THE IMPACT OF SECURITY SHOCKS ON ELECTRICITY IMBALANCES:
AN EMPIRICAL ANALYSIS

by

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ABSTRACT

This study examines how military-related security shocks and system responses are associated with electricity imbalances in Ukraine during wartime. The core question is whether attacks, air raid alerts, and electricity outages help explain short-term deviations in electricity generation and consumption after accounting for the power system's internal dynamics and regular time patterns. Existing research on electricity imbalances primarily focuses on market functioning under relatively stable conditions, while paying less attention to how power systems behave under persistent military pressure and high uncertainty. The empirical analysis is based on hourly data covering the period from 2022 to 2025. The dataset combines electricity imbalance data with information on air raid alerts, attacks, hits, and power outages. The dependent variable is total electricity imbalance, measured in MWh, with an additional logarithmic specification used to interpret relative changes and reduce the influence of extreme values. The empirical strategy relies on ARIMAX models, which are appropriate for hourly time-series data because they explicitly account for autocorrelation, persistence, and regular temporal patterns. The results show that electricity imbalances are primarily driven by internal system dynamics and strong intra-day patterns. The ARIMAX specifications substantially reduce residual autocorrelation and indicate that hour-of-day effects dominate the explanatory structure of the data. Among the external variables, the scale of air raid alerts shows the most stable positive association with imbalances, whereas attacks display a weaker and less robust negative association. Power outages do not demonstrate a statistically stable effect across specifications. Interaction effects between alerts and attacks or outages are also not statistically significant. These findings suggest that, even under wartime conditions, the Ukrainian electricity system remains strongly shaped by predictable temporal demand patterns and system inertia.

Chapter 1. Introduction

Russia's full-scale invasion of Ukraine in 2022 placed enormous pressure on the Ukrainian electricity system. Repeated attacks on energy infrastructure, air raid alerts across the country, emergency repairs, and forced outages changed the way the electricity market operates. Under these conditions, maintaining the stability of the power system became not only a technical and economic issue, but also a matter of national security. One important indicator of this stability is the electricity imbalance, which reflects the difference between expected and actual electricity generation and consumption.

Electricity imbalances are important because they show how difficult it is for the system operator and market participants to balance the system in real time. Under normal conditions, imbalances typically arise from forecasting errors, sudden changes in demand, volatility in renewable energy, or market behavior. In wartime Ukraine, however, additional factors may influence the balancing process. Military attacks can damage infrastructure and disrupt system operations. Air raid alerts can change household and business electricity consumption. Power outages may also be introduced as a response to shortages or operational stress. Because of this, wartime conditions create a unique situation in which security shocks may disrupt the normal functioning of the electricity system.

Most existing studies on electricity imbalances focus on stable market conditions. They usually examine market design, balancing prices, forecasting quality, or regulatory mechanisms. Much less attention has been paid to how electricity systems behave during war or under constant security pressure. This creates an important research gap. Ukraine is a particularly valuable case because the electricity system has continued operating despite repeated attacks and ongoing uncertainty.

This study addresses this gap by combining hourly electricity imbalance data with information on attacks, hits, air raid alerts, and power outages. The main goal is to examine whether these wartime factors are associated with electricity imbalances after accounting for the system's internal dynamics and regular time patterns. This distinction is important. If imbalances are mainly driven by attacks and other security shocks, then policy should focus mostly on emergency protection and infrastructure defense. However, if imbalances are driven mainly by internal persistence and predictable daily cycles, then policy should also focus on forecasting, demand management, balancing capacity, and operational planning.

The empirical analysis uses ARIMAX models with hourly data for the period 2022–2025. Time-series models are necessary because electricity imbalance data are highly autocorrelated, meaning that current imbalances depend strongly on previous hours and regular daily patterns. ARIMAX models make it possible to study the relationship between wartime variables and electricity imbalances while also accounting for the time-series structure of the data.

The main contribution of this study is twofold. First, it creates a high-frequency wartime dataset that combines electricity market indicators with security-related variables. Second, it shows that electricity imbalances in Ukraine during wartime are driven mainly by internal system dynamics and strong intra-day patterns, while external security shocks have weaker and less stable effects. Among the external variables, the scale of air raid alerts has the most consistent relationship with imbalances, while attacks and outages show weaker results. These findings suggest that improving wartime energy resilience requires not only protecting infrastructure from attacks, but also improving forecasting, balancing flexibility, and the ability of the system to manage short-term disruptions.

Chapter 2. Literature Review

2.1 ELECTRICITY IMBALANCES AND POWER-SYSTEM STABILITY

Electricity systems must constantly maintain balance between electricity generation and electricity consumption. When supply and demand do not match, electricity imbalances appear. These imbalances create operational pressure for the power system and force system operators to activate balancing mechanisms in real time.

Many researchers argue that electricity balancing has become more difficult in recent years because modern electricity systems are more complex and more volatile than before. In *"Forecasting Intra-Hour Imbalances in Electric Power Systems"* (Salem et al.), the authors state that "keeping the electricity production in balance with the actual demand is becoming a difficult and expensive task" . The paper explains that electricity systems continuously experience unexpected changes in demand and supply, which creates balancing challenges.

The literature also shows that electricity imbalances are closely connected to power-system stability. Salem et al. explain that imbalances can lead to frequency deviations and therefore threaten secure system operation . This means that imbalance dynamics are important not only economically, but also technically and operationally.

Some studies view electricity balancing not simply as a technical process but as a broader market equilibrium. In *"Electricity Balancing as a Market Equilibrium"* (Eicke et al.), the authors explain that imbalance volumes and imbalance prices are influenced by supply, demand, outages, forecast errors, and market participant behavior . The paper argues that electricity balancing systems contain feedback loops: operational problems affect market behavior, and market behavior then affects future imbalances again .

This idea is especially relevant for wartime Ukraine. During the war, the electricity system experienced not only technical disruptions caused by attacks and outages, but also behavioral and operational responses from system operators, businesses, and consumers.

2.2 TIME-SERIES DYNAMICS AND INTRADAY PATTERNS

A major theme in the literature is that electricity imbalances have strong time dependence. In other words, current imbalance levels are strongly connected to previous imbalance levels and to regular hourly demand patterns.

Many studies show that electricity imbalance series are highly dynamic, volatile, and autocorrelated. In *“Forecasting Intra-Hour Imbalances in Electric Power Systems”* (Salem et al.), imbalance data are described as “non-periodic, non-stationary and noisy” . This means that imbalance values change continuously over time and are difficult to model using simple static methods.

Similarly, *“Evaluating System Imbalance Forecasting Models for the United Kingdom Electricity Market.”* (Avis and Lee) finds that lagged imbalance values are among the strongest predictors of future imbalance behavior . The authors show that imbalance systems contain strong persistence, meaning that previous system conditions continue affecting the following hours.

Another important finding in the literature is the presence of strong intraday patterns. Many studies show that imbalance levels naturally differ between nighttime, morning, daytime, and evening periods.

For example, in *“Probabilistic Forecasting of Power System Imbalance Using Neural Network-Based Ensembles”* (Van Gompel et al.), the authors find that imbalance volatility strongly depends on the time of day . Salem et al. also explain that sudden imbalance changes often occur at the beginning of operating hours because electricity demand does not perfectly follow hourly production schedules .

In *"Probabilistic Forecasting of Electricity Spot and Imbalance Prices"* (Goretti, Duffy, and Lowery), the authors identify clear daily and weekly imbalance patterns. They show that imbalance levels are usually lower during nighttime hours and higher during daytime peak periods .

These findings are very important for the Ukrainian case because they suggest that electricity imbalances are influenced not only by wartime shocks, but also by the internal daily structure of the electricity system itself.

2.3 EXTERNAL SHOCKS, VOLATILITY, AND OPERATIONAL UNCERTAINTY

Another important topic in the literature is the role of external shocks and uncertainty in electricity systems. Most existing studies focus on renewable-energy volatility, forecasting errors, outages, and changing market conditions. However, these mechanisms are also highly relevant for wartime electricity systems.

Many papers show that modern electricity systems become more unstable when uncertainty increases. In *"Machine Learning for System Imbalance Forecasting"* (Avis and Lee), the authors argue that forecasting errors and structural market changes are major drivers of imbalance volatility.

Similarly, *"Probabilistic Forecasting of Electricity Spot and Imbalance Prices"* (Goretti, Duffy, and Lowery) explains that balancing markets become increasingly important under conditions of high uncertainty and operational instability .

Many studies also use exogenous variables to explain imbalance behavior. For example, Van Gompel et al. include weather conditions, renewable generation, cross-border electricity exchanges, and load forecasts as explanatory variables. Goretti et al. similarly use demand forecasts and renewable-generation indicators in their ARIMAX models.

This literature supports the broader idea that external system conditions strongly affect imbalance behavior. In the Ukrainian case, these external variables include military attacks, air raid alerts, and emergency outages.

At the same time, very little literature examines electricity imbalances during active military conflict. Most existing studies focus on stable market systems, even when those systems experience volatility from renewable generation or market uncertainty. Ukraine therefore represents a unique case where electricity-system operation occurs under repeated missile attacks and large-scale security disruptions.

One of the few papers directly connected to wartime power-system operation is *"Assessment of the Resilience of the Power System Operating Under Systematic Terrorist Attacks"* (2025). The study analyzes how repeated missile and drone attacks affect the resilience of the Ukrainian electricity system. The authors argue that if recovery processes take longer than the interval between attacks, the power system gradually loses resilience. The paper also discusses emergency outages, electricity imports, repairs, and load shedding as key balancing and stabilization mechanisms during wartime.

2.4 TIME-SERIES AND FORECASTING APPROACHES

The literature strongly suggests that electricity imbalance systems require dynamic time-series methods rather than simple static regressions. Because imbalance data are highly autocorrelated and strongly influenced by time patterns, many researchers argue that standard OLS models are often insufficient.

Several papers therefore use ARIMA, ARIMAX, or machine-learning forecasting models. In *"Comprehensive Forecasting of California's Energy Consumption"* (Moslemi et al., 2023), the authors explain that ARIMAX models are especially useful because they allow researchers to include external variables together with time-series dynamics.

Similarly, Goretti et al. use ARIMAX models because they can capture exogenous variables together with daily and weekly seasonality.

The literature also emphasizes that lagged imbalance dynamics are extremely important. Avis and Lee show that lagged imbalance indicators are among the strongest predictors in electricity imbalance forecasting. Salem et al. similarly demonstrate that historical imbalance values and temporal features already contain substantial predictive information.

Recent Ukrainian research also highlights the unstable nature of wartime imbalance data. In *"Short-Term Forecasting of Electricity Imbalances in the Ukrainian Power System Using LSTM Models"* (Blinov et al., 2025), the authors show that Ukrainian imbalance series contain strong spikes, large volatility, and non-stationary behavior during the wartime period . The paper argues that traditional statistical models often struggle to capture these complex dynamics under unstable wartime conditions.

Overall, the literature strongly supports the use of dynamic time-series approaches that combine autoregressive structure with external explanatory variables. This provides the methodological basis for the ARIMAX framework used in the present study.

