Electricity Price Forecasting and Market Analysis in Australia's National Electricity Market for Solar Farms

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Submitted for the degree of Master of Data Science Capstone Project

6th November 2024

Abstract

Solar Farms often suffer from financial losses due to the volatile nature of the National Electricity Market. This spot price is influenced by external factors such as demand, generation, bidding behavior, weather and more which causes intense volatility. In particular during daytime, spot prices can go low or lower than zero, which is detrimental for solar farms if not anticipated before. This project aims to conduct a market analysis to find the several factors that affect the spot price at the NEM, the factors which influence solar farms rate of generation and other market dynamics. To enable solar farm anticipate prices, this project aims to create time series-based forecasting models to fit the data and forecast spot prices.

This report begins with an introduction and need for the topic. Next, an explanation of the NEM and its structure along with market analysis is presented. Finally with literature reviews, exploratory data analysis is conducted along with model creation for both short term and long-term forecasting. Using various evaluation metrics, the best model is selected and presented.

Executive summary

This project aims to address the challenges faced by solar farms in Australia's National Electricity Market (NEM) by developing predictive models to forecast electricity prices and demand. Solar farms can often experience financial losses and operational inefficiencies due to the intermittent nature of solar energy and volatility of electricity prices especially during peak generation hours (Alvarez et al., 2021). To enable solar farms to manage production effectively, optimize bidding strategies and prevent financial losses, accurate forecasting models are crucial.

To predict electricity prices in the NEM, the proposed solution involves time series analysis using a variety of econometric models, such as ARIMA, GARCH, SVM, Prophet and more (Atique et al., 2020). The project also highlights the need for proper exogenous variables, including solar generation data, public holidays, and demand data to increase the accuracy of model forecasts. Using these variables and trends, the Prophet model emerged as a promising model, outperforming other models such as ARIMA GJR-GARCH, SVMs, and others (Mwampashi et al., 2022).

Data was fetched from numerous sources, including NEM's Data Dashboard, NEMWEB's data repository, and the Australian Government's website. Exploratory Data Analysis performed on this data revealed insights into price patterns and their relationship with other variables. To explore the various hidden patterns and trends in the data, the methodology also involves statistical testing for seasonality, hyperparameter tuning, and detailed model evaluation. Metrics such as RMSE, MAE, and sMAPE were used to assess model effectiveness alongside cross-validation. Results indicate that capping price spikes at $1,000 improves the model's stability by limiting extreme volatility.

Furthermore, market dynamics analysis was carried out to find the key influencing factors for solar farms and the NEM. Through the usage of forecasting models, solar farms can anticipate low prices and hence curtail production or use hedging strategies via the Australian Securities Exchange (ASX). Green hydrogen production and implementing BESS systems can be used to store excess electricity. Additionally, participation in Frequency Control Ancillary Services (FCAS) can provide further revenue streams by contributing to grid stability during peak demand periods.

The project concludes that advanced forecasting models are essential for solar farms to navigate the complexities of the NEM efficiently. Recommendations include further tuning of the Prophet model with additional exogenous variables and exploring new opportunities, such as interconnector constraints and weather data, to enhance predictive accuracy. Implementing these strategies will help solar farms minimize losses, stabilize revenues, and support Australia's renewable energy transition (Al-Musaylh et al., 2018).

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1. Introduction

The National Electricity Market (NEM) in Australia represents a complex competitive ecosystem where generators bid for the right to generate and dispatch electricity. These generators are often plagued by significant price volatility and market uncertainty and hence need solid market strategies to prevent financial losses. This is especially true for solar farms, which suffer from generation overheads and spot price losses due to the volatile nature of NEM's spot price (Al-Musaylh et al., 2018). With the spot price at the NEM fluctuating from negative values to peaks exceeding $16,600/MWh, price forecasting is one of the key strategies used by generators to anticipate highly volatile periods. Price forecasting is notably more important for renewables sources of electricity, particularly solar farms which are limited in generation due to a myriad of factors like solar presence. The increasing penetration of renewable energy sources has introduced new dynamics to price formation in the market, creating unique challenges for generators and market participants alike (Chapman et al., 2016).

Solar farms face unique challenges due to the "solar duck curve" phenomenon, where peak generation hours (10 AM to 2 PM) often coincide with price suppression due to oversupply (Naderi et al., 2023). This market dynamic creates a critical need for sophisticated forecasting tools that can predict such periods of low demand. And it is not just oversupply, factors such as weather variability, grid constraints, and the behavior of other market participants also affect generation for solar farms (Wilkinson et al., 2021). These challenges are particularly acute in Queensland, where the combination of high solar resources and ambitious renewable energy targets has led to rapid growth in solar farm developments.

Hence, in this report I will analyze the list of factors and market dynamics that affect solar generation and the NEM spot price. Using features sourced from the National Electricity Market's official archive, I aim to build time series forecasting models that will enable solar farms to forecast future spot prices and adjusting their business strategy accordingly to ensure positive returns on investment. This report will also serve as a comprehensive explanation of the National Electricity Market as well as suggestions on how to create alternative sources of income.

This report is written to first provide an explanation of the structure and market operations of the National Electricity Market. Next, factors influencing solar generation, market dynamics and price at the NEM are discussed. Then, exploratory data analysis is performed to grasp further insights from data and finally time series-based models are modelled on the dataset to provide forecasts.

1.1 Project Motivation

1.1.1 Market Dynamics and Price Volatility

The Queensland electricity market shows extreme price volatility which is characterized by massive price swings that can occur within minutes of each other. These price swings can occur due to multiple factors including weather conditions, network constraints, generator bidding behaviour, and demand fluctuations. The "solar duck curve" effect is particularly significant, where increased solar generation during midday hours leads to critically low spot prices and sometimes even causing negative pricing events (Wilkinson et al., 2021). This price depression during peak solar generation hours creates a unique challenge for solar farm operators, hence requiring forecasting tools to optimize revenue and operations. Understanding and predicting these price patterns is crucial for maintaining financial viability and making informed operational decisions.

1.1.2 Financial Implications and Risk Management

Solar farms face complex financial challenges that extend beyond simple revenue generation. Operating costs, including maintenance, staffing, and equipment replacement, must be balanced against variable income streams affected by price volatility. Battery storage systems, while offering potential solutions for price optimization, require significant capital investment and management strategies. Risk management becomes extremely important in this environment, where incorrect price predictions can lead to significant financial losses. Hence these financial considerations drive the need for accurate price forecasting.

1.2 Project Objectives

The aim of the project is to enable solar farms to make educated decisions to escape the price volatility and hence ensure financial security. Based on this, the objectives of the project include

1. To use time series analysis to understand the various patterns and trends in the behavior of NEM's spot price
2. To perform short-term and long-term forecasting using time series-based models and compare the various models through evaluation metrics
3. To perform a thorough market analysis and find the various dynamics that affect solar generation and NEM's spot price. This will include NEM Market Operations to external factors to government incentives and more.

Since the NEM is a vast network spanning multiple Australian States, to specify the number of factors only the state of Queensland was considered during modelling. Each of the Australian state have unique circumstances which affect their Regional Reference Price, and hence this project focuses on Queensland's RRP.

1.3 Privacy and Ethics Statement

This project does not have privacy or ethical concerns. All the data was sourced from official archives which are openly available to everyone to encourage transparency in market operations. The data does not contain any PII data, or any sensitive information related to any person or organization. Furthermore, Institution access was utilized for literature review of academic publications, ensuring ethical access and usage. Finally, since the project to create models and perform market analysis for the benefit of solar farms and to an extent policymakers, there are no ethical implications of the project.

2. Background

The National Electricity Market is one of the world's longest interconnected power system and electrical grid, spanning over 5000 kilometres in length. It is responsible for supplying electricity to most of the Australian states except Western Australia and Northern Territory, which are excluded due to the large geographical distance being present between their respective network grids and the NEM's eastern grid. The NEM comprises of various electric generators competing for the opportunity to supply electricity at the spot market through a bidding process (Marshall et al., 2021).

Electricity within the NEM is generated, transmitted, distributed, and consumed in real time. Unlike traditional commodity markets where products can be stored, electricity must be supplied and consumed instantaneously (National Electricity Market – DCCEEW, 2023). This fundamental characteristic shapes how the market operates, with supply needing to match demand at all times to maintain grid stability. The NEM is governed by market rules established by the Australian Energy Market Commission (AEMC), while compliance and enforcement activities are overseen by the Australian Energy Regulator (AER) (Spot and contract markets, n.d.).

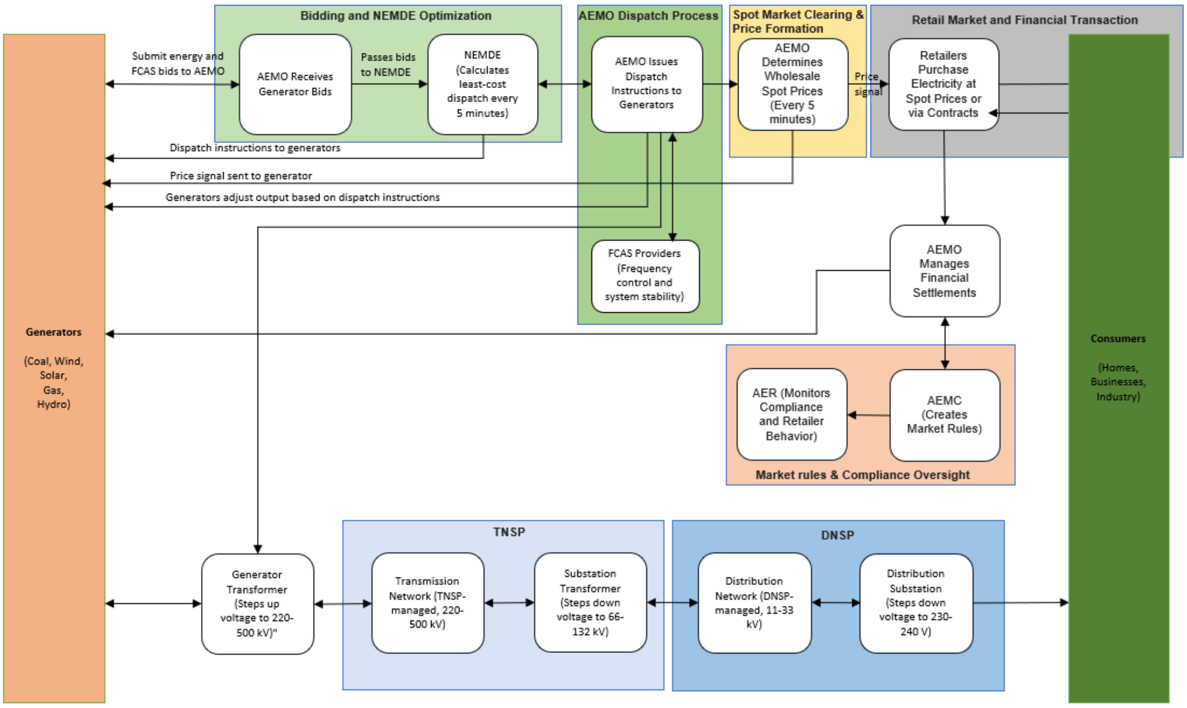
The NEM acts as a gross pool market, requiring all electricity generated and consumed to go through the electricity grid mechanism operated by the AEMO. All generators, retailers, consumers rely on the AEMO and hence interact through AEMO's centralized system. Generators compete to supply electricity by submitting bids into the market, with dispatch decisions and prices determined every five minutes based on supply, demand, and grid constraints (Spot and contract markets, n.d.).

