upward direction is the situation where a balancing unit sells energy to the system by increasing its production

or decreasing its consumption in line with the instructions given by the system operator and downward direction is the situation that a balancing unit takes energy from the system by decreasing its production or increasing its consumption in line with the instructions given by the system operator. These instructions are given with two different tag values. The instruction with the label value 0 is given to eliminate the supply-demand imbalance and the instructions with label value 1 is given to eliminate the transmission constraints. Instructions with a label value of 2 used to be show the accepted bids in order to create secondary capacity but removed after 2018.

All market participants participating in the balancing power market are obliged to submit their available generation capacity and balancing units that can to take minimum of 10 MW upward or downward regulating offers within 15 minutes are obliged to participate in balancing power market. Balancing power market starts every day at 14:00 pm, after the end of day-ahead market. Then, balancing power market participants must submit the available capacity (EAK, Emre Amade Kapasite) values, the definite daily generation program (KGUP, Kesinleşmiş Günlük Üretim/Tüketim Programı) which contains the hourly generation values, and their upward/downward offers for the generation facilities registered in their name to the system operator until 16:00 pm. Upward and downward offers are arranged in price order for each hour by the system operator. The system operator shall inform the relevant market participants with the instructions regarding the bids that are found suitable for the purpose of eliminating the energy deficit or surplus that occur / foreseen in the system and to eliminate the system constraints.

The offers in the balancing power market can be submitted at 15 levels, separately for upward and downward. When submitting an offer, upward offer prices must be greater than or equal to the market clearing price for the same hour. Similarly, downward offer prices must be less than or equal to the market clearing price for the same hour. Starting from the lowest of the upward offer prices if the system direction shows the energy deficit and the highest of the downward bid prices if the system direction shows the energy surplus, bid price corresponding to the net order volume determined by considering all the bids given within the scope of the balancing power market is called the system marginal price. Market participants are obliged to cover the cost arises in case of not notifying the unfulfilled instructions within 4 hours and causing a different SMP to be determined with this action. With this obligation, it is aimed to manage the

function of instruction reconciliation and the process of SMP determination properly. Similar to balancing power market participants, day-ahead market and intraday market participants must avoid causing the energy imbalances. To prevent deviations between the day-ahead bids and the actual energy output, 3% deviation penalty is applied to the price where between MCP and SMP the higher one in the direction of purchase and the lower one in the direction of the sell. Market participants can join the intraday market to avoid this penalty and fulfill their offer. However, if the offer still cannot be fulfilled, the penalty is applied.

4.2 Installed Power and Production by Resources

Due to the climate change concerns transition to the clean energy brings a major structural change in the electricity systems generation profile around the world. Following the same trend, grid mix of Turkey consists of variety of sources including renewables. The total installed power of primary energy resources, which was 91.3 GW in 2019, reached to 96.7 GW as of February 2021. As can be seen from the distribution of the installed power on the basis of resources in the Figure 4.3, the largest share of the installed power belongs to natural gas power plants (TEİAŞ, *Santral Kurulu Güç Raporları (Power Plant Installed Capacity Reports)*, 2021).

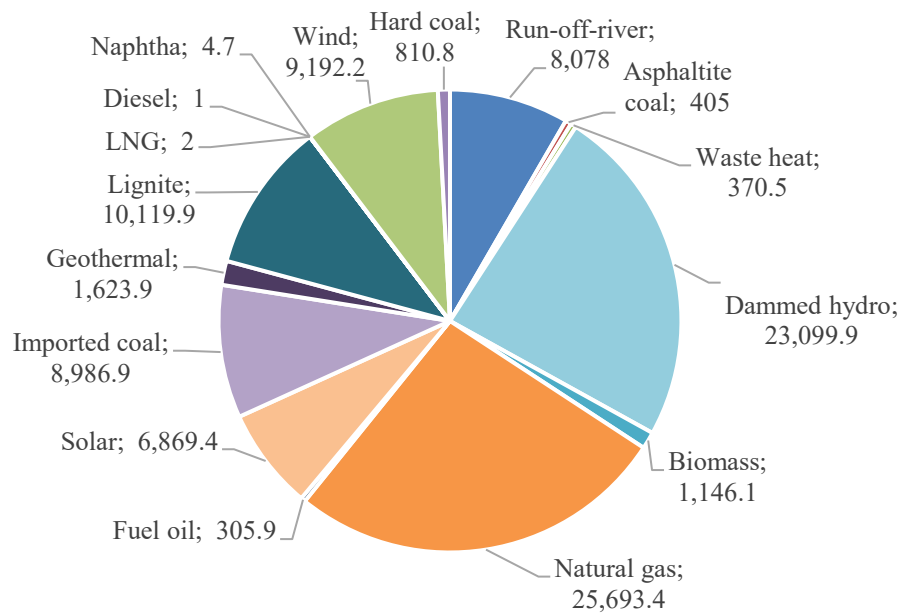


Figure 4.3 : Installed power by resources (MW).

Natural gas has a share of 27%, followed by dammed hydro power plants with 24% in the total installed capacity for electricity generation. With the incentives provided to renewable energy plants, an increase in the installed power share of these resources has been achieved. Share of wind power plants has raised to 9.5% from 8.3%, and solar generation to 7.1% from 6.6% compared to 2019. The distribution of the production in Turkey in 2020 by a variety of resources is shown in the Figure 4.4. Total production raised to 305 GW in 2020 from 303 GW in the 2019 (TEİAŞ, *Aylık Elektrik Üretim Tüketim Raporları (Monthly Electricity Generation Consumption Reports)*, 2020).

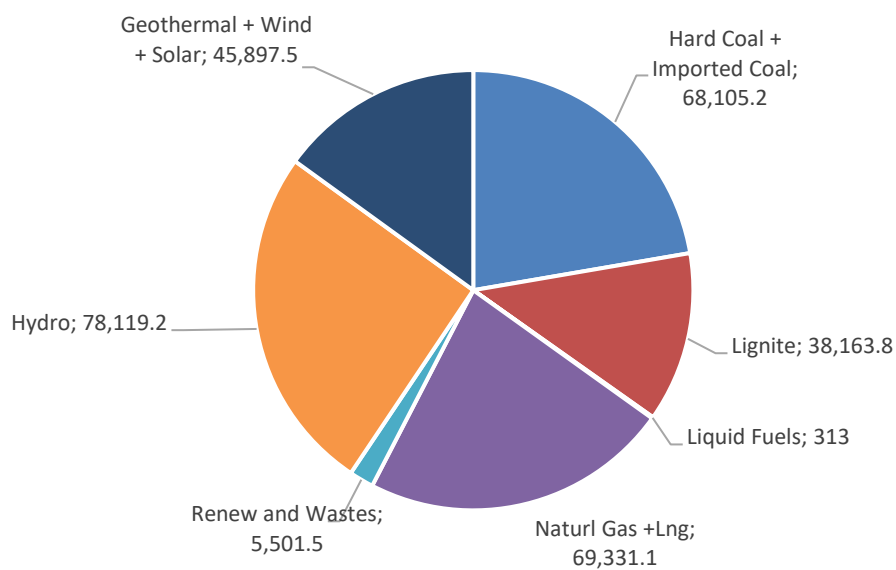


Figure 4.4 : Production by resources (GWh).

It can be seen from the figure above that the electricity generation still heavily depends on conventional fossil fuels. However, the distribution of production by resources has changed over the years. The share of coal power plants in production has increased over the years, especially in the last few years while the share of natural gas decreased, as can be seen from Figure 4.5.

At the end of 2019, coal-based production plants provided 37% of the total production. At this rate, incentives given to domestic coal have a great contribution. Although it is known that the emitted greenhouse gasses which coal plants are responsible for are higher than other sources. However, considering grid security, a grid mixture composed of high variety of sources is preferred by many countries over the world. But still there are even more incentives for renewable generation resources than there are for conventional resources.

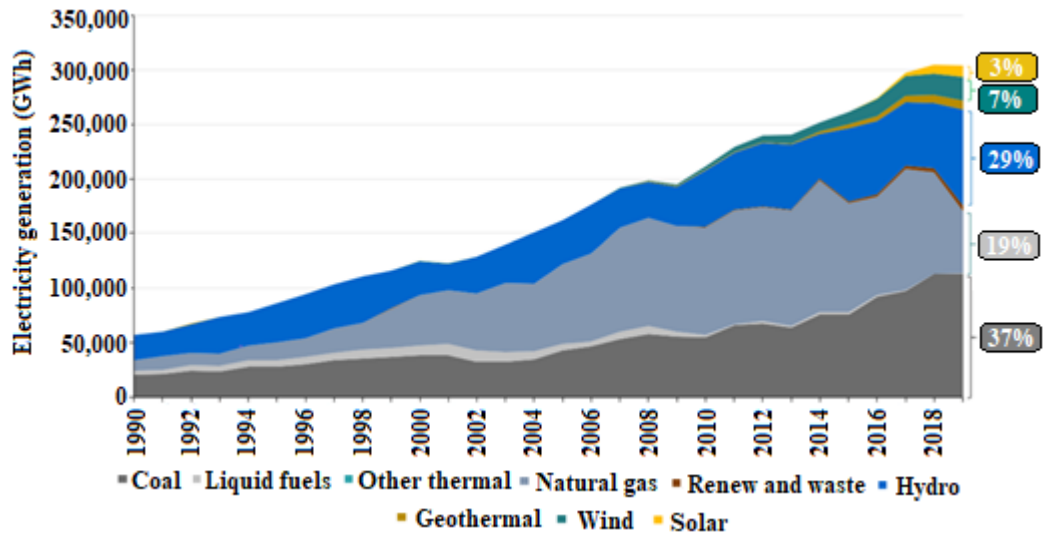


Figure 4.5 : Annual development of production by resources (GWh).

As of 2017, renewable energy plants, especially solar contribution to production increased greatly which can be seen in Figure 3.5 (TEİAŞ, *Elektrik Üretim İletim İstatistikleri (Electricity Generation Transmission Statistics)*, 2019). Similarly, YEKDEM incentives given to domestic and renewable energy resources has a great role in this increment. Although YEKDEM first started in 2005, it took a few years to reach a considerable installed capacity considering installation periods and legal procedures. After that, increasing currency rate over the past years which, as a result, increased the profit of electricity generation in each YEKDEM plant and continuous decreasing in technology, renewable generation installation keeps on increasing rapidly. The rise on production of hydroelectric power plants with dam also draws attention. Extraordinary rainfalls have been effective in the formation of this situation, and 2019 is considered as an exceptional year. On the other hand, increases in other renewable energy sources can be seen in their share in production.

4.3 Market Statistics

With the vision of contributing to Turkey being regional energy trade center, EXIST works on operating energy markets in an efficient, transparent, and reliable manner. Thus, through Transparency Platform, EXIST publish hourly data such as generation, market prices, instruction volumes and other power related data. It also stores the historic data open to public access. With this source being in use, to better present the market conditions, data from EXIST is examined.

When we look into the average electricity prices of the day ahead, the market clearing price was 260 TL/MWh (41.11 EUR/MWh) in 2019 and it increased to 278.72 TL/MWh (35.19 EUR/MWh) in 2020. While the highest MCP was 500 TL/MWh (75.83 EUR /MWh) in 2019, it becomes 982 TL/MWh (110.64 EUR /MWh) in 2020. In both years, the lowest MCP was 0 TL/MWh. Figure 4.6 shows a boxplot with the diurnal day-ahead market prices in Turkey.

