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Predicting Electricity Consumption Using Time Series Algorithms and Utilizing Energy Storage:

Mitigating Negative Price Impacts to Encourage New Investments in the Finnish Electricity Market

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ABSTRACT:

The Finnish electricity market is undergoing a significant transformation with the increasing integration of renewable energy sources such as wind and solar. While these developments align with global decarbonization goals, they have introduced challenges like price volatility and negative pricing, deterring investments in grid infrastructure and renewable energy projects. This thesis explores a dual approach to address these issues by combining advanced time series forecasting models with battery energy storage systems (BESS).

Three forecasting models—ARIMA, Support Vector Machines (SVM), and Long Short-Term Memory (LSTM)—are employed to predict electricity consumption with high accuracy, leveraging hourly consumption data segmented by seasons. The results demonstrate that the machine learning model, particularly LSTM, outperforms ARIMA in capturing nonlinear and temporal patterns, achieving average accuracy of 99.93%. These forecasts provide critical insights for grid operators to balance supply and demand effectively.

Additionally, the study investigates the role of BESS in stabilizing the Finnish electricity market. BESS mitigates price volatility by storing excess electricity during low-demand periods and discharging it during peak demand, reducing financial losses from negative prices and enhancing renewable energy integration. The economic feasibility, environmental benefits, and regulatory landscape for BESS deployment in Finland are analyzed, emphasizing their potential to support a sustainable and resilient energy market.

This research contributes to the field of smart grid analytics by demonstrating how advanced forecasting models and energy storage solutions can address the unique challenges of renewable energy integration. The findings have implications for policymakers, grid operators, and investors, offering a pathway to stabilize the Finnish electricity market and foster investments in renewable energy, aligning with Finland's broader climate and energy goals.

KEYWORDS: Time series forecasting, Negative prices, Renewable energy, Energy storage, ARIMA, SVM, LSTM, BESS, Grid management.

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Abbreviations

Abbreviation	Definition
AI	Artificial Intelligence
ACF	Auto-Correlation Function
ADF	Augmented Dickey-Fuller Test
AR	Auto-Regression
ARIMA	AutoRegressive Integrated Moving Average
BESS	Battery Energy Storage System
CV	Cross Validation
DER	Distributed Energy Resources
DSOs	Distribution System Operators
DSM	Demand-Side Management
EMS	Energy Management System
ESS	Energy Storage System
EV	Electric Vehicle
EPR	Extended Producer Responsibility
FCR	Frequency Containment Reserves
FCR-D	Containment Reserve for Disturbances

FCR-N	Frequency Containment Reserve for Normal Operations
FFR	Fast Frequency Reserves
GW	Gigawatt
GWh	Gigawatt-hour
IoT	Internet of Things
LCOS	Levelized Cost of Storage
LSTM	Long Short-Term Memory
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MG	Microgrid
MG-EMS	Microgrid Energy Management System
MWh	Megawatt-hour
PACF	Partial Auto-Correlation Function
RBF	Radial Basis Function
RED	Renewable Energy Directive
RES	Renewable Energy Sources
RMSE	Root Mean Squared Error
RNNs	Recurrent Neural Networks
SOC	State of Charge
SVM	Support Vector Machines
SVR	Support Vector Regression
TSOs	Transmission System Operators
V2G	Vehicle-to-Grid
VRES	Variable Renewable Energy Sources

1 Introduction

The Finnish electricity market has evolved rapidly, especially with the increased integration of renewable energy sources like wind, solar, and nuclear power. In 2023, Finland installed an additional 1.6 GW of nuclear capacity with Olkiluoto 3, bringing its total nuclear generation to 4.37 GW. Furthermore, wind and solar power installations reached 6.94 GW and 1 GW, respectively, by the end of the year (Priyanka Shinde, 2024). While these additions have supported Finland's renewable energy portfolio, they have also introduced new market challenges. The biggest challenge among them is the increase in price volatility, including frequent instances of negative pricing. This negative pricing is driven by excess electricity supply, low demand, and a lack of flexibility within the energy grid (Behabtu et al., 2020).

1.1 Background of the study

Renewable energy has significant impacts on electricity consumption forecasting in several ways due to its intermittent and variable nature. Some of these impacts are as follows:

1. Increased variability in supply as wind and solar energy are weather-dependent, making their production fluctuate throughout the day and year (Rana et al., 2023). This variability adds complexity to consumption forecasting because the availability of renewable energy changes, affecting overall grid supply. As a result, electricity consumption patterns may shift, especially when renewable energy sources either reduce the need for traditional energy generation or create periods of surplus supply.
2. Integration challenges as renewable energy integration adds uncertainty to the grid. For example, sudden changes in wind or sunshine can lead to unexpected dips or surges in power generation, forcing grid operators to adjust demand-supply balance quickly. Therefore, forecasters need to account for these fluctuations and develop models that can adapt to sudden changes in supply in order to accurately predict consumption and demand (Kumar Dubey et al., 2021).

3. Demand-side flexibility as the variability of renewable energy might encourage more flexible consumption behaviors. For example, when renewable energy is abundant, industries or consumers might adjust their consumption to take advantage of lower costs. Accurate forecasting needs to account for these shifts in consumer behavior and how they may change based on renewable energy availability (Kalteh, 2016).
4. Increased demand for short-term forecasting as renewable energy's intermittency creates a need for short-term and real-time consumption forecasts. Unlike traditional energy sources, which are more predictable, renewable energy requires more frequent updates to forecasts to ensure grid stability and efficient market operations. This intermittency adds complexity to the forecasting models, as they need to handle shorter time frames with higher accuracy.
5. Impact on energy storage systems as renewables become more dominant. Batteries and other energy storage systems are used to smooth out supply (Khajeh et al., 2023). Forecasting needs to factor in when and how these storage systems will be called upon to meet demand when renewable energy generation dips or store excess energy supply when renewable energy generation increases.

In essence, renewable energy makes consumption forecasting more complex due to its intermittent and variable nature. Accurate models must adapt to fluctuations in supply, changes in consumer behavior, and market pricing effects caused by renewable energy generation.

Negative prices, occurring when supply significantly surpasses demand, have become the main theme of the Finnish electricity market. In 2023, Finland recorded 467 hours of negative prices, the highest in Europe, which signifies a substantial financial loss for electricity producers who are forced to pay consumers to absorb excess generation (Priyanka Shinde, 2024). This pattern continued in 2024, with Finland experiencing 169 negative price hours by May, surpassing neighboring countries. Specific events, such as

November 24, 2023, when prices plummeted to -500 EUR/MWh due to a supply miscalculation, underscore the severity of this issue. The resultant financial instability poses challenges not only for electricity producers but also for potential investors, who may view the Finnish electricity market as unpredictable and financially risky (Barteková & Ziesemer, 2019).

1.2 Research gap, question and objectives

The transition toward renewable energy sources (RES) has transformed the global energy landscape, including Finland's electricity market. This shift has introduced challenges, such as, negative electricity prices, driven by supply-demand imbalances during periods of high renewable generation (Lieskoski et al., 2024). Negative prices do not only hinder profitability but also discourage investments in new capacity (Entezari & Fuinhas, 2024). Addressing these issues requires innovative solutions, including advanced Battery Energy Storage Systems (BESS) and accurate forecasting methods to stabilize the market and incentivize new investments (Ramos et al., 2021).

Achieving a stable balance between supply and demand, therefore, is essential to mitigating financial losses and ensuring that the Finnish energy market remains attractive to investors. Time series forecasting algorithms offer a viable solution by providing accurate electricity consumption predictions that can help grid operators anticipate fluctuations and adjust supply more effectively.

Traditional methods like Autoregressive Integrated Moving Average (ARIMA) have long been utilized for time series forecasting due to their capacity to model linear trends and seasonality effectively (Linardatos et al., 2023). For example, ARIMA has been applied to analyze electricity price volatility in European markets and assess renewable energy's impact on power systems (Entezari & Fuinhas, 2024). ARIMA decomposes time series data into trend, seasonality, and noise components, which allows it to make accurate short-term predictions based on historical patterns (Petropoulos et al., 2022).

However, ARIMA's reliance on stationary data limits its performance in dynamic systems characterized by nonlinear fluctuations and abrupt changes, as observed in renewable-dominant grids (Fan et al., 2021).

To address these limitations, machine learning approaches, such as, Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks have gained prominence. SVM excels in capturing nonlinear dependencies in time series data, making it effective for environmental data prediction and streamflow forecasting (Camastra et al., 2022).

On the other hand, LSTM networks, designed for sequential data, have demonstrated exceptional performance in learning long-term dependencies and complex temporal patterns, particularly, in renewable energy applications (Reddy & Prasad, 2018).

However, accurate consumption forecasting alone may not be sufficient to address the structural issues driving negative prices. The Finnish energy market suffers from a lack of flexibility, especially, in handling surplus electricity. Nuclear power plants, for example, face ramping limitations and must often operate at a steady output, even when demand falls. Additionally, interconnector availability impacts Finland’s ability to export excess electricity to neighboring countries, which further contributes to supply abundance and negative prices (Priyanka Shinde, 2024). Introducing energy storage solutions, such as, battery systems, can help alleviate these issues by storing excess generation during low-demand periods and releasing it when demand rises. This flexible storage capability can absorb supply shocks and reduce reliance on costly corrective measures, making the market more resilient to volatility (Zhu et al., 2015).

Battery energy storage systems have emerged as essential technologies in renewable-dominant energy markets, offering the ability to store excess electricity during periods of low demand and release it when needed, thus mitigating price volatility and enhan-

cing grid stability (Parthasarathy et al., 2021). In Finland, BESS have shown their potential to improve market reliability and support renewable energy integration, particularly, when combined with hybrid systems, such as, hydrogen storage or Vehicle-to-Grid (V2G) systems (Chamout et al., 2024). For instance, studies on hybrid hydrogen-battery systems in off-grid applications have demonstrated their effectiveness in managing seasonal energy variations, while V2G systems provide flexibility by utilizing electric vehicles as distributed storage resources (W. Lee et al., 2024).
Despite the advantages of BESS, their deployment requires sophisticated optimization strategies, often relying on time series forecasting. Accurate forecasts of electricity consumption, generation, and price dynamics are critical for optimizing storage operations and mitigating the economic impacts of negative prices (Pereira & Saraiva, 2012).

1.3 Definitions and scope of the study

Renewable energy refers to energy derived from natural sources, such as solar energy, wind, hydropower, geothermal heat, and biomass.
Unlike fossil fuels, renewable energy sources produce little to no greenhouse gas emissions and contribute to sustainable energy production.

Negative prices occur during surplus supply, such as, during times of high renewable energy output (e.g., strong winds or sunny days). Also, negative prices could occur during low-demand times. When negative prices occur producers must pay to offload excess electricity. Forecasting models must consider how these periods of surplus supply might lead to decreased or shifted consumption patterns, as consumers may adjust to take advantage of low or negative prices (Hirvonen et al., 2020).

Time series forecasting is a statistical and machine learning technique used to predict future values based on historical data (Schmid et al., 2025).
In electricity consumption prediction, time series forecasting involves analyzing historical electricity usage patterns and identifying trends, seasonality, and fluctuations to make accurate future demand predictions.

Auto-regressive integrated moving average (ARIMA) is a statistical time series forecasting model that predicts future values based on past observations by capturing trends, seasonality, and dependencies in the data (Pierre et al., 2023).
In electricity consumption prediction, ARIMA is used to model historical electricity demand patterns and generate accurate short- to medium-term forecasts.

SVMs, a machine learning technique, use kernel functions to identify the optimal hyperplane that separates data points, making them adept at capturing non-linear relationships and forecasting with higher precision in diverse conditions (Amjady & Keynia, 2009).

LSTM networks, a type of recurrent neural networks (RNNs), are particularly well-suited to time series forecasting because they can overcome the problem of vanishing gradients faced by traditional RNNs, making them capable of modeling complex patterns in electricity demand and adjusting for factors like seasonal variations and sudden demand shifts (Rahman et al., 2023). Their ability to handle noisy, multivariate inputs makes LSTM well-suited for scenarios involving variable renewable generation and electricity consumption.

Given these advantages, SVMs and LSTM networks can significantly improve the accuracy of consumption forecasts, providing a more nuanced approach to grid management and mitigating price volatility in Finland.

Energy storage refers to the process of capturing and storing electrical energy for later use, allowing for better grid stability, efficiency, and energy management.
When it comes to electricity consumption, energy storage systems help balance supply and demand by storing excess electricity during periods of low demand and releasing it when demand is high.

A battery energy storage system (BESS) is a technology that stores electrical energy in rechargeable batteries and releases it when needed. With relation to electricity consumption, BESS helps stabilize the grid, optimize energy use, and enhance the efficiency of renewable energy sources.

Grid management refers to the process of monitoring, controlling, and optimizing the flow of electricity within a power grid to ensure a stable, reliable, and efficient supply. Grid management involves balancing generation, transmission, and distribution to meet fluctuating demand while maintaining system stability.

By combining time series forecasting with battery storage solutions, this research aims to create a holistic approach to mitigating negative prices in the Finnish electricity market. Accurate predictions of electricity consumption can allow grid operators to manage supply more effectively, while storage solutions provide the necessary flexibility to respond to demand fluctuations in real-time (Belabbas et al., 2019). The integration of these technologies has the potential to stabilize market dynamics, reducing financial losses for producers and fostering a more favorable investment climate in the renewable energy capacity.

This study will focus on implementing and evaluating time series algorithms—ARIMA, SVM, and LSTM—for electricity consumption forecasting in Finland, addressing the unique challenges posed by the country’s renewable energy integration. Additionally, the research will explore how battery storage solutions can complement predictive modeling, creating a robust framework for managing supply-demand imbalances and encouraging new investments in the Finnish renewable energy sector (Parthasarathy et al., 2021).

In addition to technical advancements, policy and market strategies play a crucial role in encouraging BESS adoption and renewable energy investment (Kök et al., 2018). Regulatory frameworks in Finland, which emphasize market-based solutions, have a direct impact on electricity pricing and energy storage deployment. Policies addressing price volatility, investment incentives, and grid connectivity are essential for fostering a stable and sustainable energy market (Brahmendra Kumar et al., 2024).

This study will contribute to the field of smart grid analytics by providing a deeper understanding of the role of advanced forecasting and battery energy storage solutions in stabilizing the Finnish electricity market. By demonstrating how accurate predictions and increased flexibility can prevent financial losses during surplus periods, this research aims to enhance the stability and sustainability of the Finnish electricity market and encourage investors to invest more money in new reneweable energy production projects, aligning with broader goals of decarbonization and energy security.

1.4 Structure of the study

This thesis is structured into five main chapters, each addressing a key aspect of the research. Chapter one (Introduction) provides an overview of the Finnish electricity market, the challenges posed by negative pricing, and the research objectives. Chapter two (Literature review) provides a comprehensive background on the topic, helping readers understand the current state of research in electricity consumption prediction, time series algorithms, and energy storage. Chapter three (Methodology) outlines the dual research approach, detailing the process of electricity consumption prediction using time series models (ARIMA, SVM, and LSTM) and the qualitative analysis of Battery Energy Storage Systems (BESS). Chapter four (Results) presents the implementation of the forecasting models, their evaluation metrics, and comparative performance. Also, chapter four explores the economic feasibility, environmental impact, regulatory incentives, and operational benefits of battery energy storage systems in Finland. Finally, Chapter five (Summary and conclusions) synthesizes the findings, discusses the implications of improved forecasting and BESS adoption, and provides recommendations for future research and energy market policies. The structured approach ensures a comprehensive analysis, integrating both technical and policy perspectives to address the challenges of negative electricity prices and investment uncertainty in Finland's renewable energy sector.