2.1 Structure of the National Electricity Market

The NEM not only comprises the centralized system that is responsible for deciding the dispatch of electricity through generators for retailers but also contains the actual physical electricity grid itself. This grid passes through the states of Queensland, New South Wales (and the Australian Capital Territory), Victoria, South Australia, and Tasmania. Each region functions as a separate pricing zone, and hence has prices differing across regions based on demand, availability, and transmission constraints. All the regions are interconnected through interconnectors, allowing electricity to flow from one region to another to help meet local demand (Industry education courses, 2024).

Electricity is transmitted across the NEM by high voltage transmission lines. However, these lines are often affected by thermal limits, stability margins and outages. Hence, constant monitoring is required by the AEMO to ensure constant grid stability and prevent failures. To ensure supply of electricity always is equal to current demand, AEMO uses NEMDE which allocates the generators for a dispatch interval appropriately. These generators rely on a diverse mix of fuel sources and hence are coal-fired plants, gas turbines, solar farms, wind farms and more. However, Australia still relies heavily on burning fossil fuels, with 80% of the current production stemming from non-renewable sources.

The electricity generated at various plants is unsuitable for long distance transport, and hence at most generator plants a step-up transformer is used to raise the voltage. This process allows electricity to be transmitted efficiently while low current reduces transmission loss. Once the stepped-up electricity is sent through transmission lines to various regions of the NEM and arrives closer to the consumer regions, it enters substation transformers which step down the voltage for safe entry in the distribution network. The distribution network covers the various consumer regions and hence is more delicate than transmission network. Once electricity enters the distribution network, additional distribution substations further reduce the voltage to levels appropriate for local distribution lines which carry the now 230-240 V voltage to residential houses (Industry education courses, 2024).



Flowchart of NEM's structure and flow

2.2 Market Operations

The Market Operations of NEM define the process through which generators define their bids, place them at the NEM followed by the NEMDE choosing generators for deployment at the dispatch stage and more.

2.2.1 Pre-Dispatch Forecasting

The first step towards electricity dispatch involves the Australian Energy Market Operator (AEMO) predicting the future demand. This pre-dispatch forecasting predicts the prices 24-48 hours by incorporating key factors such as

1. Weather conditions: Forecasts include general regions temperature, rainfall and cloud cover, wind speed, solar irradiance and more. These are considered since weather directly impacts renewable sources of electricity generation and consumption.

2. Demand patterns: Historical demand patterns are used by the NEM to forecast how future demand will be like. These demand patterns include higher demand during peak summer and peak winter times, weekday/holiday trends and more. Such patterns contribute greatly to fluctuations.

3. Planned maintenance or outages: All planned outages are factored into the pre-dispatch calculations to indicate availability of supply and status of transmission lines.

This forecast gives generators insight into expected market conditions and helps them prepare bids for the upcoming dispatch intervals. These forecasts are updated regularly to improve forecast accuracy as the market moves closer to real-time dispatch.

2.2.2 Bidding Process

Based on the pre-dispatch forecasts, generators place bids in the NEM which indicate the amount of electricity they are willing to generate and at what price. Each generator can divide the generation bids into up to ten price bands (Industry education courses, 2024). These price bands offer flexibility to the generators by dividing portions of the total capacity at different prices. Generators also consider other factors while deciding bids. These factors include weather forecasts for renewable plants while fuel costs for non-renewable plants, operational costs, functioning overheads, start-up, and shut-down costs and more.

In the NEM, there are three types of bids primarily. These include:

1. Daily Bids, which are submitted by generators at 12:30 pm the day before delivery. These bids are 5-minute offers across 2-day periods.

2. Re-Bids, which are updated bids submitted by generators.

3. Default Bids, which are standing bids submitted by generators. These bids are stored in the AEMO's database and act as default bid for the generator if no daily bid is placed. This ensures that the generator remains available in the engine even if no explicit daily bid is placed.

Since the NEM prioritizes dispatching lower cost generators first, generators submit low bids to ensure dispatch, especially during periods of low demand when only the cheapest generators are called upon. However, during periods of sudden high demand when renewable energy is not readily available, generators often bid higher to ensure maximum profit. The NEM also allows rebidding prior to dispatch, allowing participants to rebid their price or capacity closer to dispatch intervals if market conditions change (Industry education courses, 2024). This flexibility allows them to respond to sudden demand changes, generator outages, or shifts in weather conditions. However, rebidding practices are closely monitored by the Australian Energy Regulator (AER) to prevent manipulative behavior.

2.2.3 The National Electricity Market's Dispatch Engine (NEMDE)

The NEMDE is the software used by AEMO to determine which generator will be dispatched in each five-minute settlement period. The NEMDE's primary role is to ensure that an equal supply of electricity is meeting the current electricity demand. However, the NEMDE also balances economic efficiency (minimizing the overall spot price cost) with system security (ensuring stable and reliable grid operations). Furthermore, network transmission limitations, market conditions and other constraints are also managed by the NEMDE (Industry education courses, 2024).

Every 5 minutes, the NEMDE evaluates bids across the NEM and dispatches the optimum combination of generation units needed to meet demand after considering and prioritizing the lowest-priced offers. Generators offering electricity at 0 or negative prices are dispatched first. However, if the demand increases, the NEMDE will accordingly select generators with progressively higher bids until the demand is satisfied. The last and the highest priced generator dispatched by the NEMDE is selected as the marginal generator, and its price is determined as the spot price for the entire 5-minute dispatch interval. This means that all the generators dispatched in that particular interval will receive the same spot price regardless of their bid.

NEMDE also considers transmission network constraints when accounting for demand. To ensure grid is not overloaded in a region or to account for transmission constraints, the NEMDE will resort to dispatching higher cost generators even if cheaper generation is available in another region. An example of this can be congestion on the Queensland-NSW Interconnector or QNI, which connects the regional grids of Queensland to New South Wales. AEMO may need to dispatch higher-cost generators in NSW to meet local demand, despite cheaper power being available from Queensland. This results in price separation between the two regions, with higher spot prices in NSW and lower prices in Queensland.

2.2.4 Settlement Period & Transition from 30-Minute to 5-Minute Intervals

Historically, the NEM operated with 30-minute settlement periods. While the dispatch interval remained at 5-Minutes, prices for 6 of such five-minute intervals were averaged and set as the spot price. However, this led to generators often manipulating spot market prices. Generators would often bid at very low at the start of a 30-minute period to ensure dispatch, and then raise prices at the end of the dispatch period. This would raise the spot price of the entire period while guaranteeing deployment (Industry education courses, 2024).

To address these issues and to ensure that the spot price reflects the current market conditions, NEM transitioned from a 30-minute settlement period to a 5-minute settlement period from 1st October 2021. This ensures there is no price manipulation by generators, while also encouraging rapid response generators such as gas-peaking plants and BESS or Battery Energy Storage Systems as they can quickly respond to real time price signals and capture high prices.

2.2.5 The Ancillary Services of the NEM

Ancillary Services are one of the key services utilized by the NEM to ensure consistent grid reliability and stable operations. These services are used to maintain a constant power quality, level of electric frequency, constant voltage across the grid and to prevent mass disruptions caused by changes in supply and demand. Ancillary services, while being used the broader National Electricity Market acts as separate standalone markets. These markets are preferred by quick acting generations plants and load plants to keep the grid secure (Industry education courses, 2024). While NEM used originally long-term contracts to provide for ancillary services, the September 2001 National Electricity Code required AEMO to instead introduce competitive means of ancillary arrangements. The Ancillary Services are divided into three systems:

1. Frequency Control Ancillary Services or FCAS : Used to maintain a constant frequency of 50 Hz in the grid.

2. Network Support and Control Ancillary Services or NSCAS : Maintains constant voltage and prevents transmission constraints

3. System Restart Ancillary Services or SRAS : Restarts the grid after a major blackout.

Out of the mentioned systems, FCAS is the largest and the most active ancillary service since supply demand imbalances occur frequently and must be recovered instantly to avoid future failures.

Frequency Control in NEM works by shifting generation and demand to always be equal to each other. This is necessary because if demand is greater than generation, the frequency of electricity decreases and vice versa. Frequency Control can be further divided into two subsets, which include Regulation control and Contingency control. Regulation control is the corrections of balance in response to small deviations, while contingency control involves correction of balance after a major event has occurred, such as loss of major generating unit or massive transmission loss.

Based on Regulation and Contingency controls, there are 10 markets as shown

Regulation Control Market involves

1. Regulation Raise
2. Regulation Lower

Contingency Control Markets involves

1. Very fast raise (1 second)
2. Vert fast lower (1 second)
3. Fast raise (6 second)
4. Fast lower (6 second)
5. Slow raise (60 second)
6. Slow lower (60 second)
7. Delayed raise (5 minute)
8. Delayed lower (5 minute)

Wind and solar farms are increasingly participating in FCAS by integrating battery storage, helping them manage variability and earn additional revenue. Revenue from FCAS markets provides an important incentive for fast-response assets, particularly batteries, which may not earn consistent income from energy-only markets due to price volatility.

2.3 The Retail Market

The Retail Market is the interface between electricity generators and the end consumers. Electricity retailers act as middlemen, though which they buy electricity from the NEM (through generators) and supply it to households and businesses at their fixed price.