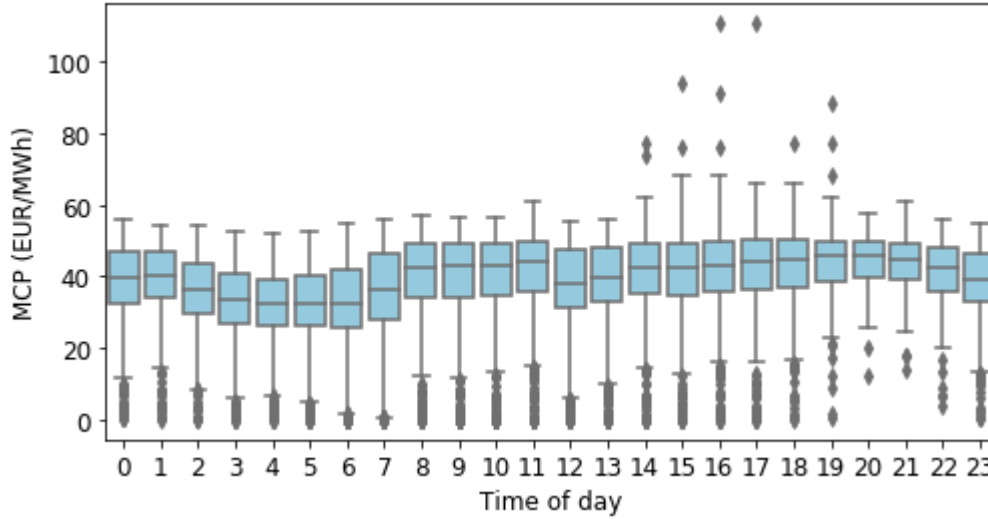


Figure 4.6 : Diurnal day-ahead market price in 2020 (EXIST, 2021).

Daily profile also vary between weekdays and weekends as can be seen in the Figure 4.7 below. Especially during daytime, Sunday has lower average values since the production decrease.

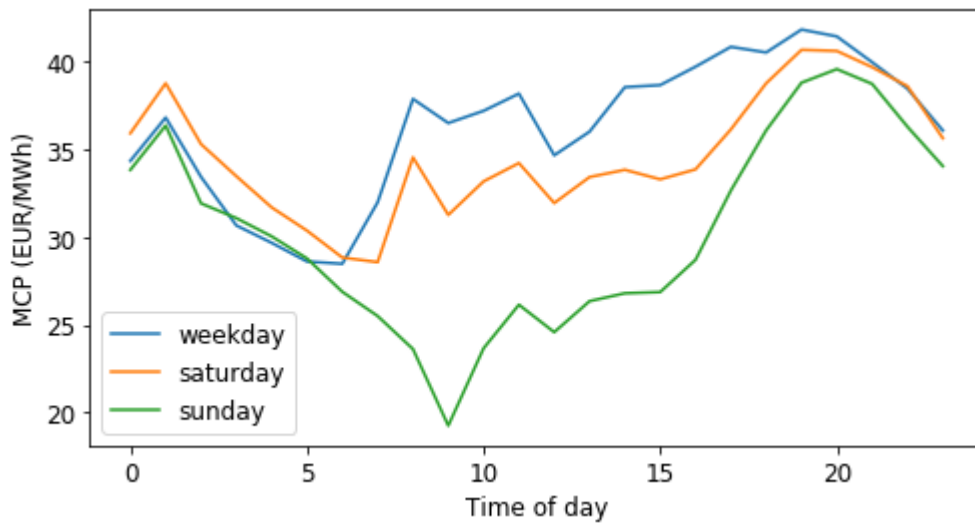


Figure 4.7 : Diurnal mean day-ahead market prices of weekday, Saturday and Sunday of 2020.

In the years of 2020, average market clearing price during weekdays was 287.09 TL/MWh (41.33 EUR/MWh), Saturday average was 274.10 TL/MWh (39.52 EUR/MWh) which is closer to weekday since some manufacturers also works on Saturdays, and Sunday average was 241.16 TL/MWh (34.59 EUR/MWh). In the balancing power market, the average system marginal price, which was 253.46 TL/MWh in 2019, was 272.29 TL/MWh in 2020. While the highest SMP was 487.15 TL/MWh in 2019, it reached the maximum level of 2000 TL/MWh in 2020. In both years, the lowest SMP was the minimum level of 0 TL/MWh. The total transaction volume of the day ahead market in 2020 increased by 27 percent compared to 2019 and reached 51,863,881,746 TL (6,438,958,837 EUR), while the total trading volume of the intraday market increased by 38 percent compared to 2019 and reached 1,915,892,872 TL (237.860.240 EUR). Matching trading volume in the day ahead market was 181,364,682 MWh in 2020, while the matched volume in the intraday market was 6,618,653 MWh.

According to the balancing power market data for 2020, out of 8784 hours of the year, 3528 hours of energy surplus and 4819 hours of energy deficit were experienced. One-year (8784-hour) energy surplus, deficit, and balance, in other words the system direction, according to the three-time tariff results is as shown in Figure 4.8. Three-time tariff consists of three-time periods; day, puant and night. Day is the period from 06:00 to 17:00, puant is from 17:00 to 22:00 and, night is from 22:00 to 06:00.

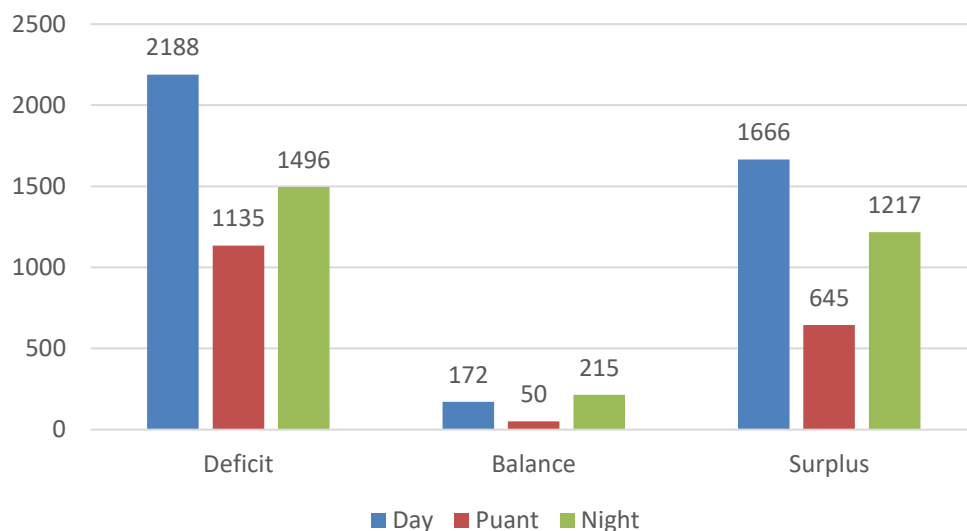


Figure 4.8 : System direction comparison in the basis of three-time tariff (EXIST, 2021).

In balancing market, procurement and settlement is operated by the transmission system operator. Everyday market participants submit their production and consumptions base of their forecasts and production plans. However, it cannot always be fulfilled. Total system imbalance resulting from prediction errors, system maintenance and failure is calculated by the transmission system operator and then, the system imbalance is compensated by activating reserve capacity provided from balancing service providers.

The imbalances are settled with balancing service providers by system operator applying an imbalance price which is called system marginal price as mentioned previously in this section. Unlike day-ahead market and intraday market which are based on forecasts, in balancing market real-time information is used which becomes available after the previous markets closed. The reservation and activation of reserve capacity is therefore referred as the procurement side of the balancing market, and reserve capacity providers are paid for their capacity and activation (Brijs et al., 2015).

Imbalance occurs at energy surplus or deficit. In case of increase in supply or decrease in demand, positive imbalance occurs, system frequency increases and to reduce it the system operator gives a downward instruction order. The downward reserves can be consumers who increase their electricity consumption or suppliers who lower their output amount. Conversely, in case of decrease in generation or increase in demand, a negative imbalance occurs, system frequency decreases and the system operator give an upward instruction order to increase it back to 50 Hz. The upward reserves can be suppliers who increase their electricity generation or consumers who lower their consumption amount.

To further examine the balancing market, boxplots of upward, downward instruction volumes and net imbalance volumes over several years are presented in Figure 4.9 As the figure demonstrates, the upward and downward instruction volumes are higher during the daytime. Average upward instruction volume decreased over the years. Mean upward instruction volume was 950 MWh in 2018 and decreased to 607 MWh in 2020. Meanwhile yearly mean downward instruction volume increased from 262 MWh in 2018 to 364.6 MWh in 2020 although it was not a constant increase. As can be seen from the figures, 2019 has much higher value with 706 MWh compared to other two years.

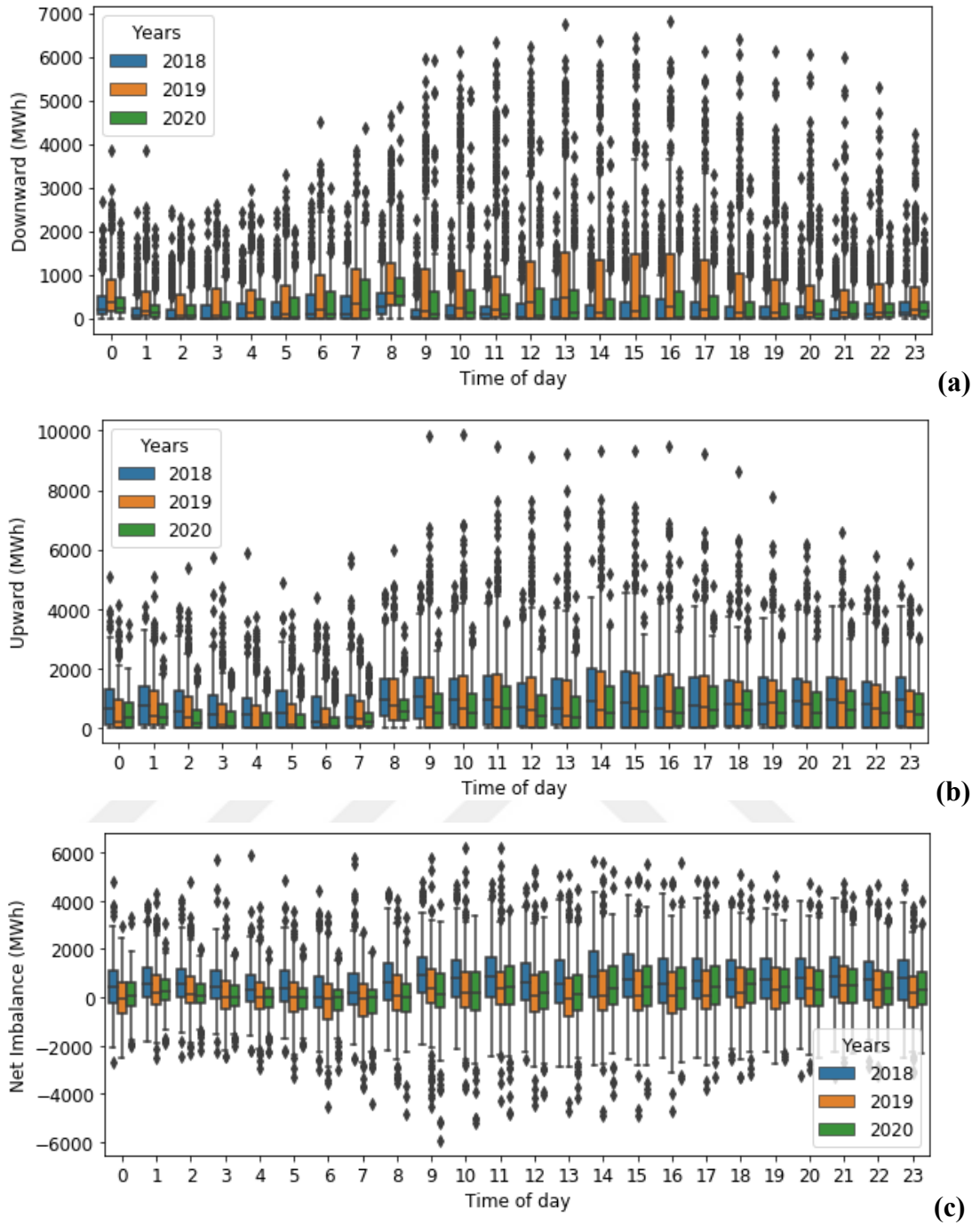


Figure 4.9 : Imbalance volumes: (a) upward, (b) downward and (c) net.