2 Literature review

Electricity consumption forecasting is essential for ensuring grid stability, optimizing energy distribution, and integrating renewable energy sources. Accurate forecasting enables effective energy planning, reducing operational costs and enhancing supply-demand balance (Makridakis et al., 2018). However, challenges such as negative electricity prices, renewable energy intermittency, and energy storage optimization require advanced forecasting techniques and integration with grid management strategies (Mathis et al., 2019). Electricity consumption forecasting needs to be integrated with energy storage systems such as battery energy storage systems for comprehensive grid management as energy storage can capture and store energy for later use, ensuring a stable and reliable power supply.

This chapter reviews the existing literature on time series forecasting, negative prices, renewable energy, energy storage, ARIMA, SVM, LSTM, battery energy storage systems, and grid management.

2.1 Time series forecasting in electricity markets

Time series forecasting refers to predicting future values based on historical data trends. In electricity markets, it plays a crucial role in balancing supply and demand, enabling utilities to optimize generation schedules and market strategies (Hyndman & Athanasopoulos, 2019). Accurate demand forecasting also supports real-time grid operation and price stability, especially in deregulated electricity markets where price volatility can be significant (Weron, 2014).

2.1.1 Traditional time series forecasting models

Statistical methods such as AutoRegressive Integrated Moving Average (ARIMA) has been extensively used for electricity demand forecasting. Box and Jenkins (1970) introduced ARIMA as a powerful model for handling stationary time series data. The ARIMA model provides robust short-term predictions by capturing seasonal and trend components (Taylor, 2003). However, the model struggles with non-linearity and sudden demand fluctuations caused by external shocks, making it less effective for forecasting under renewable energy penetration (Hyndman et al., 2002).

2.1.2 Advanced forecasting models

Machine learning and deep learning techniques have emerged as superior alternatives for electricity demand forecasting. Support Vector Machines (SVM) leverage pattern recognition capabilities to detect complex relationships in electricity demand data, outperforming ARIMA for medium-term forecasts (G. Zhang et al., 1998). Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, capture long-range dependencies in electricity demand, improving forecasting accuracy in volatile energy markets (Hochreiter & Schmidhuber, 1997). Hybrid models that integrate ARIMA with LSTM or XGBoost have been shown to enhance predictive performance by combining statistical and deep learning features (T. Zhang et al., 2022).

Despite advances in forecasting techniques, studies on hybrid forecasting models often lack real-world validation in operational energy markets. Additionally, few studies focus on the role of predictive modeling in electricity consumption forecasting, particularly in relation to negative price events and renewable energy fluctuations (Makridakis et al., 2018). Addressing these gaps is essential for improving forecasting accuracy and market efficiency.

2.2 Negative prices in electricity markets

Negative electricity prices occur when supply exceeds demand, often due to high renewable energy generation and market constraints (Kou et al., 2013). These events are becoming more frequent in the Finnish electricity market with substantial wind and some solar capacity.

2.2.1 **Predictive models for negative prices**

Machine learning models, including SVM and LSTM have been applied to predict negative price events with increasing accuracy (T. Zhang et al., 2022). ARIMA models remain useful for short-term predictions but struggle with extreme price fluctuations (Weron, 2014).

There are Limited studies on forecasting electricity consumption and its impact on negative electricity prices. Also, few models integrate storage strategies and grid flexibility into negative price mitigation frameworks.

2.3 Grid management

Grid management refers to the real-time monitoring, optimization, and control of electricity distribution and consumption to maintain power balance, stability, and efficiency in the energy network (Hashmi et al., 2021).

Vehicle-to-grid (V2G) integration plays a critical role in grid management by leveraging the charging and discharging capabilities of grid-connected electric vehicles (GEVs) to provide multi-time scale power balancing and peak-shaving services (Li et al., 2021).

By scheduling charging/discharging of V2G based on grid load variations, which can be predicted using time series algorithms, the energy system may reduce frequency fluctuations and prevents voltage instability.

Since renewable energy sources (e.g., solar, wind) are intermittent, V2G enables flexible grid management by storing excess renewable power and injecting it into the grid when needed.

2.4 Energy storage and grid management

Energy storage refers to the process of capturing and storing energy for later use, ensuring a stable and reliable power supply. Energy storage systems (ESS) are essential for stabilizing power grids, improving energy efficiency, and integrating intermittent renewable energy sources. Electrochemical energy storage systems (e.g., batteries and

supercapacitors) play a pivotal role in modern energy infrastructure, especially in smart grids and demand-side energy management (Mathis et al., 2019).
Electrochemical storage, such as batteries (e.g., lithium-ion, flow batteries), supercapacitors, and hybrid systems store energy via chemical reactions.

Energy storage plays a critical role in grid management by enhancing power quality, peak load balancing, and renewable energy integration. Energy storage contributes to grid management as it helps mitigate demand fluctuations by storing excess energy during low-demand periods and discharging during peak demand. Also, ESS enable real-time demand-side management (DSM), optimizing electricity consumption (Trahey et al., 2020).

Energy storage helps integrate renewable energy as it addresses the variability of renewable sources (e.g., solar and wind) by storing surplus energy and releasing it when needed. This enhances grid reliability by preventing power shortages during low-generation periods.

Batteries and supercapacitors help stabilize grid frequency by injecting or absorbing power in response to grid fluctuations. Also, batteries and supercapacitors reduce voltage instability, preventing blackouts and equipment failures (Chao et al., 2019).

Energy storage facilitates the transition towards distributed energy resources (DERs) and microgrid operations. Also, ESS enhance grid resilience by enabling independent energy storage at the local level.

2.5 Battery energy storage systems and grid management

Battery Energy Storage Systems (BESS) are electrochemical energy storage solutions that store electricity for later use, playing a crucial role in stabilizing power supply, supporting renewable energy integration, and ensuring efficient energy management.
BESS in microgrids are essential for load curve smoothing, power reserve support, and

optimal energy dispatch. BESS plays a pivotal role in grid management, particularly in microgrid energy management (MGEM), where it is used to optimize energy dispatch in both grid-connected and standalone microgrids (Murty & Kumar, 2020).
BESS can store surplus energy from renewable sources like solar and wind. Also, BESS can supply power instantaneously during peak demand or outages. Furthermore, BESS can balance supply and demand in real-time for enhanced grid stability (Bui et al., 2020). Moreover, BESS improve energy efficiency and reduce greenhouse gas emissions by minimizing reliance on fossil-fuel generators.

2.6 The theoretical framework of this study

This study connects electricity consumption forecasting, electricity negative prices controlling, battery energy storage systems deployment, and grid management within a unified theoretical framework. The interaction between these elements is shown in Figure 1.

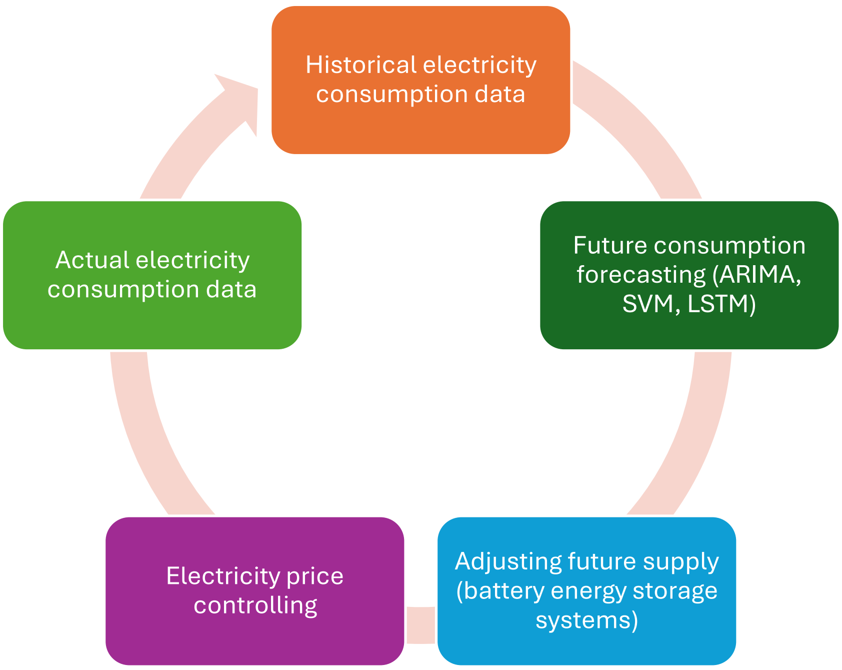

Figure. 1 Theoretical framework for electricity consumption forecasting, electricity negative prices controlling, BESS deployment, and grid management

3 Methodology

This study consists of a hybrid research methodology which consists of a quantitative research approach to predict electricity consumption and a qualitative research approach to evaluate the potential of batteries as an energy storage system in the Finnish energy market.

Another qualitative approach was used through interviews to gain deeper insights into the practical applicability of advanced forecasting models and battery energy storage systems (BESS) in real-world grid operations and strategic energy planning in the Finnish energy market.

3.1 Predicting electricity consumption future values

Accurate forecasting of electricity consumption is crucial for maintaining grid stability, optimizing energy resources, and mitigating financial risks associated with demand-supply imbalances.

3.1.1 Data collection and sources

This study utilizes the electricity consumption data obtained from the Fingrid website. The dataset consists of quarter-hourly electricity consumption records collected over a one-year period, spanning from December 2023 to December 2024.

Due to seasonal variations in electricity demand, the data has been segmented into three distinct seasons: winter, spring, and autumn.

3.1.2 Data processing

Electricity consumption patterns exhibit strong seasonal variations due to changes in temperature, daylight hours, and energy demand fluctuations. To enhance prediction accuracy, the dataset is segmented into three seasons, as shown in Table 1.

Table 1 Seasonal segmentation of electricity consumption data

Season	Time period	Validation data
Winter	Dec 2023 – Mar 2024	May 2024
Spring	Apr 2024 – Jul 2024	September 2024
Autumn	Aug 2024 – Nov 2024	December 2024

Electricity consumption data may contain missing values due to sensor malfunctions, data transmission errors, or incomplete records. Handling the missing values is crucial to ensure the accuracy and reliability of predictive models.

In this study, missing values are computed using the following approaches:

Linear interpolation which is used when the missing values are scattered and not consecutive, a linear interpolation method is applied to estimate values based on surrounding data points, ensuring smooth transitions in the dataset.

Mean **i**mputation which is used when a large gap exists in the data, the missing values are replaced with the mean electricity consumption of the respective season to maintain consistency.

The raw electricity consumption dataset consists of quarter-hourly observations. To align the dataset with the time resolution required for the forecasting models, the data is aggregated into hourly intervals by calculating the average consumption within each hour using the following formula:

$$X_h = \frac{X_t + X_{t+1} + X_{t+2} + X_{t+3}}{4} \tag{1}$$

Where X_h represents the average electricity consumption for a given hour and X_t, X_{t+1}, X_{t+2}, X_{t+3} are the four quarter-hourly consumption values in that hour.

To ensure that the electricity consumption data is suitable for SVM and LSTM, a normalization process is implemented. This process standardizes the data by bringing all values into a consistent scale, preventing large numerical values from dominating smaller ones in the predictive models. Normalization is particularly important for SVM and LSTM as it enhances stability and convergence during training.

The Min-Max normalization method is applied, which rescales the data to a range between 0 and 1 using the following formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

where X' is the normalized value, X is the original electricity consumption value, X_{min} is the minimum electricity consumption in the dataset, and X_{max} is the maximum electricity consumption in the dataset.

3.1.3 Feature selection for SVM and LSTM

The features include historical electricity consumption figures of the first 24 hours which serve as regressors (X_s) over each 4-month period of the season under analysis. The 24 hours data points are updated after every single prediction of the next hour by moving forward to include the next data point and drop the first data point from the 24 hours. This process is implemented continuously until the last data point of the season under analysis.

3.1.4 Modeling approach

Seasonal prediction models were built by splitting each season data into 80% for training and 20% for testing. Then, the models were cross validated using data over one-month period from a different season.

80% of the Winter data from December 2023 to March 2024 was used to train the model. Then, the model was tested to predict the hourly electricity consumption of the test data of that season. After that, the model was cross validated by predicting the hourly electricity consumption of the cross-validation data from May 2024.

The same approach was used for the Spring data from April 2024 to July 2024 and the Autumn data from August 2024 to November 2024.

After that, the two models were cross validated by predicting the hourly electricity consumption of September 2024 and December 2024, respectively.

3.1.5 Evaluation metrics

Root mean squared error (RMSE), r-squared, and mean absolute error (MAE) are used to evaluate prediction accuracy, as these metrics provide insights into the average deviation and overall fit of the predictions to actual consumption. Mean absolute percentage error (MAPE) is calculated for each model to evaluate the overall accuracy of it within each season and each cross-validation month (N. U. Lee et al., 2018).
R-squared measures the proportion of variance in the dependent variable that is predictable from the independent variables. It is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

where y_i is the actual value of the target variable for the i^{th} observation, $\hat{y}_i$ is the predicted value for the i^{th} observation, $\bar{y}$ is the mean of the actual values, and n is the number of observations.

Mean absolute error (MAE)
MAE measures the average magnitude of the errors in a set of predictions, without considering their direction (i.e., the difference between predicted and actual values). It is calculated as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

Where y_i is the actual value for the i^{th} observation, $\hat{y}_i$ is the predicted value for the i^{th} observation, and n is the total number of observations.

Mean absolute percentage error (MAPE)
MAPE expresses the error as a percentage of the actual values. It is used to measure the accuracy of the predictions in terms of relative error. MAPE formula is as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{5}$$

Where y_i is the actual value for the i^{th} observation, $\hat{y}_i$ is the predicted value for the i^{th} observation, and n is the number of observations.

Root mean squared error (RMSE)
RMSE is the square root of the average of the squared differences between the actual and predicted values. It penalizes large errors more heavily than MAE:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

Where y_i is the actual value for the i^{th} observation, $\hat{y}_i$ is the predicted value for the i^{th} observation, and n is the number of observations.

3.1.6 Model selection

Time series model (ARIMA) and machine learning models (LSTM, SVM) are selected based on their suitability for handling seasonal trends and periodic data patterns. These models are fine tuned to be seasonal-specific models to be able to capture within-season patterns.

3.1.7 Auto-regressive integrated moving average (ARIMA)

ARIMA is the basic model for time series forecasting that is particularly effective for short-term predictions in stationary time series data. In this study, the model uses consumption values of the last two hours to predict the next hour.

The model combines three components: Auto-Regression (AR), Integration (I), and Moving Average (MA). The model is typically used when data show temporal dependencies and autocorrelations (Kontopoulou et al., 2023). ARIMA components are as follows:

1. Auto-Regressive (AR). This component models the variable as a linear combination of its past values (lags).
2. Integrated (I). Integration is used to make a non-stationary time series stationary by differencing, i.e., calculating changes between consecutive observations.
3. Moving Average (MA). This component models the variable as a linear combination of past forecast errors, accounting for fluctuations due to noise.

An ARIMA model is represented as ARIMA (p, d, q), where p is the number of lag terms in the AR part, d is the number of times the data have been differenced to achieve stationarity, and q is the number of lag terms in the MA part.
The mathematical formulation of ARIMA (p, d, q) combines the AR, I, and MA components.