2.4 The Financial Market

Participants of the NEM often need to manage price volatility due to the highly competitive spot market in its trading periods. Hence, generators and retailers often rely on financial markets which complement the NEM's wholesale energy market by providing participants with hedging instruments to manage price risks. These contracts made are strictly between the generator and the retailer, with AEMO not being involved in or having knowledge of any contract made (Spot and contract markets, n.d.).

These hedging instruments are called derivatives and are exchanged through cash flows (Australian Securities Exchange, n.d.). These cash flows can help either mitigate losses or boost profits based on the set prices. The major types of derivatives include:

1. Swaps

Swaps allow two parties to lock a fixed price for a set duration and a set volume of electricity. For that decided duration, if the NEM spot price exceeds the fixed price of the contract, the generator will compensate the balance to the retailer. Conversely, if the agreed upon price is lower than the spot price, the retailer will compensate the generator with the difference.

2. Options

Options are contracts that allow a party to buy or sell electricity at a determined price, however they are not obligated to do so. This allows the party to determine a fixed price in the future to ensure loss mitigation, but if conditions are favorable the party can simply defer to the market price to ensure greater profit.

There are further two types of options, called Call and Put Options. Call Options protect retailers from rising prices, while Put Options guarantee a minimum price for generators.

3. Caps, Floors and Collars

Buyers and sellers use Caps and Floors respectively, to certify an upper limit on the price buyer will pay and on a lower limit on the price that a seller receives to combat the volatility of the spot market. These Caps and Floors combine to form a price band called Collars.

2.5 The Australian Securities Exchange

The Australian Securities Exchange or ASX also provides various standardized futures and options contracts for electricity which are widely used by generators and retailers to hedge against the price risks in the NEM.

Unlike swaps, electricity futures are agreements to buy or sell electricity at a determined price on a specified date in the future. Futures give stability by locking in revenue regardless of the fluctuations. However, while this protects both the generators and the retailers from the volatility of the NEM spot market, this does not guarantee the difference between the actual price and contract price. Hence while in swaps the generators will be compensated by retailers if spot price increases, futures contract may cause generators to miss favorable spot prices. ASX futures are highly standardized in terms of contract size, maturity dates, and price increments, making them ideal for participants who want transparency and liquidity (Australian Securities Exchange, n.d.).

Derivatives play a critical role in the NEM by enhancing financial stability and reducing price volatility. Retailers use derivatives to offer consumers stable electricity prices, while generators secure predictable revenues to cover operational costs. The ASX further strengthens the market by providing price signals and encouraging investment in electricity infrastructure. As a result, electricity derivatives ensure the smooth functioning of both the physical and financial markets in the NEM (Australian Securities Exchange, n.d.).

3. Market Analysis & Factors Affecting Solar Farms and Prices in the NEM

The profitability and operation of solar farms are dependent on various factors related to NEM and other market dynamics. Identification of such factors can help solar farms anticipate them or reduce/amplify their impact to ensure profits. These factors collectively impact price stability, operational efficiency, and revenue streams, either directly by affecting solar generation itself or indirectly through external market forces.

3.1. Renewable Energy Target (RET) and Large generation Certificates (LGCs)

The Renewable Energy Target is a major policy designed to increase the percentage share of renewable in Australia's Electricity mix. This policy was first introduced back in 2001 and since then has undergone several revisions, with its current goal of having 33000 Gigawatt-hours of electricity per annum by 2030 to come from renewable sources. This goal is aimed to reduce greenhouse gas emissions while also promoting renewable plants such as wind, solar and hydroelectric systems.

As a compensation and promotion to renewable energy plants for producing electricity and to make such projects financially viable, the RET policy provides a certificate called Large Generation Certificate to utility renewable plants. Each Megawatt-hour of electricity produced from renewable sources is awarded one LGC, and these LGCs can be traded by generators with retailers who need to fulfil their RET compliance obligations for a price. Hence these certificates introduce a new form of income to renewable plants such as solar, promoting them to operate even at times of negative spot price at the NEM and offsetting some of the risks of spot price volatility.

However, these LGCs are also subject to market supply and demand dynamics and hence their price often fluctuates. Hence, generators form forward LGC contracts similar to financial market contracts with retailers to lock in predictable income streams. Other factors such as changes in government policies and oversupply of LGCs can also reduce LGC's price. However, RET and LGCs as a whole play a critical role in fostering greater renewable development by enhancing financial stability.

3.2. Green Hydrogen and Curtailment Reduction

To ensure grid stability at all times, especially during excessive electricity production when demand suddenly decreases, the AEMO oftens has generators reduce their output down to a certain threshold. This process of reduction when generation exceeds demand or when network constraints prevent power from being transmitted to where it's needed is called Curtailment. Solar farms are particularly affected by curtailment as solar irradiance reaches its zenith at noon when demand is low and being offset by FiTs or residential solar production. The other case when curtailment occurs is when the transmission infrastructure is not capable of carrying excess electricity to far away load centres forcing AEMO to reduce generation. Curtailment leads to revenue loss since generators need to scale down their maximum potential to abide by AEMO's instructions. Curtailment becomes more common as renewable energy penetration increases, especially in regions with high solar and wind output but limited interconnection capacity. As more distributed solar PV systems (e.g., rooftop installations) supply local electricity needs, large-scale solar farms face increased competition, contributing to negative spot prices during the day (Yildiz et al., 2023).

One solution to curtailment is utilizing green hydrogen. Green hydrogen is the clean hydrogen produced by electrolysis of water where the electricity was produced from renewable sources. This hydrogen has multiple industrial uses, mostly as a fuel. Hence, during curtailment hours, solar farms can divert their electricity generated to instead produce green hydrogen and sell it, hence earning back the lost revenue. Green hydrogen's uses as a fuel are widespread, with it being used as an energy source through fuel cells or in industries for transport, heating, and chemical production, or be used by solar farms as a form of "fuel" during evening when there is no sun (Oliveira et al., 2021).

Despite the opportunity offered by green hydrogen, there are various challenges that must be faced with its production during curtailment. Some of these include.

1. High Capital: The mechanisms for performing electrolysis at a large scale are extremely expensive and hence investing in green hydrogen production first needs a high capital investment

2. Conversion losses: Converting electricity to green hydrogen and then converting it back to electricity has efficiency losses, with the electricity produced being lower than original.

3. Adequate Infrastructure: Apart from high capital investments, large infrastructure is needed for proper storage and transport of green hydrogen which can be difficult to acquire for solar farms.

3.3. Demand Factors and Weather-related demand fluctuations.

Weather plays a crucial role in both demand the generation in the NEM. Demand for electricity rises and falls based on season and daily temperature variations, a few examples of such being.

1. During hot summer days, demand spikes due to widespread air conditioning usage in urban areas

2. Similarly, during cold winter days, demand spikes again due to widespread heater usages

Similarly, weather plays a significant role in generation too, with bright sunny days having high solar irradiance and hence boosting solar generation (Tang et al, 2018). Cloud covers, storms or bushfires reduce solar output leading to shortfalls in generation and increasing the NEM Spot price. However, factors such as time and day also influence the demand. Demand is lower in the mornings and at noon time, leading to low spot prices. However, come evening when offices shut down and people return home, demand sees a notable surge. Similarly, weekdays have much higher average spot price compared to weekends and holidays. These daily and weekly patterns also influence spot price to a degree and hence must be considered by generators and NEM.

Unexpected weather changes often deviate demand from what was anticipated in pre-dispatch forecasts, causing FCAS to maintain grid stability while the NEMDE adjusts for demand changes in the next dispatch interval. However, this sudden increase causes price volatility and can even cause prices to spike if the deployed generators can anticipate conditions to persist in the next dispatch period. For example, an overestimation of demand can cause oversupply, driving prices down or into negative territory, while an underestimation can result in sudden price spikes as higher-cost generators must be dispatched urgently. Solar farms that rely on pre-dispatch forecasts to plan their bidding strategies are often caught off guard by these forecasting errors, which disrupt their ability to align output with favorable market conditions.

3.4. Impact of Rooftop Solar Growth, Feed in Tariffs and Renewable Energy Zones (REZs)

Australian Government promotes renewable adoption, with the easiest adoption being rooftop solar panel installation in residential households and small businesses. This allows households to generate their own electricity during the day, enabling them to not rely on retailers for electricity but also offsetting the overall electricity demand during sunlit hours. This results in loss of demand which reduces need of electricity generation by large utility solar farms, hence resulting in curtailment and negative prices in the NEM. Solar farms experience price cannibalization, which is a situation where the abundance of solar generation during certain periods pushes down electricity prices, making it difficult for individual solar projects to remain profitable. The impact is particularly severe in regions with high rooftop solar penetration, such as South Australia, where daytime spot prices frequently drop to zero or below. As more consumers adopt solar-plus-storage systems, further reducing their dependence on grid electricity, the demand for grid-supplied energy is expected to decline even more, posing long-term challenges for solar farms.

Another reason for curtailment is Feed-in Tariff, which provide financial incentives to households by having retailers pay households money for any excess electricity exported into the grid. While this massively increases the renewable penetration, it also leads to renewable oversupply (Lan et al, 2020). Hence, solar farms are recommended to adopt Battery Energy Storage Systems (BESS) which enable them to store electricity generated and use it during peak evening price spikes. Other options include green hydrogen adoption as discussed (Lan et al, 2020).

While rooftop solar and distributed generation are reshaping electricity consumption patterns, the development of transmission infrastructure and Renewable Energy Zones (REZs) is crucial for enabling large-scale renewable projects, including utility-scale solar farms, to thrive. Many solar farms are located in remote areas with excellent solar resources but limited transmission capacity. The lack of adequate grid infrastructure often results in bottlenecks and curtailment, where transmission constraints prevent generated power from reaching demand centres, causing revenue losses for solar farms.

To address these challenges, REZs are being developed to cluster renewable projects within regions where grid upgrades and new transmission lines are being built to support higher volumes of renewable energy. By coordinating the construction of generation capacity and transmission infrastructure, REZs aim to reduce grid congestion and ensure that renewable energy flows efficiently from remote areas to urban centres. These zones also help optimize network planning by concentrating investments in areas with high resource potential, reducing costs for developers and enabling more consistent power flows (Queensland Government, n.d.).

However, while REZs offer significant opportunities, they also introduce new challenges. Multiple generators operating within the same REZ may compete for limited transmission capacity, leading to price cannibalization during periods of high output. Additionally, transmission projects are often subject to regulatory delays and community opposition, which can slow the deployment of infrastructure and increase costs (Queensland Government, n.d.). Solar farms located outside of designated REZs may struggle to access the grid, facing higher marginal loss factors (MLFs) that reduce the revenue they receive for each unit of electricity generated.