Overall, negative imbalance of the system decreased while net imbalance decreased compared to 2018. In all years upward instruction volume is higher which also states that the system tends to have energy deficit than surplus.

The relation of net imbalance volume and balancing market price was mentioned in the Literature Review section before. It is a known fact that net imbalance volume has strong relation with the price of balancing market. The case of Turkish market is no exception as can be seen in the Figure 4.10.

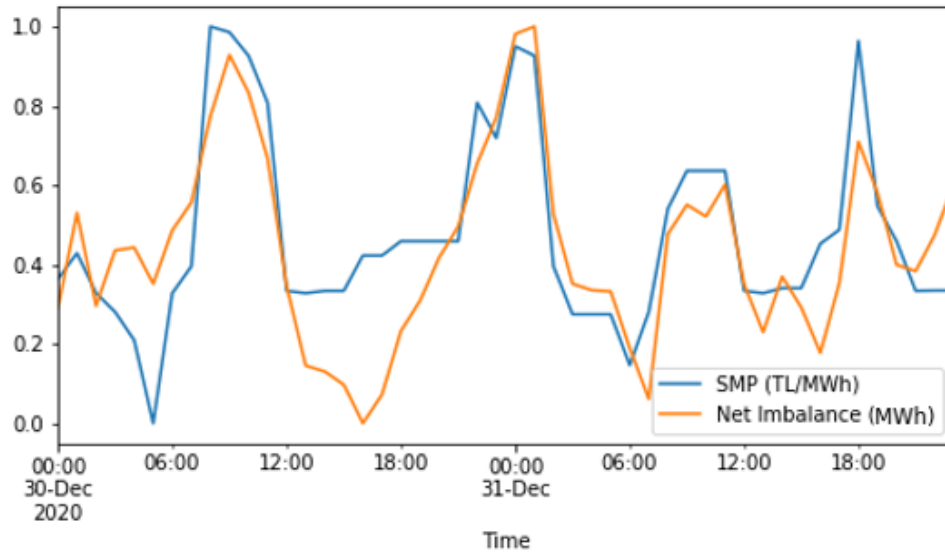


Figure 4.10 : SMP - Net imbalance volume relation.

In the figure 48 hours values of system marginal price and net imbalance volume values were given. The values were normalized between the range of 0.0 to 1.0 to better visualize directional behavior where rises and falls mostly occurs at the same time. To numerically describe the relation, their correlation was calculated, and the result for last 48 hours of 2020 was 0.773. Again, the correlation of SMP and net imbalance volume in the last week of 2020 was 0.769 and the correlation of the whole year was appeared to be 0.745.

5. NET IMBALANCE VOLUME DATA GENERATION APPLICATION

5.1 Current Situation in Turkey

Market participants place their bids in the day-ahead market based on their production plans and forecasts. However, those forecasted values can be change by the physical delivery time. For grid security purposes, participants that cause imbalance is penalized. Intraday market act as a bridge between day-ahead and power balancing market. Market participants can rearrange their bids by participating in the intraday market to avoid the imbalance penalty. But depending on the price that will occur in balancing market, they could choose not to participate intraday market and accept the penalty.

Currently in Turkey, rather simple approach is being used by market participants for their daily action, knowing the high correlation between net imbalance volume and SMP. An intuitive selection base on expert opinion is made by looking at the net imbalance volume values of the past week, and then the price is obtained by looking at the price occurred at the corresponding net imbalance level. For that reason, a more scientific approach was presented in this study.

5.2 Data

Market price in the day-ahead market determined by generation and consumption bids. That is why not meeting the promised actions and causing imbalance is penalized by the system operator. A chance to mitigate the penalty is possible by participating in the intraday market. In the event that the forecast made 3 hours prior to the delivery time compared to the one made a day before, the market participant can make a transaction on intraday market where bids for two hours later can be made after notifying the system operator. Although intraday is a market which is enabling taking actions close to physical delivery, market participants may choose not to participate in the intraday market and accept the penalty depending on the system marginal price occurring in the balancing market. To prevent any diversity among the day-ahead bids

and the actual energy output, 3% deviation penalty is applied to the price where between MCP and SMP the higher one in the direction of purchase and the lower one in the direction of the sell.

Under the expectation that the SMP will be higher than the MCP in real time, those who have a deficit in the purchase direction will be able to purchase electricity from the intraday market up to $SMP * 1.03$ since the price they will be exposed to in real time for the electricity they cannot buy will be $SMP * 1.03$. Those who have an excess on the sales direction will be willing to sell at any price above $MCP * 0.97$, because their excess production will be taken to $MCP * 0.97$ by EPIAŞ.

Similarly, under the expectation that the SMP will be lower than the MCP in real time, those who have a deficit in the purchase direction will be able to purchase electricity from the intraday market up to $MCP * 1.03$ since the price they will be exposed to in real time for the electricity they cannot buy will be $MCP * 1.03$. Those who have an excess on the sales direction will be willing to sell at any price above $SMF * 0.97$, because in case of imbalance, their excess production will be taken to $SMF * 0.97$ by EPIAŞ. That is why, to decide the action, a prediction on system marginal price is needed. However, the latest system marginal price announcement is the value of 5 hours previous, and the closest intraday market action is for 2 hours later. On the other hand, instruction volume announcement is made after the end of each hour. For example, if we the hour is currently 6 pm, the closest contract can be made for 8 pm and actual data announcement belongs to 5 pm.

Therefore, an estimate of 3 hours ahead is required. Considering the high instruction volume-price relation in the market, predicting the instruction volume which has a closer forecast date is more beneficial and would give more accurate results. That is why in this paper generation of the instruction volume data is proposed. For this purpose, hourly up and down regulation instruction data was obtained from EXIST Transparency Platform. It first used for market examination as presented in the section 4.3 Market Statistics, and for the model application both up and down regulation volume data with codes 0, 1 and 2 were obtained separately. Then by subtraction of downward regulation instruction sum from upward regulation instruction sum, net instruction volume was calculated. In Figure 5.1 below the autocorrelation and partial autocorrelation graphs of net instruction volume is given.

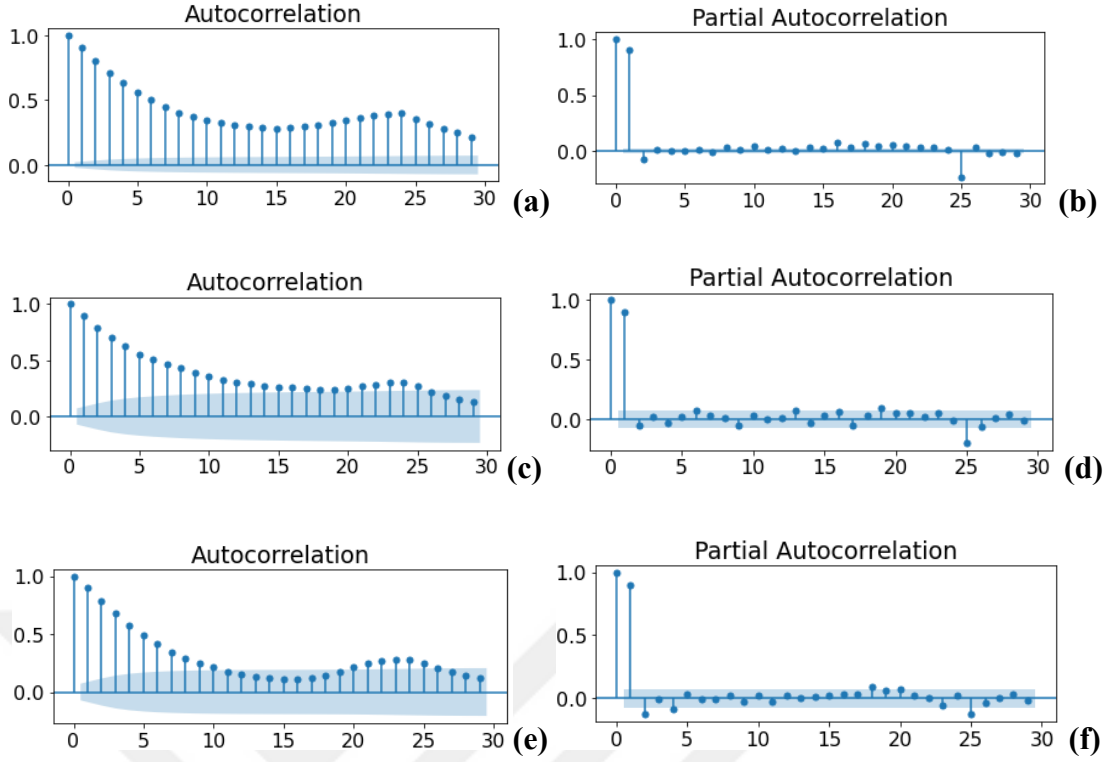


Figure 5.1 : Autocorrelation - partial autocorrelation graph pairs belonging to (a) - (b) the year 2020, (c) - (d) December 2020 and (e) - (f) January 2021.

The autocorrelation indicates how the net instruction volume is correlated to itself. In other words, it measures the persistence within the whole series of time or space. Smooth time series are reflected in the autocorrelation function as damping out steadily with lag. While large values occur at low frequencies and small values occur at high frequencies. Thus, smooth series are characterized as series where most of their power is at low frequencies.

The partial autocorrelation function is the partial correlation of a time series with its own lagged values, removing the indirect impact at all shorter lags. In the model December 2020 – January 2021 data were used to simulate a month-long action and to compute the accuracy of the results. Starting from December 1, 2020, a month-long (744 hours) data were used as the input to form the transition matrix. 1-hour, 2-hours and 3-hours forward data were generated at each step and compared with the actual volume.