1. Auto-regressive (AR) component (AR(p)). The component models a variable as a function of its past values:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t \tag{7}$$

where y_t is the value at time t, c is a constant, ϕ_1, ϕ_2, …, ϕ_p are coefficients for each lag, and ϵ_t is the error term at time t.
2. Integrated (I) component. Differencing is applied to make a series stationary. If d=1, the first difference of y is used:

$$y'_t = y_t - y_{t-1} \tag{8}$$

For higher values of d, the differencing process is repeated until stationarity is achieved.
3. Moving average (MA) component (MA(q)). The component accounts for dependencies between a time series observation and past error terms. The component models the current value as a function of past forecast errors:

$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \tag{9}$$

where μ is the mean of the series, ϵ_t is the error term at time t, and θ_1, θ_2, …, θ_q are the coefficients for each lagged error.

4. Combined ARIMA model. When these components are combined, an ARIMA (p, d, q) model is generally written as:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} \tag{10}$$

where y'_t represents the differenced series after d applications of differencing.

The workflow of ARIMA

The model follows a structured workflow to analyze time series data to ensure stationarity, determine optimal parameters, and generate accurate forecasts. The process involves data differencing, model identification, parameter selection, model fitting, diagnostic checking, and forecasting to effectively capture trends and seasonal patterns in electricity consumption data.

1. Data differencing is applied to determine d by differencing the data to make it stationary, confirmed with the Augmented Dickey-Fuller (ADF) test. The ADF test is used to determine whether a time series is stationary, which is necessary for ARIMA modeling. Stationarity means that the statistical properties of the series (mean, variance) do not change over time. The ADF test is a modified version of the Dickey-Fuller test that includes lagged terms to account for higher-order autocorrelation.

The ADF test is based on estimating the following regression equation:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \cdots + \delta_p \Delta y_{t-p} + \epsilon_t \tag{11}$$

where $\Delta y_t = y_t - y_{t-1}$ is the first difference of the series y_t, α is a constant (drift term), β_t is a deterministic trend term, γ is the coefficient of y_{t-1} (key parameter), δ_i are the coefficients of lagged differences, and p is the number of lagged difference terms.
The ADF test checks the null hypothesis that $\gamma = 0$, which suggests that the series has a unit root (i.e., is non-stationary). If $\gamma < 0$ and significantly different from zero, the series is likely stationary. However, if $\gamma = 0$, the series has a unit root and is non-stationary. The test statistic for the ADF test is computed, and it is compared to critical values. If the test statistic is less than the critical value, the null hypothesis is rejected, indicating that the series is stationary.

2. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots will be used to estimate p and q. Peaks in the ACF suggest the order of MA terms, while peaks in the PACF suggest AR terms (James & Tripathi, 2021).

3. The Autocorrelation Function (ACF) measures the correlation between observations in a time series separated by different lags. It quantifies the degree of similarity between the time series and a lagged version of itself, helping identify patterns like seasonality or autocorrelation.

For a given lag k, the autocorrelation ρ_k is defined as:

$$\rho_k = \frac{\sum_{t=k+1}^{n}(y_t - y^-)(y_{t-k} - y^-)}{\sum_{t=1}^{n}(y_t - y^-)^2} \tag{12}$$

where y_t is the value of the series at time t, y^- is the mean of the series, and n is the total number of observations.
The ACF plot shows ρ_k for different lags k, helping to determine the order q of the moving average (MA) component in ARIMA. Significant peaks in the ACF plot indicate strong autocorrelation at those lags.

4. The Partial Autocorrelation Function (PACF) measures the correlation between observations at different lags, controlling for the correlations at shorter lags. It provides the direct correlation between observations separated by k lags, removing any intermediate effects from the correlations at shorter lags.

The PACF at lag k, denoted by ϕ_{kk}, is calculated by fitting an autoregressive model of order k (AR (k)) to the data and extracting the coefficient for y_{t-k}. The PACF at lag k can be computed by solving the following system of equations (Yule-Walker equations):

$$\begin{cases} \rho_1 = \phi_{11} \\ \rho_2 = \phi_{21}\phi_{11} + \phi_{22} \\ \rho_3 = \phi_{31}\phi_{11} + \phi_{32}\phi_{22} + \phi_{33} \\ \vdots \\ \rho_k = \sum_{j=1}^{k} \phi_{kj} * \rho_{k-j} \end{cases} \tag{13}$$

where ρ_k are the autocorrelations at lag k, and ϕ_{kj} represents the PACF at different levels.

3.1.8 Support vector machines (SVM) in time series data

Support Vector Machines are supervised learning algorithms initially designed for classification tasks but can be used in time series analysis by transforming the prediction task into regression, predicting a future value. When applied to time series, SVM uses past values of the series as features to predict a target outcome. In this research, SVM is used to predict future electricity consumption values.

In time series analysis, the goal is to predict the next data point. This is done by creating lagged features from past values, using SVM to learn the relationship between these lagged features and the target outcome. For example, regression in time series might predict the next value or a series of future values. SVM solves the regression task by finding a hyperplane that best fits the data while maximizing the margin between the points and the hyperplane.

SVM mathematical formulations for time series data

In the case of time series data, support vector regression (SVR) is used to predict a continuous value, the next data point in a time series. SVR modifies SVM to approximate the following function (Moura et al., 2011).

$$f(x) \; = \; w \cdot x + b \tag{14}$$

The objective function for SVR is as follows:

$$\min_{wb} \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{n} L\epsilon(y_i, f(x_i)) \tag{15}$$

where $\parallel w \parallel^2$ regularizes the model to prevent overfitting, C controls the trade-off between model complexity and prediction error, and $L\epsilon(y_i, f(x_i))$ is the epsilon-insensitive loss function:

$$L\epsilon(y_i, f(x_i)) \; = \; max(0, \mid y_i - f(x_i) \mid -\epsilon) \tag{16}$$

where ϵ defines the margin around the prediction within which errors are ignored.

Dual formulation and kernel

SVM for regression can be implemented by using a dual formulation by introducing Lagrange multipliers α_i and α_i^*. This allows for efficient computation, especially in high-dimensional data, and focuses on support vectors—the critical data points.

The dual formulation can be expressed as follows:

$$f(x) \; = \; \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(\mathrm{x}_i, x) + b \tag{17}$$

where α_i and α_i^* are the Lagrange multipliers for the data points, $K(\mathrm{x}_i, x)$ is the kernel function.

Kernel function

The kernel function $K(\mathrm{x}_i, x)$ allows SVM to operate in a transformed feature space, enabling it to handle non-linear relationships. The kernel that is used in this research is the radial basis function (RBF) kernel. The radial basis function kernel is one of the most used kernels in support vector machine (SVM), particularly, in regression tasks. The core idea of using an RBF kernel is to transform the data into a higher-dimensional space where a linear decision boundary can be more easily found to predict outcomes (Tan et al., 2012).

In time-series forecasting, RBF-based SVM is used to capture the temporal dependencies and non-linear patterns in time-series data.

$$K(\mathrm{x}_i, x) \;=\; exp^{\left(-\frac{\|xi-x\|^2}{2\sigma^2}\right)} \tag{18}$$

The SVM is applied to the time series electricity consumption data by transforming time series to supervised format, where the model creates lagged values of the past 24 hours as input features (X_s) and predicts the next hour (y), and the target values will be the actual electricity consumption instances within the data collection time window. Then, the SVM is trained for regression where SVR is used to approximate the next value by minimizing errors.

This approach allows SVM to make robust predictions in time series tasks by focusing on support vectors and using kernels to capture non-linear patterns, making it a versatile tool for complex temporal data.

3.1.9 Long short-term memory (LSTM) in time series data

LSTM is a type of recurrent neural networks (RNNs) specially designed to learn long-term dependencies, making it effective for time series forecasting. Unlike standard

RNNs, which suffer from the vanishing gradient problem (where information from earlier time steps is lost during backpropagation), LSTMs maintain information over long sequences through a unique memory cell and gating mechanism (Zaheer et al., 2023). In time series data, LSTMs are used to capture sequential dependencies by maintaining an internal memory of past observations, which is essential for predicting future values based on historical trends. In this study, the model creates lagged values of the last 24 hours (Xs) as input features and predicts the next hour (y), and the target values will be the actual electricity consumption instances within the data collection time window.

An LSTM cell consists of three key gates—forget gate, input gate, and output gate—that control the flow of information. Each gate decides whether to keep, update, or discard information at each time step, allowing the network to manage long-term and short-term information.

The description of each component and the associated mathematical equations are as follows:

1. The forget gate

The forget gate decides what portion of the previous cell state C_{t-1} should be retained or forgotten for the current time step t.

The formula of the forget gate is as follows:

$$F_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{19}$$

where F_t is the forget gate output, determining which parts of the cell state to keep, W_f is the weight matrix for the forget gate, h_{t-1} is the hidden state from the previous time step (output from the previous cell), x_t is the current input, b_f is the bias term, and σ is the sigmoid activation function, producing values between 0 and 1.

The forget gate output F_t is then applied to the previous cell state C_{t-1}, controlling which information to keep.

2. The input gate

The input gate determines what new information should be added to the cell state for the current time step.

Firstly, the input gate itself is calculated as:

$$I_t = \sigma\,(W_i \cdot [h_{t-1},\ x_t] + b_i) \tag{20}$$

where I_t is the input gate output, deciding the amount of new information to add, $W_i$is the weight matrix for the input gate, and b_i is the bias term.

After that, a vector of candidate values $\widetilde{C_t}$ is created, which represents the potential new information that could be added to the cell state:

$$\widetilde{C_t} = tanh\,(W_C \cdot [h_{t-1},\ x_t] + b_C) \tag{21}$$

where $\widetilde{C_t}$ is the candidate cell state values, scaled between -1 and 1 by the hyperbolic tangent activation function tanh, W_C is the weight matrix for generating the candidate cell state, and b_C is the bias term.

The input gate decides how much of $\widetilde{C_t}$ should be added to the cell state.

3. Updating the cell state

After that the cell state C_t is updated by combining information from the forget gate and the input gate.

The formula for updating the cell state is as follows:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \tag{22}$$

where C_t is the updated cell state for the current time step, $f_t \cdot C_{t-1}$ is the portion of the previous cell state retained, controlled by the forget gate, and $i_t \cdot \widetilde{C_t}$ is the new candidate values scaled by the input gate, representing new information added to the cell state. This update ensures that the cell state retains essential long-term information while integrating relevant new data.

4. The output gate

The output gate determines the information to pass from the cell state to the hidden state h_t, which will be the output for this step and serve as input to the next step. Firstly, the output gate itself is calculated as:

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{23}$$

where O_t is the output gate value, deciding what part of the cell state to pass on, W_o is the weight matrix for the output gate, and b_o is the bias term.

The final hidden state h_t, which is also the output of the LSTM cell, is then computed by applying O_t to the cell state C_t as follows:

$$h_t = O_t \cdot tanh(C_t) \tag{24}$$

where h_t is the hidden state and output of the LSTM cell for the current time step. The hidden state h_t is used for prediction or passed to the next LSTM cell in a sequence. The cell state C_t carries forward the memory of past information, which helps the LSTM remember long-term dependencies.

3.2 Batteries as an energy storage system

3.2.1 Research paradigm

This study employs a qualitative research approach to explore the role of batteries as energy storage systems in stabilizing the Finnish electricity market. Qualitative methods allow for a nuanced understanding of complex phenomena, particularly when addressing policy implications, market dynamics, and technological challenges (Weyant, 2022).

Document analysis was selected as the primary method due to its effectiveness in examining existing records, policies, and reports that provide insight into the Finnish energy sector (Bowen, 2009).

3.2.2 Data collection

The study relies on a systematic review and analysis of publicly available documents relevant to the Finnish electricity market and battery energy storage systems. The documents include:

- Government energy policies and regulations.
- Reports from Finnish energy authorities, such as Fingrid and the Ministry of Economic Affairs and Employment.
- Industry white papers from energy companies and battery manufacturers operating in Finland.
- Academic research articles and conference proceedings related to energy storage systems.

The selection criteria for documents were based on their relevance to the research objectives, publication credibility, and their focus on energy storage technologies within the Finnish market. Sources were identified through database searches (e.g., Scopus, Google Scholar) and government websites. Some search words were used to find relevant research papers, such as energy storage systems, battery energy storage system, grid stability, and renewable energy integration.

3.2.3 Data analysis

Document analysis was conducted using thematic analysis to identify recurring patterns and themes in the data (Braun & Clarke, 2006). The process involved several steps:

1. Data familiarization: Reading and re-reading the documents to gain a comprehensive understanding of the content.

2. Coding: Highlighting key sections of the text that relate to the research objectives, such as operational challenges, economic benefits, and policy frameworks for battery storage systems.
3. Theme development: Grouping the codes into broader themes, such as grid stabilization, renewable energy integration, and cost-efficiency of battery systems.
4. Interpretation: Synthesizing the findings to provide insights into the role of batteries in mitigating electricity market volatility and promoting sustainability.

3.2.4 Ethical considerations

Since this study utilizes publicly available documents, there are minimal ethical concerns. However, all sources were cited appropriately to maintain academic integrity and avoid plagiarism. Care was taken to ensure that the analysis accurately reflects the context and intent of the original authors (Bowen, 2009).

3.2.5 Assumptions and limitations

This study assumes that the selected documents provide a representative and comprehensive view of the Finnish electricity market and battery energy storage systems. However, the analysis may not fully capture unpublished or proprietary industry data, which could introduce a limitation in understanding private-sector innovations or challenges. Additionally, while document analysis provides rich related insights, it does not allow for direct engagement with stakeholders, which could offer complementary perspectives.

By adopting a document analysis approach, this study seeks to provide a detailed understanding of the role of batteries in stabilizing the Finnish electricity market. This methodology enables the exploration of policies, market conditions, and technological advancements, forming a robust foundation for addressing the research objectives.

3.3 Practical applicability of advanced forecasting models and BESS

Semi-structured interviews were conducted with professionals and stakeholders in the Finnish energy sector to obtain first-hand industrial management viewpoints using a systematic qualitative data collection approach. The purpose of these interviews is to gain deeper insights into the practical applicability of advanced forecasting models and battery energy storage systems (BESS) in real-world grid operations and strategic energy planning.

The interviews questions are designed to explore several key areas as follows:

- The applicability of electricity consumption forecasting and BESS solutions at industrial scale,
- The prerequisites for successful implementation, beyond algorithmic capabilities (e.g., regulatory, infrastructure, data availability),
- The impact on business operations, investment strategies, and risk management,
- The current status and future plans for adopting such technologies within the Finnish energy companies, and
- The perceived alternatives or competing technologies in smart grid development and energy market balancing.

These interviews are expected to complement the integrated model-based and BESS evaluation findings by providing real-world scenario, enabling a better understanding of both the technical feasibility and managerial considerations involved in deploying forecasting-based grid support using BESS in Finland.

4 Results

This chapter presents the results of the study, analyzing the effectiveness of various forecasting models and battery energy storage systems (BESS). The findings are structured to address the research objectives, providing insights into the accuracy of time series forecasting models, the impact of renewable energy integration on grid stability, and the role of BESS in demand-side management. Given the increasing share of variable renewable energy sources (VRES) in Finland, this study evaluates the effectiveness of advanced time series predictive models in mitigating grid instability and negative price occurrences.

By leveraging ARIMA, LSTM, and SVM models, this research assesses their ability to forecast electricity demand accurately while examining how BESS solutions contribute to peak load balancing and frequency containment reserves (FCR). The outcomes from cross-validation further enhance the reliability of the findings, offering a comprehensive view of the study's contributions to smart grid analytics. Ultimately, this study aims to provide a deeper understanding of how advanced forecasting and battery energy storage solutions can stabilize the Finnish electricity market, supporting the transition to a more resilient and sustainable energy system.