3.5 Potential Changes in Market Regulations & Policies in the Future

NEM's regulatory scenario is dynamic, and any changes or reforms in policies can impact solar farms. While the NEM promotes higher renewable penetration, there is also a push to lower the spot price in the NEM which can negatively affect solar farms. Even government policies affect regulations, with the Renewable Energy Target (RET) having achieved its goal already, leaving questions about which new policy is replace it or will it undergo a new revision.

One of the major prospective market mechanisms is the possible introduction of a capacity market. A capacity market would reward generators that remain available constantly even if not dispatched. This would benefit solar farms with BESS but for others that rely on sun only for generation this may be a drawback and force them to install BESS. Other prospective market rules such as dynamic network tariff could charge generators a comparatively higher price if a congestion occurs.

Australian Government's drive to reduce fossil fuel and coal powered plants may led to implementation of more carbon pricing schemes or schemes such as RET which would benefit solar farms, but with a widespread increase in solar farms especially in REZ can bring down prices further but only at daytime, which is a factor that must be considered by the government before policy making (Chapman et al, 2016).

3.6 Competition from other renewable sources and FCAS participation

Solar farms greatest competition in the NEM is not against non-renewable sources of electricity but other against wind energy in particular. While both solar and wind are renewable energy, their generation times and outputs complement each other, with wind producing more electricity overnight and during cooler months, while solar producing more electricity during the day. However, with widespread wind farms installation, chances of a price cannibalism risk have increased as both sources compete for dispatch.

Wind farms have a general advantage over solar because they are not tied to daytime generation unlike solar, and hence by being able to produce electricity for cheap during evening peaks can guarantee dispatch by the NEMDE. Hybrid renewable projects that combine wind, solar, and storage which allow for more flexible operation also pose a challenge to traditional solar farms as they can bid more strategically into the market by aligning output with price spikes.

Hence, as the NEM gravitates towards its goal of 100% renewable penetration, solar farms need to adjust their strategies and undergo changes such as BESS installation or green hydrogen adoption to ensure they remain profitable and dependable (Industry education courses, n.d.). Alternatively, solar farms can look to participate in FCAS Markets which are comparatively less competitive as they prefer fast action generators, something which solar farms with BESS can easily adapt to. Even if not to completely rely on FCAS, solar farms can use their extra margin of generation to bid in FCAS Markets and hence diversify their revenue streams, apart from receiving LGCs for renewable production regardless.

4. Literature Review

This section focuses on the various academic research and papers or publications considered to identify the best model for the particular Australian case. Since price forecasting is a regression problem, is it defined as an ideology in which multiple independent variables are used to help predict a dependent target variable (Hippert et al., 2001). However, due to NEM's spot price being a time variant variable, particularly time series models will be used to forecast, with a majority focus being on the historical values of spot price. Price forecasting plays a major role in not just NEM but in all energy markets, helping stakeholders and participants in making informed decisions regarding investment and more. In detail,

1. Increasing efficiency: Solar farms, through proper forecasting can understand how the spot prices are going to be in the future and change their generation and bidding strategy accordingly. In case of peak daylight with low forecasted price, solar farms can prepare green hydrogen or BESS systems to avoid generating electricity at very low or negative price risk, hence avoiding losses.

2. Risks Management: An idea of future price can help solar farms prepare hedges through financial markets, preventing them from particularly low prices or high volatility. These forecasts can also be used by investors looking to build/invest in solar farms to calculate ROI in the future.

3. Market Stability: As said earlier, AEMO can use price forecasting to ensure market remains aligned with the actual demand and hence reminds stable (Zhang et al., 2020)

For all time series models (and for machine learning models) historical data is evidently the most important data. By analysing historical price movements, patterns and trends, models can help identify key trends, seasonality effects and any cyclic nature of data which can repeat and affect future predictions (Box et al., 2015). An example of such cyclic nature of price was discussed in the previous section, in which demand increases during peak summer and winter, hence driving up prices. Similarly, for weekends and holidays prices are considerably lower than on weekdays. Hence, these type of cyclic nature help models forecast appropriately (Weron, 2014).

However, as much as historical patterns of price are informative in exploring the trends over time, there are other factors which directly affect the price values. These factors, while being independent can impact price by inducing volatility or spikes (Gujarati & Porter, 2009). In the NEM, some major independent factors, which will now be called exogenous factors, include weather conditions, policies, fuel prices (for non-renewable sources), generation and demand, renewable penetration and more. Hence, incorporating exogenous variables into our time series forecasting models will help the models better understand the relationship between variables and hence provide better overall accuracy (Taylor & McSharry, 2007).

Now, forecasting electricity prices can broadly fall in two categories, namely short-term forecasting, and long-term forecasting. Each of these methods while being completely same differ in the forecasting horizon, and hence models facilitating these also differ in nature. Short term forecasting can be defined as forecasting the target variable (here, electricity prices) in small horizons, such as minutes to a day or maximum two days. For the NEM's solar farms, such short-term forecasting can be useful since NEM releases pre-dispatch data of 48 hours, and hence short-term forecasting can help them plan their generation and bids (Taylor & McSharry, 2007). Hence, models used for short term forecasting need to be able to successfully capture the volatility of data and fluctuations in demand while also keeping in mind speed of running (Weron, 2014). Widely used models for such tasks are ARIMA, smoothening techniques and ML algorithms.

On the other hand, long term forecasting consists of predictions of a week, month or more. This type of forecasting can be used by solar farms to anticipate changes in trend over time, and hence decide financial market investment through hedging to ensure financial safety, or to plan any upgrades and more. Long term forecasting models need to be able to capture seasonality, trends, and patterns in the dataset. Models that are widely used to perform long term forecasting include Facebook's Prophet, Long-Short Term Memory models and more.

Short term forecasting data often requires highly granular data, which can be satisfied by NEM's transition to 5-minute data. Hence, we can use this 5-minute dataset for short term forecasting and resample it to higher frequencies for long term forecasting and fit a myriad of models. This project particularly employs traditional time series models rather than complex neural networks to avoid overly long computational times and memory issues. In particular, models that can successfully capture the data patterns and hence have been widely used in similar projects or academic research were selected (Box et al., 2015). Due to limited memory and to avoid large computational costs, a few models were not fully discovered to ensure practicality. Hence, the models used are discussed below.

ARIMA models or Autoregressive Integrated Moving Average models and its subparts are one of the most widely used time series models due to their sheer ease of use yet accurate results and interpretability (Box et al., 2015). ARIMA model is made of three independent parts working together, which are Autoregressive (AR), integrated (I) part and Moving Average (MA) part. Each of the three parts of ARIMA models are used to capture one aspect of the data. The AR part is used to identify the relationship between an observation and the specified version of lagged observations, while the MA part is used to identify the relationship between an observation and error from moving average of previous observations. Lastly, the integrated part of ARIMA is used to state how many times differencing needs to be performed on the dataset to ensure it is stationary.

ARIMAX models are an extension of ARIMA models that use exogenous variables, hence allowing for external factors which may influence the target variable as well as target variables own historical features. This inclusion enhances the overall prediction of ARIMA models (Taylor & McSharry, 2007). For instance, in forecasting NEM's spot price, variables such as solar irradiance, temperature, and humidity can significantly impact electricity generation from solar farms, thereby affecting spot prices.

Seasonal ARIMA models or SARIMA models are another extension of ARIMA models that uses seasonality features into normal ARIMA models, making them suitable for data which have a myriad amount of seasonality. SARIMA models include seasonal autoregressive and moving average terms, as well as seasonal differencing, to capture periodic fluctuations in the data (Weron, 2014). In the context of electricity markets, SARIMA models are particularly useful for capturing seasonal variations in demand and supply, such as increased electricity usage during summer or winter months due to temperature extremes (Makridakis et al., 1998). These seasonal patterns are critical for accurate short-term and medium-term forecasting of spot prices. However, SARIMA models are computationally expensive when dealing with data that is highly granular. Despite this drawback, SARIMA models remain a valuable tool for capturing complex seasonal dynamics in energy price forecasting, provided that sufficient computational resources are available.

GARCH models or Generalized Autoregressive Conditional Heteroskedasticity are models used to estimate the volatility of returns in financial data. These models are one of the best at measuring the fluctuations of data and predicting them, which is why they also found widespread usage outside of financial time series. GARCH models provide better predictions when there are clear volatility fluctuations with low volatility period being followed by high volatility periods.

GARCH models have two widely known extensions, called Exponential GARCH or EGARCH and Glosten-Jagannathan-Runkle GARCH or GJR-GARCH. EGARCH models further enhance the GARCH framework by allowing for asymmetries in the volatility response to positive and negative shocks. This is particularly relevant in energy markets, where negative shocks (e.g., sudden drops in demand) may have a different impact on volatility compared to positive shocks (e.g., unexpected spikes in demand). Similarly, GJR-GARCH introduces an additional term to capture asymmetries in the conditional variance similar to EGARCH. The GJR-GARCH model allows the conditional variance to respond differently to positive and negative shocks.

ARIMA-GARCH models combine the ARIMA models for modelling the mean of time series models along with GARCH models for modelling the volatility. A combined ARIMA-GARCH model can capture both the time-based trends along with fluctuations.

Moving on, Support Vector Machines are also one of widely sought for machine learning models due to their accurate results in both regression, classification, and outlier detection tasks. SVMs are also known for their effectiveness in high dimensional data and their ability to navigate through complex nonlinear relationships in regression problems through the usage of kernel functions. In time series analysis SVMs have given good results, an example of which being Zhao, Wu, and Deng (2020), which demonstrated that SVM-based models outperform traditional linear models in forecasting target variable by effectively capturing non-linear dependencies and interactions among variables. SVMs are particularly robust to overfitting while providing flexibility but are computationally expensive particularly on large datasets.

Another model used particularly for long term forecasting is Facebook's Prophet. Prophet is an open-source tool that is designed to forecast time series variables that have a strong seasonal effect with multiple seasonalities. Prophet however has not yet seen widespread usage in electricity price forecasting, particularly in the NEM. However, with its ability to use seasonality, holidays, changes in trend make it suitable to be used for NEM spot price forecasting effectively. Prophet has in built seasonality but also allows for custom seasonalities to be added, making it easy to use and to set up hyperparameters. Prophet is also said to be highly resilient to missing data, which will not be useful as NEM sourced data does not have any missing values. Prophet can also be used on large datasets and is computationally feasible, making it a strong contender for modelling price.