5.3 ARIMA Application

In this study, ARIMA model used to compare its results with the results of Markov chain approach.

5.3.1 Synthetic generation of net imbalance volume data

In the ARIMA model, 744 hours data between 01-12-2020 00:00:00 and 31-12-2020 23:00:00 were used as the input in the first step and following 3 hours were forecasted. At each step, the window for past values which is the input for the model and the output windows were shifted by 1 hour in order to generate the new values. At each shift, a new ARIMA model was used according to the new input dataset. The ARIMA models were selected based on the best Akaike information criterion (AIC) value and this window shift was done for a month to simulate a month-long action of a market participant. In the 93% of the times d selected as 1 and, on the rest, it selected as 0. Other parameters, p and q , took the value 5 at most. From the continuous shift, 1-hour, 2-hours and 3-hours forward net imbalance volume values were obtained based on the forecast results of each model. ARIMA results with different model parameters were used to synthesize generation of 1, 2 and 3 hours forward net imbalance volume values. In Figure 5.2 measured net imbalance volume data were compared with synthetic data which was generated by using the ARIMA models.

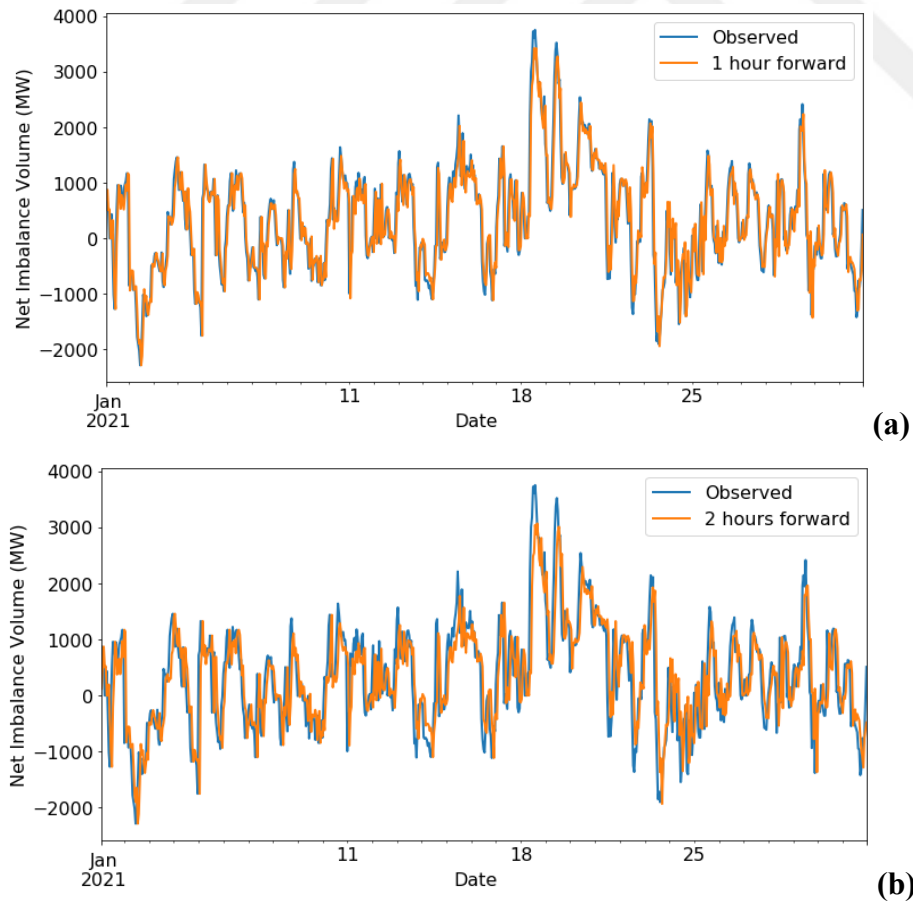


Figure 5.2 : Observed and predicted net imbalance volume data with ARIMA for (a) 1 hour forward, (b) 2 hours forward and (c) 3 hours forward, on first month of 2021.

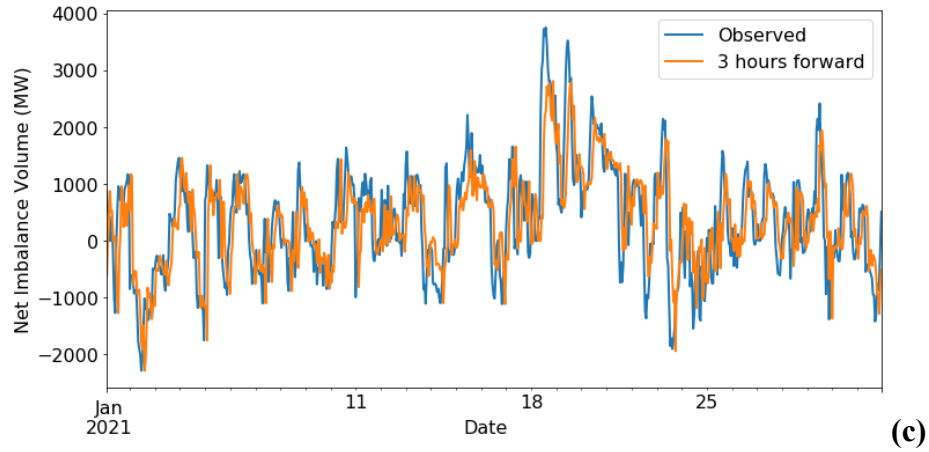


Figure 5.2 (continued): Observed and predicted net imbalance volume data with ARIMA for (a) 1 hour forward, (b) 2 hours forward and (c) 3 hours forward, on first month of 2021.

The test value was not presented to the model as input before the estimation time. First, the data was predicted for 3 hours ahead and then the observed value of the latest hour was used as input for the new data prediction step. In order to compare the same timeframe, first two hours of 1 hour ahead data and first hour of 2 hours ahead data were excluded. So, the three generated data set would be for the same 742 h which starts from 01-01-2021 02:00:00 and ends at 31-01-2021 23:00:00.

5.3.2 Predicted data distribution

A visual representation of data distribution can be displayed by a histogram. Thus, while comparing the generated data with observed ones their histograms were drawn. 1, 2 and 3 hours forward generated net imbalance volume data were given in the Figure 5.3 below together with observed data

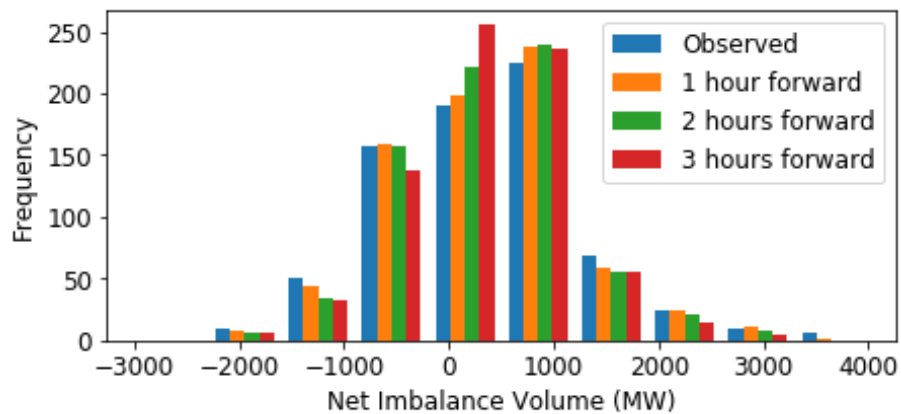


Figure 5.3 : Probability distribution of observed and generated net imbalance volume with ARIMA (MW).

A good match seen between the distribution of data obtained by using the ARIMA method and observed ones. From a closer look to separate relations of observed and predicted values for different times ahead were given in Figure 5.4.

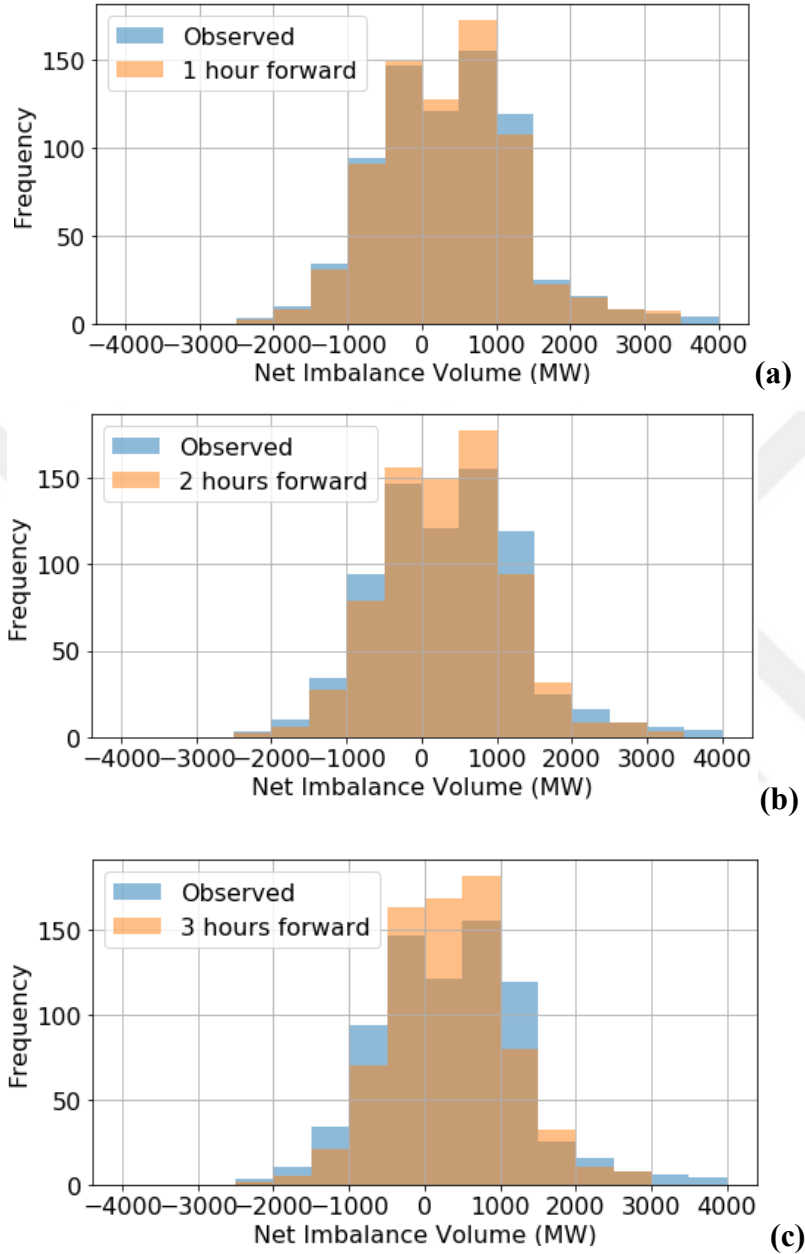


Figure 5.4 : Histogram of observed values with (a) 1 hour (b) 2 hours and (c) 3 hours forward data predicted with ARIMA.

5.3.3 Autocorrelation and statistical parameters

Autocorrelation is a heavily used measure in time series analysis. The degree of dependence of net imbalance volume value at a given hour on its values of the previous hours can be quantified by the autocorrelation coefficient. The comparison of observed and predicted data autocorrelation functions were given in the in Figure 5.5.