4.1 ARIMA model

Firstly, the PACF plot was used as it is useful for determining the order p of the Auto-Regressive (AR) component in ARIMA, as it shows only the direct correlations for each lag.

After running the ADF, ACF, and PACF tests on the data, the following results were obtained:

ADF statistic: -4.35, p-value: 0.00036, where the critical values are 1%: -3.43, 5%: -2.86, and 10%: -2.57

Since the ADF statistic (-4.35) is lower than the critical values at the 1%, 5%, and 10% levels, and the p-value is less than 0.05, we can reject the null hypothesis. This means that the data is stationary, and no differencing is needed.

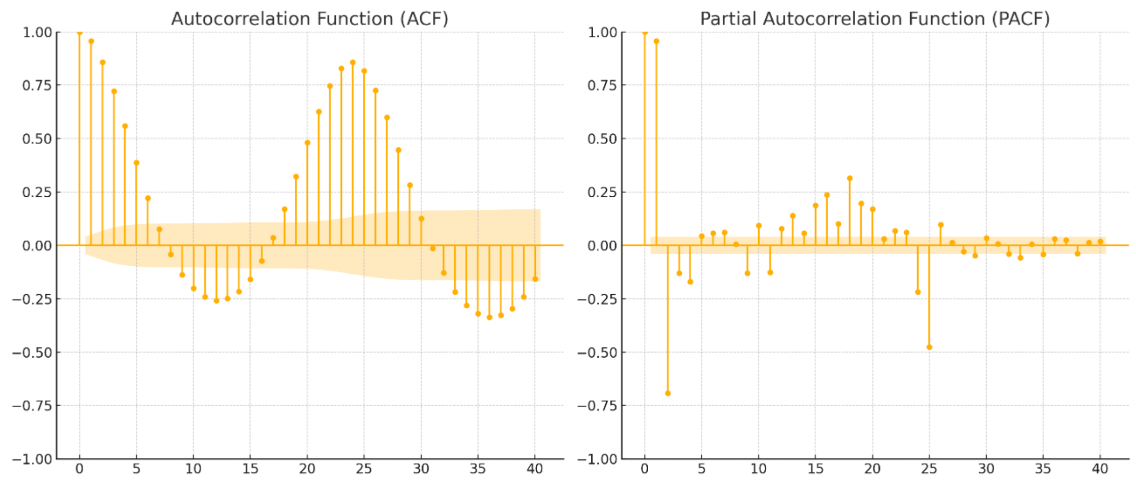

Figure. 2 ACF and PACF plots

The ACF plot shows a slow decay in the autocorrelation which suggests that the series may exhibit some short-term dependencies.
On the other hand, the partial autocorrelation plot shows significant spikes at lag 1 and possibly at other lower lags.

Based on the insights derived from Fig. 1, the following ARIMA parameters were chosen to build the model: p (AR term) = 2, d (differencing term) = 0, and q (MA term) = 0.

The model was trained using the chosen p, d, and q values and the training dataset from the electricity consumption time series data.
Then, the model was tested and cross validated using the test dataset and the cross-validation dataset, respectively, to predict the next hour by iteratively using predicted values as inputs.

In this research, root mean square error (RMSE), R-squared, mean absolute error (MAE), and mean absolute percentage error (MAPE) were used to assess the performance of the model.
Table 2 can be used to evaluate the prediction accuracy of the ARIMA model (N. U. Lee et al., 2018).

Table 2 MAPE value evaluation

MAPE	Evaluation
0% MAPE < 10%	Very accurate prediction
10% MAPE < 20%	Relatively accurate prediction
20% MAPE < 30%	Relatively reasonable prediction
50% MAPE	Inaccurate Forecast

Table 3 shows the performance of the ARIMA model across the Winter, Spring, and Autumn seasons test datasets and their respective cross-validation datasets.

Table 3 Performance evaluation of the ARIMA model

Evaluation metrics	Data from December 2023 to March 2024	Data from April 2024 to July 2024	Data from August 2024 to November 2024	CV data, May 2024	CV data, September 2024	CV data, December 2024
RMSE (MWh)	163.08	173.41	181.18	156.60	145.29	161.94
R-squared	0.97	0.93	0.94	0.94	0.94	0.97
MAE (MWh)	116.43	110.01	130.72	113.15	108.24	121.08
MAPE (%)	0.012	0.014	0.013	0.014	0.013	0.011
Average accuracy	98.79	98.54	98.68	98.57	98.65	98.88

The datasets used to train and test the ARIMA model indicate that Finland's actual electricity consumption fluctuates in the range of 6580–13,000 MWh per hour.
Given this scale, the following insights can be concluded:
RMSE ranges from 145.29 MWh (Sep 2024) to 181.18 MWh (Aug-Nov 2024).
This means that in the worst case (Aug-Nov 2024), ARIMA's predictions deviate by an average of 181.18 MWh per hour. Compared to total consumption (6,800–13,000 MWh), this represents 1.39% to 2.66% of total demand.

MAE ranges from 108.24 MWh (Sep 2024) to 130.72 MWh (Aug-Nov 2024).
A MAE of 108 MWh means that, on average, ARIMA's forecast deviates by this amount per hour.
In relative terms, this is approximately 1.66% of peak demand (13,000 MWh) and 1.59% of minimum demand (6,800 MWh).

Model performance over time
R-squared drops from 0.97 (Dec-Mar 2024) to 0.93 (Apr-Jul 2024).
This decline suggests that the model's ability to explain consumption variability weakens over time.
The model likely performs best in periods with less extreme consumption variations.

Seasonal retraining
The increase in RMSE and MAE over time suggests that the ARIMA model loses predictive accuracy if left unadjusted.
Thus, Re-training the model every 3–6 months is recommended to mitigate these inconsistencies in the model performance.

Figure. 3, Figure. 4, Figure. 5, Figure. 6, Figure. 7, and Figure. 8 present the ARIMA model's electricity consumption forecasts compared to actual test data over time. The x-axis represents time in hours, while the y-axis shows electricity consumption in MWh. The blue line represents the test data, while the orange line represents the ARIMA model's forecasts. The alignment between the two curves indicates that the ARIMA model captures the trend and short-term fluctuations of electricity consumption effectively. However, slight deviations suggest that while the model performs well in tracking consumption patterns, some variations and sudden peaks may not be fully captured.

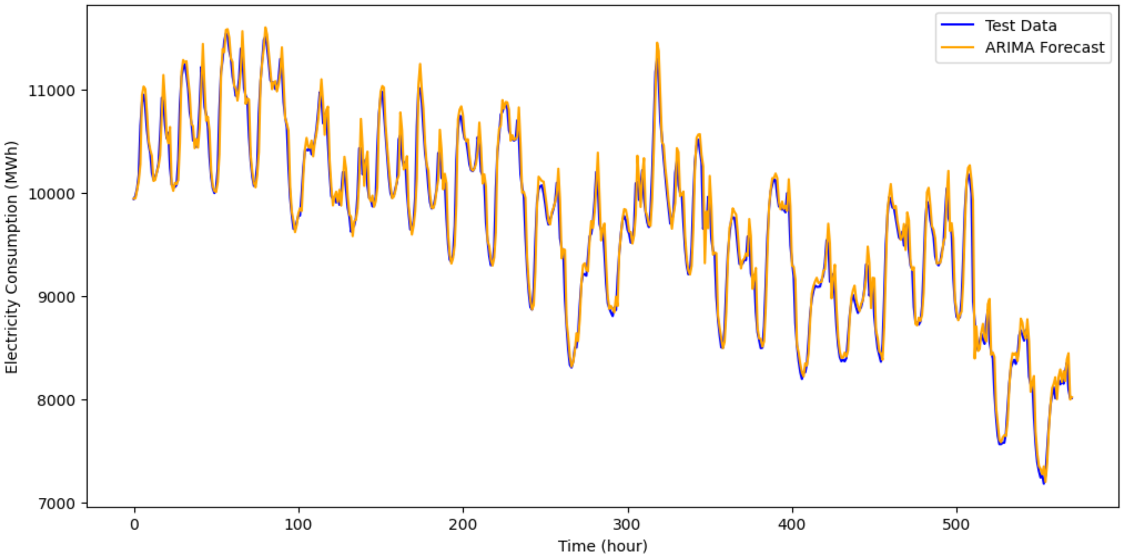

Figure. 3 ARIMA model prediction plot for the test data from Decemebr 2023 to March 2024

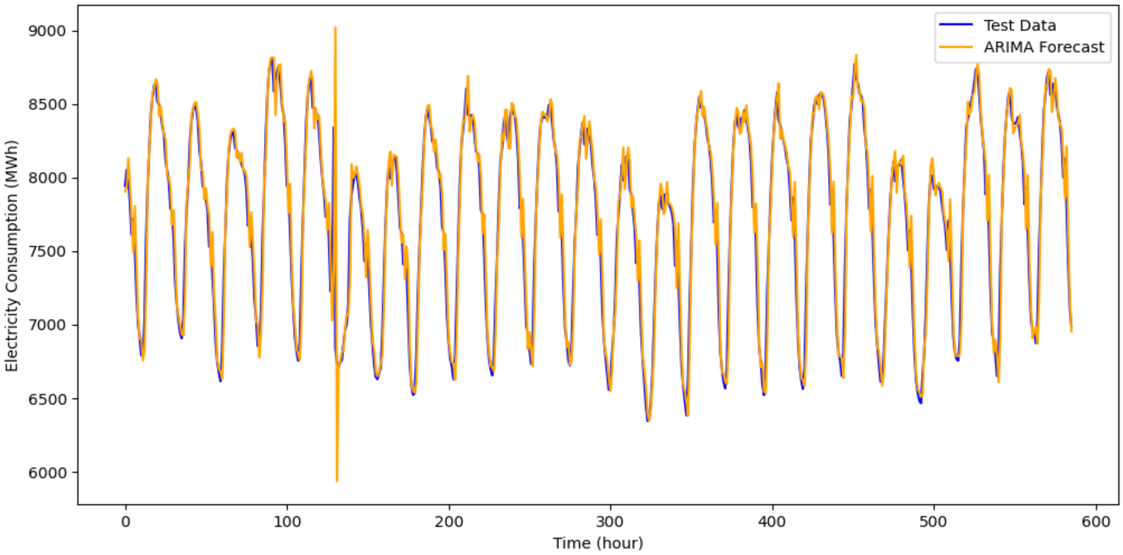

Figure. 4 ARIMA model prediction plot for the test data from April 2024 to July 2024

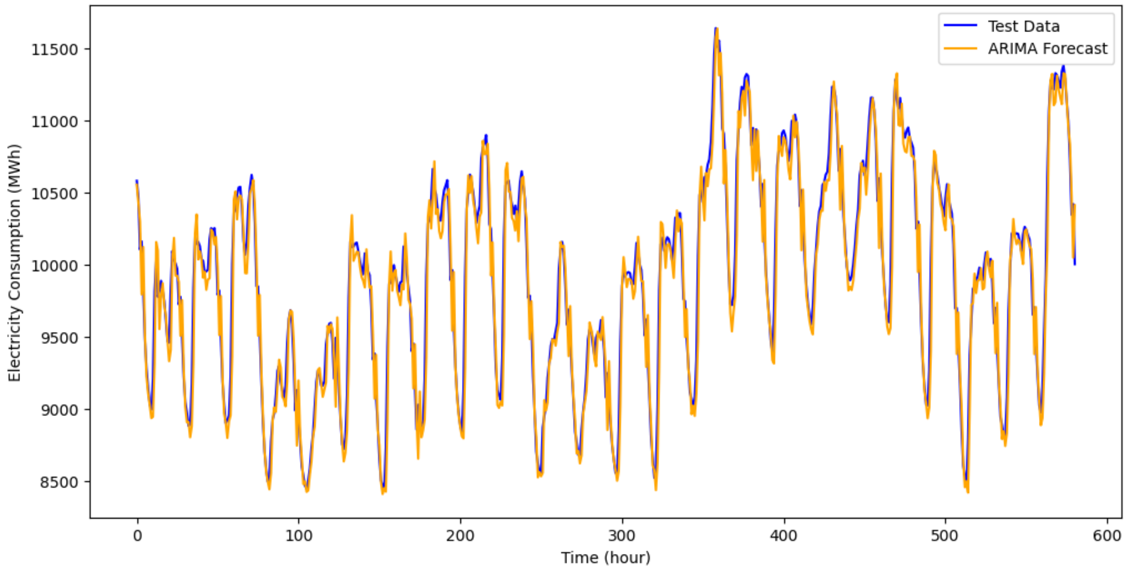

Figure. 5 ARIMA model prediction plot for the data from August 2024 to November 2024