2.5 RESEARCH GAP

Existing literature provides extensive evidence that electricity imbalances are dynamic, volatile, and strongly dependent on temporal system structure. Many studies also show that outages, forecasting uncertainty, renewable volatility, and operational disruptions affect imbalance behavior.

However, most previous research studies electricity systems operating under relatively stable market conditions. Existing papers mainly focus on renewable integration, electricity-market efficiency, balancing prices, and forecasting performance.

Much less attention has been paid to electricity imbalance dynamics during wartime conditions and persistent military pressure. In particular, there is very limited research examining how attacks, air raid alerts, and emergency outages affect electricity imbalances after accounting for internal system dynamics and regular hourly patterns.

This study contributes to the literature by combining high-frequency wartime electricity data with military-related variables and time-series modeling. Unlike most previous studies, the analysis focuses specifically on the relationship between wartime security shocks, system responses, and electricity imbalances in an active conflict environment.

Chapter 3. Research Question and Hypotheses

3.1 RESEARCH QUESTION

The main objective of this study is to explain the short-term dynamics of electricity imbalances in Ukraine during wartime. In this paper, electricity imbalance refers to the hourly deviation between expected and actual conditions in the power system, measured through the total volume of positive and negative imbalances in MWh. The study focuses on total imbalance rather than net imbalance because the main interest is the overall level of system stress and instability, not whether the deviation is positive or negative.

The research focuses on how wartime conditions may influence the balancing process in the Ukrainian electricity system. Since 2022, the system has operated under constant military pressure, including attacks on infrastructure, large-scale air raid alerts, emergency operational decisions, and periods of forced outages. These conditions may affect both electricity consumption and the ability of the system operator to maintain balance in real time.

The research question is formulated as follows:

How do military-related shocks and system responses affect electricity imbalances in Ukraine?

The study examines whether wartime variables such as attacks, hits, air raid alerts, and outages are associated with changes in electricity imbalances. Attacks and hits represent direct security shocks, while alerts and outages reflect broader operational and behavioral responses within the electricity system.

At the same time, the analysis accounts for the fact that electricity imbalances are also shaped by internal system dynamics and regular temporal patterns. Electricity demand and balancing processes naturally vary across different hours of the day and days of the week. To account for these patterns, the study uses ARIMAX models with hourly and weekday controls. This approach makes it possible to separate the role of predictable system behavior from the role of external wartime shocks.

3.2 HYPOTHESES

Based on the research question, the study tests the following hypotheses:

H1: Military attacks increase power imbalances.

This hypothesis assumes that military attacks create sudden disruptions in the electricity system. Attacks may damage infrastructure, interrupt generation or transmission processes, increase uncertainty in system operations, and affect electricity consumption patterns. As a result, balancing supply and demand in real time may become more difficult, leading to larger electricity imbalances.

H2: The more areas under air alert, the bigger the power imbalances.

This hypothesis assumes that large-scale air raid alerts affect the behavior of households, businesses, and system operators. When more oblasts are simultaneously under alert, electricity demand patterns may become less predictable, operational decisions may change, and overall system uncertainty may increase. Therefore, a wider geographic scale of alerts is expected to be associated with higher electricity imbalances.

H3: Power imbalances are higher during daytime and peak hours and lower at night.

This hypothesis reflects the regular temporal structure of electricity demand and balancing processes. Electricity consumption is typically lower and more stable during nighttime hours, while daytime and peak hours are associated with higher and more variable demand. Because balancing the system becomes more difficult during periods of high consumption, electricity imbalances are expected to increase during the day and decrease at night.

H4: With more areas under alert, the impact of attacks and outages on power imbalances increases.

This hypothesis assumes that the effect of attacks and outages may become stronger under conditions of broader security pressure. When a large number of regions are simultaneously under air alert, the electricity system may already be operating under elevated uncertainty and stress. In such conditions, additional shocks such as attacks or outages may have a larger impact on electricity imbalances than under normal circumstances

Chapter 4. Methodology and Data

4.1 DATA

The empirical analysis uses a high-frequency hourly dataset covering the period from 2022 to 2025. The unit of observation is one hour. The final dataset combines several sources: electricity imbalance data, power outage data, missile and drone attack data, and air raid alert data. All variables are aggregated or transformed to the same hourly level, which allows the models to connect security events and system responses to the dynamics of electricity imbalances.

The core energy variable is the total electricity imbalance. The original imbalance data include positive and negative imbalances. These are aggregated into *total_imbalance_mwh*, which measures the total imbalance magnitude in each hour. This measure is appropriate for the study because the research question focuses on system stress and instability rather than on whether the imbalance is positive or negative.

Power outage data are used to construct indicators of whether outages were introduced in a given hour. The variable *outages_introduced* captures the current-hour presence of outages, while *outage_lag_1h* captures whether outages were present in the previous hour. This distinction allows the model to test both immediate and delayed associations.

Attack data are used to construct *attack_dummy* and *hits_dummy*. The first variable identifies hours with a recorded attack, while the second captures hours with recorded hits. These variables represent direct security shocks. However, an important limitation is that attack variables can only be matched to the hourly dataset when sufficiently precise timing is available. Therefore, these variables may understate the total wartime pressure on the system.

Air raid alert data are used to measure the geographic scale of security risk. The variable *oblasts_under_alert* counts how many oblasts were under alert during a given hour. The variable *alert_lag_1h* captures the number of oblasts under alert in the previous hour. These variables are important because they capture not only direct physical threats, but also the behavioral and operational environment in which electricity consumption and balancing decisions occur.

Table 1. Descriptive Statistics of Key Variables; author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

Table 1 presents descriptive statistics for the main variables used in the analysis. The average electricity imbalance equals about 1044 MWh, although imbalance levels vary substantially over time. On average, around 4–5 oblasts were under air raid alert in a given hour. Attack hours were relatively rare, while outages were introduced more frequently. Overall, the statistics show that the dataset captures both wartime pressure and significant variation in electricity-system conditions.

Variable	Mean	SD	Min	Max
Total Imbalance (MWh)	1044.06	825.95	0	16591.79
Oblasts Under Alert	4.49	5.39	0	25.00
Attack Hour (0/1)	0.02	0.14	0	1.00
Outages Introduced	0.09	0.29	0	1.00

Source: author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

4.2 DEPENDENT VARIABLE

The dependent variable in this study is total electricity imbalance, measured in megawatt-hours (MWh). It shows the overall size of deviations between electricity generation and electricity consumption in the system during each hour. Higher values mean that it is more difficult for the system operator to keep supply and demand balanced in real time.

The study uses total imbalance instead of net imbalance because the main goal is to measure the overall level of instability in the system, not the direction of the deviation. In other words, the analysis focuses on how large the imbalance is, regardless of whether the system has too much or too little electricity.

The models are estimated using both the original imbalance values and a logarithmic transformation of the variable, written as *log(total_imbalance_mwh + 1)*. The logarithmic version helps reduce the influence of extremely large imbalance values, which are common during periods of stress or disruption. It also makes the results easier to interpret in relative terms, approximately as percentage changes. Adding 1 allows the logarithm to be calculated even in hours when the imbalance equals zero.

Figure 1 shows the daily dynamics of electricity imbalances in Ukraine during 2022–2025. The graph demonstrates that imbalance levels were highest and most volatile during the early stages of the full-scale invasion, when the electricity system experienced severe operational disruptions and uncertainty. Several large spikes are visible during this period, indicating episodes of extreme imbalance pressure. Over time, the series becomes more stable and less volatile, suggesting gradual adaptation of the electricity system to wartime conditions. However, fluctuations remain present throughout the entire period, showing that the system continued to operate under persistent operational stress.

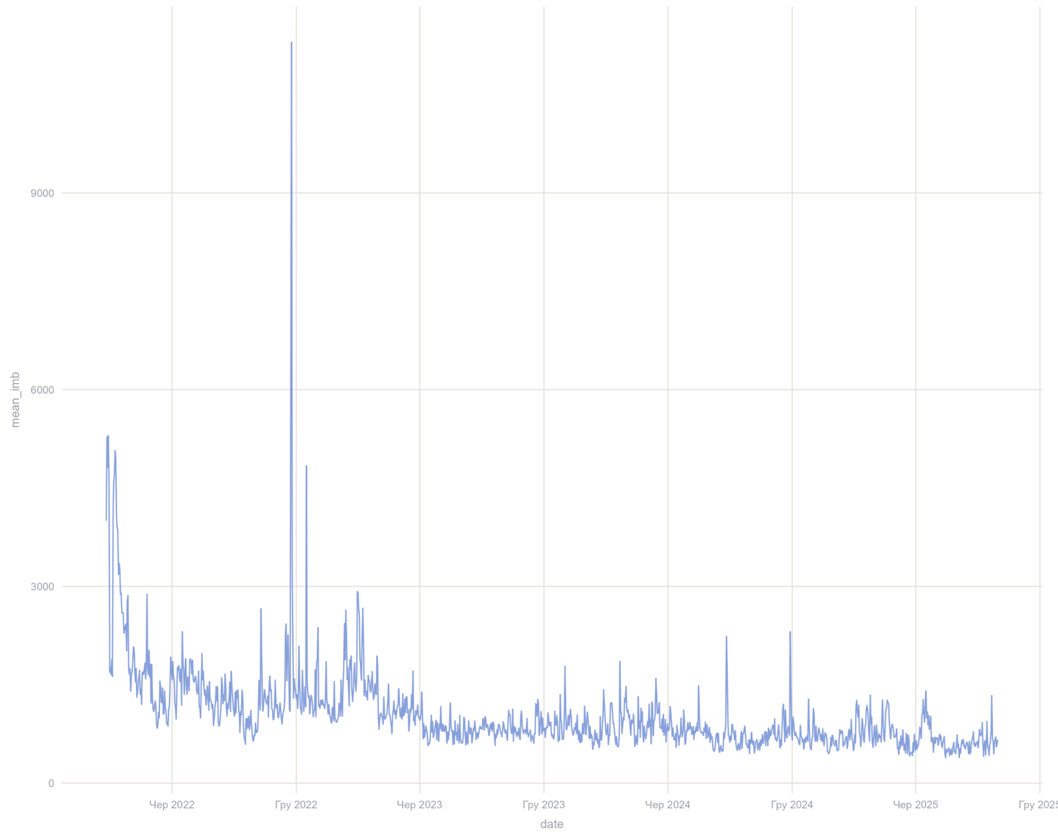

Figure 1. Electricity Imbalance Daily Trend (2022–2025); author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

4.3 INDEPENDENT VARIABLES

The independent variables used in the analysis are divided into four main groups.

The first group includes variables related to power outages. The variable *outages_introduced* is a binary indicator showing whether outages were introduced during a given hour. The variable *outage_lag_1h* shows whether outages were present in the previous hour. This lagged variable is included because the effect of outages may continue even after the initial hour.

The second group captures direct military-related shocks. The variable *attack_dummy* identifies hours in which attacks were recorded, while *hits_dummy* identifies hours with recorded hits. These variables are used to measure the possible impact of wartime events on electricity imbalances. Attacks and hits may affect the system through infrastructure damage, operational disruptions, changes in electricity consumption, or increased uncertainty. However, these variables should be interpreted carefully because the dataset only includes attacks that can be matched to a specific hour.