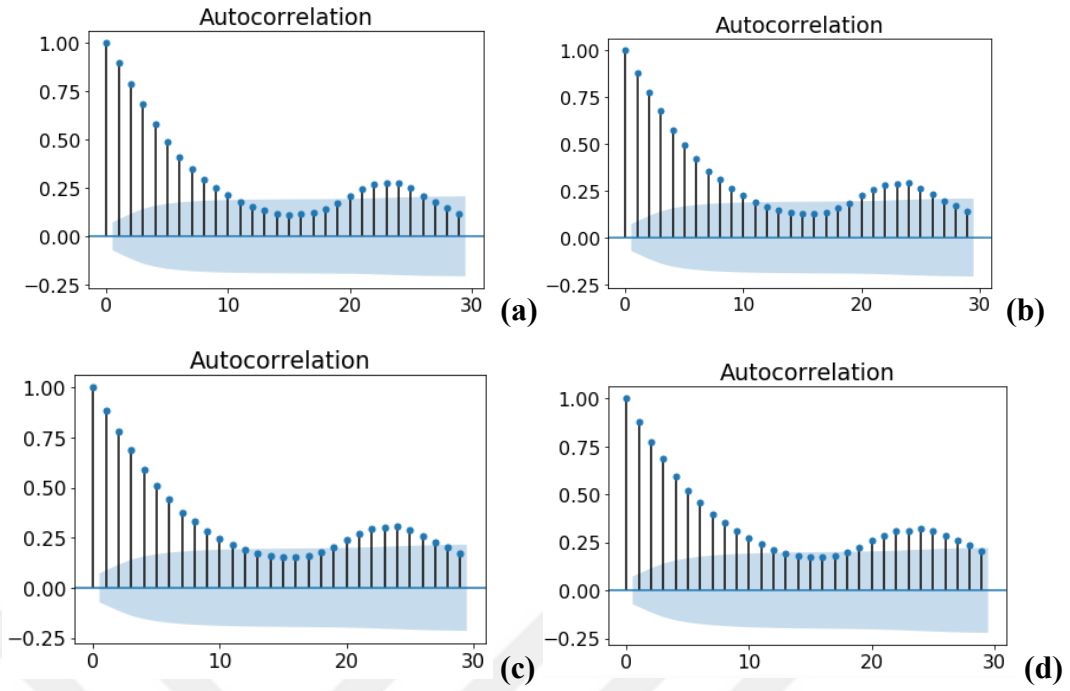


Figure 5.5 : Autocorrelation function graphs: (a) Observed (January 2021), (b) 1 hour forward (January 2021), (c) 2 hours forward (January 2021), (d) 3 hours forward (January 2021).

Statistical metrics are quantitative measurements that used for data validation. In this section coefficient of determination (R^2), mean bias error (MBE), normalized (by the range of data) mean bias error (NMBE), root-mean-square error (RMSE), normalized (by the range of data) root-mean-square error (NRMSE), mean and standard deviation (std) were the metrics that used to compare the results of synthetic data to observed data. Overall statistical parameters that used to evaluate the generated data with ARIMA was given in Table 5.1.

Table 5.1 : Statistical parameters evaluated for ARIMA results for January 2021.

Forward	R^2	MBE	NMBE	RMSE	NRMSE	mean	std
Observed	-	-	-	-	-	341.956	950.478
1 hour	0.806	4.651	0.001	418.262	0.069	337.304	893.402
2 hours	0.599	10.358	0.002	601.446	0.1	331.598	828.845
3 hours	0.429	15.115	0.003	717.839	0.119	326.841	778.493

As seen in the hourly mean price profiles, daily profile also varies within a week and predicted data result difference between weekdays, Saturdays and Sundays were given in Table 5.2 below.

Table 5.2 : Statistical parameters evaluated for ARIMA for January 2021 on day of week basis.

	Day of week	R ²	MBE	NMBE	RMSE	NRMSE	mean	std
Obs.	weekday	-	-	-	-	-	542.07	917.714
	saturday	-	-	-	-	-	-256.146	942.365
	sunday	-	-	-	-	-	102.911	777.409
1 hour	weekday	0.787	20.005	0.004	423.397	0.077	522.065	860.169
	saturday	0.814	-71.205	-0.016	405.260	0.092	-184.940	923.919
	sunday	0.720	16.276	0.005	409.356	0.128	86.635	720.462
2 hours	weekday	0.564	43.321	0.008	605.205	0.110	498.749	796.051
	saturday	0.592	-152.737	-0.035	599.477	0.135	-103.409	897.458
	sunday	0.424	35.555	0.011	587.475	0.184	67.356	652.175
3 hours	weekday	0.377	60.392	0.011	723.516	0.132	481.678	743.755
	saturday	0.383	-208.370	-0.047	737.292	0.167	-47.776	865.763
	sunday	0.245	49.191	0.015	672.872	0.210	53.720	614.408

R square is a good metric to compare the results with other studies since it is a scale-free score which means that it is regardless of the values being small or large. To better visualize results calculated depending on the day of week, results from Table 5.2 was given in the Figure 5.6 below to better show their comparison.

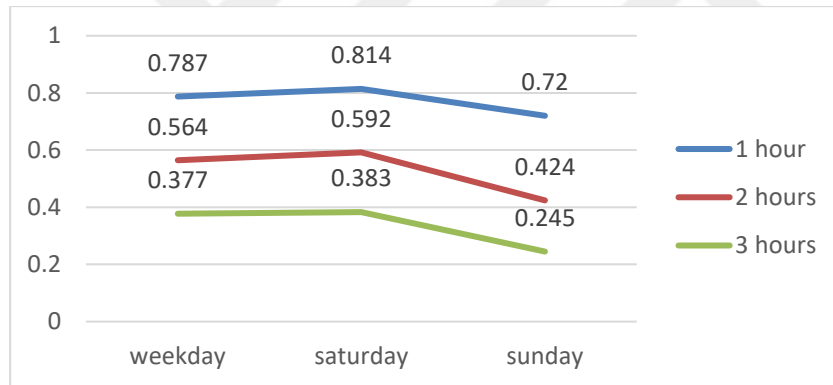


Figure 5.6 : R square in ARIMA.

Finally, to show the difference between the observed data and three predicted data, distribution of residuals for all three generated datasets was given in Figure 5.7.

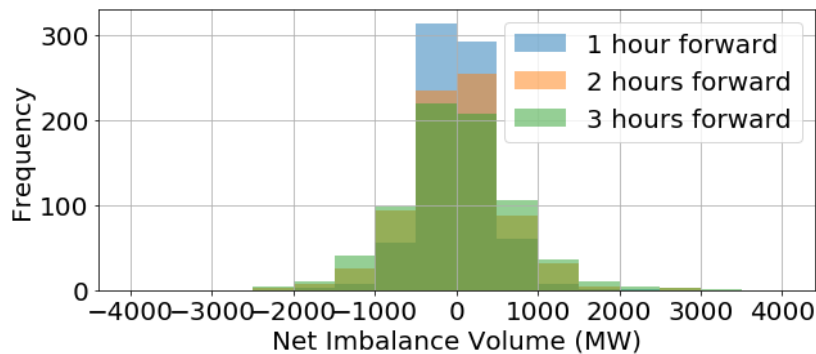


Figure 5.7 : Residual histogram.

5.4 Markov Chain Application

5.4.1 Formation of transition matrix

The net instruction volume data set was used to obtain the transition probability matrix. In order to form the first-order Markov transition matrix, dataset was divided into several intervals. In the calculations Python programming language was used. The range of volume was set between -8000 MW and 8000 MW to include all possible instruction levels of the past values. Then, volume data was split into 33 states, with an upper and lower limit difference of 500 MW. The data was binned into the corresponding states. Bin placement was done between ± 250 MW range where 600 MW net imbalance volume value would fall into the 500 MW bin.

First, a 33×33 empty matrix was created. The values in the dataset placed in the corresponding bin based on defined rules. By looking at the state transition, each transition was recorded with increasing its position in the matrix by one. Then by dividing each element in each row to the sum of that row, transition probabilities p_{ij} from a state at time t to another state at time $t + 1$, of each state were obtained. Thuswise, data was used to create the transition matrix which shows the probability of moving from one state of net instruction volume to another given the current net instruction volume level. Some elements of the first-order transition matrix were shown in Figure 5.8 below.

0	...	0	0	0	0	0	0	0	0	0	...	0
...	...	...	...	...	...	...	...	...	...	...	...	...
0	...	0.14	0.29	0.14	0.14	0.14	0	0	0	0	...	0
0	...	0.14	0.51	0.27	0.08	0	0	0	0	0	...	0
0	...	0	0.16	0.47	0.31	0.06	0	0	0	0	...	0
0	...	0.01	0.03	0.17	0.49	0.24	0.06	0.01	0	0	...	0
0	...	0	0	0.01	0.22	0.57	0.16	0.04	0	0	...	0
0	...	0	0	0	0.04	0.25	0.49	0.18	0.03	0	...	0
0	...	0	0	0	0	0.06	0.27	0.51	0.14	0.02	...	0
0	...	0	0	0	0	0	0.08	0.21	0.56	0.13	...	0
0	...	0	0	0	0	0	0.07	0.27	0.33	0.20	...	0
...	...	...	...	...	...	...	...	...	...	...	...	...
0	...	0	0	0	0	0	0	0	0	0	...	0

Figure 5.8 : Markov chain transition matrix.

The example matrix shown above was formed by using the 744 hours data between 01-12-2020 00:00:00 and 31-12-2020 23:00:00. Since 33 states were selected

considering maximum and minimum values of the past years and no such high and low values occurred at defined period of time, most of the transition probabilities aside from diagonal part in the middle of the matrix were zero. To better visualize the transition matrix, graphical representation of the matrix was given in Figure 5.9.