While these are traditional time series models, complex models such as neural networks are also implemented for time series forecasting and have achieved good results. Amongst these neural networks, Long Short-Term Memory, or LSTM networks, which are a specialized form of Recurrent Neural Networks have gathered acclaim due to their ability to retain information over long periods. Studies have shown that LSTM outperform traditional models when it comes to short term forecasting. LSTM models have become a significant tool in time series forecasting, particularly due to their capacity to model non-linear relationships and manage long-term dependencies across various domains. In the field of energy forecasting, LSTM has proven particularly effective. For instance, Fatema et al. (2020) employed LSTM models within smart grid frameworks to predict electricity demand and prices, leveraging their ability to capture non-linear trends in complex energy systems. Similarly, Almazrouee et al. (2020) explored hybrid forecasting approaches for long-term electricity generation in Kuwait, emphasizing the importance of integrating methods like Prophet and Holt-Winters while also recognizing the value of LSTM's adaptability in forecasting scenarios that involve multiple inputs and long-time horizons.

The integration of LSTM with other techniques has been a recurring theme in several studies, highlighting the benefits of hybrid models. Zheng et al. (2020) proposed a hybrid EMD-LSTM-XGBoost framework for load forecasting, demonstrating that combining LSTM's temporal modelling with XGBoost feature-ranking capabilities improved forecast accuracy. This synergy between models illustrates the potential of LSTM when enhanced with feature selection techniques. In the realm of electricity price prediction, Li and Becker (2020) applied LSTM with cross-border market coupling data to handle the dynamic nature of electricity markets, showing how LSTM's versatility allows it to incorporate various exogenous inputs seamlessly into forecasting frameworks.

Gao Gao et al.,	ARIMA (4,1,2)	ARIMA outperformed ANN with persistence.
Zhongfu Tan et al.	Wavelet-ARIMA-GARCH	GARCH for volatility modelling.
Zhongyang Zhao et al.	ARIMA-GARCH	Regular ARIMA GARCH.
Javier Contreras et al.	ARIMA	Basic ARIMA for electricity prices.
Bitirgen & Başaran Filik	XGBoost	XGBoost outperforms ARIMA.
James W. Taylor et al.	Exponential Smoothing	Handles seasonality in demand.
Huiting Zheng et al.	EMD-LSTM-XGBoost	Used a combination of LSTM and XGBoost for feature ranking.
Asha Sunki et al.	ARIMA, LSTM, Prophet	Multi-model approach for stocks.

Xingdan Huang et al.	ARIMA-GARCH, LSTM	ARIMA-GARCH models volatility.
Minhao Wang	Wavelet-LSTM	Wavelet-LSTM captures non-linear trends.
A. Shiri et al.	SVM	Considers oil and gas prices as features.
Ya Gao et al.	LASSO-LSTM	LASSO selected optimal LSTM features.
Mojtaba Pourghorban & Siab Mamipour	Wavelet-ARIMA-GARCH	Handles non-linear patterns and volatility.
Tang, N et al., (2018)	Support Vector Regression	SVR used for precise prediction of solar power generation.
Ballestrín, J. et al. (2022)	ARMA (1,1)	ARMA (1,1) for soiling forecasting in solar plants.
Atique, S. et al. (2019)	ARIMA(0, 1, 2)(1, 0, 1)30	ARIMA model for daily solar energy forecasting.
Atique, S. et al. (2020)	SARIMA, SVR, ANN	Comparison between SARIMA, SVR, and ANN.
Liu, H., & Shi, J. (2013)	ARMA-GARCH	ARMA-GARCH for short-term electricity price volatility.
Al-Musaylh, M. S. et al. (2018)	MARS, SVR, ARIMA	MARS, SVR, ARIMA for electricity demand forecasting.
Zhongfu Tan et al.	Wavelet-ARIMA-GARCH	Enhanced with GARCH for volatility modelling.
Zhongyang Zhao et al.	ARIMA-GARCH	Captures both mean and volatility.
Sharma, K et al., (2022)	FB-Prophet	Captures trends, seasonality, and holiday effects
Guo, L et al., 2021	Hybrid Prophet-SVR	integrates Prophet for seasonal components and SVR for non-linear patterns
Almazrouee, A. I et al., 2020	Prophet with multi-regressors.	External regressors gave better predictions

The impact of renewable energy on electricity markets, policy, and sustainability in Australia and beyond has been the subject of extensive research. Gonçalves and Menezes (2021) highlight the influence of renewables, especially solar and wind, on electricity prices within Australia's National Electricity Market (NEM). They reveal how increased renewable penetration can alter price distributions and market bidding behaviours. With higher renewable uptake, prices have shown increased variability, particularly within moderate price ranges, as examined by the Australian Energy Council (2021). This variability, though moderated by storage and interconnection investments, can add seasonal price effects, especially from solar energy production.

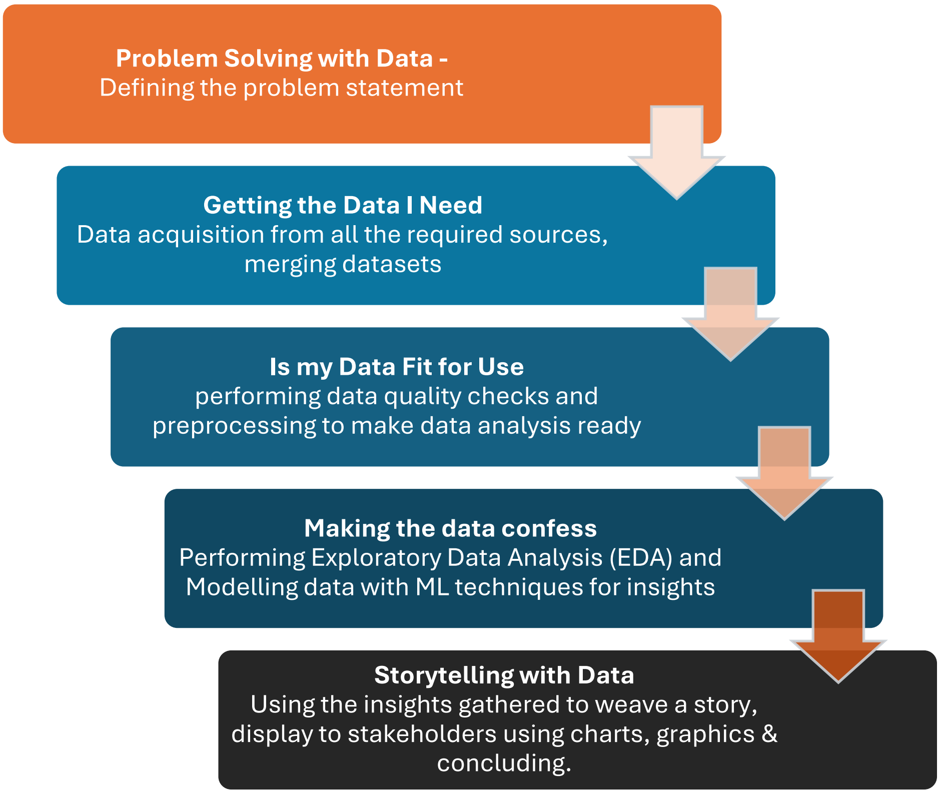
Renewable energy policy in Australia is also important, as analyzed by Yang, Sandu, and Li. Policies like feed-in tariffs (FITs) and renewable energy certificates (RECs) are crucial, with Lan et al. (2020) examining the role of FITs in Southeast Queensland to encourage solar PV adoption. FITs are shown to impact adoption rates significantly, offering environmental and economic benefits. Chapman (2016) added to this by evaluating Australia's residential solar policy and highlighting the mixed successes and challenges in incentivizing household solar PV adoption.

Wang (2024) further explores renewable energy certificates in Australia and the UK, illustrating how REC markets manage the balance of supply and demand. This comparison showcases how REC markets are used in stabilizing renewable energy contributions while providing financial incentives for further renewable investments.

Additionally, as renewable penetration influences traditional energy markets, the exploration of green hydrogen, as studied by Rodrigues de Oliveira et al. (2021) in the Iberian context, shows how electricity prices influence the viability of hydrogen production. This goes on to show how green hydrogen with proper investment can soon become a game changer in the way electricity is utilized and how fuel is stored. Even if the resultant electricity from green hydrogen is lower from what was used to create it, it is provides positive ROI when considering that electricity would have gone to waste.

Together, these studies demonstrate the importance of renewable energy policies, market mechanisms like RECs, and innovations in green energy alternatives, such as green hydrogen. By reducing greenhouse gas emissions and fostering cleaner energy production, these support Australia's renewable energy goals and reveal broader implications for global electricity markets.

5. Methodology



This section will define the methodology used to approach the project. Since this project is a Data Science project, an approach technique taught in University of Queensland's DATA7001 Introduction to Data Science will be used. This technique divides the problem into five major sequential steps. These steps include:

1. Problem solving with data:

The first step to any data science problem involves analysing the problem statement. This way, we can picturize the target while defining the rules and supporting arguments.

2. Getting the data i need:

This subsection involves fetching the required data from data sources and merging the data together to form the necessary dataset. Through this section, we can understand the scope of our dataset.

3. Is my data fit for use:

Acquired datasets are often of various data types, of various time periods or might have issues such as varying scales, missing data and more. Hence, this section involves techniques to standardize the dataset.

4. Making the data confess:

This section involves modelling various machine learning or time series models to fit on the data, revealing insights

5. Storytelling with data:

This final section involves concluding the results in a graphical manner with an explanation that will satisfy the original problem statement.

Since the problem statement has already been defined along with a comprehensive literature review, we can directly initiate with data acquisition.

5.1 Getting the Data I Need

Since the project entirely involved National Electricity Market overseen by AEMO which is a government body, all data was directly fetched from the official NEM website. NEM stores historical data to encourage transparency of operations and hence almost all historical data was fetched.

AEMO stores month-wise historical electricity demand and price data in its data dashboard. Hence, these datasets were downloaded and combined together to form a single dataset for usage. Overall, this dataset contained the "SETTLEMENTDATE" column which defined the dispatch interval, the "TOTALDEMAND" column which defined the total demand in MW for that particular dispatch interval, and finally the "RRP" column which stands for Regional Reference Price and defines the spot price for the particular dispatch interval.

Next, holiday dataset was required and was fetched from Australian Government's official data.gov.au website, which offered machine readable historical datasets for usage. This dataset contained the particular holiday date, holiday name, its description, and the state in which it is celebrated. The dataset contained holidays from 2021 till 2024.