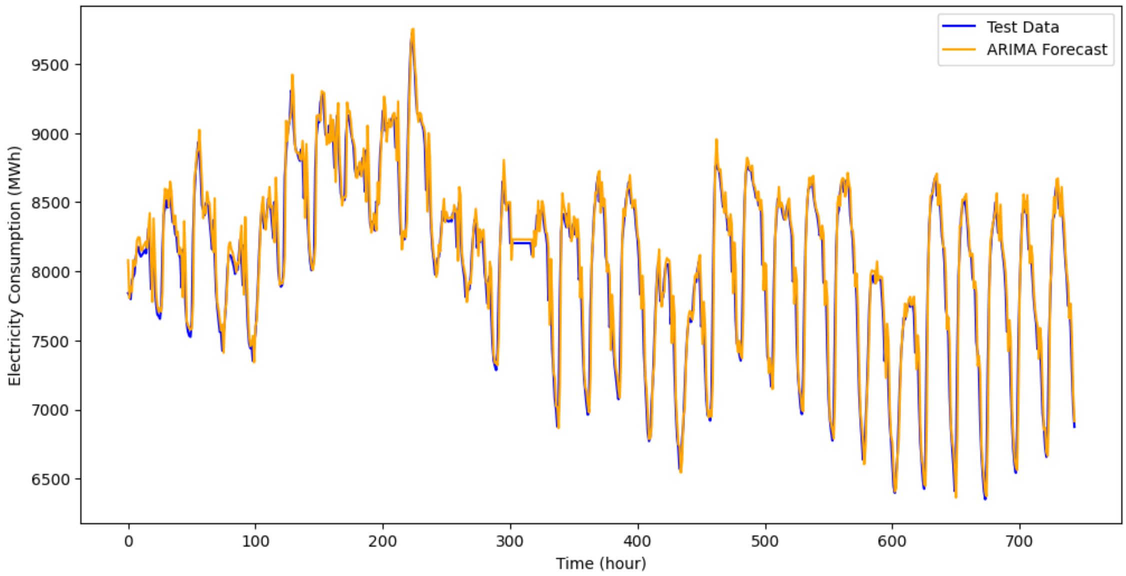

Figure. 6 ARIMA model prediction plot for the data from May 2024

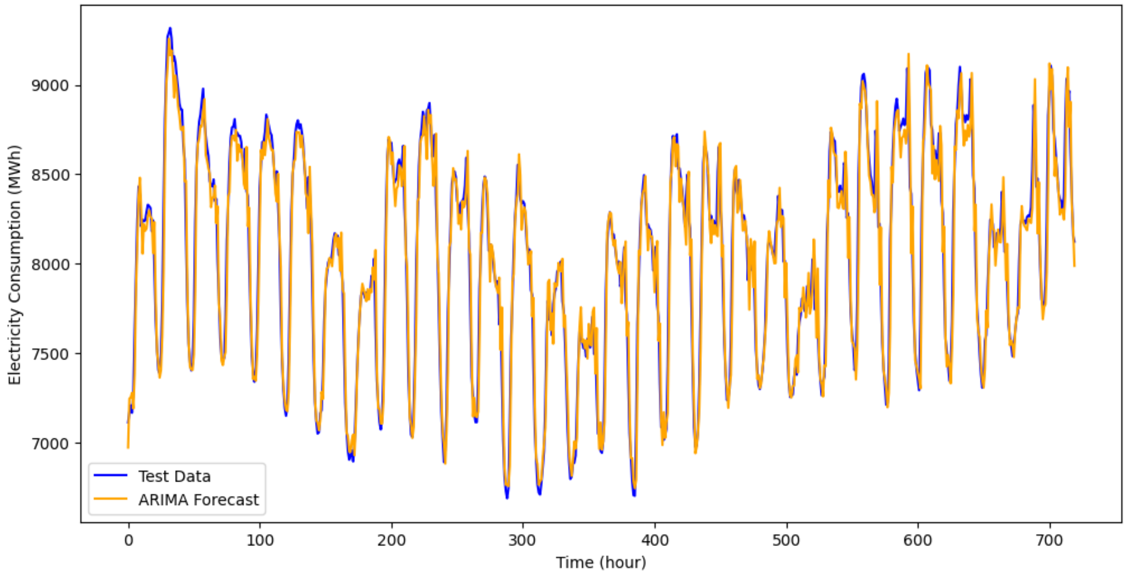

Figure. 7 ARIMA model prediction plot for the data from September 2024

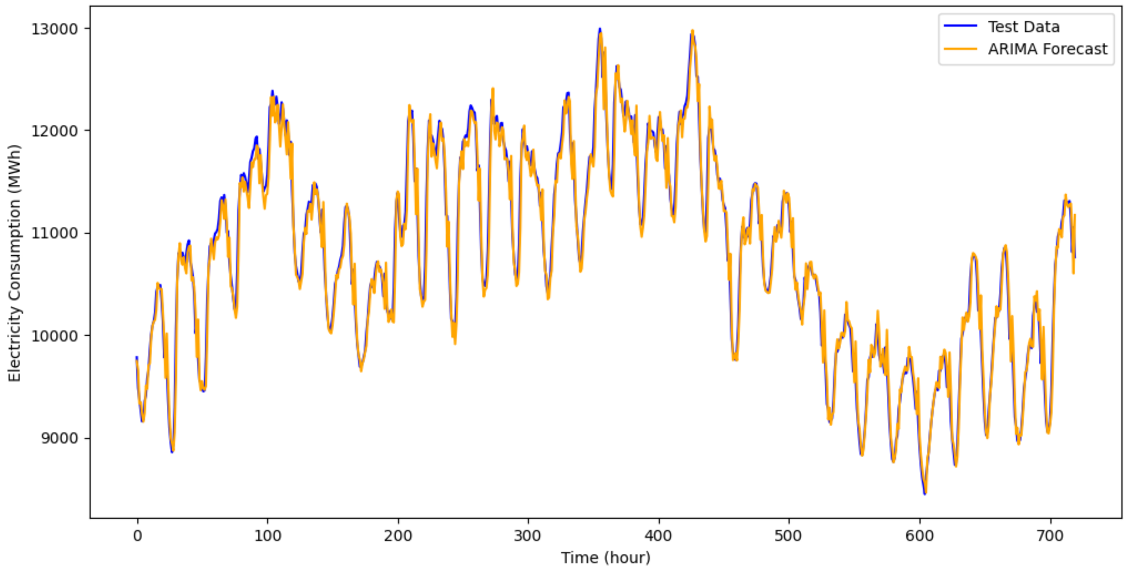

Figure. 8 ARIMA model prediction plot for data from December 2024

4.2 SVM model

Table 4 shows the performance of the SVM model across the Winter, Spring, and Autumn seasons test datasets and their respective cross-validation datasets.

Table 4 Performance evaluation of the SVM model

Evaluation metrics	Data from December 2023 to March 2024	Data from April 2024 to July 2024	Data from August 2024 to November 2024	CV data, May 2024	CV data, September 2024	CV data, December 2024
RMSE (MWh)	1142.42	121.04	253.20	197.34	191.14	179.80
R-squared	-0.60	0.96	0.87	0.90	0.89	0.97
MAE (MWh)	670.55	72.27	172.18	151.75	150.63	138.29
MAPE (%)	0.08	0.01	0.02	0.02	0.02	0.01
Average accuracy	92.22	99.04	98.29	98.08	98.11	98.69

The datasets used to train and test the SVM model indicate that Finland's actual electricity consumption fluctuates in the range of 6580–13,000 MWh per hour.
Given this scale, the following insights can be concluded:

RMSE ranges from 121.04 MWh (Apr-Jul 2024) to 1,142.42 MWh (Dec 2023 - Mar 2024), indicating a major issue with the model's predictions in the first period.

MAE fluctuates between 72.27 MWh (Apr-Jul 2024) and 670.55 MWh (Dec-Mar 2024). An error of 670.55 MWh per hour represents a significant deviation from the actual consumption figures.
In contrast, during April–July 2024, the MAE drops to 72.27 MWh, which is a low error (almost 0.7% of peak demand).

Model instability

The negative R-squared (-0.60) in Dec-Mar 2024 suggests that the model performs worse than a simple mean baseline prediction, indicating a fundamental problem in this period.

R-squared improves to 0.96 in Apr-Jul 2024 and 0.97 in Dec 2024, meaning the model explains almost all variance in those periods.

This huge variability in R^2 shows that the SVM model is highly sensitive to seasonal changes, making periodic re-training critical.

Importance of seasonal model retraining

Drastic changes in RMSE, MAE, and R^2 suggest that SVM requires frequent re-training to handle seasonal shifts.

Apr-Jul 2024 model achieves the highest accuracy (99.04%) with the lowest RMSE (121.04 MWh), indicating the model performed optimally when demand patterns were more stable. However, from Aug-Nov 2024, RMSE jumps to 253.20 MWh, and R^2 drops to 0.87, suggesting that changes in electricity consumption patterns degraded performance. A rolling update every 3-6 months would help mitigate these inconsistencies.

Figure. 9, Figure. 10, Figure. 11, Figure. 12, Figure. 13, and Figure. 14 illustrate the performance of the SVM model in forecasting electricity consumption by comparing predicted consumption values (orange) with actual test consumption values (blue) over time. The SVM model effectively captures periodic fluctuations and general consumption trends, particularly in cases where the demand follows a consistent pattern. However, discrepancies emerge during periods of sharp demand variations, such as Figure. 9, where the model struggles to adapt to sudden spikes and dips in consumption. In some instances, the predicted values tend to smooth out extreme variations, leading to underestimation during peak loads and overestimation during demand drops. Despite these limitations, the SVM model demonstrates a reasonable level of accuracy in tracking overall electricity consumption trends, making it suitable for applications where stable and periodic consumption patterns dominate.

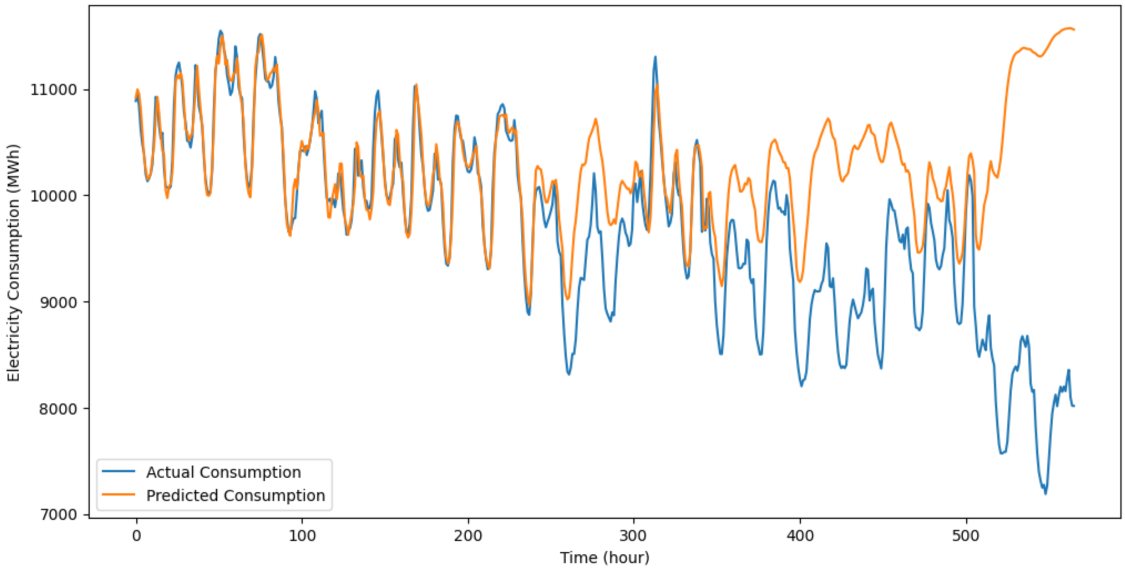

Figure. 9 SVM prediction plot for the test data from December 2023 to March 2024

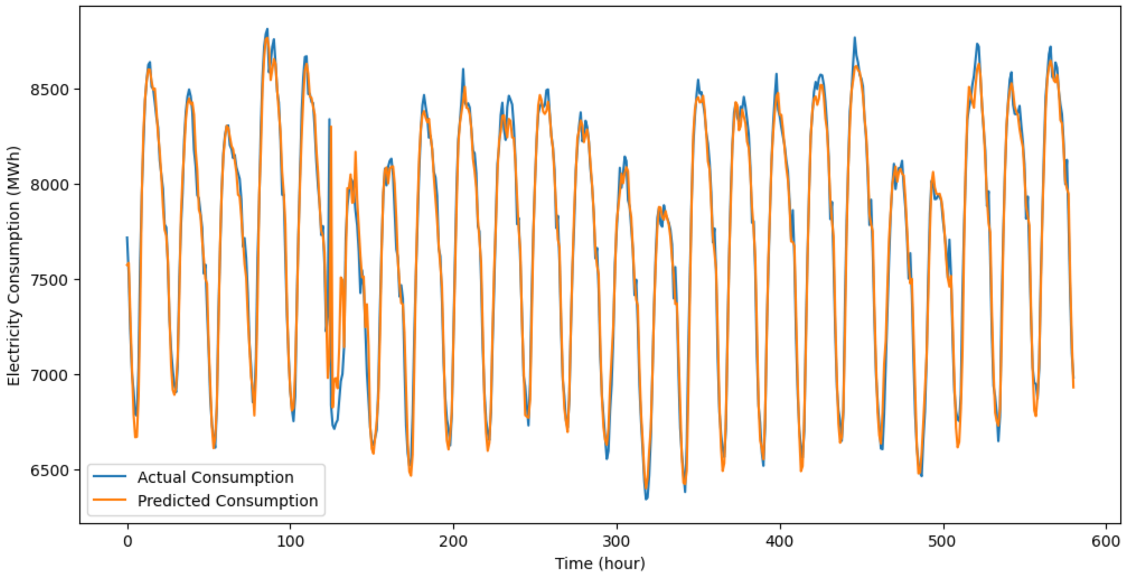

Figure. 10 SVM prediction plot for the test data from April 2024 to July 2024

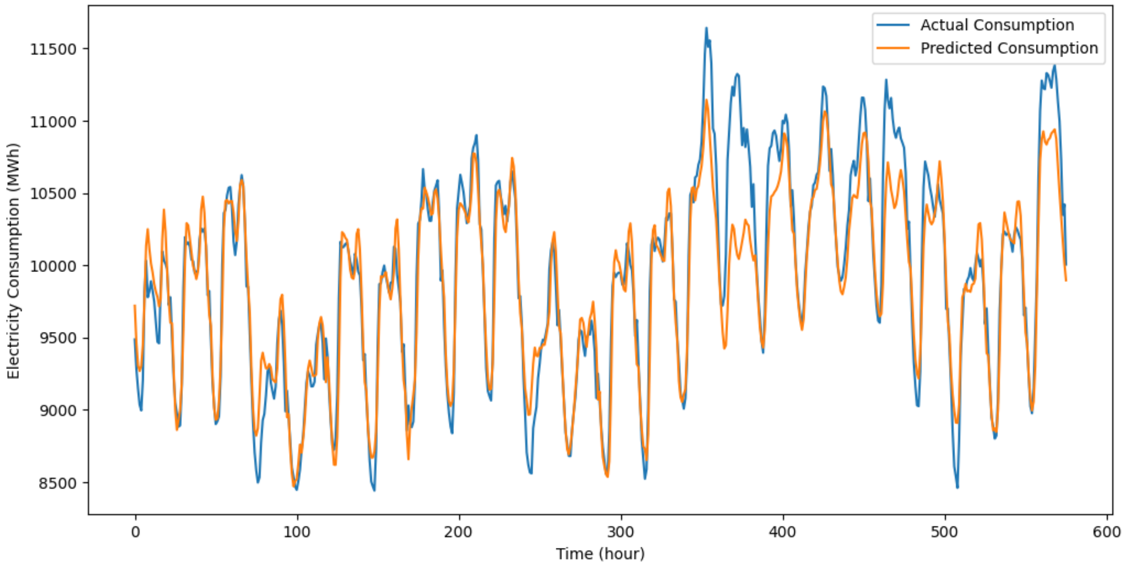

Figure. 11 SVM prediction plot for the test data from August 2024 to November 2024