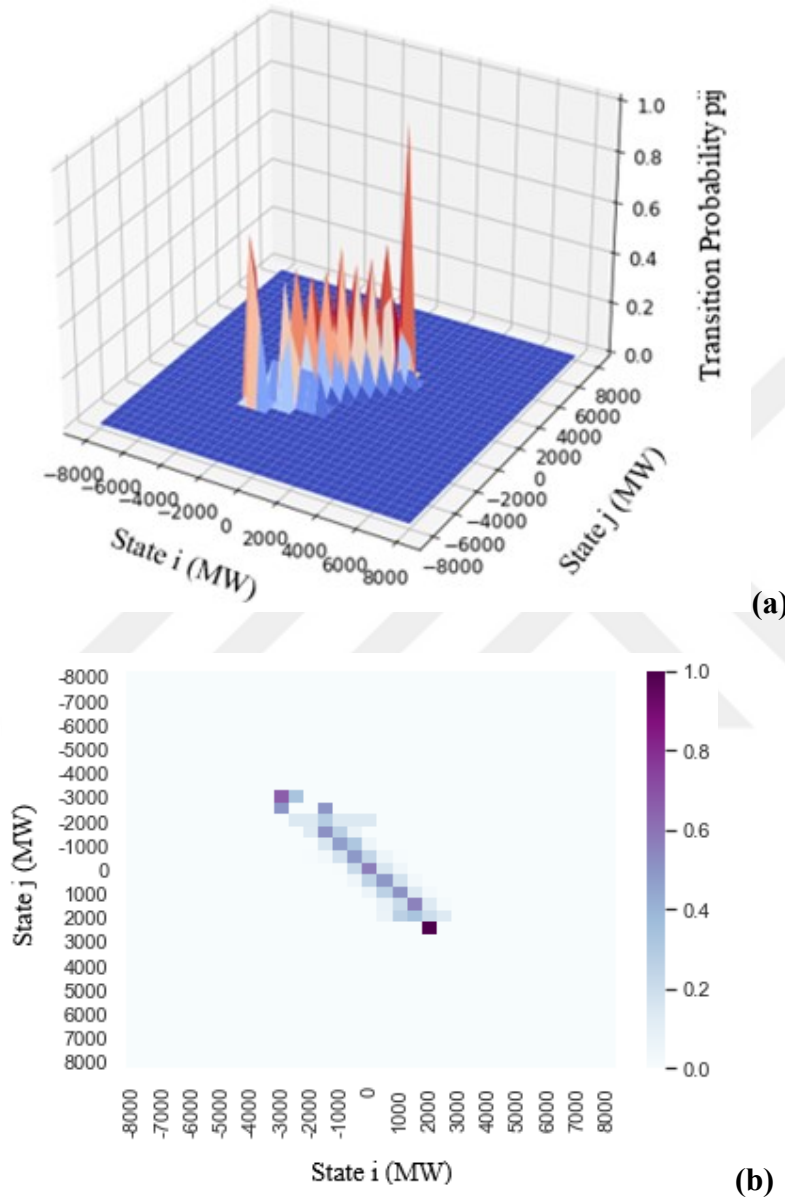


Figure 5.9 : Graphical presentation of transition matrix elements of the first order Markov chain: (a) 3D plot and (b) heat map.

As can be seen in the figure, probabilities with greater values come across with the diagonal elements, which means the probabilities of net imbalance volume were more likely to remain in the initial state. Moreover, positions of non-zero transition probabilities are gathered around the diagonal part, which makes transitions from an initial state to a state which is far away from the initial state is much less possible.

5.4.2 Synthetic generation of net imbalance volume data

Transition matrix shows the transition probabilities, p_{ij} , of net imbalance volume in state i at hour t to state j at hour $t + 1$ given n net imbalance volume states. The basis of future likelihood of synthetic net imbalance volume generations was provided by this matrix. As applied in many other studies, an initial state could be adopted randomly to generate next states. But in this study the initial state was chosen as the latest announced net imbalance volume state. After transition matrix was formed and the starting state was chosen as the latest occurrence of net imbalance volume state, 1-hour, 2-hours, and 3-hours forward net imbalance volume states were generated.

For this, Python `numpy.random.choice` function was used which generates a random sample from a given 1 dimensional array or an integer based on the probabilities associated with each entry array or value. By given the array of all possible state transmission probabilities from the current state to the function, next states were generated. To avoid synthetic data which moves only in increments of 500 MW, a random number was generated by using Python `numpy.random.uniform` function which draw samples from a uniform distribution by given the lower and upper boundaries of the output interval. The number which was generated based on the value of previous hour to provide some continuity. For this purpose, a constant value was assigned. In this method, the upper and lower boundaries were selected according to the following rules:

- a. If the current state is smaller than the next state, the value will be drawn from a uniform distribution of -constant to 0.
- b. If the current state and next state are the same, the number will be drawn from a uniform distribution within $\pm$ half of the constant value.
- c. And, if the current state is greater than the next state, the value of the number will be drawn from a uniform distribution of 0 to constant.

After the number was drawn, it was added to the next state to generate the next value which will be somewhere between the current and the next states. In this method, the constant value was assigned as 249 to keep the next value within the defined state boundaries and prevent the generated next state from another state change.

Since the generation of the next values are random and can be change at each run, the generation process was repeated for 100 times. The example of net imbalance volume

data generation for 100 iterations for 6 hours starting from 01-01-2021 00:00:00 until 01-01-2021 05:00:00 was shown in Figure 5.10 below.

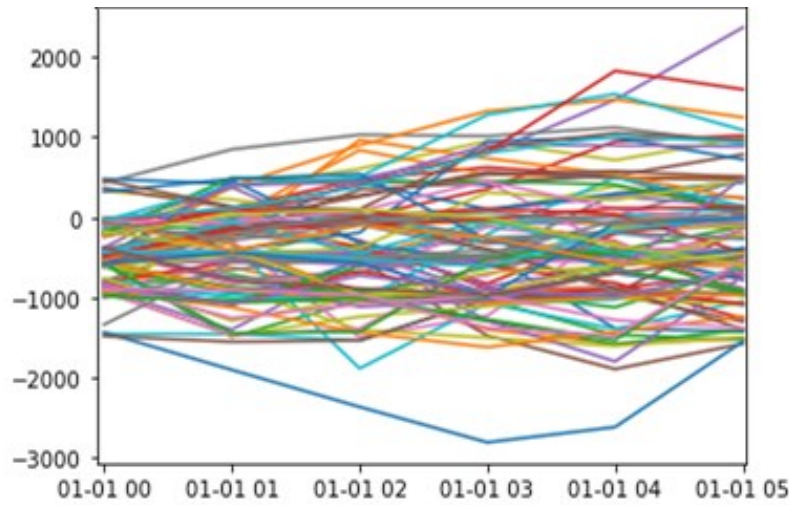


Figure 5.10 : Example plot of 100 iterations for 6 hour net imbalance volume generation with Markov Chain.

The transition matrix for the example was formed by using the 744 hours data between 01-12-2020 00:00:00 and 31-12-2020 23:00:00, and starting value was -513.12 MW. From 100 iterations, a distribution was obtained for each hour and the mean of this distribution was assigned as the value of that hour. Considering the last input data for the transition matrix belongs to 31-12-2020 23:00:00, 1 hour forward generation would be 01-01-2021 00:00:00, 2 hours forward would be 01-01-2021 01:00:00 and 3 hours forward would be 01-01-2021 02:00:00. The histogram of the distribution of time 01-01-2021 02:00:00 was given in Figure 5.11.

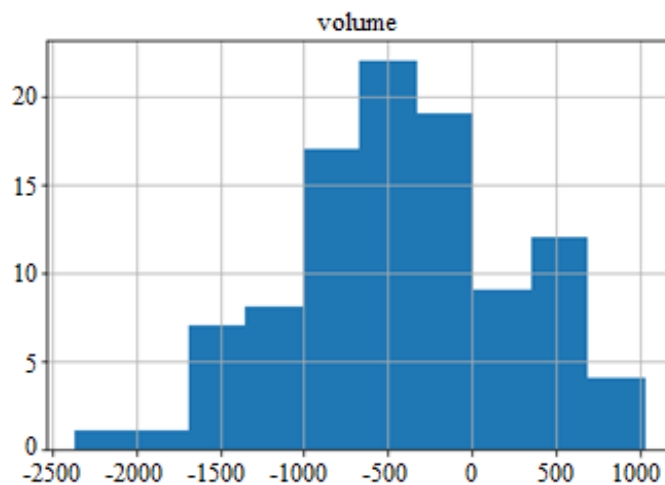


Figure 5.11 : Distribution of generated net imbalance volume values for 01-01-2021 02:00:00.

Considering the initial net imbalance value of -513.12 MW, values around -500 state has higher frequency out of the 100 values. As stated in the previous section, remaining in the current state has higher occurrence while jump to far away states have lower occurrence.

Figure 5.10 and Figure 5.11 were only the first step of simulating hourly net imbalance volume data generation action of a market participant which carried on for a month in this study. At each step, the windows for past values which is the input to form transition matrix were shifted by 1 hour.

Similarly, the output generation was also shifted in order to generate the new values. In this case, with 1 hour of shift the last input data for the transition matrix would be the real value of 01-01-2021 00:00:00. This time 1 hour forward generation would be 01-01-2021 01:00:00, 2 hours forward would be 01-01-2021 02:00:00 and 3 hours forward would be 01-01-2021 03:00:00.

At each shift, a new transition matrix was formed, and this window shift was done for a month to simulate a month-long action of a market participant to later use in forecasting the price and finally decided whether to participate in the intraday market or accepting the penalty. From the continuous shift, 744 transition matrices were formed, and 1-hour, 2-hours and 3-hours forward net imbalance volume values were obtained from each transition matrix following the latest occurrence. In order to compare the same timeframe, first two hours of 1 hour ahead data and first hour of 2 hours ahead data were excluded. So, the three generated data set would be for the same 742 h

A model with first-order Markov chain is defined and used to synthesize generation of 1, 2 and 3 hours forward net imbalance volume values. Although the method can be used for long term data generation while preserving the statistical parameters of the time series that used as input to create the transition matrix, in this method it is used only for a few hours of data generation at each step.

Considering observed imbalance volumes were announced each hour, new net imbalance volume value generated by shifting the input and output windows. These steps were applied each hour for a month period. In Figure 5.12 measured net imbalance volume data were compared with synthetic data which was generated by using the Markov chains method.

The test value was not presented to the model as input before the estimation time. First, the synthetic data were generated for considered hours ahead of time. After that for the new data generation steps, test value of latest hour was used as input, as if occurred imbalance volume has newly announced.