The third group measures the overall security situation through air raid alerts. The variable *oblasts_under_alert* counts how many oblasts were under air alert during a given hour. This variable reflects both the scale and geographic spread of security threats. The lagged variable *alert_lag_1h* captures whether the effect of alerts may continue into the following hour.

The fourth group includes time-control variables. The variables *hour_factor* and *weekday_factor* are used to control for regular daily and weekly patterns in electricity demand and balancing processes. Electricity consumption naturally changes throughout the day, with different patterns during nighttime, morning, daytime, and evening hours. Including these controls helps separate normal temporal patterns from the possible effects of wartime shocks.

Figure 2 shows the correlations between the main variables used in the analysis. The strongest correlation is between total electricity imbalance and its lagged value (0.95). This means that imbalance levels are highly persistent over time and that current imbalance levels are strongly correlated with previous hours. This result supports the use of ARIMAX models, which are designed to capture time-series dynamics.

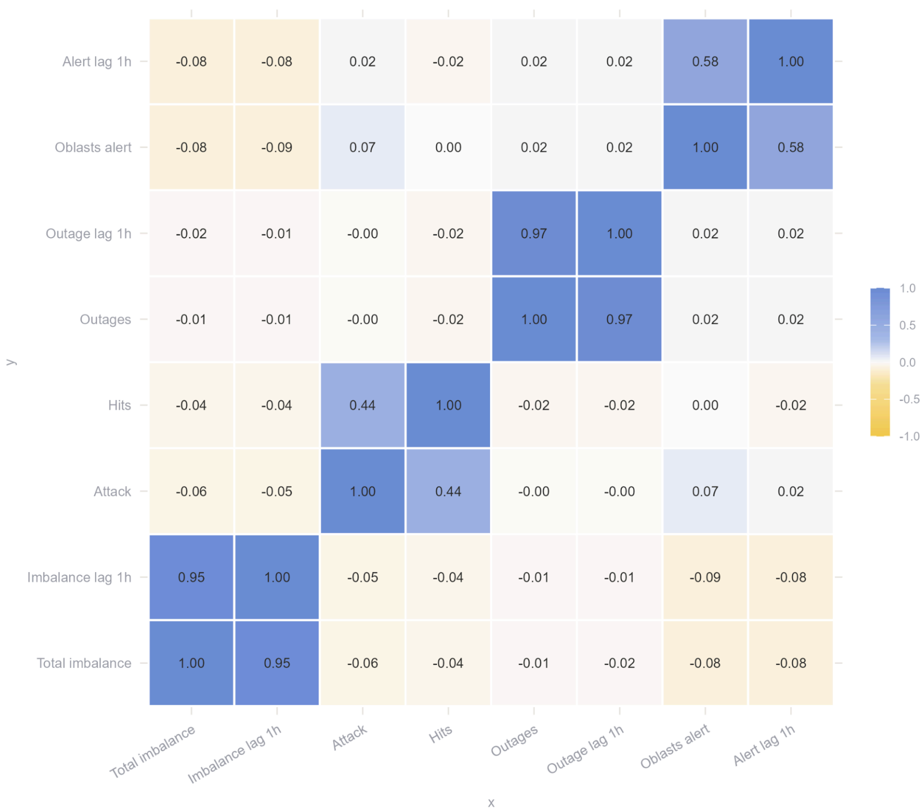

Figure 2. Correlation matrix; author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

Strong positive correlations also appear between outages and lagged outages (0.97) and between oblasts under alert and lagged alerts (0.58). This suggests that outages and security conditions often continue across several hours rather than changing immediately. The relationship between attacks and hits is moderate (0.44), which is expected because not every attack directly results in infrastructure damage.

Overall, the correlation matrix does not indicate serious multicollinearity problems and confirms the importance of persistence and temporal patterns in the dataset.

4.4 EMPIRICAL STRATEGY

The empirical analysis is based on several ARIMAX model specifications. ARIMAX models are used because electricity imbalance data are hourly time-series data and therefore have a strong time dependence. In other words, imbalance levels in one hour are closely related to imbalance levels in previous hours. A simple regression model may therefore produce misleading results because it does not properly account for autocorrelation and persistence in the data.

ARIMAX models combine time-series dynamics with external explanatory variables. This makes it possible to account for the internal behavior of the electricity system while also estimating the relationship between electricity imbalances and wartime variables such as outages, attacks, hits, and air raid alerts.

The first specification is the main ARIMAX model with time controls. It includes the main wartime variables together with hourly and weekday controls. The second specification extends the model by adding interaction effects between alerts and attacks or outages. This allows the analysis to test whether the effect of attacks and outages becomes stronger when more oblasts are simultaneously under air alert. The third specification is a logarithmic ARIMAX model, where the dependent variable is transformed as *log(total_imbalance_mwh + 1)*. This specification reduces the influence of extreme values and allows the coefficients to be interpreted approximately as relative or percentage changes.

The general ARIMAX framework can be written as: $Y_t = X_t\beta + u_t$, where (u_t) follows an ARIMA ((p,d,q)) process.

Several econometric issues are important for this study. First, hourly electricity data are highly autocorrelated, meaning that neighboring observations are strongly related to each other. Second, the volatility of electricity imbalances may change between normal periods and crisis periods, creating heteroskedasticity. Third, some variables may be partly endogenous. For example, outages may sometimes be introduced as a response to expected system stress rather than as an independent cause of imbalances.

The study addresses these issues in several ways. Hourly and weekday controls are included to capture regular time patterns. ARIMAX models are used to directly account for autocorrelation and persistence in the data. In addition, diagnostic checks are performed using residual autocorrelation measures, especially ACF1. The ARIMAX models show ACF1 values close to zero, which suggests that the models capture the time-series structure reasonably well.

At the same time, the results should be interpreted carefully. The analysis focuses on identifying systematic relationships rather than proving strict causal effects. Although ARIMAX models improve the treatment of time-series dynamics, they do not fully eliminate issues such as endogeneity or measurement error. Therefore, the findings should be understood as evidence of stable associations between wartime factors and electricity imbalances rather than definitive causal estimates.

4.5 STATIONARY TEST

Before estimating the ARIMAX models, the study tests whether the electricity imbalance series is stationary. This step is important because time-series models require the underlying series to have stable statistical properties over time.

To test for stationarity, the Augmented Dickey-Fuller (ADF) test is applied to the hourly electricity imbalance series. The test produces a Dickey-Fuller statistic of -18.797 with a p-value below 0.01. Therefore, the null hypothesis of a unit root is rejected.

The results suggest that the electricity imbalance series is stationary and suitable for ARIMAX estimation. In practical terms, this means that the ADF test suggests that the series is sufficiently stationary for ARIMAX estimation and fluctuates around a relatively stable level over time. This supports the use of ARIMAX models for analyzing the relationship between wartime variables and electricity imbalances.

4.6 AUTOCORRELATION STRUCTURE OF ELECTRICITY IMBALANCES

Before estimating the ARIMAX models, the study examines the autocorrelation structure of the electricity imbalance series. This step is important because hourly electricity data are usually highly dependent on previous observations. If strong autocorrelation is present, simple regression models may produce biased inference and incorrectly estimate the importance of explanatory variables.

Figure 3 presents the autocorrelation function (ACF) and partial autocorrelation function (PACF) for the total electricity imbalance series. The ACF plot shows very strong positive autocorrelation at short lags. The first lag has a correlation close to 0.9, indicating that imbalance levels are highly persistent from one hour to the next. The autocorrelation then declines gradually rather than disappearing immediately, which suggests that imbalance dynamics contain substantial temporal dependence.

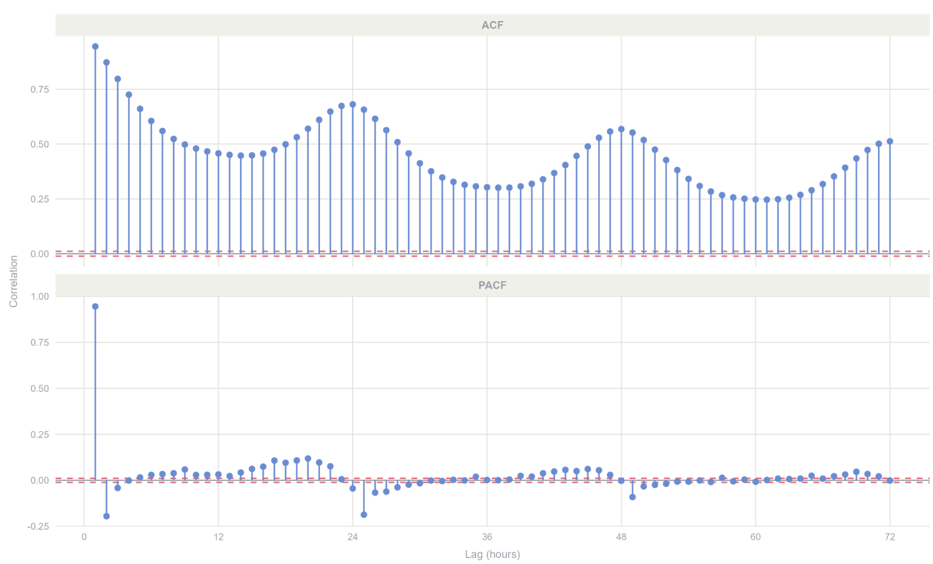

Figure 3. Autocorrelation Structure of Total Electricity Imbalance; author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

The ACF plot also reveals clear cyclical behavior around the 24-hour and 48-hour lags. This indicates strong intra-day seasonality and confirms that electricity imbalances follow regular daily operational patterns. Such patterns are expected in electricity systems because demand and generation conditions systematically differ between nighttime, morning, daytime, and evening periods.

Overall, the autocorrelation analysis demonstrates that the electricity imbalance series cannot be treated as independent observations. The strong persistence and intra-day temporal structure justify the use of dynamic time-series methods instead of simple static regression models. In particular, these results motivate the use of ARIMAX specifications, which explicitly account for autoregressive dynamics while simultaneously incorporating external wartime variables such as attacks, outages, and air raid alerts.

Chapter 5. Results

5.1 MODEL 1: ARIMAX SPECIFICATION WITH TIME CONTROLS

Model 1 estimates electricity imbalances using an ARIMAX model that includes wartime variables together with hourly and weekday controls. The results show that electricity imbalances are influenced mainly by the internal behavior of the electricity system and by regular daily demand patterns.

The ARIMA(1,1,3) model shows strong persistence in the imbalance series. The autoregressive coefficient ($AR(1) = 0.84, p < 0.001$) is large and highly statistically significant (*see Appendix B, Table B.1*). This means that imbalance levels in the current hour are strongly connected to imbalance levels in previous hours. In other words, once the system experiences high imbalance levels, these effects tend to continue for some time. The moving-average terms are also statistically significant, which suggests that short-term shocks affect the system, but their influence gradually decreases over time as the system adjusts.

Among the wartime variables, the clearest and most stable effect is observed for *oblasts_under_alert.* The coefficient is positive and statistically significant ($\beta \approx 0.74, p < 0.05$). This means that when more oblasts are simultaneously under air alert, electricity imbalances tend to increase. One possible explanation is that large-scale alerts create uncertainty and may change normal patterns of electricity consumption and system operations. For example, households, businesses, and system operators may react differently during periods of widespread alerts, making the balancing process more difficult.