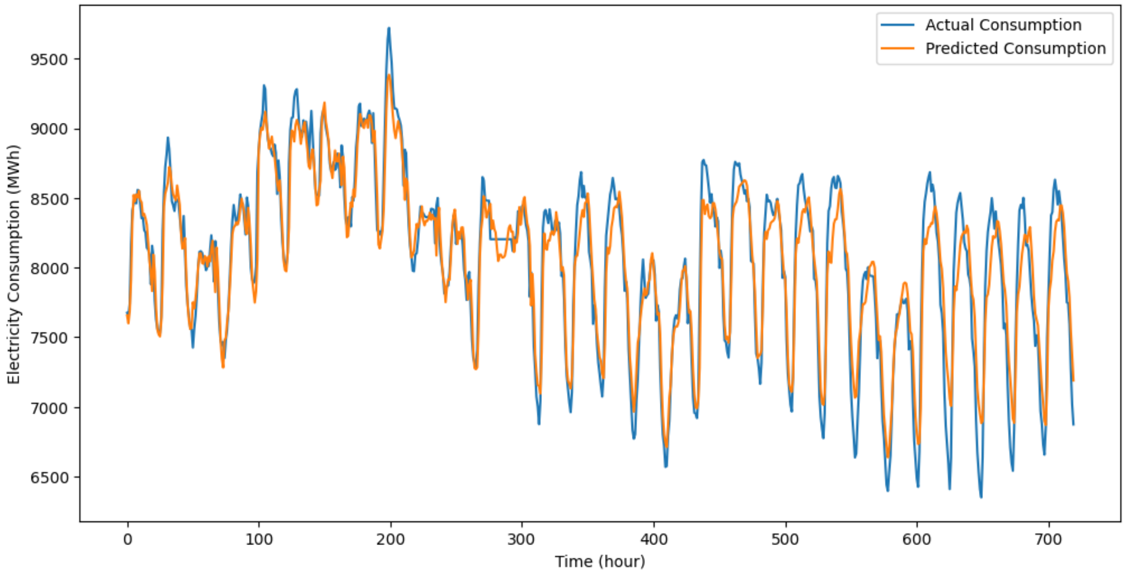

Figure. 12 SVM prediction plot for the data from May 2024

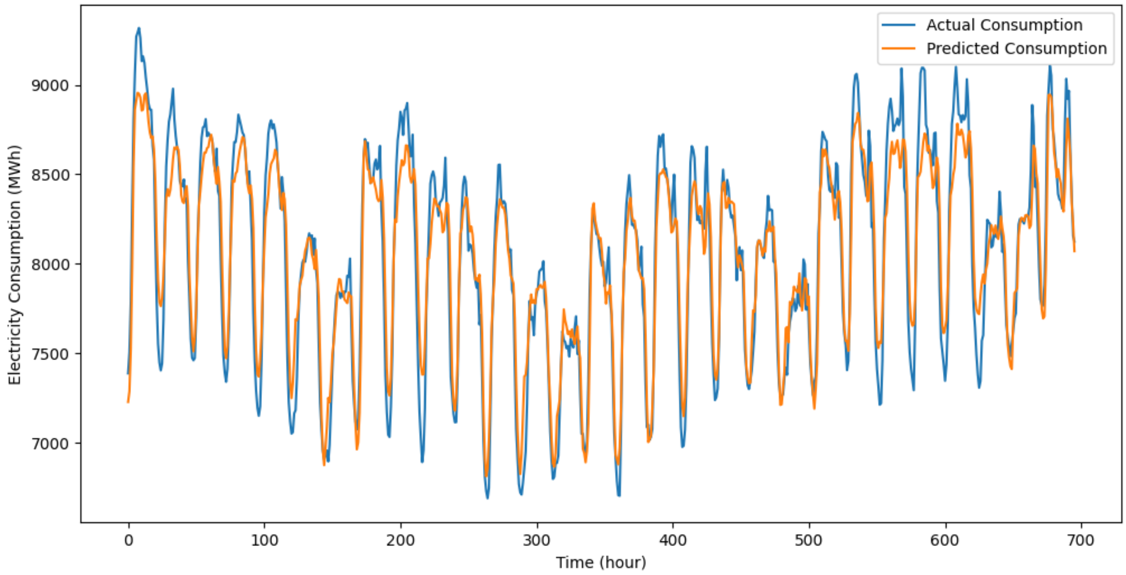

Figure. 13 SVM prediction plot for the data from September 2024

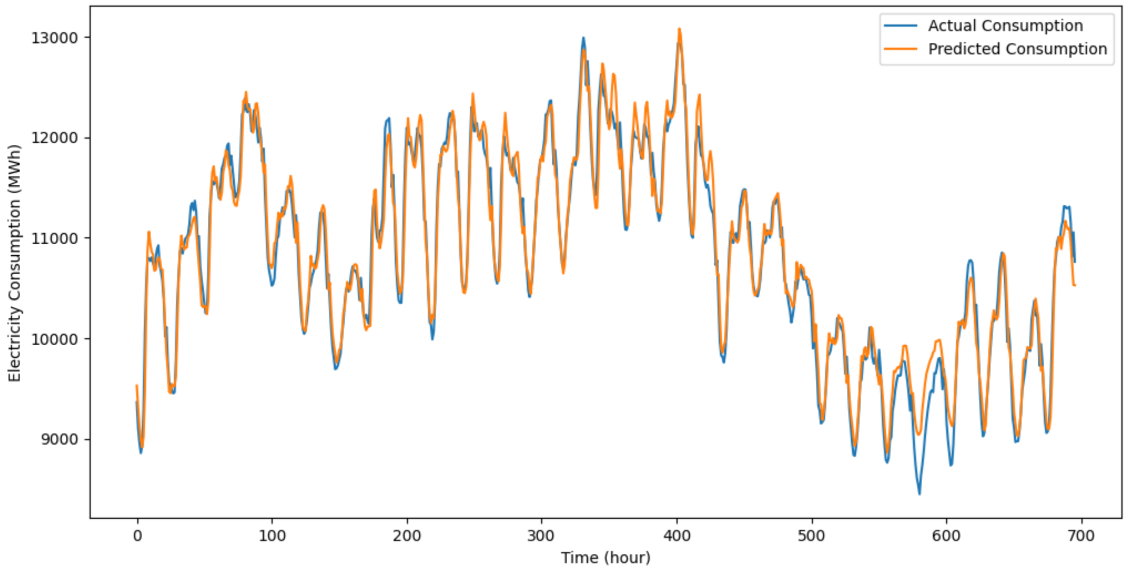

Figure. 14 SVM prediction plot for the data from December 2024

4.3 LSTM model

Table 5 shows the performance of the LSTM model across the Winter, Spring, and Autumn seasons test datasets and their respective cross-validation datasets.

Table 5 Performance evaluation of the LSTM model

Evaluation metrics	Data from December 2023 to March 2024	Data from April 2024 to July 2024	Data from August 2024 to November 2024	CV data, May 2024	CV data, September 2024	CV data, December 2024
RMSE (MWh)	9.81	5.66	7.01	12.21	8.69	5.72
R-squared	0.99	0.99	0.99	0.99	0.99	0.99
MAE (MWh)	6.73	3.52	4.90	8.65	6.07	4.13
MAPE (%)	0.0007	0.0005	0.0004	0.001	0.0007	0.0003
Average accuracy	99.93	99.95	99.95	99.89	99.92	99.96

The datasets used to train and test the LSTM model indicate that Finland’s actual electricity consumption fluctuates in the range of 6580–13,000 MWh per hour.
Given this scale, the following insights from Table 5 and Figure. 15 can be concluded:

RMSE values between 5.66 MWh and 12.21 MWh mean the LSTM model's errors are nearly negligible compared to total consumption.

MAE ranges from 3.52 MWh to 8.65 MWh, which translates to an absolute deviation of 0.03% to 0.07% from actual consumption.

R-squared remains 0.99 across all periods, meaning the model effectively captures the variance in electricity consumption.

Seasonal model retraining
Higher RMSE in May 2024 (12.21 MWh) and September 2024 (10.85 MWh) suggests that electricity demand fluctuates more unpredictably in these months.

These fluctuations reinforce the importance of seasonal re-training. A rolling update every 3–6 months would ensure the model adapts to demand pattern shifts.

Implications for energy management

The low RMSE and MAE indicate high reliability—meaning operators can confidently use LSTM-based forecasts for scheduling power generation and balancing supply-demand.

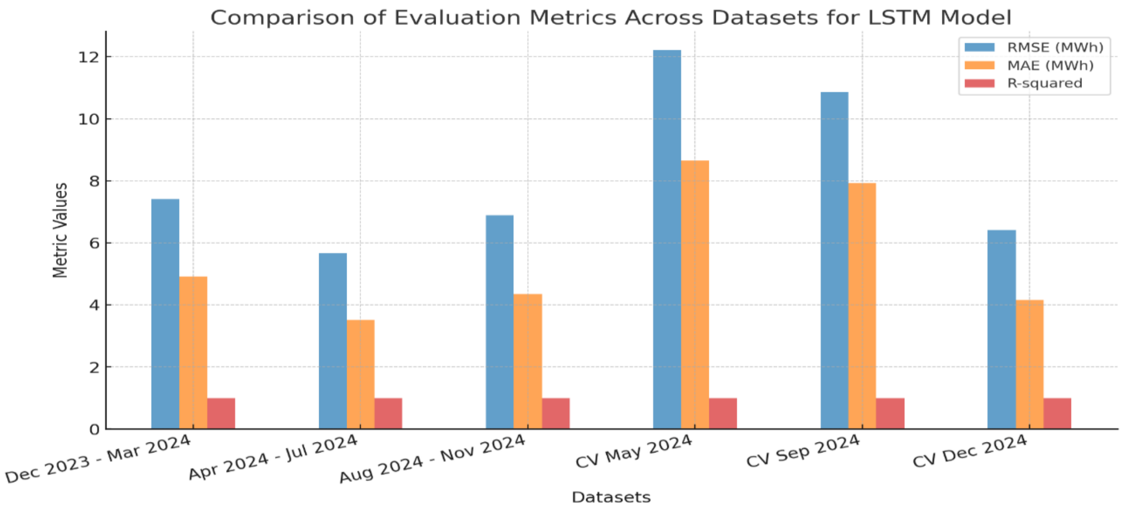

Figure. 15 Comparison of evaluation metrics across datasets for LSTM model

Figure. 16, Figure. 17, Figure. 18, Figure. 19, Figure. 20, and Figure. 21 illustrate the performance of the LSTM model in forecasting electricity consumption, comparing predicted consumption values (orange) with actual test consumption values (blue) over time. The LSTM model demonstrates strong predictive capabilities, effectively capturing both short-term fluctuations and long-term trends in electricity demand. The model aligns well with actual consumption patterns, particularly in cases where demand exhibits periodic variations. The model's ability to tracking recurring trends and handling complex time dependencies highlights its suitability for energy forecasting applications. The results emphasize LSTM's advantage over traditional models in learning dynamic consumption patterns, making it a valuable tool for smart grid energy management and load forecasting.

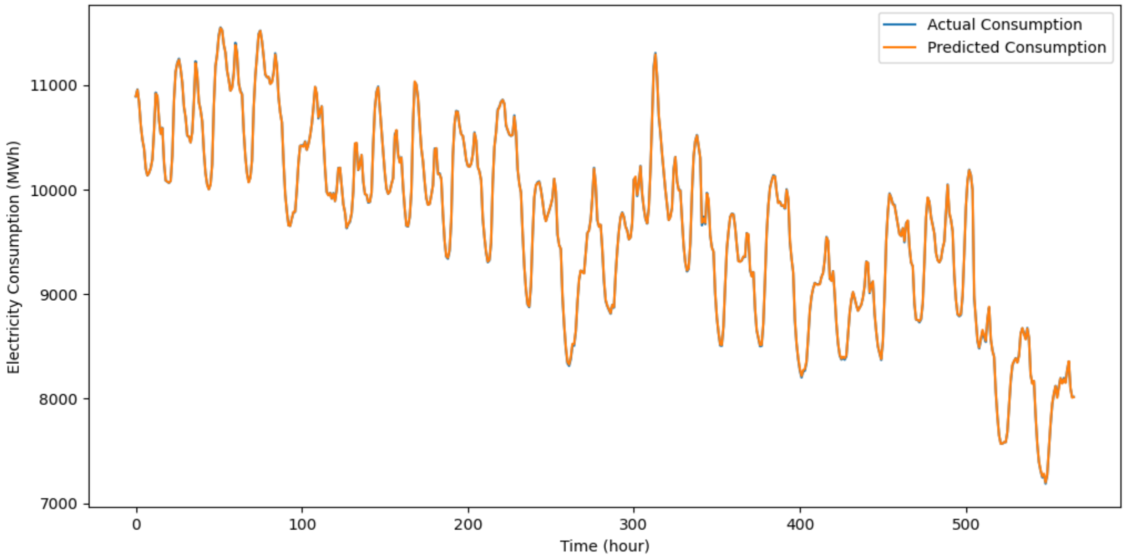

Figure. 16 LSTM prediction plot for the for the data from December 2023 to March 2024