Generation data was fetched from NEM's nemweb Electricity Data Model archives. This dataset is also archived monthly and contains the Scada values of the total amount of electricity dispatched in the particular settlement period (aka dispatch interval). This dataset however contained records of all the generators that were deployed in the particular settlement period and hence would require filtering.

Finally, interconnector data was also fetched from the aforementioned Electricity Data Model. This dataset, also grouped by settlement period, also contained information on each of the 5 interconnectors present in the NEM along with the metered amount of electricity dispatched, the lower and high limits and other information.

Weather data was not utilized as a model variable. Due to weather being vastly varying in the entire state of Queensland, it was difficult to select one weather station close to the diverse locations of solar farms in Queensland and acquire its weather data. Moreover, the data available in the official Australian Government Bureau of Meteorology website was daily weather data which was a higher resampled data than the 5-minute granularity required. NEM itself considers weather from various locations and treats them separately for pre-dispatch forecasting. Hence, weather data was not utilized.

5.2 Is my Data Fit for Use

Data preprocessing is necessary for data fetched from various sources due to common issues such as missing values in the data, mismatched types, data not being standardized across variables, identifying outliers or anomalies and so on. However, data fetched from AEMO does not require any preprocessing. This is because AEMO calculates generation, interconnector values and demand in Megawatt, price in Australian Dollars and holiday is datetime. Hence, all variables currently used share either similar datatype or are already scaled appropriately for most time series models. AEMO's real time monitoring also ensures there is no missing data. However, all our data is fetched from various sources and hence needs to be combined in a single column with unnecessary columns dropped.

The demand and price dataset were used as the base dataset for all others. In the holiday dataset, columns which were not required such as holiday name and description were dropped. Additionally, since the holiday dataset also contained holidays from other states, these rows were subsequently dropped. The holiday dataset was then merged into the demand and price dataset based on the settlement date column in a Boolean format. This meant for all the 288 rows which signified one day (5-minute data * 288 is 24 hours), if that day were a holiday, the "is_holiday" column would be 1 otherwise 0.

For the generation data, the first row was a descriptive row and was dropped. Next, the dataset contained all the generators that were deployed in a particular dispatch interval along with their DUID or Dispatchable Unit Identifier and their respective generation amount. Since this NEM data was across all the states, only the generation plants in Queensland were needed to be filtered out. Hence, for finding the generation plants in Queensland, opennem website was used. Opennem website allows the user to filter based on generation source material by state. This allowed me to gather all the 35 operating solar farms and their respective DUIDs. Furthermore, all 89 generation plants in NEM were also filtered through their DUIDs and the rest were dropped. Next, these generators were then aggregated based on sum based on the common settlement date, with their columns added to the demand and price dataset based on settlement date column.

Finally, for the interconnector dataset, the descriptive rows were dropped. Furthermore, columns which signified the upper and lower limit were dropped. To account for simplicity, the total transmission loss column was not considered. The actual metered flow of electricity through the interconnectors was used, and the dataset was filtered for N-Q-MNSP1 and NSW1-QLD1, the two interconnectors that are connected to Queensland (to New South Wales). These two interconnectors, Queensland – New South Wales Interconnector and the Terranora Interconnector were then aggregated to show the total interconnector data for a dispatch interval and hence added to the main dataset.

5.3 Making the Data Confess

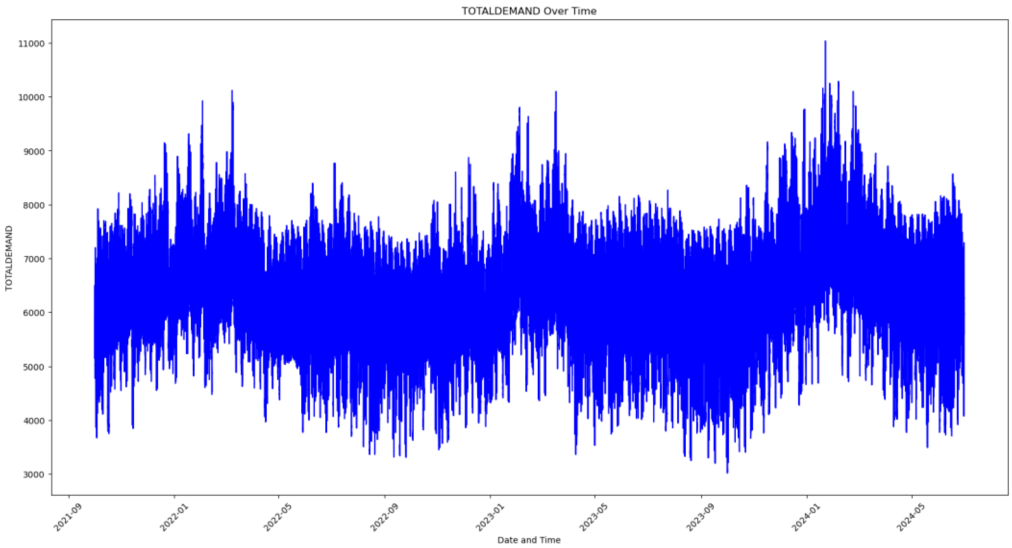
	SETTLEMENTDATE	TOTALDEMAND	RRP	is_holiday	METEREDMWFLOW	SCADAVALUE	TOTAL_SCADAVALUE
0	2021-10-01 00:05:00	5693.27	43.09	0	-244.37471	-0.106	5760.865758
1	2021-10-01 00:10:00	5635.79	54.00	0	-197.66650	-0.106	5715.296714
2	2021-10-01 00:15:00	5605.89	61.15	0	-206.39658	-0.106	5666.516675
3	2021-10-01 00:20:00	5594.89	54.56	0	-253.06460	-0.106	5702.972977
4	2021-10-01 00:25:00	5517.08	54.00	0	-209.05068	-0.106	5587.545325

The final dataset had 289152 rows across 7 columns as shown. This is because the dataset was fetched from 1st October 2021 till 30th June 2024 (Hence, 1004 days * 24 hours * 60 minutes / 5-minute data).

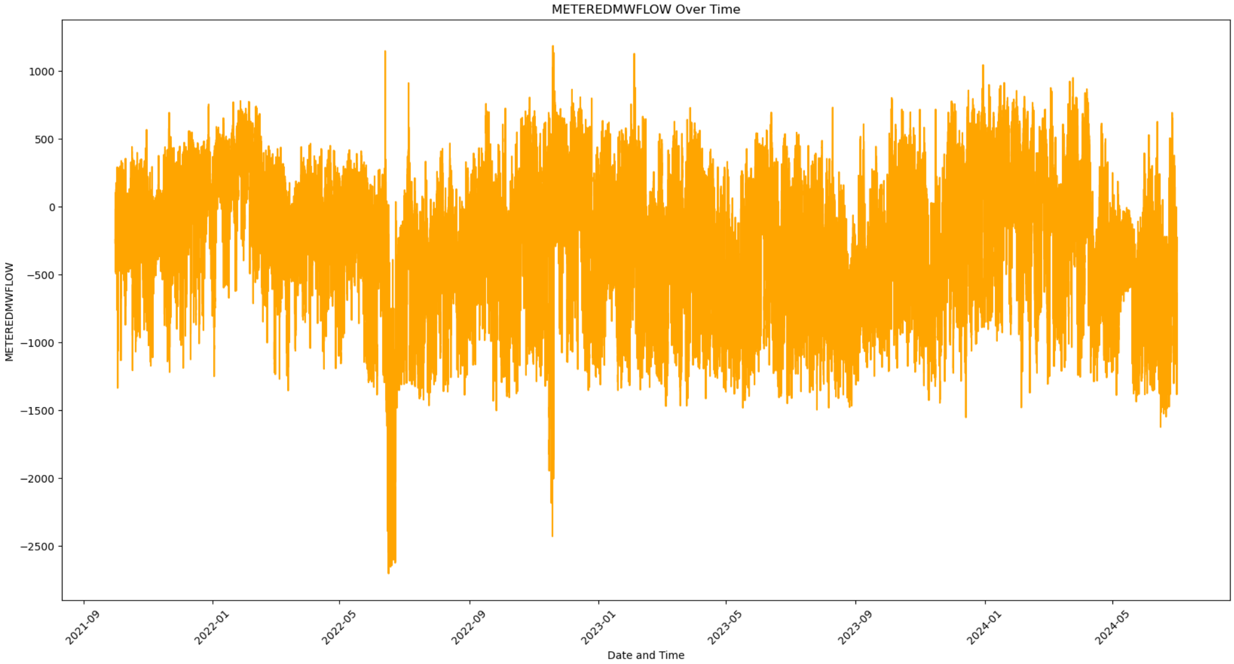
	TOTALDEMAND	RRP	is_holiday	METEREDMWFLOW	SCADAVALUE	TOTAL_SCADAVALUE
count	289152.000000	289152.000000	289152.000000	289152.000000	289152.000000	289152.000000
mean	6117.862686	136.270170	0.041833	-258.065725	483.059625	6404.705796
std	1033.353791	484.872998	0.200207	465.480088	595.438540	858.555791
min	3016.910000	-1000.000000	0.000000	-2704.326360	-1.665460	3937.843064
25%	5416.440000	56.100000	0.000000	-572.400093	0.036630	5765.161096
50%	5992.055000	90.730000	0.000000	-223.696700	6.594460	6304.047122
75%	6798.625000	145.960000	0.000000	82.934595	1059.877116	6940.785169
max	11036.200000	16600.000000	1.000000	1186.117130	2267.502021	10532.438471

The dataset shows that the value of price ranges from -1000 AUD (the market floor value) and 16600 AUD (the market ceiling value). However, the mean value or the average RRP over time is AUD 136 which shows that normally the spot price of the NEM stays under 200 AUD, but occasionally sees price spikes. Moreover, these price spikes have increased the median value of 90.73, showing that the price spikes caused the data to have a positive skew.