The variable *alert_lag_1h* is also positive, although it is only moderately statistically significant ($p \approx 0.08$). This suggests that the effect of air raid alerts may continue into the following hour and not disappear immediately after the alert period.

The variable *attack_dummy* has a negative coefficient ($\beta \approx -13.4$) and is weakly significant ($p \approx 0.08$). This result does not support the hypothesis that attacks increase electricity imbalances. Instead, it suggests that imbalance levels may become slightly lower during attack periods. One possible explanation is that attacks reduce economic activity and electricity consumption for short periods of time, which may temporarily reduce the overall imbalance volume. However, this effect is not very strong and should be interpreted carefully.

The variable *hits_dummy* is not statistically significant. This means that recorded hits do not show a clear independent relationship with electricity imbalances in the estimated model.

The outage variables (*outages_introduced* and *outage_lag_1h*) are also statistically insignificant. This suggests that outages do not have a stable direct effect on electricity imbalances in this specification. One possible explanation is that outages are introduced as a controlled operational tool designed to stabilize the system during periods of stress rather than to create additional instability.

The strongest effects in the entire model are observed for the hourly control variables. Starting from the morning hours, electricity imbalances increase substantially and remain high throughout most of the daytime period. The largest coefficients appear between approximately 10:00 and 14:00, where imbalance levels are higher by around 680–830 MWh compared to the baseline hour. These results strongly support the hypothesis that electricity imbalances are heavily influenced by regular daily demand cycles and peak-hour consumption patterns.

The weekday effects are much weaker compared to the hourly effects. Most weekday variables are not statistically significant. Only *weekday_factor6* is statistically significant at the 5% level, suggesting somewhat lower imbalance levels on that day compared to the reference category.

The average electricity imbalance during different hours of the day across wartime periods (see Appendix A, Figure A2) . In all periods, imbalance levels rise during the daytime, reach their highest point around midday, and then fall again in the evening and at night. The graph also shows that imbalance levels were much higher in 2022, while in later periods the system became more stable and balanced.

Overall, the results show that electricity imbalances in Ukraine during wartime are driven mainly by internal system dynamics and strong intra-day demand patterns, while wartime variables have weaker and less stable effects. Among the external variables, the scale of air raid alerts shows the most stable positive relationship with imbalance levels.

5.2 MODEL 2: ARIMAX WITH INTERACTION EFFECTS

Model 2 extends the previous ARIMAX specification by adding interaction effects between air raid alerts and wartime variables. The purpose of these interaction terms is to test whether the impact of attacks and outages changes depending on the overall security situation in the country. In other words, the model examines whether attacks or outages have a stronger effect on electricity imbalances during periods when a larger number of oblasts are simultaneously under air alert.

The overall time-series structure of the model remains almost unchanged compared to the previous specification. The autoregressive coefficient ($AR(1) \approx 0.84$, $p < 0.001$) remains large and highly statistically significant, showing strong persistence in electricity imbalances over time (*see Appendix B, Table B.2*). This means that current imbalance levels continue to depend strongly on previous system conditions. The moving-average terms also remain statistically significant, suggesting that short-term shocks still affect the system but gradually disappear over time as the system adjusts.

The main wartime variables become weaker in this specification. The variable *attack_dummy* is no longer statistically significant ($p \approx 0.78$), and its coefficient becomes much smaller compared to the previous model. This suggests that after accounting for interaction effects, attacks themselves do not show a stable independent relationship with electricity imbalances. The variable *hits_dummy* also remains statistically insignificant.

The outage variables continue to show weak and statistically insignificant effects. Both *outages_introduced* and *outage_lag_1h* remain insignificant, suggesting that outages do not have a stable direct effect on imbalance levels. This result is consistent with the interpretation that outages are often introduced as a controlled operational mechanism intended to stabilize the electricity system during periods of stress.

The variable *oblasts_under_alert* remains positive and statistically significant ($\beta \approx 0.66$, $p < 0.05$). This means that electricity imbalances tend to increase when more oblasts are simultaneously under air alert. This result remains one of the most stable findings across all model specifications.

The most important addition in this model is the interaction effects. The variable *outages_x_alerts* measures whether the effect of outages changes when more regions are under air alert. The coefficient for this interaction term is positive ($\beta \approx 1.22$), which means that the relationship moves in the expected direction. This suggests that outages may become somewhat more disruptive during periods of broader security pressure and large-scale alerts. In practical terms, when the electricity system is already operating under heightened uncertainty, the introduction of outages could potentially create additional balancing difficulties.

However, the effect is not statistically significant ($p \approx 0.17$). This means that the model does not provide strong enough evidence to conclude that outages systematically become more important during periods of widespread alerts. Although the coefficient is positive, the statistical uncertainty around the estimate is too large to confidently confirm this relationship.

The second interaction variable, *attack_x_alerts*, measures whether attacks have a stronger effect on electricity imbalances during periods when more oblasts are under alert. The coefficient is negative and statistically insignificant ($p \approx 0.20$). This result suggests that the effect of attacks does not consistently increase with the scale of air raid alerts. In other words, attacks do not appear to become significantly more destabilizing during periods of broader security pressure.

These interaction results are important because they directly relate to Hypothesis H4. The original expectation was that attacks and outages would have larger effects on electricity imbalances when the overall security environment became more severe. The positive sign of *outages_x_alerts* partly supports this idea, since it suggests that outages may become more disruptive under large-scale alert conditions. However, because the interaction effects are statistically insignificant, the evidence remains weak and unstable. Therefore, the results do not provide strong support for the hypothesis that attacks and outages systematically become more harmful during periods of broader security pressure.

One possible explanation is that the Ukrainian electricity system has adapted to operating under high-security-risk conditions. Even during periods of large-scale alerts, balancing procedures and operational responses may continue functioning relatively consistently. Another possible explanation is that large-scale alerts already affect the overall system environment through behavioral and operational changes, making additional interaction effects difficult to identify separately.

The hourly effects remain the strongest part of the model. Starting from the morning hours, electricity imbalances increase sharply and remain high throughout most daytime periods. The largest coefficients again appear between approximately 10:00 and 14:00, where imbalance levels are higher by around 680–830 MWh relative to the baseline hour. These results strongly confirm that regular daily demand patterns explain a much larger share of imbalance variation than wartime shocks or interaction effects.

The weekday effects remain relatively weak. Most weekday variables are statistically insignificant, although *weekday_factor6* continues to show somewhat lower imbalance levels compared to the reference category.

Overall, Model 2 produces results that are very similar to the previous specification. Internal system dynamics and regular daily demand patterns continue to explain most of the variation in electricity imbalances. Among the external variables, the scale of air raid alerts remains the most stable factor associated with higher imbalance levels. At the same time, the interaction effects do not provide strong evidence that attacks or outages become significantly more disruptive during periods of broader security pressure.

5.3 MODEL 3: LOG-ARIMAX SPECIFICATION

Model 3 estimates a logarithmic ARIMAX specification in which the dependent variable is transformed as *log(total_imbalance_mwh + 1)*. This transformation reduces the influence of extremely large imbalance values and makes the model more stable during periods of unusually high volatility. In addition, the coefficients can now be interpreted approximately as relative or percentage changes in electricity imbalances.

The time-series structure of the model becomes more complex compared to the previous specifications. The ARIMA component is estimated as an ARIMA(3,1,2) process. The autoregressive terms (AR(1), AR(2), and AR(3)) are all highly statistically significant. The first autoregressive coefficient is especially large ($AR(1) \approx 1.51$, $p < 0.001$), showing strong persistence in electricity imbalances over time (*see Appendix B, Table B.3*). The negative second and third autoregressive terms suggest that the adjustment process is more dynamic and wave-like rather than purely linear. This means that the effect of previous imbalances gradually weakens and changes over time instead of disappearing immediately.

The moving-average terms are also highly statistically significant. The coefficients ($MA(1) \approx -1.80$ and $MA(2) \approx 0.80$) indicate that short-term shocks affect the system strongly, but the system gradually absorbs and corrects these shocks over time.

Among the wartime variables, the strongest and most stable result again comes from *oblasts_under_alert*. The coefficient is positive and close to statistical significance ($p \approx 0.056$). Although the magnitude of the coefficient is small, the interpretation is important because the model is logarithmic. The result suggests that when more oblasts are simultaneously under air alert, electricity imbalances tend to increase slightly in relative terms. This finding remains consistent with the previous models and supports the idea that large-scale security alerts create additional uncertainty and disrupt normal balancing processes.

The lagged alert variable (*alert_lag_1h*) is positive but statistically insignificant. This suggests that the impact of alerts is strongest during the current hour and weakens afterward.

The attack variable (*attack_dummy*) has a negative coefficient ($\beta \approx -0.015$) and is weakly statistically significant ($p \approx 0.069$). In approximate percentage terms, this suggests that imbalance levels may decrease by around 1–2% during attack periods. As in the previous models, this result does not support the hypothesis that attacks increase electricity imbalances. One possible explanation is that attacks temporarily reduce economic activity and electricity demand, which may lower overall imbalance volumes.

The variable *hits_dummy* remains statistically insignificant, indicating that recorded hits do not show a stable independent relationship with electricity imbalances. The outage variables also remain statistically weak. The coefficient for *outages_introduced* is positive and close to statistical significance ($p \approx 0.053$), suggesting that outages may be associated with slightly higher imbalance levels.

However, the effect remains small and not fully stable across specifications. The lagged outage variable (outage_lag_1h) is statistically insignificant.

The hourly effects continue to be the strongest part of the model. Because the model is logarithmic, these coefficients can be interpreted approximately as percentage differences relative to the baseline hour. Starting from the morning hours, imbalance levels increase significantly and remain elevated throughout most daytime periods.

The largest effects are observed between approximately 10:00 and 14:00 (*hour_factor10 ≈ 0.63, hour_factor11 ≈ 0.72, hour_factor12 ≈ 0.76).* These coefficients suggest that electricity imbalances during peak daytime hours are roughly 60–75% higher than during the baseline nighttime hour. This strongly confirms that regular daily demand cycles are the main factor explaining imbalance variation in the Ukrainian electricity system.

The weekday effects are relatively small but several become statistically significant in the logarithmic specification. Most weekday coefficients are negative, suggesting slightly lower imbalance levels on those days relative to the reference category. However, the size of these effects remains much smaller than the hourly effects.

Overall, Model 3 confirms the main conclusions of the previous specifications. Electricity imbalances in Ukraine during wartime are driven mainly by internal system dynamics and strong daily demand patterns. External wartime variables generally show weaker and less stable effects. Among them, the scale of air raid alerts remains the most consistent factor associated with higher imbalance levels, while attacks and outages show limited and unstable relationships with the dependent variable.

5.4 COMPARISON OF MODEL PERFORMANCE METRICS

The comparison results (see Table 2) show that Model 1 and Model 2 perform almost identically. Their AIC, BIC, ME, and RMSE values are extremely similar, which suggests that adding interaction effects does not meaningfully improve model performance. This result is also consistent with the regression outputs, where the interaction variables were statistically insignificant.