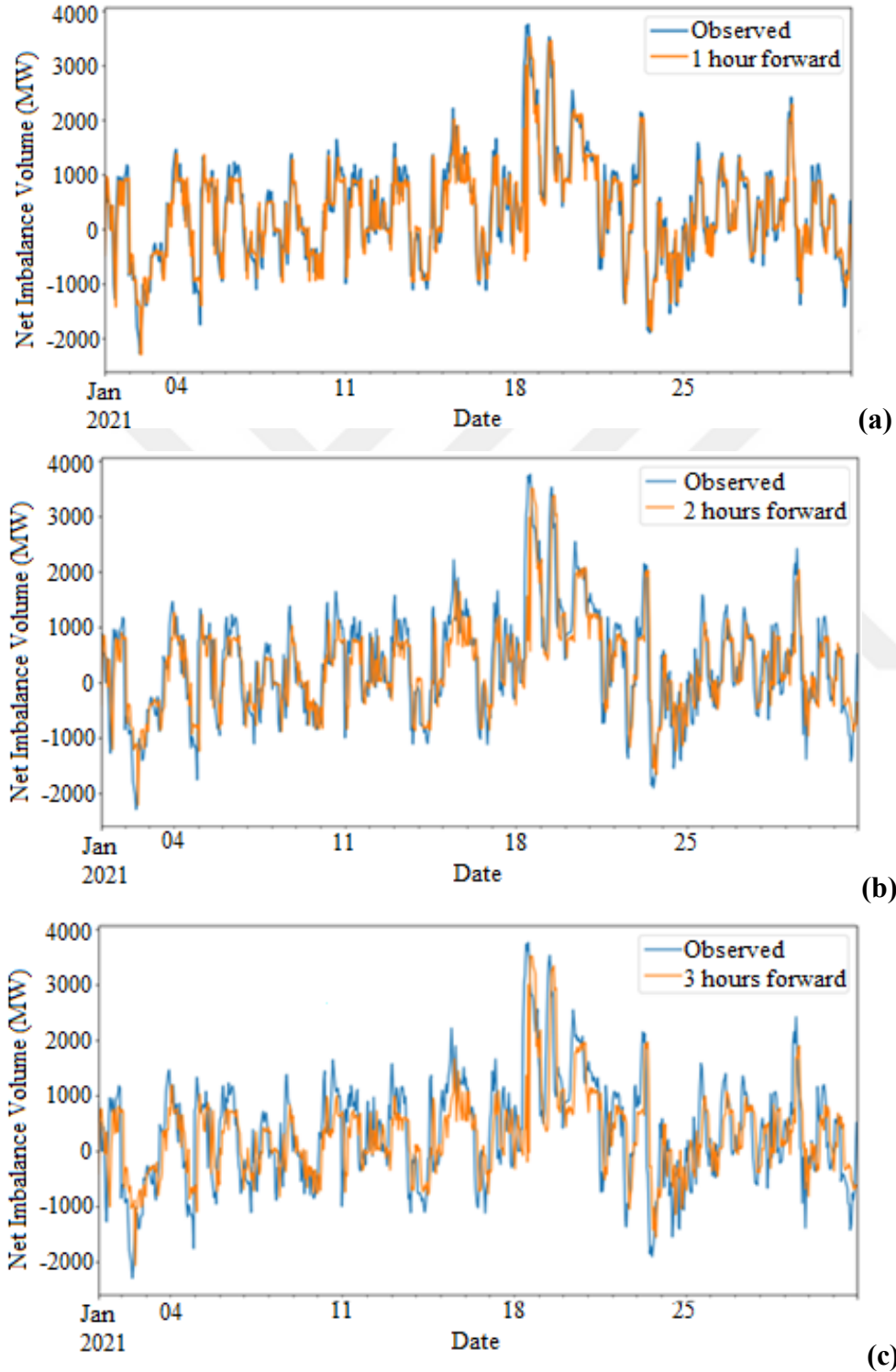


Figure 5.12 : Observed and generated net imbalance volume data with Markov chain for (a) 1 hour, (b) 2 hours and (c) 3 hours forward on first month of 2021.

5.4.3 Generated data distribution

1, 2 and 3 hours forward generated net imbalance volume data distribution compared with the observed data in the Figure 5.13 below together with observed data.

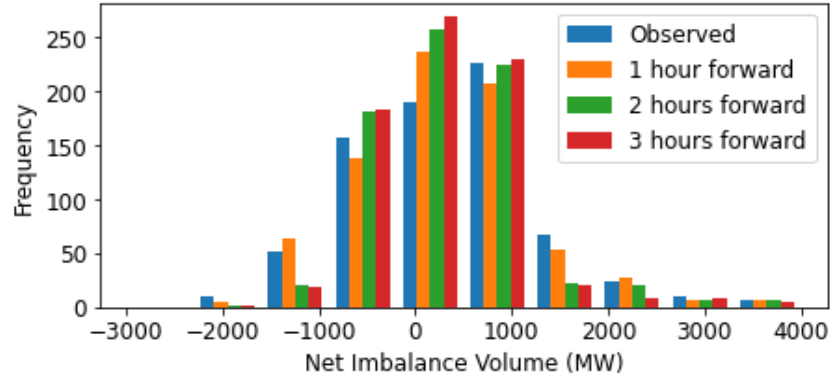


Figure 5.13 : Probability distribution of observed and generated net imbalance volume with Markov chain (MW).

Markov chain method and observed data distributions has a good match. However, the shapes of generated data diverge away from observed data as the prediction time went further. From a closer look to separate relations of observed and generated values for different times ahead were given in Figure 5.14.

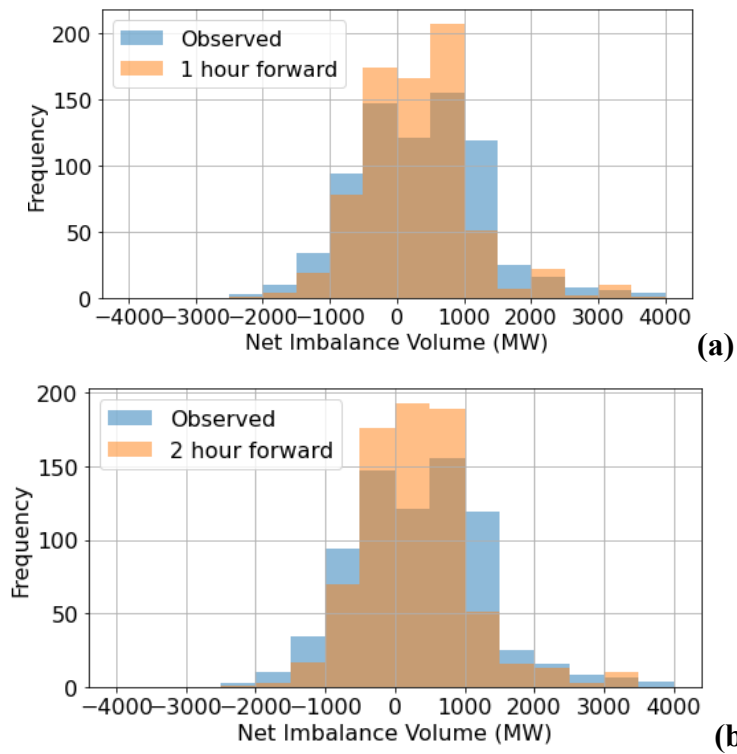


Figure 5.14 : Histogram of observed values with (a) 1 hour (b) 2 hours and (c) 3 hours forward data generation with Markov chain.

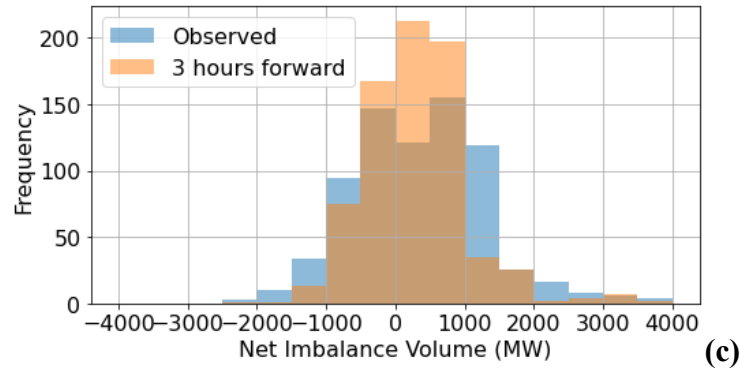


Figure 5.14 (continued): Histogram of observed values with (a) 1 hour (b) 2 hours and (c) 3 hours forward data generation with Markov chain.

5.4.4 Autocorrelation and statistical parameters

The relationship between observed net imbalance volume and the observation of its prior values were graphically summarized by autocorrelation function plots in Figure 5.15 below.

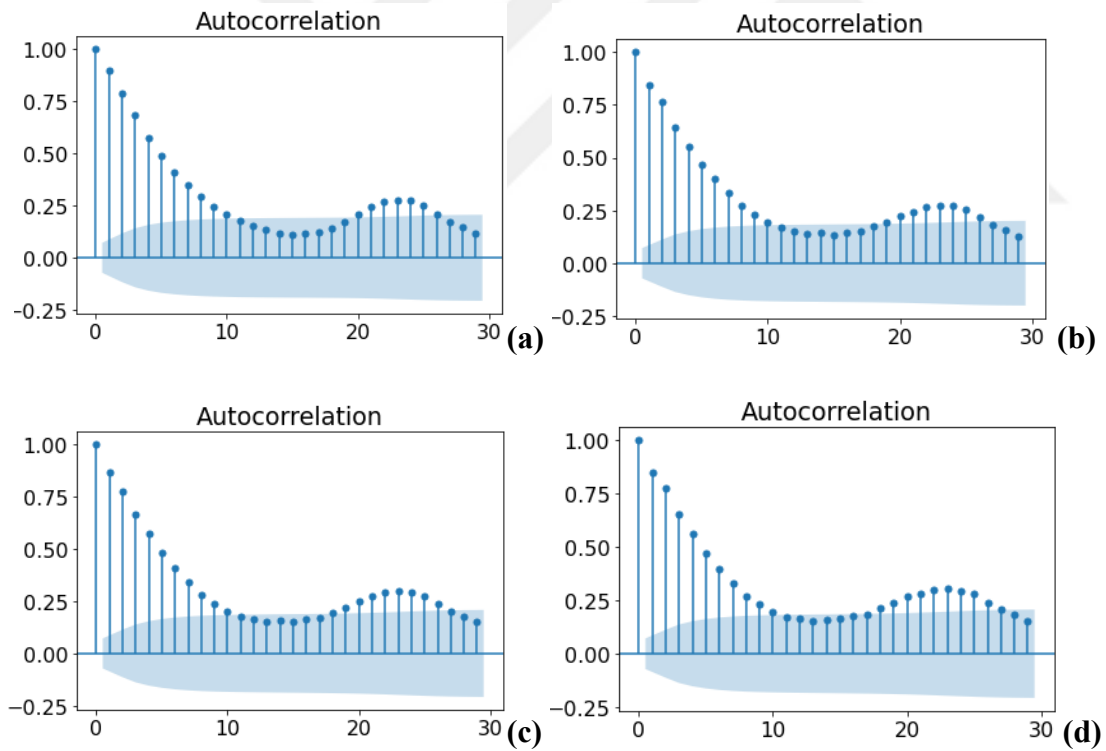


Figure 5.15 : Autocorrelation function graphs: (a) Observed (January 2021), (b) 1 hour forward (January 2021), (c) 2 hours forward (January 2021), (d) 3 hours forward (January 2021).

Same statistical metrics that used in ARIMA result evolution were used to evaluate the generated data was given in Table 5.3 below.

Table 5.3 : Statistical parameters evaluated for Markov Chain for January 2021.

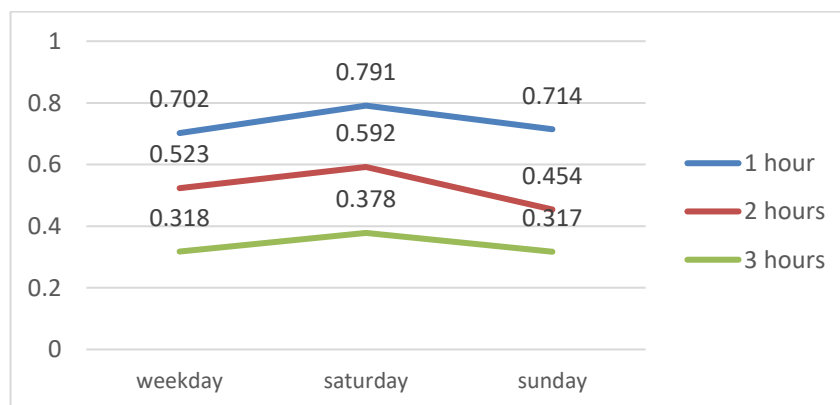
Forward	R ²	MBE	NMBE	RMSE	NRMSE	mean	std
Observed	-	-	-	-	-	341.956	950.478
1 hour	0.749	26.616	0.004	476.310	0.079	315.340	874.336
2 hours	0.576	44.323	0.007	618.251	0.102	297.633	801.654
3 hours	0.398	65.158	0.011	736.771	0.122	276.797	740.299

Daily profile difference between weekdays, Saturdays and Sundays were given in Table 5.4 below.