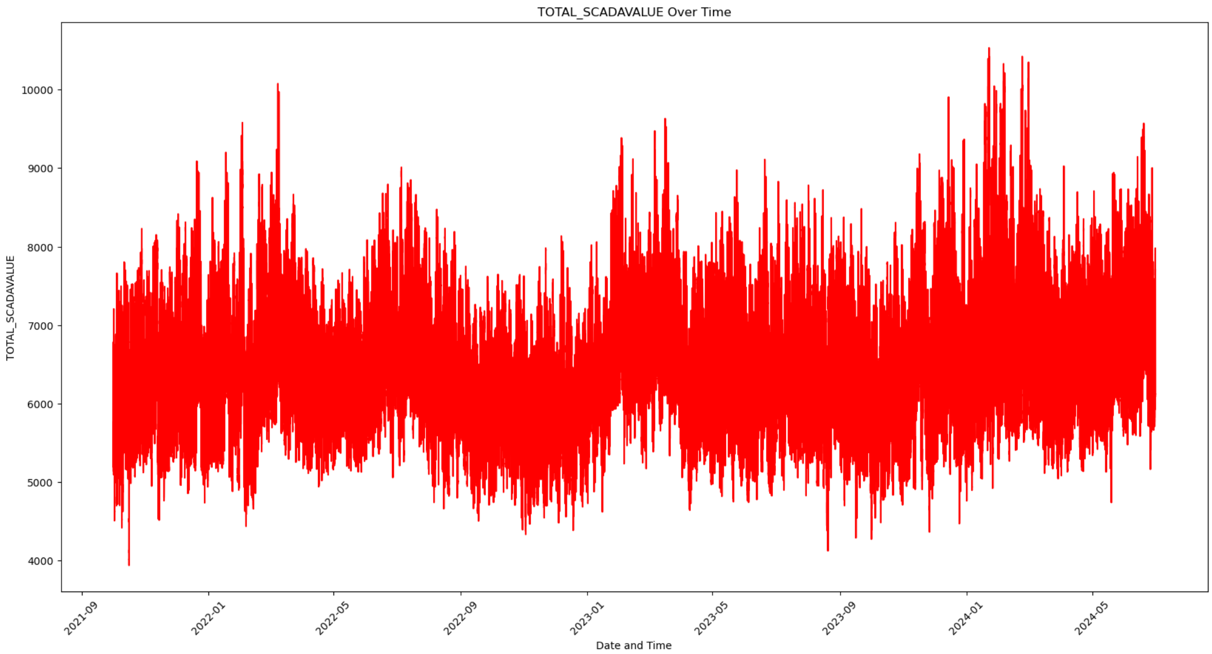
For demand, the mean and median values are almost similar, implying a bell curve distribution. Meanwhile SCADAVALUE column which showcases the solar generation data also has a massive difference in mean and median, which displays that on most days, solar generation is small, but there are some periods with very high solar output, possibly during sunny, cloud-free days. However, the negative generation values do not make sense, and the only hypothesis is erroneous or included noise input by Scada systems during monitoring. Hence, 0 was imputed for all places wherever solar generation was negative.



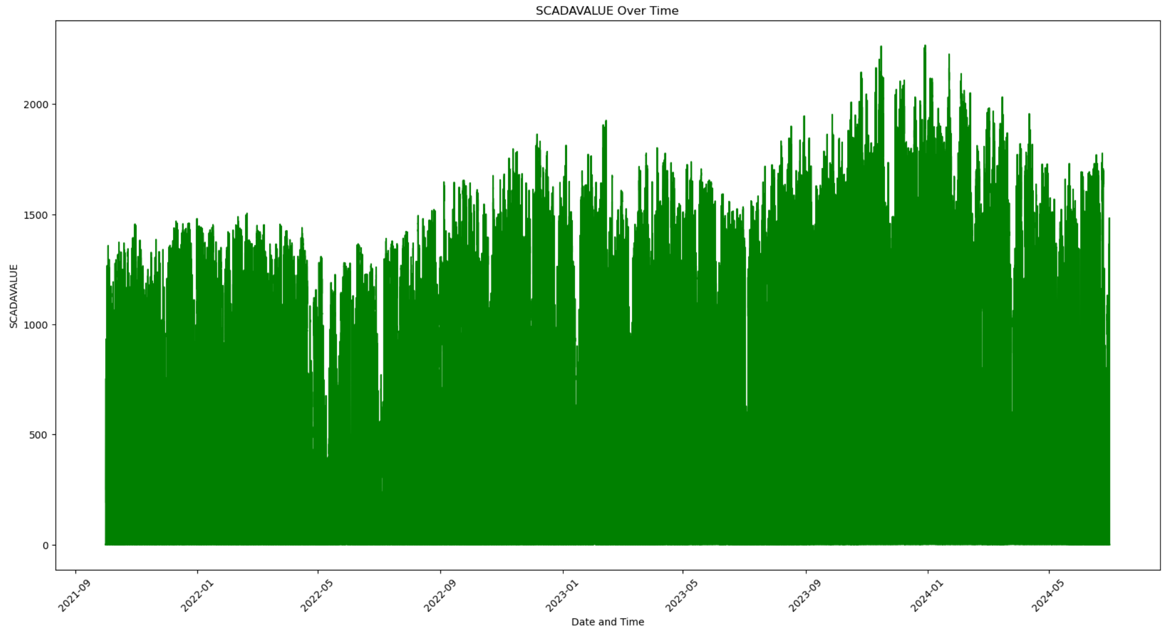
Total Demand over Time



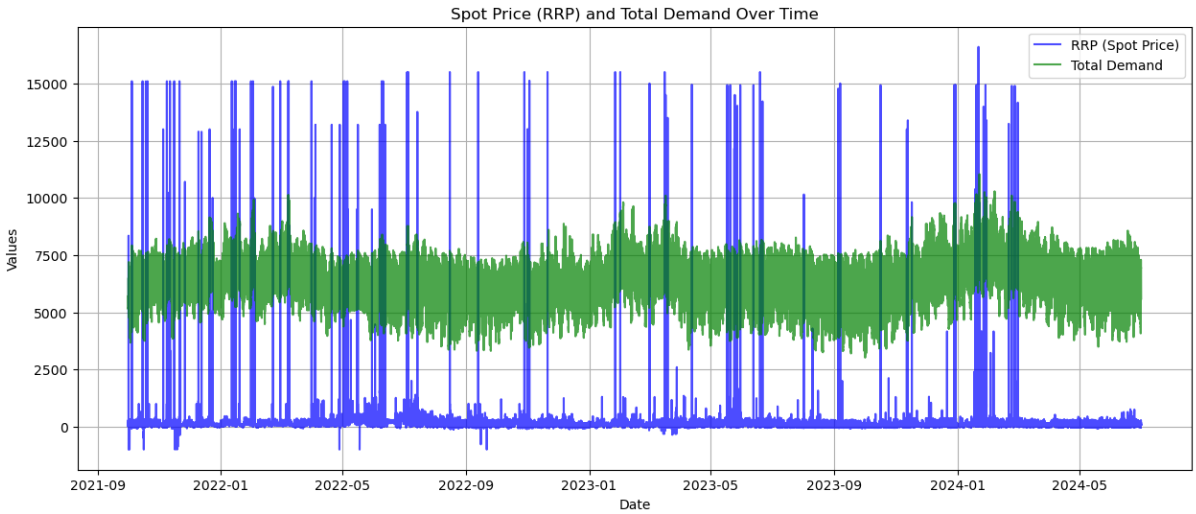
The flow of electricity through interconnector over time



Total Electricity Generation over time



Solar Generation over Time



Depiction of Spot Price and Demand over time

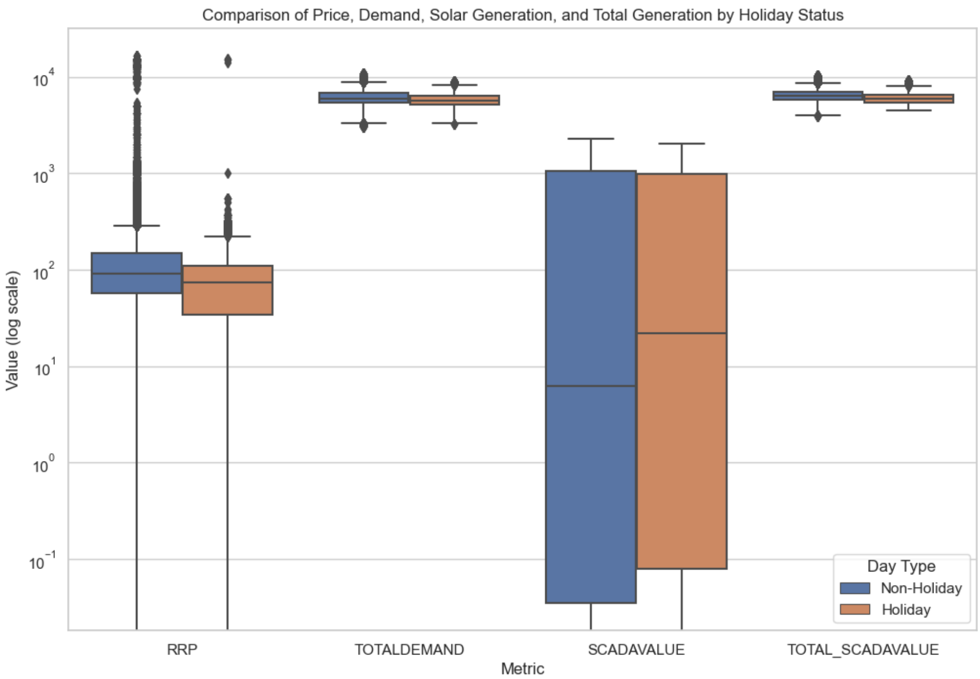
Furthermore, IQR analysis on price revealed:

Outlier Thresholds for RRP: Lower Bound = -78.69000000000003, Upper Bound = 280.75

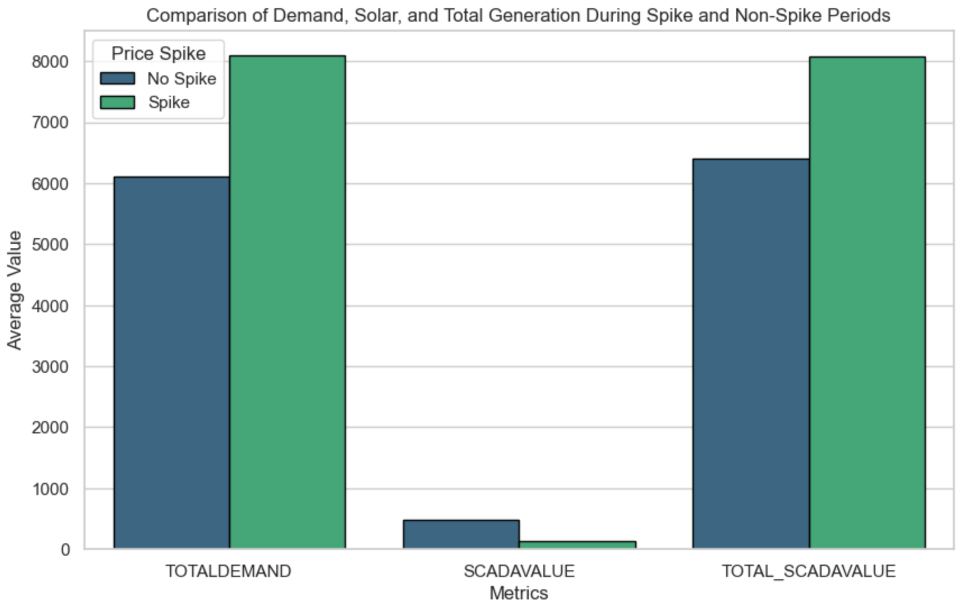
This signified that any price above 281 dollars was an outlier.