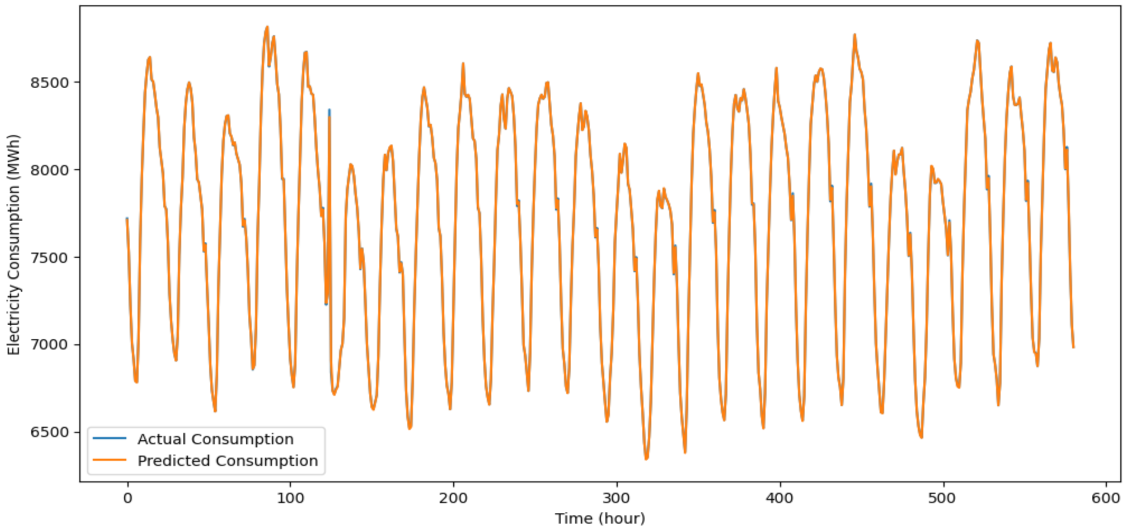

Figure. 17 LSTM prediction plot for the data from April 2024 to July 2024

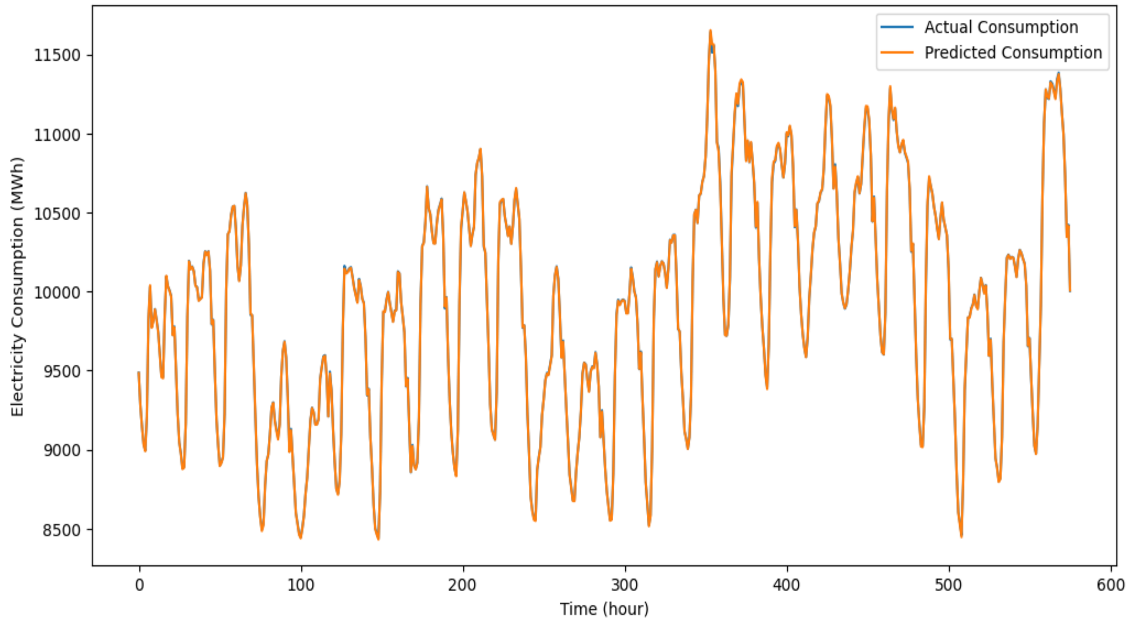

Figure. 18 LSTM prediction plot for the data from August 2024 to November 2024

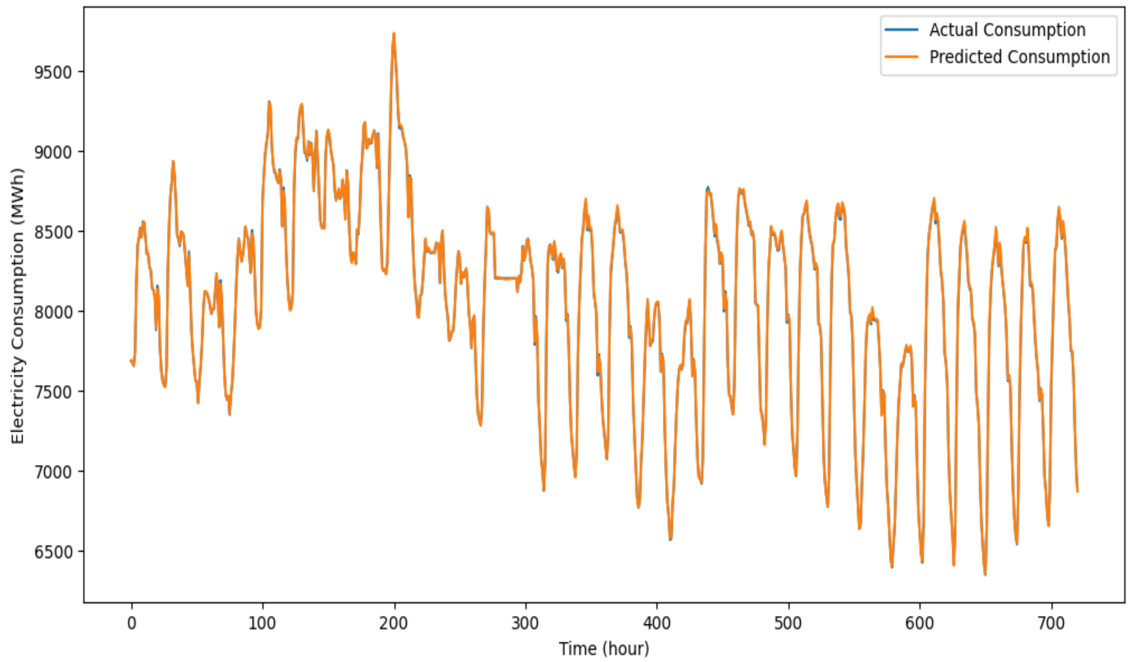

Figure. 19 LSTM prediction plot for the data from May 2024

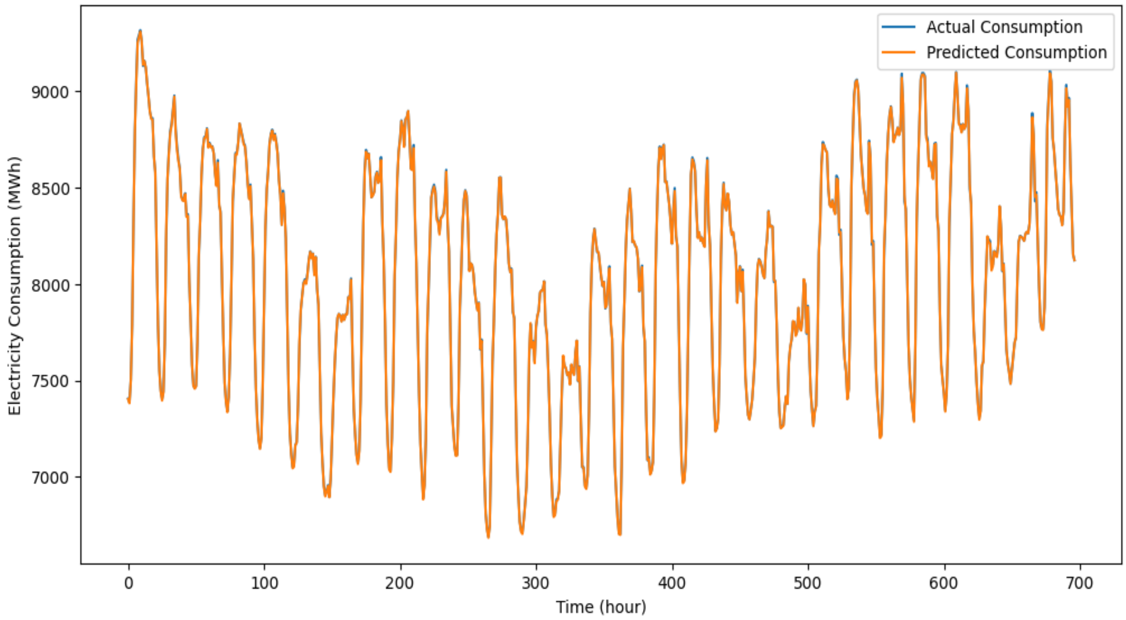

Figure. 20 LSTM prediction plot for the data from September 2024

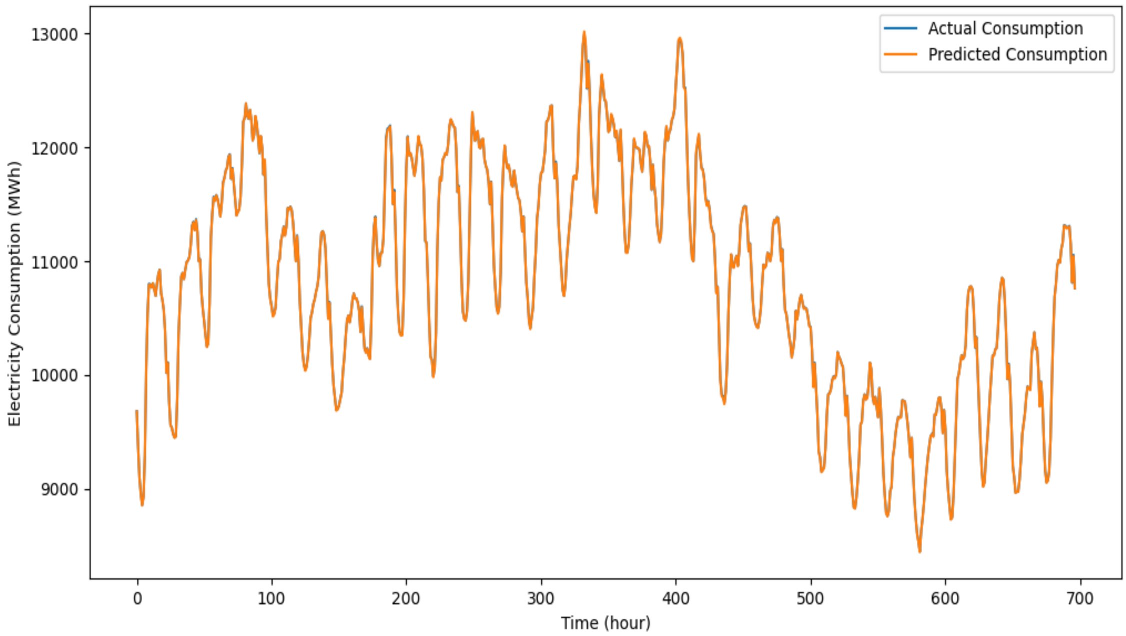

Figure. 21 LSTM prediction plot for the data from December 2024

4.4 Qualitative insights on battery energy storage systems (BESS)

Battery energy storage systems (BESS), particularly lithium-ion batteries, offer rapid response times and high efficiency, making them suitable for grid stabilization and balancing intermittent renewable energy sources like wind and solar. In 2020, Neoen commissioned the Yllikkälä power reserve one in Lappeenranta, a 30 MW/30 MWh battery storage facility, marking the largest such installation in the Nordic countries at that time. This facility underscores the growing role of battery storage in Finland's energy strategy (fingridlehti.fi, 2020). The adoption of (BESS) holds substantial potential for electricity operators in Finland. The potential benefits span multiple operational, economical, and regulatory dimensions.

Negative prices deter investments in renewable energy and grid infrastructure. With better forecasting of consumption patterns, operators can justify investments in storage and flexible generation, demonstrating that these systems can capture and manage value even during periods of oversupply. Also, operators can support policymaking by informing policymakers on the necessary incentives to stabilize markets and promote investment in technologies like energy storage and demand-side management.

4.4.1 Economic feasibility of BESS in multi-use applications

The economic feasibility of battery energy storage systems (BESS) is a critical factor influencing their adoption in multi-use applications. As highlighted by Zakeri and Syri (2015), BESS offers the potential to enhance the efficiency and flexibility of electricity grids by enabling peak shaving, load leveling, and renewable energy integration. In Finland, where energy price fluctuations and market volatility are significant concerns, multi-use applications of BESS can create economic value by addressing these challenges while optimizing energy storage utilization.

However, the economic viability of such applications often depends on scale and financing structures. For example, Denholm et al. (2013) argue that multi-use systems become cost-effective when operational savings from multiple services—such as frequency regulation and arbitrage—outweigh installation and maintenance costs. In the Finnish setting, supporting business models that incentivize multi-functional use of BESS can improve their economic appeal. Collaborative frameworks involving grid operators, energy companies, and policymakers are vital for enabling economies of scale and improving financial returns.

4.4.2 Environmental benefits in reducing fossil fuel reliance

One of the most significant advantages of BESS is its potential to facilitate a transition away from fossil fuels. By storing renewable energy during periods of surplus and discharging it during high-demand periods, BESS helps mitigate the intermittency of solar and wind power (Lund et al., 2015). This capability is especially relevant in Finland, where ambitious renewable energy targets have increased the need for reliable storage solutions.

Research by IRENA (2022) underscores the environmental benefits of BESS, noting that their adoption can lead to substantial reductions in greenhouse gas emissions when integrated with renewable energy systems. Additionally, de Oliveira et al. (2020) highlight that the environmental impact of BESS can be minimized through lifecycle management, such as recycling and repurposing of batteries. For Finland, integrating BESS with large-scale wind power installations in remote areas could significantly reduce reliance on backup fossil fuel generation while ensuring grid stability and energy security.
BESS enables higher penetration of renewable energy sources by mitigating the intermittent nature of wind and solar power. This contributes to decarbonizing electricity production and meeting environmental targets.

4.4.3 Regulatory incentives shaping BESS adoption in Finland

Regulatory incentives are pivotal in accelerating the adoption of BESS, particularly in markets like Finland, where energy policy frameworks are highly developed. Schmidt et al. (2017) emphasize that clear and predictable regulatory policies are essential to attract investment in energy storage technologies. In the Finnish electricity market, existing policies focus on promoting renewable energy generation, but specific incentives for BESS remain underdeveloped.

Nonetheless, Finland has the potential to leverage EU-level directives, such as the Renewable Energy Directive (RED II), which encourages member states to adopt energy storage solutions for achieving climate goals. According to Raj et al. (2022), policy instruments such as tax credits, subsidies, and performance-based incentives can significantly reduce the financial burden of BESS installations, encouraging wider adoption. Additionally, regulatory mechanisms that facilitate market participation for energy storage operators, such as capacity markets or ancillary service markets, could further enhance the economic prospects of BESS in Finland.

4.4.4 Environmental benefits of battery recycling

Battery recycling significantly reduces the environmental footprint of BESS by minimizing waste and recovering valuable materials. Modern lithium-ion batteries used in BESS contain materials such as lithium, cobalt, nickel, and manganese, which are resource-intensive to extract and process. Recycling these materials helps decrease the demand for mining and reduces associated environmental degradation (Harvey et al., 2020). In Finland, where sustainability and resource efficiency are national priorities, battery recycling aligns with the broader strategy of achieving a carbon-neutral economy by 2035 (Finnish Government, 2020).

Additionally, recycling batteries prevents hazardous materials, such as toxic heavy metals, from leaching into the environment. This is particularly important in Finland, where strict environmental regulations require companies to manage waste responsibly (Krook et al., 2014). By implementing effective recycling programs, Finland may mitigate potential risks to soil and water quality associated with battery disposal.

4.4.5 Economic and resource security

Recycling supports resource security by recovering critical materials, reducing Finland's dependence on imports for raw materials essential for battery production. The European Union has classified lithium and cobalt as critical raw materials due to their importance in energy technologies and their limited geographic availability (European Commission, 2020). By investing in recycling infrastructure, Finland can reduce reliance on global supply chains and ensure a stable supply of materials for domestic battery manufacturing and energy storage projects.

Finland is already a leader in the mining and refining of battery materials, with companies like Keliber involved in lithium production. Recycling complements this industry by closing the loop on material use, further strengthening Finland's position as a hub for battery technology in Europe (Lahtinen et al., 2021).
BESS provides opportunities for electricity operators to reduce operational costs and optimize resource use. The economic viability is often tied to factors like levelized cost of storage (LCOS), system efficiency, and maintenance costs. For example, second-life batteries have a lower upfront cost compared to new batteries, making them attractive for cost-sensitive applications such as peak shaving or frequency regulation (Lieskoski et al., 2024).

4.4.6 Circular economy and policy framework

Battery recycling aligns with Finland's circular economy objectives, which emphasize the reuse, recycling, and efficient utilization of resources. The country has actively implemented EU directives, such as the batteries directive, which mandates the collection and recycling of spent batteries. Finland's Ministry of the Environment has also supported initiatives to develop advanced recycling technologies and promote industry collaboration.

Research and development efforts in Finland focus on improving recycling processes to maximize material recovery rates while minimizing energy consumption. Innovations in hydrometallurgical and pyrometallurgical recycling techniques are key areas of progress, ensuring the economic and environmental feasibility of battery recycling (Martins et al., 2021).
Second-life batteries further reduce the environmental footprint by extending the life cycle of materials and deferring recycling (Lieskoski et al., 2024).

4.4.7 Operational flexibility and reliability

BESS enables electricity operators to manage supply and demand dynamically. In Finland, several case studies, such as those involving Fortum and Elenia, highlight how BESS support grid stability and improve reliability. For instance, in the Kuru region, BESS is integrated into Elenia's medium-voltage network to ensure uninterrupted power supply during outages and provide reserve power for transmission system operators (TSOs) (Ramos et al., 2021).

BESS contributes to grid flexibility by storing excess electricity during periods of low demand and releasing it during peak times (Castillo & Gayme, 2014). This capability is vital for balancing the grid in Finland, where electricity consumption varies significantly across seasons. During high wind energy production or low consumption periods, BESS prevents curtailment by storing surplus energy, enhancing the efficiency and sustainability of the grid (Lieskoski et al., 2024). Electricity operators benefit from the flexibility and scalability of BESS, particularly for grid balancing and renewable energy integration. The ability to store energy during low demand and release it during peak hours helps manage the grid more effectively, improving reliability and reducing dependency on fossil-fuel-based peaking plants (Lieskoski et al., 2024).

BESS can address voltage and thermal limit violations in distribution networks, ensuring operational reliability. By optimizing the siting and sizing of BESS, operators can improve the voltage profile across grid nodes, especially in rural and low-density areas of

Finland. Research has shown that optimal placement of BESS can mitigate localized instability during peak load periods, enhancing the reliability of the grid (Laaksonen, 2022).

BESS plays a crucial role in providing ancillary services, particularly frequency containment reserves (FCR). The rapid response capability of BESS makes it ideal for services such as frequency containment reserve for normal operations (FCR-N). These services are vital for maintaining frequency stability in the grid and are becoming increasingly valuable as Finland transitions to a renewable-dominated energy system (Ammous et al., 2023).

BESS can effectively address under-voltage and congestion challenges in distribution networks. The properly sited BESS can maintain voltage levels within acceptable limits, thereby improving the quality of electricity supplied to consumers. This capability is particularly valuable in regions with high renewable penetration and limited infrastructure (Laaksonen, 2022).