Table 2. Comparison of ARIMAX Model Performance Metrics (AIC, BIC, ME, RMSE)

Model	**AIC**	**BIC**	**ME**	**RMSE**
Model 1	437560,6	437895	-0,45	247,69
Model 2	437561,1	437912,2	-0,45	247,68
Model 3	-994,91	-643,81	0	0,24

Source: author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

At the same time, the Log-ARIMAX specification has substantially lower AIC and BIC values than the level models. This indicates that the logarithmic specification provides the best overall fit among the estimated models. In addition, Model 3 shows the lowest forecasting error values, with ME close to zero and a very small RMSE. This suggests that the logarithmic transformation helps stabilize the series and improves the model’s ability to capture electricity imbalance dynamics.

Overall, the model comparison suggests that interaction effects add little explanatory value, while the Log-ARIMAX specification describes wartime electricity imbalance behavior more effectively than the level-based models.

5.5 ACTUAL VS FITTED

Figure 4 compares the actual electricity imbalance values with the fitted values generated by the Log-ARIMAX specification. The graph presents the last 500 hourly observations of the sample. Because the model is estimated in logarithmic form, the values are shown as *log(total imbalance + 1)*.

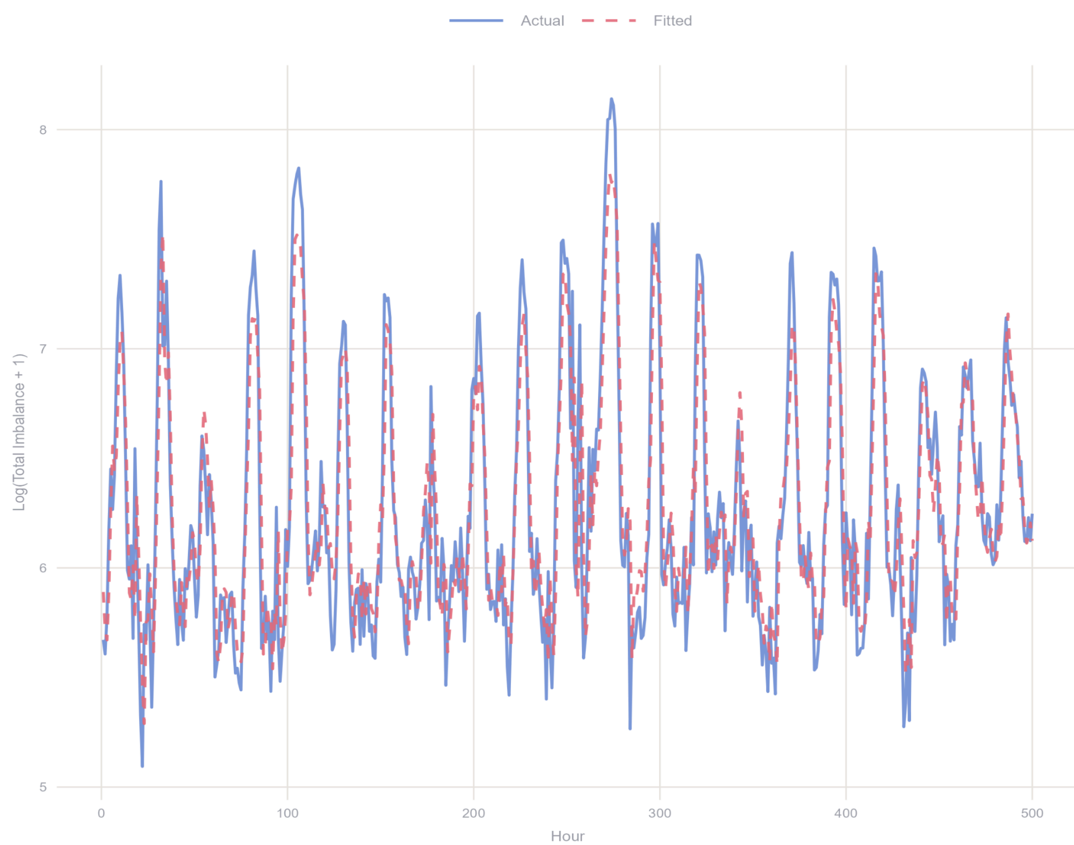

Figure 4. Actual vs Fitted Values — Log-ARIMAX Model; author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

Overall, the fitted series follows the actual imbalance dynamics relatively closely. The model successfully captures the general movement of the series, including both regular fluctuations and most short-term spikes. In particular, the fitted values reproduce the strong cyclical intra-day structure visible in the data, which confirms that the ARIMAX specification effectively accounts for hourly persistence and daily operational patterns.

The graph also shows that the model performs especially well during normal operating periods, where fitted and actual values almost overlap. During periods of very sharp imbalance spikes, the fitted series tends to smooth some of the most extreme fluctuations. This is expected because the logarithmic transformation reduces the influence of unusually large observations and stabilizes variance in the series.

Importantly, the fitted values do not appear systematically biased upward or downward across time. This suggests that the model captures the main temporal structure of the imbalance process reasonably well. The close alignment between actual and fitted values provides additional evidence that the Log-ARIMAX specification is appropriate for modeling wartime electricity imbalance dynamics.

At the same time, some deviations between actual and fitted values remain during periods of sudden volatility. These differences likely reflect unexpected operational disruptions, abrupt wartime shocks, or other short-term factors that are difficult to predict fully even with dynamic time-series models.

5.6 24-HOUR FORECAST: LOG-ARIMAX MODEL

To further evaluate the dynamic behavior of electricity imbalances, the study generates a short-term forecast using the Log-ARIMAX specification. Figure 5 presents a 24-hour ahead forecast together with 80% and 95% confidence intervals. The last 72 historical observations are included to provide context for the forecasted dynamics.

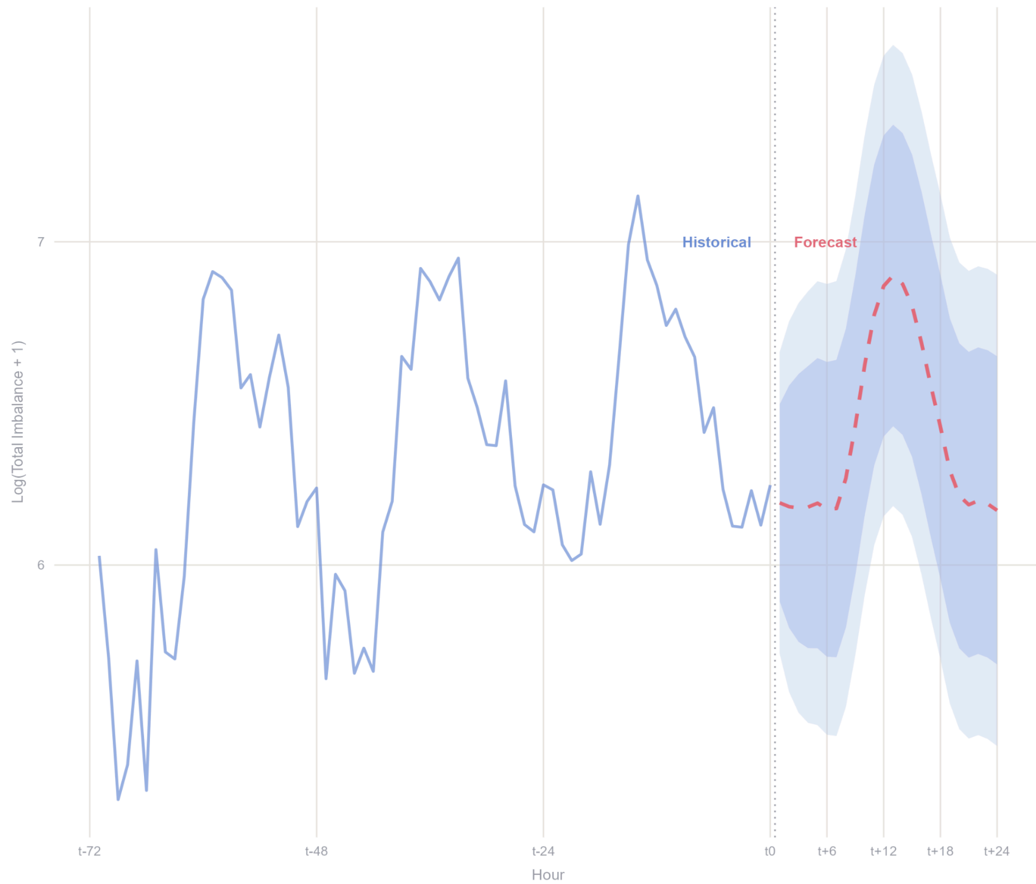

Figure 5. 24-hour Forecast — Log-ARIMAX Model; author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

The forecast suggests that electricity imbalances are expected to remain relatively stable in the short run, while continuing to follow clear intra-day patterns. At the beginning of the forecast horizon, the predicted imbalance remains close to recent historical levels, with forecast values around 6.18–6.20 in logarithmic form. The model then projects a temporary increase in imbalance levels during the middle of the forecast horizon, reaching a peak of approximately 6.90 before gradually declining again toward the end of the 24-hour period.

This forecast pattern is consistent with the strong intra-day seasonality identified earlier in the analysis. The predicted rise and decline in imbalance levels likely reflect regular daily demand cycles and operational balancing behavior rather than purely random fluctuations. The forecast therefore provides additional evidence that electricity imbalance dynamics in Ukraine are strongly influenced by predictable temporal structure.

The confidence intervals widen gradually as the forecast horizon increases. This is expected in time-series forecasting because uncertainty accumulates over time. The 95% confidence intervals are substantially wider than the 80% intervals, indicating greater uncertainty around longer-horizon predictions. Nevertheless, the forecast intervals remain relatively bounded, suggesting that the model captures the main structure of the imbalance process reasonably well.

At the same time, the widening forecast bands also reflect the unstable wartime environment in which the Ukrainian electricity system operates. Unexpected attacks, emergency outages, rapid demand shifts, or operational disruptions may generate deviations from the predicted path that cannot be fully anticipated by the model.

Overall, the forecasting exercise demonstrates that the Log-ARIMAX specification is capable of reproducing both the persistence and intra-day cyclical behavior of electricity imbalances while also quantifying the uncertainty surrounding short-term wartime electricity-system dynamics.

Chapter 6. Conclusions and Recommendations

6.1 MAIN FINDINGS OF THE STUDY

This study examined how wartime security shocks and system responses are associated with electricity imbalances in Ukraine during the period of Russia's full-scale invasion. The analysis focused on hourly electricity imbalance data for 2022–2025 and combined information on air raid alerts, attacks, hits, and power outages within a dynamic time-series framework.

The main objective of the study was to determine whether wartime factors help explain electricity imbalances after accounting for the internal dynamics of the electricity system and regular temporal patterns. To address this question, the study used several ARIMAX model specifications, including interaction models and a logarithmic specification designed to reduce the influence of extreme values and improve model stability.