Table 5.4 : Statistical parameters evaluated for Markov Chain for January 2021 on day of week basis.

	Day of week	R ²	MBE	NMBE	RMSE	NRMSE	mean	std
Obs.	weekday	-	-	-	-	-	542.07	917.714
	saturday	-	-	-	-	-	-256.146	942.365
	sunday	-	-	-	-	-	102.911	777.409
1 hour	weekday	0.702	43.998	0.008	500.357	0.091	498.072	849.614
	saturday	0.791	-58.073	-0.013	428.925	0.097	-198.073	881.698
	sunday	0.714	38.589	0.012	414.145	0.129	64.321	688.192
2 hours	weekday	0.523	81.684	0.015	633.123	0.115	460.386	792.274
	saturday	0.592	-132.375	-0.030	599.715	0.136	-123.771	808.061
	sunday	0.454	64.729	0.020	571.797	0.179	38.181	589.392
3 hours	weekday	0.318	120.208	0.022	757.389	0.138	421.862	742.104
	saturday	0.378	-189.658	-0.043	739.898	0.167	-66.488	735.142
	sunday	0.317	89.682	0.028	639.799	0.200	13.229	525.299

A pattern can be seen in the value. To better visualize this patten, coefficient of determination results calculated depending on the day of week, results from Table 5.2 was given in the Figure 5.16 below to better show their comparison.

**Figure 5. 16:** R square in Markov Chain.

Finally, to show the difference between the observed data and three synthetic data, distribution of residuals for all three generated datasets was given in Figure 5.17.

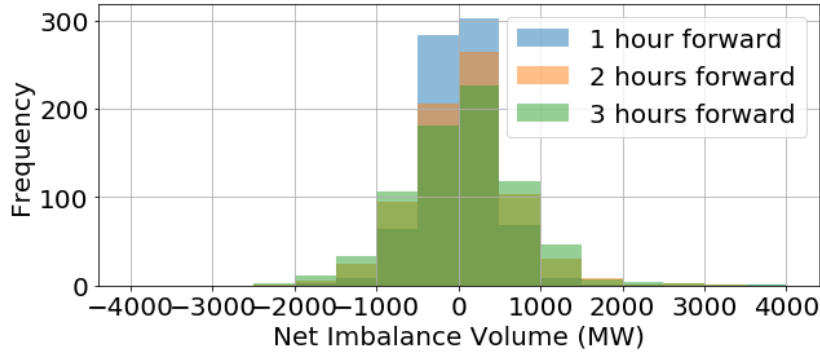


Figure 5. 17: Residual histogram.

5.5 Results and Discussion

Observed and generated net imbalance volume data comparison graphs showed that synthetic values are close to observed ones. In the Markov chain histograms while the observed data has a bimodal histogram, which has two data peaks, only data generated for 1 hour forward has similar pattern. Other two histograms have single peak in the middle.

On the other hand, in ARIMA result histograms, the forecasted values have closer pattern to the observed data. In all three graphs, forecasted data has bimodal histogram similar to the observed data. As the prediction is made for a more distant date, the shapes of histograms diverge away from observed data for both the synthetic and forecasted data.

In the autocorrelation function graphs, each graph shows the same oscillatory behavior, typical of distinctive diurnal patterns, with higher daily net imbalance volume at noon than at early in the morning. Particularly observation of the existence of a peak within a 24-hour interval shows that a strong correlation exists between net imbalance volumes at the same hour of consecutive days. This pattern can be the result of increasing uncertainty caused by increase in generation from renewable sources during day since higher forecast errors leads to higher instruction volume need for frequency balancing.

On the statistical metrics, coefficient of determination results is close between Markov chain and ARIMA models where ARIMA results has slightly higher accuracy in all three prediction times. And in each model the accuracy of coefficient of determination gets lower as data generated for further from latest observation time. On the other hand,

other metric results were low which can be noted as a satisfactory accordance between the observed and the generated net imbalance volume data.

Highest coefficient of determination values occurred on Sunday in all three generated data with Markov chain and all three of the forecasted data with ARIMA, followed closely by weekdays and lowest values occurred on Saturday. This was interpreted as the cause of highest and lowest value difference occurring depending on the day of week, which is highest on Sunday, followed closely by weekday and lowest on Saturday.

In general, ARIMA method showed slightly better performance than Markov chain approach in most of the metrics. ARIMA and Markov chain results of R square, RMSE and NRME are given side by side in the Table 5.5.

Table 5.5 : R^2 , RMSE and NRMSE comparison of ARIMA and Markov chain results on day of week basis.

	Day of week	R^2 – ARIMA	R^2 – Markov Chain	RMSE– ARIMA	RMSE– Markov Chain	NRMSE– ARIMA	NRMSE– Markov Chain
Obs.	weekday	-	-	-	-	-	-
	saturday	-	-	-	-	-	-
	sunday	-	-	-	-	-	-
1 hour	weekday	0.787	0.702	423.40	500.36	0.077	0.091
	saturday	0.814	0.791	405.26	428.93	0.092	0.097
	sunday	0.720	0.714	409.36	414.15	0.128	0.129
2 hours	weekday	0.564	0.523	605.21	633.12	0.110	0.115
	saturday	0.592	0.592	599.48	599.72	0.135	0.136
	sunday	0.424	0.454	587.48	571.80	0.184	0.179
3 hours	weekday	0.377	0.318	723.52	757.39	0.132	0.138
	saturday	0.383	0.378	737.29	739.90	0.167	0.167
	sunday	0.245	0.317	672.87	639.80	0.210	0.200

In the 2 and 3 hours forward results, Markov chain has similar or better results than ARIMA method during Sunday and Saturday. Weekday results are also close in 2 and 3 hours forward comparison while the highest difference occurred in 1 hour forward weekday data.

ARIMA has closer standard deviation value to observed data in all categories, however difference with the results of Markov chain is much smaller in the results of weekdays. ARIMA and Markov chain results for MBE, RMBE and mean are given the Table 5.6. Markov chain has closer MBE, NMBE and mean values to the observed data in all three Saturday values.

Table 5.6 : MBE, NMBE and mean comparison of ARIMA and Markov chain results on day of week basis.

	Day of week	MBE – ARIMA	MBE – Markov Chain	NMBE– ARIMA	NMBE– Markov Chain	mean – ARIMA	mean – Markov Chain
Obs.	weekday	-	-	-	-	542.07	542.07
	saturday	-	-	-	-	-256.146	-256.146
	sunday	-	-	-	-	102.911	102.911
1 hour	weekday	20.005	43.998	0.004	0.008	522.065	498.072
	saturday	-71.205	-58.073	-0.016	-0.013	-184.940	-198.073
	sunday	16.276	38.589	0.005	0.012	86.635	64.321
2 hours	weekday	43.321	81.684	0.008	0.015	498.749	460.386
	saturday	-152.737	-132.375	-0.035	-0.030	-103.409	-123.771
	sunday	35.555	64.729	0.011	0.020	67.356	38.181
3 hours	weekday	60.392	120.208	0.011	0.022	481.678	421.862
	saturday	-208.370	-189.658	-0.047	-0.043	-47.776	-66.488
	sunday	49.191	89.682	0.015	0.028	53.720	13.229

When comparing the residuals values of 1, 2 and 3 hours forward generated data, and looking at all results of the metrics, the results deteriorate as the date went further away.

6. CONCLUSIONS AND RECOMMENDATIONS

Markov chain is a useful and easy method to apply for time series data generation. It represents the transition of elements from one state to another over time and the number of past time steps influencing the probability distribution of the present state gives the order of the chain. In the study, the method utilized uses first order Markov chain to generate a few hours forward net imbalance volume data and repeats its action with the addition of new inputs.

Proposed method in this study has a low computational requirements and cost, easy to implement and is able to represent the autocorrelation function of recorded data. Unlike other studies that point forecast the SMP which has a longer prediction window due to late announcement of price data, this study proposes to generate net imbalance volume data with the ability to obtain more input before the closest market action hour. After generating the net imbalance volume with a closer prediction time, SMP then can be calculated using the high correlation between net imbalance volume and system balancing price which was not a part of the study but a suggestion for the further studies. For the purpose of using net imbalance volume data as a preview for market actions, Markov chain approach was applied and ARIMA model applied for comparison of result accuracies, since ARIMA is a widely used data-driven model.

In the ARIMA model 744 hours of data used as input to predict the following 3 hours and at each step, the window for input and output shifted by 1 hour. In the Markov chain approach, depending upon the imbalance volume time series of past two years, it was seen that 33 states of size 500 MW would be needed to capture all possible states of net imbalance volume. Dependence level on the previous instances was examined by looking at the autocorrelation function of the past data. The model has been used to generate 1 hour, 2 hours and 3 hours forward synthetic net imbalance volume data. The time series were obtained to be able to validate the generated data sets by continuing the data generation action for a month period. And then to determine how well the statistical properties of the observed net imbalance volume time series were preserved, generated time series were examined.

Data distribution graphs has showed that both methods produced close results to the observed data. Although showing more deviation than ARIMA model in the histograms, the presented method was able to preserve the general characteristics of the observed data. Autocorrelation function exhibits that the proposed model was also able to preserve the daily oscillatory behavior similar to the observed one. On the statistical metrics, results are close between Markov chain and ARIMA models where ARIMA results has slightly higher accuracy in general. In each model the accuracy gets lower as data generated for further from latest observation time. On the other hand, MBE, NMBE, RMSE, NRMSE values are low which can be noted as a satisfactory accordance between the observed and the generated net imbalance volume data. Mean values were also close to the observed one considering the state range was 500 MW.

In general, ARIMA method showed slightly better performance than Markov chain approach in most of the metrics. Markov chain has closer mean value to the observed data in all three Saturday results. In the 2 and 3 hours forward predictions, Markov chain had similar or better results than ARIMA method during Saturday and Sunday predictions in terms of coefficient of determination, RMSE and NRMSE. Additionally, Markov chain has closer MBE, NMBE and mean values to the observed data in all three Saturday values. In the day of week comparison, the highest coefficient of determination values occurred on Saturday, followed closely by weekdays and lowest values occurred on Saturday in both models. This was interpreted as the cause of highest and lowest value difference occurring depending on the day of week, which is highest on Sunday, followed closely by weekday and lowest on Saturday. And the reason for having smaller differences between the metric results of ARIMA and Markov chain approach on weekday can be having less weekend input compared to weekday input.

To further improve the results, a smaller bin range can be used like 200 MW. Higher order transition can also be considered in future research. State range can be changed dynamically with each window shift and can be between maximum and minimum occurrences of the input time series to improve the performance. As stated before, synthetic net imbalance volume values may be utilized as the input for balancing market price forecasts and power plant operation optimization models.

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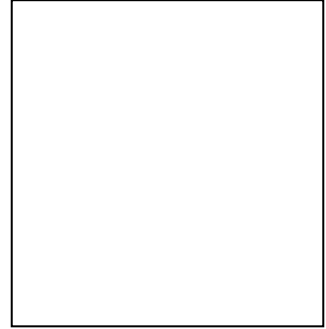
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