4.4.8 Economic efficiency

BESS contributes to cost savings and efficiency improvements by enabling behind-the-meter optimizations. This includes reducing energy costs for customers by storing energy during negative or low-price periods and discharging it during peak demand. Moreover, operators can use BESS to participate in frequency regulation markets, such as frequency containment reserve for normal operation (FCR-N), which provides additional revenue streams (Ramos et al., 2021). BESS present significant opportunities for electricity operators in Finland. As the Finnish electricity market experiences increased renewable energy production, especially from variable renewable energy sources (VRES), such as wind and solar, the role of BESS has become increasingly critical. According to Lieskoski et al. (2024), utility-scale BESS installations in Finland have reached approximately 0.2 GWh in capacity, with an additional 0.4 GWh planned. These systems help operators stabilize electricity grids by providing frequency containment reserves (FCR) and fast frequency reserves (FFR), offering an immediate response to fluctuations caused by VRES (Lieskoski et al., 2024).

BESS can enhance economic viability for operators by participating in energy markets. In Finland, participation in FCR-N markets is particularly lucrative. The FCR-N revenues often surpass those from energy arbitrage, making BESS a highly attractive investment for electricity operators. For instance, in 2022, the rising electricity prices led to a significant boost in the profitability of BESS operations (Laaksonen, 2022).

4.4.9 Renewable energy integration

BESS facilitates the integration of renewable energy sources by mitigating intermittency issues. For instance, the Lemene project in Marjamäki showcases how BESS stabilizes a microgrid with significant renewable energy inputs, such as solar power, ensuring a consistent energy supply while reducing reliance on non-renewable resources (Ramos et al., 2021).

The integration of renewable energy into the grid introduces intermittency, posing challenges for grid stability (Xu & Singh, 2012). BESS offers a solution by storing excess energy during low demand or high supply and discharging it during peak demand, effectively smoothing renewable energy fluctuations. This flexibility is critical for countries like Finland, where renewable energy sources are becoming a major part of the energy mix (Ammous et al., 2023).

4.4.10 Reduced wear and tear on infrastructure

By managing peak loads and providing ancillary services, BESS minimizes stress on traditional power generation and distribution systems. For example, BESS installations have been employed to reduce mechanical wear on hydropower plants by smoothing demand fluctuations (Ramos et al., 2021).

4.4.11 Scalability and multi-customer environments

The deployment of BESS allows for scalable solutions that cater to multiple customer segments, including distribution system operators (DSOs), transmission system operators (TSOs), and end-users. Finland's advanced smart grid infrastructure and hourly metering capabilities further enhance the integration of BESS into the electricity market (Ramos et al., 2021).

4.4.12 Regulatory and market adaptations

Although the Finnish regulatory environment encourages innovation, challenges remain in fully integrating BESS into the electricity market. Issues such as market access, revenue stacking, and ownership restrictions need to be addressed. However, ongoing initiatives, such as the Smart Grid Forum, aim to align regulations with technological advancements, fostering broader adoption of BESS (Ramos et al., 2021). BESS enables participation in Finland's reserve markets, such as the frequency containment reserve for disturbances (FCR-D) and frequency containment reserve for normal operation (FCR-N). The financial viability of these systems is supported by their ability to generate revenue from multiple sources, including providing balancing services and engaging in electricity trading. This diversification aligns with the Finnish transmission system operator Fingrid’s goal of maintaining a balanced grid amid the rapid integration of renewables (Lieskoski et al., 2024).

Supportive regulations and incentives are critical to BESS adoption (Adeyinka et al., 2024). Finland’s battery strategy aims to create a sustainable ecosystem by promoting battery reuse and recycling, aligning with EU directives such as the Battery Directive and the Green Deal targets. Regulatory frameworks provide stability and encourage investment, fostering innovation in battery technologies and applications (Lieskoski et al., 2024).

The adaptability of BESS to market and regulatory conditions further underscores their potential. For instance, the study by Laaksonen (2022) observes that higher electricity prices in 2022 significantly improved the profitability of BESS operations compared to 2021. This flexibility enables operators to align their strategies with evolving market dynamics and maximize their returns.

4.4.13 Challenges and future directions

Despite its benefits, battery recycling faces challenges such as the high costs of advanced recycling technologies and logistical issues related to the collection and transportation of spent batteries. Addressing these challenges requires coordinated efforts among stakeholders, including policymakers, recycling companies, and battery manufacturers.

Finland has an opportunity to lead the way in developing scalable recycling systems by leveraging its expertise in clean technologies and fostering partnerships across the EU. Incentivizing research and innovation in recycling, coupled with policies that promote extended producer responsibility (EPR), can further strengthen the role of battery recycling in Finland's energy transition. Despite its benefits, the adoption of BESS in Finland faces economic and regulatory challenges, including high initial costs and the complexity of integrating these systems with existing grid infrastructure (Y. H. Zhou et al., 2016). However, regulatory changes, such as eliminating double taxation on stored electricity, and incentives for renewable energy projects have significantly improved the economic feasibility of BESS (Lieskoski et al., 2024).

The high initial costs of BESS, uncertainty in battery lifespan, and technical complexities such as state-of-health assessment remain as barriers. Addressing these challenges through advanced diagnostic tools, improved recycling processes, and stable policy support is crucial for maximizing the potential of BESS in Finland (Lieskoski et al., 2024).

In conclusion, the strategic deployment of BESS in Finland presents a transformative opportunity for electricity operators to enhance grid reliability, integrate renewable energy, and achieve economic benefits. However, unlocking its full potential requires addressing regulatory barriers and optimizing business models for multi-customer environments.

Battery recycling is an integral part of Finland's strategy to achieve sustainable energy storage and a circular economy. By reducing environmental impacts, enhancing resource security, and supporting domestic industries, recycling complements Finland's ambitious climate and energy goals. With continued investment in technology and supportive policies, Finland can establish itself as a global leader in battery recycling and sustainable energy systems.

This qualitative analysis of BESS reveals critical patterns in their economic, environmental, and regulatory dimensions. While the economic feasibility of multi-use applications remains a challenge, innovative business models and collaborative frameworks can improve financial viability. From an environmental perspective, BESS provides significant benefits by its recycling applicability, supporting renewable energy integration, and reducing dependence on fossil fuels. Regulatory incentives, particularly those aligned with EU directives, can further shape the adoption of BESS in Finland, creating a more sustainable and resilient energy market. These insights demonstrate the transformative potential of BESS in addressing Finland's energy challenges while supporting its renewable energy transition.

4.5 Interviews insights into the practical applicability of advanced forecasting models and BESS

During the interviews, it became evident that many industry professionals were not yet in a position to provide definitive answers to those interviews questions, emphasizing the novelty of this study.

The responses indicated that, while the research topic is timely and relevant, the methods and technologies presented in this thesis—particularly forecasting-based grid support using BESS—have not yet been widely tested or adopted in the field.
As a result, most participants recognized the potential of the proposed approach but emphasized the need for further field testing and real-world validation before strategic or operational insights could be meaningfully discussed. This reinforces the thesis's contribution as a foundational study, offering analytical support and direction for future applied research and pilot projects in the Finnish energy landscape.

5 Summary and conclusions

The performance of the three models—ARIMA, SVM, and LSTM—was evaluated based on their ability to predict electricity consumption. Accuracy is a critical metric for determining the predictive capability of these models, revealing important insights into their performance.

The ARIMA model achieved an average accuracy of 98.68%. This high level of performance highlights the strength of ARIMA in capturing non-linear dependencies and trends in time series data.

The support vector machine (SVM) model underperformed the ARIMA model with an average accuracy of 97.41%. This performance underscores SVM’s ability to handle complex and nonlinear relationships in the data. The kernel functions in SVM, particularly the radial basis function (RBF), allow SVM to model intricate patterns that are not easily captured by traditional statistical models like ARIMA.

The long short-term memory (LSTM) model achieved an average accuracy of 99.93%, placing it above ARIMA. LSTM's architecture, designed to capture long-term dependencies and sequential patterns, is highly effective in time series prediction.

The results demonstrate that both LSTM and ARIMA models outperform the SVM machine learning model in terms of accuracy. The LSTM model's slightly higher accuracy compared to ARIMA indicates its suitability for scenarios where the data exhibits highly nonlinear characteristics. On the other hand, the LSTM model's near-perfect accuracy suggests its robustness in handling sequential data, making it an excellent choice for predicting tasks where temporal dependencies are crucial.

These findings have some practical implications as follows:
The ARIMA model, despite its high accuracy, remains computationally expensive compared to the machine learning models SVM and LSTM.

Studies using ARIMA models report MAPE values of from 2.5% to 3.5% for electricity consumption prediction (Gai et al., 2019). In comparison, the ARIMA model in this study demonstrates higher accuracy.

The SVM model offers a balanced approach, excelling in tasks where capturing temporal dynamics and sequence dependencies is essential, such as load forecasting and demand management.
Recent studies show that hybrid SVM models with proper preprocessing achieve MAPE values as low as 0.5% to 1.5% (X. Zhou et al., 2022). These models outperform the standalone SVM in this study, which has MAPE ranging from 0.01 to 0.08.

The LSTM model, with its superior performance, is well-suited for applications requiring precise predictions, such as optimizing electricity pricing and grid management. Studies using LSTM models report MAPE values from 0.5% to 1.0% for electricity consumption prediction (Sharma et al., 2024). The LSTM in this study significantly outperforms these benchmarks, achieving MAPE values as low as 0.03%, setting a new standard for precision.

By leveraging the strengths of each model, hybrid approaches or ensemble methods could further enhance prediction accuracy and robustness. Additionally, the performance of these models demonstrates the growing importance of advanced machine learning techniques in tackling complex challenges in the energy sector.

Predicting electricity consumption and utilizing battery energy storage systems can play a critical role in mitigating negative prices during high supply or low demand scenarios in day-ahead and intraday electricity markets.

This role can be explained as follows:
Better demand-supply matching

Accurate electricity consumption forecasting allows energy producers, grid operators, and market participants to balance electricity supply with demand. When demand is underestimated or supply overproduced (e.g., due to unexpected renewable energy generation), the market faces excess electricity, leading to negative prices. Predicting electricity consumption helps the day-ahead market as producers can schedule generation to match anticipated demand more accurately, avoiding overproduction. Also, consumption prediction can help the intraday market as operators can make real-time adjustments to account for updated demand forecasts, reducing the chances of supply-demand imbalances.

Efficient use of energy storage systems (ESS)

Battery energy storage systems (BESS) can store excess electricity when prices are low (or negative) and discharge it when prices are high. By predicting electricity consumption, ESS operators can optimize charging/discharging by aligning storage operations with forecasted demand patterns, reducing oversupply during low-demand periods. Also, predicting consumption can reduce curtailment by absorbing surplus renewable energy (e.g., solar or wind) that might otherwise go to waste, thus stabilizing the grid. For example, during low-demand hours, batteries can store excess electricity instead of forcing producers to pay for negative prices. During peak-demand periods, the stored energy can be sold back to the grid at higher prices.

Informed price forecasting

Electricity prices in the day-ahead and intraday markets are highly sensitive to supply-demand imbalances. Accurate demand forecasting feeds directly into price models, enabling proactive strategies as market participants can anticipate periods of negative pricing and adjust biding strategies or generation schedules. Also, accurate demand forecasting can stabilize the market behavior as with reliable consumption predictions, speculative actions that worsen price volatility are minimized.

Reduced renewable energy curtailment

Renewable energy sources like wind and solar are often the main contributors to negative prices, as they have low marginal costs and cannot easily adjust output. Predicting electricity consumption helps maximize renewable integration by aligning consumption forecasts with renewable generation to absorb excess energy. Also, electricity demand prediction may encourage flexible consumption by predicting when demand is low, operators can promote demand-side response programs to shift consumption (e.g., incentivizing EV charging during excess supply).

Grid stability and ancillary services

High supply and low demand can destabilize the grid by causing frequency fluctuations. Accurate consumption predictions assist grid operators in scheduling ancillary services like frequency regulation and load balancing, preventing grid instability during oversupply. Also, automated systems such as demand-response automation can shift or curtail load based on real-time forecasts, mitigating negative prices.

In the Finnish electricity market, negative prices have been observed during periods of high wind energy generation and low demand. Predicting consumption allows producers to reduce unnecessary generation in advance. Also, storage operators can charge batteries during these periods. On the other hand, consumers can increase consumption (e.g., pre-heating buildings) when prices are forecasted to drop.

By leveraging consumption forecasts and battery energy storage systems, these measures work together to align supply with demand, reducing negative price events and improving market efficiency.

The findings of this study are influenced by the unique characteristics of the Finnish electricity market, including its regulatory framework, energy mix, and market dynamics. Finland's electricity market operates under a system that emphasizes renewable energy integration, such as wind and solar, and encourages energy storage systems to mitigate variability in supply. While these conditions make Finland an ideal case study for exploring battery energy storage systems (BESS), the results of this study may not be directly applicable to other regions with different market conditions. For instance, countries with less penetration of renewable energy or differing regulatory incentives might not experience the same benefits or challenges as outlined in this study.

Moreover, Finland's cold climate significantly influences electricity consumption patterns, particularly in the winter months when heating demands peak. These seasonal factors may not align with countries in tropical or temperate climates, which have different consumption and production profiles. Consequently, while the findings are valuable for regions with similar characteristics, caution must be exercised when applying them to global settings.

Exclusion of broader economic factors

This study focuses exclusively on electricity consumption patterns and the role of battery energy storage systems, without addressing broader economic factors that could influence energy market dynamics. For example, variables such as global energy prices, economic growth, and trade policies were not included in the analysis. These factors play a critical role in shaping investment decisions and market behaviors, and their exclusion limits the application of the study.

Additionally, while the study investigates the economic feasibility of BESS, it does not delve into macroeconomic considerations, such as the potential impacts of inflation, interest rates, or government fiscal policies on energy storage investments. The absence of these broader factors creates a narrow scope, potentially overlooking some drivers that could affect the adoption and effectiveness of BESS.

On the other hand, an effort was made to incorporate practical industry perspectives through interviews with professionals working in the Finnish electricity sector. These interviews were intended to provide related insights into the feasibility and potential impact of implementing advanced forecasting models and BESS solutions in real-world operations. However, the discussions revealed that the current level of adoption and field experience with such integrated approaches remains limited, emphasizing the novelty of this study. Most interviewees acknowledged the relevance and urgency of the topic but noted that their organizations had not yet advanced to a stage where they could evaluate the business or operational implications in detail. The interviews' feedback served to validate the theoretical premise of the thesis, while also underscoring the need for further empirical research, demonstration projects, and pilot testing to assess how these methods can be deployed in practice.

In conclusion, while the study provides valuable insights to predict electricity consumption and the potential of BESS in the Finnish electricity market, its findings should be considered within the specific conditions of Finland and should not be generalized without considering broader economic and regional factors. Future research could address these limitations by incorporating comparative analyses across multiple regions and integrating macroeconomic variables into the evaluation framework.

Proposed future research

An integrated model for energy management to address the ongoing challenges in energy management. This study recommends future research on a comprehensive model that integrates energy production prediction, electricity consumption forecasting, and battery energy storage systems (BESS). This model aims to optimize energy resource utilization, stabilize electricity markets, and support renewable energy integration. Future research could focus on pilot programs within the Finnish electricity market to validate the proposed model. Collaboration with grid operators, renewable energy producers, and policymakers will be essential to address technical and regulatory challenges.

The proposed research aims to provide a holistic approach to energy management that aligns with Finland’s clean energy goals while offering a scalable solution for global energy markets. By integrating predictive analytics with storage technologies, this model has the potential to revolutionize the way energy resources are managed and utilized.

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