The empirical results show that electricity imbalances in Ukraine during wartime are driven primarily by internal system dynamics and strong intra-day demand patterns rather than by direct wartime shocks alone. The autocorrelation analysis demonstrated that electricity imbalances are highly persistent over time and contain clear daily cyclical behavior. The ARIMAX models confirmed that imbalance levels in one hour are strongly connected to imbalance levels in previous hours. In addition, the largest effects in all model specifications were associated with hourly patterns, especially during daytime and peak-demand periods.

Among the wartime variables, the most stable result was found for the scale of air raid alerts. The variable measuring the number of oblasts under alert consistently showed a positive relationship with electricity imbalances across model specifications. This suggests that large-scale security pressure affects electricity-system behavior even when there is no direct infrastructure damage. Air raid alerts may influence electricity consumption patterns, operational decisions, and overall system uncertainty, making balancing processes more difficult.

The results for attacks and hits were weaker and less stable than initially expected. In several specifications, attacks showed a small negative association with electricity imbalances rather than a positive one. One possible explanation is that attacks temporarily reduce economic activity and electricity demand, which may lower total imbalance volumes in the short run. At the same time, these effects were not consistently statistically significant and therefore should be interpreted cautiously.

Power outages also did not demonstrate a stable independent effect across the estimated models. This finding may reflect the fact that outages are often introduced as a controlled operational response intended to stabilize the system during periods of stress rather than as an additional source of instability.

The interaction models provided only weak evidence that attacks or outages become more disruptive during periods of broader security pressure. Although some interaction coefficients moved in the expected direction, they were statistically insignificant. This suggests that the Ukrainian electricity system may have partially adapted to operating under conditions of constant wartime uncertainty and elevated security risk.

The model comparison results showed that the logarithmic ARIMAX specification performed best overall according to AIC and BIC criteria. The Log-ARIMAX model also reproduced the observed imbalance dynamics relatively well in the fitted-value analysis and successfully captured short-term cyclical patterns in the forecasting exercise. The forecasting results further confirmed that electricity imbalances in Ukraine follow strong and relatively predictable intra-day structures even under wartime conditions.

6.2 EVALUATION OF HYPOTHESES

The empirical results provide mixed support for the proposed hypotheses.

Hypothesis 1 stated that military attacks increase electricity imbalances. The estimated models do not provide strong support for this hypothesis. In several specifications, attack variables showed a weak negative association with electricity imbalances, while in other cases the coefficients were statistically insignificant. This suggests that the direct short-term effect of attacks on imbalance levels is more limited and less stable than initially expected.

Hypothesis 2 proposed that a larger number of oblasts under air raid alert increases electricity imbalances. This hypothesis is generally supported by the empirical results. The variable measuring the number of oblasts under alert consistently showed a positive relationship with imbalance levels across the estimated models. This finding indicates that broader security pressure and uncertainty are associated with higher imbalance volatility.

Hypothesis 3 stated that electricity imbalances are higher during daytime and peak-demand hours and lower during nighttime periods. The results strongly support this hypothesis. Hourly coefficients were among the largest and most statistically significant effects in all model specifications. Imbalance levels increased substantially during daytime and peak operational periods, confirming the importance of regular intra-day electricity demand patterns.

Hypothesis 4 suggested that the impact of attacks and outages becomes stronger when more oblasts are simultaneously under air raid alert. The interaction models provide only limited support for this hypothesis. Although some interaction coefficients moved in the expected direction, they were statistically insignificant. Therefore, the results do not provide strong evidence that attacks or outages become systematically more disruptive during periods of broader security pressure.

Overall, the findings suggest that electricity imbalance dynamics in wartime Ukraine are influenced more strongly by internal system persistence and regular temporal patterns than by direct military shocks alone.

6.3 POLICY IMPLICATIONS AND RECOMMENDATIONS

The findings of this study have several practical implications for managing the electricity system during wartime.

First, the results show that energy resilience during war should not focus only on protecting infrastructure from attacks. Physical protection is still very important, but a large part of electricity imbalance pressure comes from normal daily demand patterns and the internal dynamics of the power system itself. Because of this, improving system resilience also requires better forecasting, more flexible balancing capacity, demand management, and better operational planning during peak hours.

Second, the stable relationship between air raid alerts and electricity imbalances suggests that system operators could include security-related indicators in their forecasting and balancing models. Large-scale alerts may change electricity consumption patterns and operational behavior, so accounting for these factors may help reduce system stress and improve balancing decisions.

Third, the results highlight the importance of maintaining operational flexibility in the electricity system. Power outages are often used as a controlled response to stabilize the system rather than simply being a source of disruption. Because of this, system operators need reserve capacity, fast-response generation, and flexible balancing tools that can work under highly uncertain wartime conditions.

Finally, the results show the importance of continuous monitoring and real-time operational analysis during war. Electricity imbalance conditions can change rapidly throughout the day, so hourly forecasting and continuous system monitoring remain essential for maintaining power system stability.

6.4 LIMITATIONS OF THE STUDY

Despite the contributions of the study, several limitations should be acknowledged.

First, some wartime variables, especially attack indicators, could only be included when precise hourly timing was available. As a result, the dataset may not fully capture the broader operational pressure created by wartime conditions.

Second, the analysis focuses on associations rather than strict causal relationships. Although ARIMAX models improve the treatment of time-series dynamics, they do not fully eliminate issues such as endogeneity, omitted variables, or measurement error.

Third, the study uses national-level imbalance data rather than regional electricity-system information. This means that local differences in wartime disruption, infrastructure damage, and operational conditions are not fully reflected in the analysis.

Finally, wartime electricity systems are highly unstable and influenced by many unpredictable factors, including emergency operational decisions, changing military conditions, weather variability, and cross-border electricity flows. Some of these mechanisms are difficult to capture fully within a single empirical framework.

6.5 FINAL CONCLUSION

Overall, this study demonstrates that electricity imbalance dynamics in wartime Ukraine are shaped primarily by internal system persistence and predictable temporal structure, while military-related shocks create additional but comparatively weaker effects.

Even under prolonged military pressure, the Ukrainian electricity system continues to exhibit strong intra-day operational regularities and persistent balancing dynamics. This finding highlights both the resilience of the system and the importance of combining emergency-response measures with long-term operational balancing strategies.

The study contributes to the existing literature by examining electricity imbalance behavior under active wartime conditions and by demonstrating the importance of dynamic time-series approaches for analyzing highly volatile electricity-system environments.

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APPENDIX A

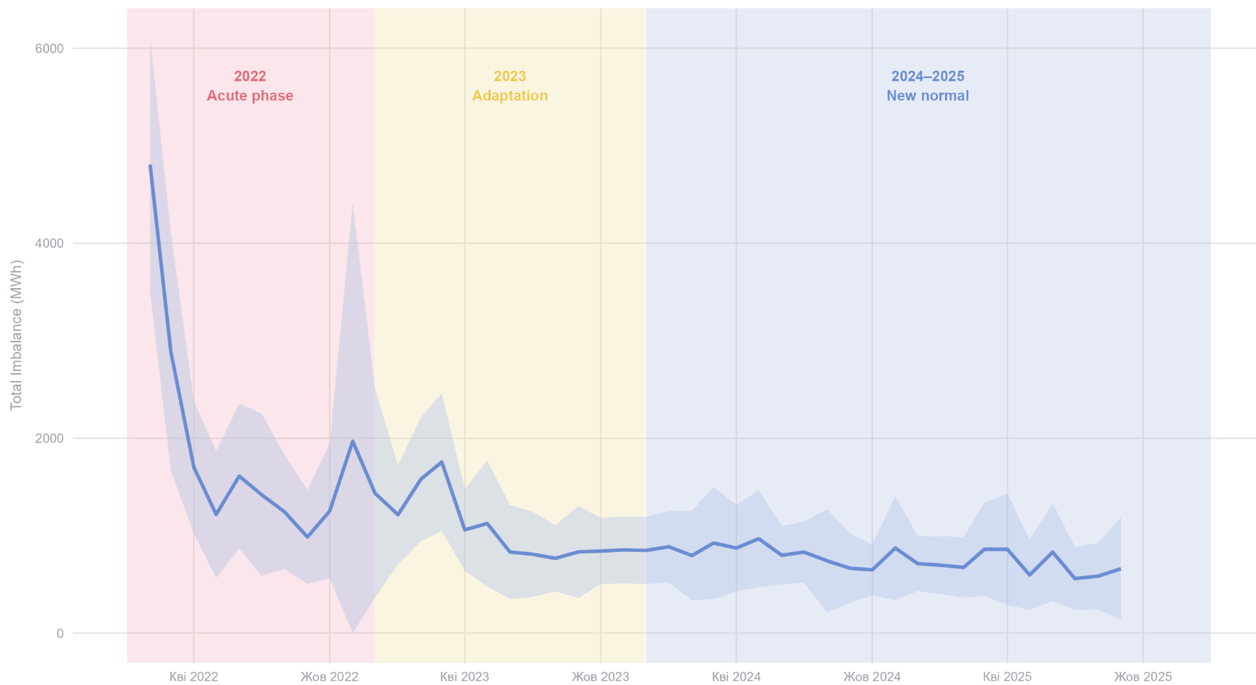

Figure A1. Evolution of Monthly Electricity Imbalances in Ukraine During Wartime Phases (2022–2025); author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

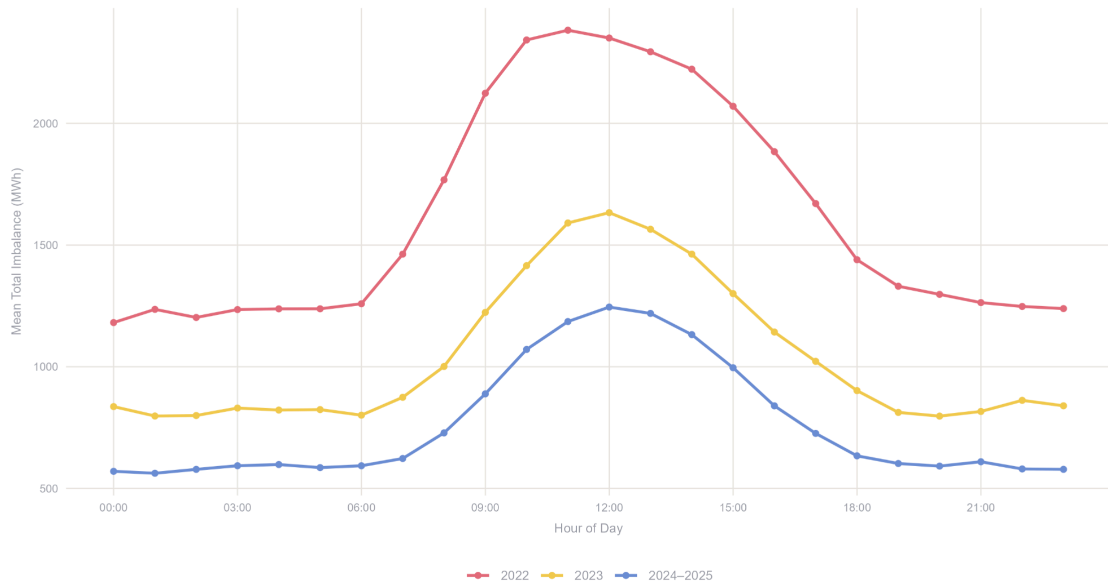

Figure A2. Intraday Patterns of Electricity Imbalances by Wartime Periods (2022, 2023, and 2024–2025); author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

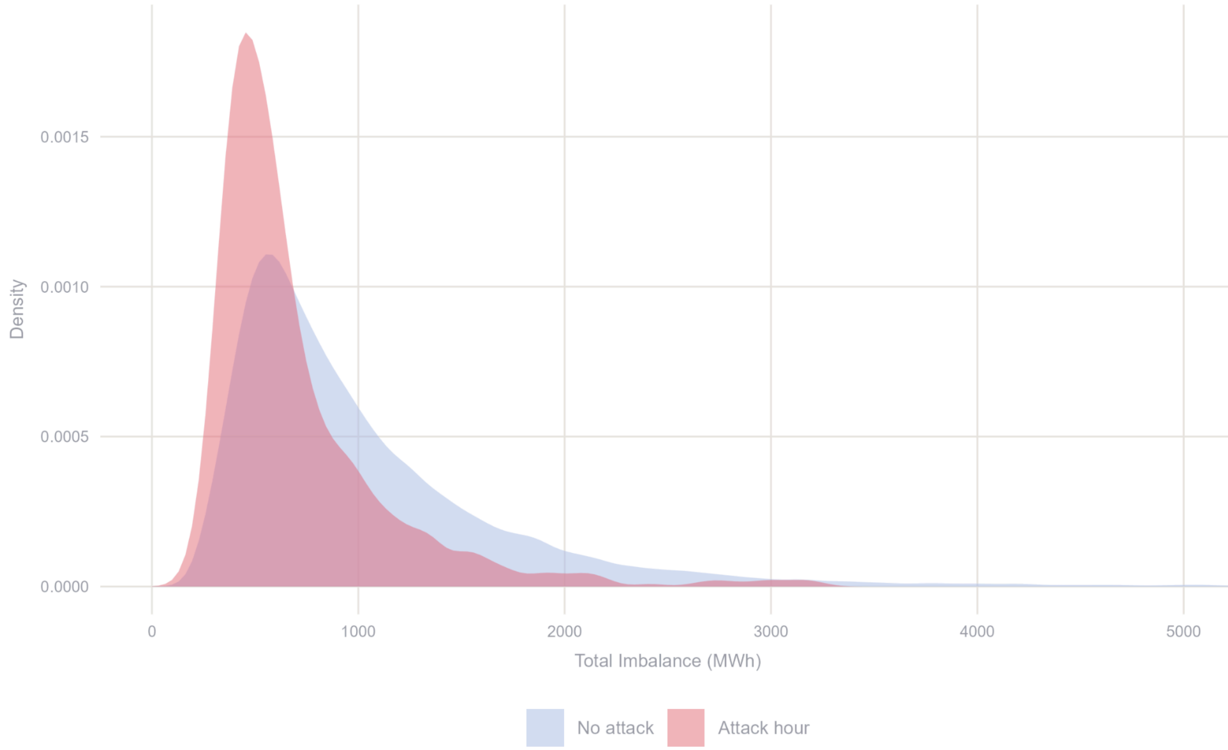

Figure A3. Imbalance Distribution: Attack vs No-Attack; author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

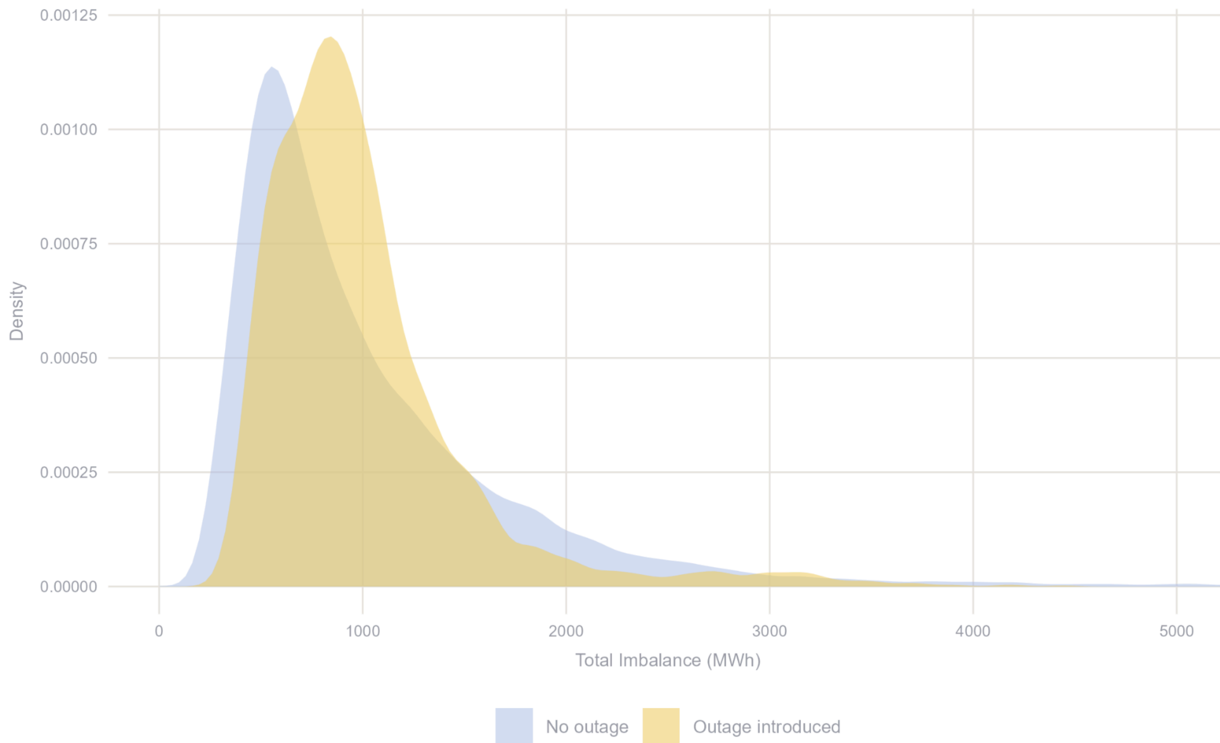

Figure A4. Imbalance Distribution: Outage vs No-Outage; author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

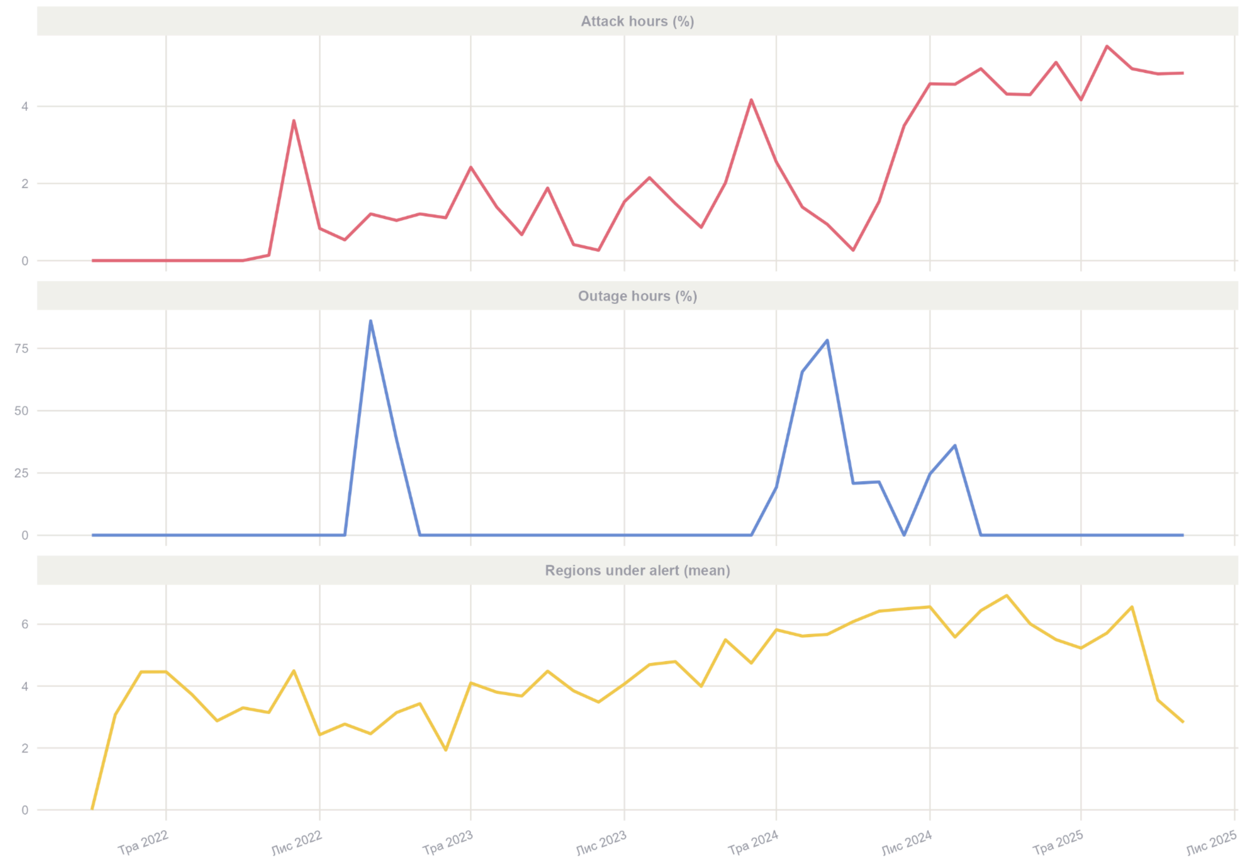

Figure A5. Security Event Intensity Over Time (2022–2025); author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

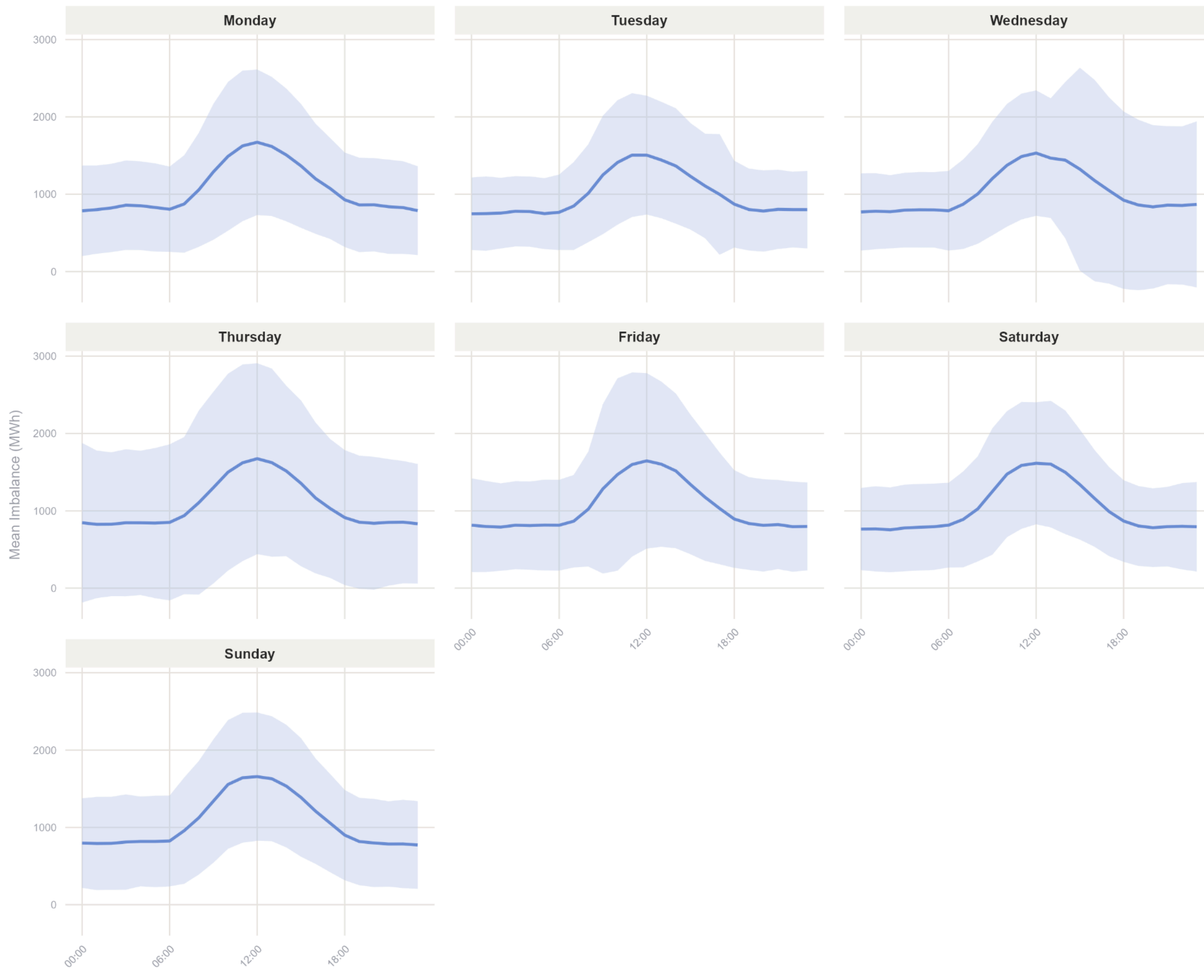

Figure A6. Mean Electricity Imbalance by Hour of Day; author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

APPENDIX B

Table B1. Results for Model 1

Variable	Coefficient	Std_Error	z_value	p_value
ar1	0,839691	0,009786	85,80135	≈ 0
ma1	-0,83535	0,011241	-74,3125	≈ 0
ma2	-0,11252	0,007312	-15,388	≈ 0
ma3	-0,02655	0,007451	-3,56289	0,000367
outages_introduced	-31,311	19,82377	-1,57947	0,114229
outage_lag_1h	22,27849	19,81201	1,124494	0,260803
attack_dummy	-13,4086	7,585673	-1,76763	0,077123
hits_dummy	13,90406	17,0686	0,814599	0,415302
oblasts_under_alert	0,744216	0,301838	2,465613	0,013678
alert_lag_1h	0,522772	0,30195	1,731319	0,083395
hour_factor1	-1,88093	7,019911	-0,26794	0,788744
hour_factor2	-1,70935	10,15774	-0,16828	0,866362
hour_factor3	22,37107	12,26814	1,823509	0,068226
hour_factor4	24,03241	13,77457	1,744694	0,081038
hour_factor5	19,06319	14,90379	1,279083	0,200868
hour_factor6	22,47004	15,77409	1,42449	0,154305
hour_factor7	106,3743	16,44672	6,467812	9,94E-11
hour_factor8	265,1203	16,94613	15,64489	≈ 0
hour_factor9	487,9744	17,28341	28,2337	≈ 0
hour_factor10	681,1548	17,50955	38,90191	≈ 0
hour_factor11	794,3165	17,646	45,01396	≈ 0
hour_factor12	827,5922	17,69092	46,78061	≈ 0
hour_factor13	782,887	17,64725	44,36311	≈ 0

hour_factor14	695,4354	17,51343	39,70869	≈ 0
hour_factor15	548,7409	17,27987	31,75608	≈ 0
hour_factor16	385,1742	16,93486	22,74446	≈ 0
hour_factor17	246,2588	16,45355	14,96691	≈ 0
hour_factor18	114,3696	15,81358	7,232369	4,75E-13
hour_factor19	49,74324	14,98285	3,320013	0,0009
hour_factor20	31,98042	13,86209	2,307042	0,021052
hour_factor21	36,78939	12,33522	2,982467	0,002859
hour_factor22	30,15849	10,19248	2,958897	0,003087
hour_factor23	20,10758	7,026908	2,861513	0,004216
weekday_factor2	-28,9058	15,8831	-1,81991	0,068773
weekday_factor3	-36,611	19,58845	-1,86901	0,061622
weekday_factor4	-34,2053	20,99512	-1,6292	0,10327
weekday_factor5	-32,7435	20,98908	-1,56002	0,118754
weekday_factor6	-49,4486	19,57427	-2,52621	0,01153
weekday_factor7	-25,0237	15,88192	-1,57561	0,115116

Source: author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

Table B2. Results for Model 2

Variable	**Coefficient**	**Std_Error**	**z_value**	**p_value**
ar1	0,839875	0,009782	85,85519	≈ 0
ma1	-0,83574	0,011238	-74,3648	≈ 0
ma2	-0,11217	0,007317	-15,3294	≈ 0
ma3	-0,02659	0,00745	-3,56882	0,000359
outages_introduced	-37,538	20,37264	-1,84257	0,065392

outage_lag_1h	22,10737	19,81214	1,11585	0,264486
attack_dummy	-3,09666	11,0863	-0,27932	0,779997
hits_dummy	9,97078	17,34783	0,574756	0,565456
oblasts_under_alert	0,656198	0,319937	2,051022	0,040265
alert_lag_1h	0,530345	0,302134	1,755332	0,079202
outages_x_alerts	1,222711	0,89913	1,359882	0,173867
attack_x_alerts	-1,40063	1,093669	-1,28067	0,200309
hour_factor1	-1,87834	7,019493	-0,26759	0,789015
hour_factor2	-1,8269	10,15642	-0,17988	0,857249
hour_factor3	22,34756	12,26754	1,821681	0,068503
hour_factor4	23,8547	13,77288	1,732006	0,083273
hour_factor5	18,9645	14,90148	1,272659	0,203139
hour_factor6	22,37006	15,773	1,418251	0,156118
hour_factor7	106,403	16,44664	6,469586	9,83E-11
hour_factor8	265,309	16,94528	15,65681	≈ 0
hour_factor9	488,0477	17,28203	28,24018	≈ 0
hour_factor10	680,8822	17,50685	38,89232	≈ 0
hour_factor11	794,3161	17,64256	45,02273	≈ 0
hour_factor12	827,5691	17,68718	46,7892	≈ 0
hour_factor13	783,0938	17,64228	44,38733	≈ 0
hour_factor14	695,5909	17,50743	39,73118	≈ 0
hour_factor15	548,7179	17,27236	31,76855	≈ 0
hour_factor16	385,2408	16,92647	22,75967	≈ 0
hour_factor17	246,3556	16,44407	14,98143	≈ 0
hour_factor18	114,4259	15,80436	7,240144	4,48E-13
hour_factor19	49,81645	14,97509	3,326622	0,000879
hour_factor20	32,18287	13,85486	2,322857	0,020187

hour_factor21	37,18492	12,32952	3,015926	0,002562
hour_factor22	30,31931	10,18895	2,975705	0,002923
hour_factor23	20,08944	7,026121	2,859251	0,004246
weekday_factor2	-28,6716	15,8866	-1,80477	0,071111
weekday_factor3	-36,4234	19,59223	-1,85907	0,063017
weekday_factor4	-32,8188	20,99607	-1,56309	0,118031
weekday_factor5	-30,6533	20,98802	-1,46052	0,144148
weekday_factor6	-47,1169	19,57259	-2,40729	0,016071
weekday_factor7	-23,5484	15,88273	-1,48264	0,13817

Source: author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.

Table B3. Results for Model 3

Variable	**Coefficient**	**Std_Error**	**z_value**	**p_value**
ar1	1,509217	0,017035	88,59444	≈ 0
ar2	-0,50815	0,01503	-33,8093	≈ 0
ar3	-0,06658	0,006196	-10,7461	≈ 0
ma1	-1,79523	0,01609	-111,576	≈ 0
ma2	0,803034	0,016003	50,18019	≈ 0
drift	-5,4E-05	0,00016	-0,33984	0,733979
outages_introduced	-0,01092	0,018987	-0,57526	0,565115
outage_lag_1h	0,036716	0,018976	1,934857	0,053008
attack_dummy	-0,01532	0,008431	-1,81724	0,069181
hits_dummy	0,016904	0,018954	0,891878	0,372458
oblasts_under_alert	0,000573	0,0003	1,912019	0,055874
alert_lag_1h	0,000203	0,0003	0,677081	0,498354

hour_factor1	-0,00237	0,007025	-0,33719	0,735971
hour_factor2	0,003528	0,009047	0,390014	0,696526
hour_factor3	0,014993	0,010455	1,434162	0,151526
hour_factor4	0,0341	0,011449	2,978493	0,002897
hour_factor5	0,019973	0,012167	1,641603	0,100672
hour_factor6	0,026433	0,012694	2,082293	0,037316
hour_factor7	0,123475	0,013075	9,443628	≈ 0
hour_factor8	0,288334	0,013332	21,62775	≈ 0
hour_factor9	0,478503	0,013473	35,51483	≈ 0
hour_factor10	0,633943	0,013556	46,76531	≈ 0
hour_factor11	0,723341	0,013606	53,16531	≈ 0
hour_factor12	0,75518	0,013621	55,44223	≈ 0
hour_factor13	0,72928	0,013606	53,59985	≈ 0
hour_factor14	0,663469	0,013558	48,93417	≈ 0
hour_factor15	0,547782	0,013464	40,68498	≈ 0
hour_factor16	0,412749	0,013311	31,00785	≈ 0
hour_factor17	0,285095	0,013071	21,81185	≈ 0
hour_factor18	0,148747	0,012722	11,69195	≈ 0
hour_factor19	0,072116	0,012239	5,892199	3,81E-09
hour_factor20	0,044352	0,011528	3,847476	0,000119
hour_factor21	0,058131	0,010511	5,530465	3,19E-08
hour_factor22	0,047278	0,009074	5,210292	1,89E-07
hour_factor23	0,023616	0,007029	3,359925	0,00078
weekday_factor2	-0,03182	0,012088	-2,63255	0,008475
weekday_factor3	-0,0379	0,013962	-2,71445	0,006639
weekday_factor4	-0,03521	0,014751	-2,38687	0,016993
weekday_factor5	-0,0286	0,014743	-1,94002	0,052377

weekday_factor6	-0,03392	0,013942	-2,43259	0,014991
weekday_factor7	-0,00997	0,012104	-0,82403	0,409924

Source: author's calculations based on a merged dataset compiled from Ukrainian electricity imbalance data, air raid alert records, missile attack data, and electricity outage information.