Seasonal Decompose (Appendix A) of the dataset shows a display of strong seasonality across daily, weekly and monthly areas. Due to the data not being across numerous years, yearly seasonality could not be gauged completely. The Augmented Dickey-Fuller (ADF) test result for the daily resampled data shows an ADF statistic of -4.88 with a very small p-value (3.82e-05). Since the ADF statistic is less than all the critical values (at 1%, 5%, and 10% significance levels) and the p-value is much below 0.05, we reject the null hypothesis that the time series has a unit root. This suggests that the daily resampled RRP data is stationary, indicating that there is no strong trend present, which is ideal for time series modelling.

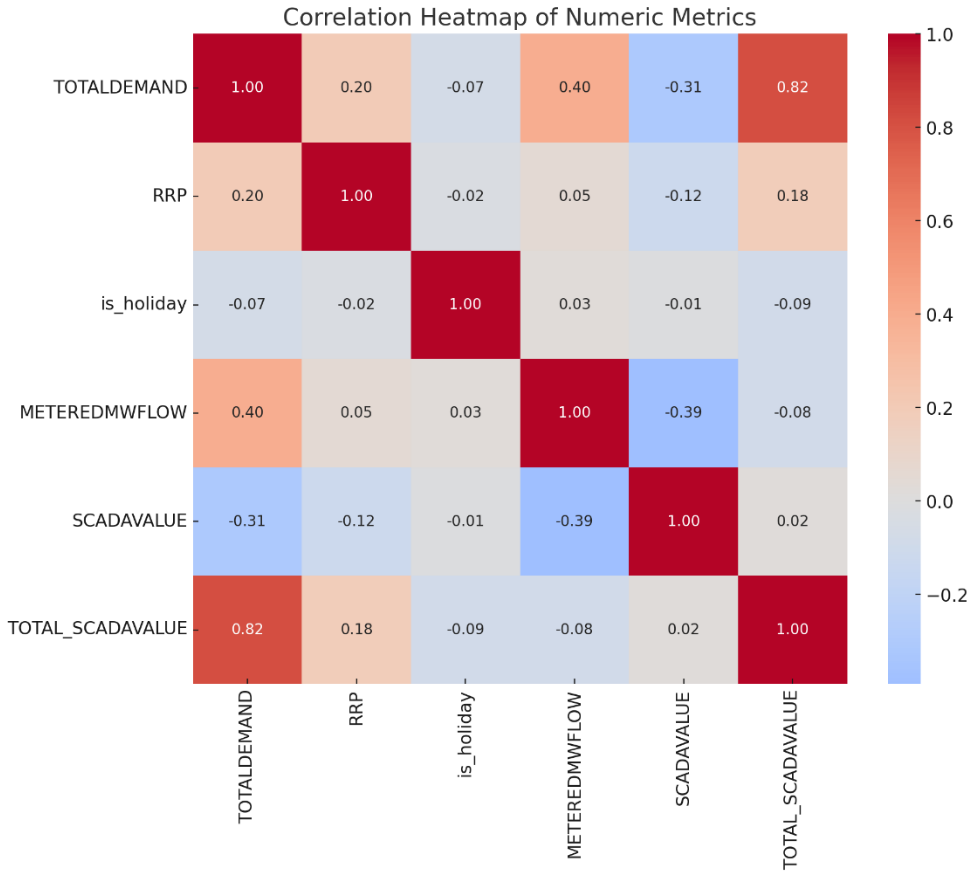
The Ljung-Box test was conducted to check for seasonality at different frequencies. Specifically, for hourly seasonality (lag of 24), the p-value was 0, which confirms significant autocorrelation at 24-hour lags, indicating strong hourly seasonality. For daily seasonality (lag of 7), the extremely small p-value also indicates significant autocorrelation, suggesting a consistent weekly pattern in the daily values. The weekly seasonality (lag of 4) has a similarly small p-value, suggesting that weekly behaviour is also correlated over time. Finally, for monthly seasonality (lag of 12), the p-value is 0.000812, which indicates that significant autocorrelation exists at the monthly level as well.



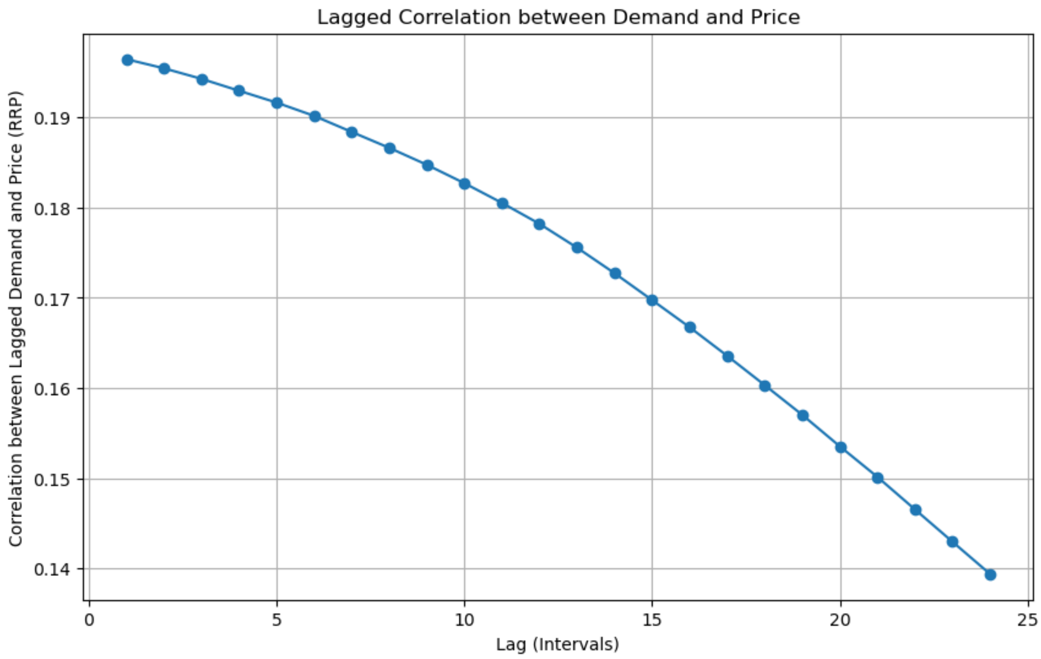
The above graph shows the variations in variables when the day is a holiday or not. Demand is generally lower on holidays compared to non-holidays, likely due to all industrial and office workplaces being shut down. Similarly, prices also are lower on holidays compared to non-holidays, which may be complimenting the lower demand. Solar generation does not seem varied and shows that regardless of holiday solar generation remains constant, however total generation shows a difference being slightly lower on holidays, also complimenting lower demand.



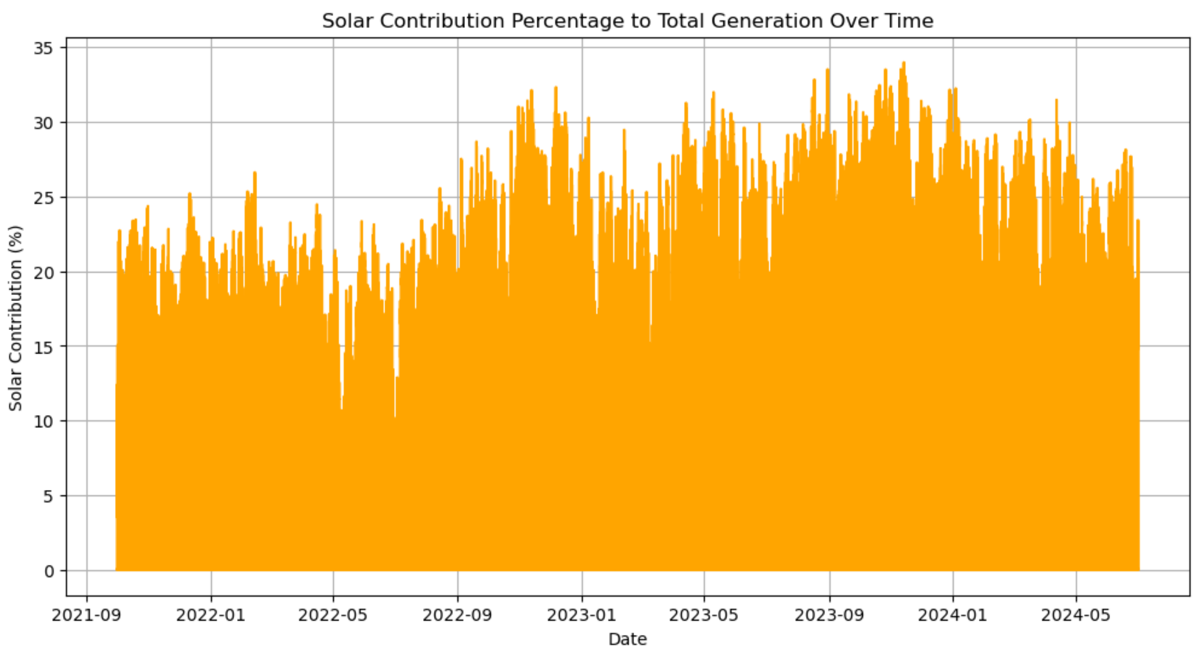
The bar chart showcases that on average, demand is much higher during price spikes (all the instances where RRP is more than 1000 is considered a spike) than compared to non-price spikes. Similarly, to provide for the jump in demand, generation is also high (basically implying NEMDE had to dispatch higher cost generators to meet demand). However for all price spikes, solar generation is much lower than on non-spike occasions, showing renewable generators could have reduced the price spike impact.



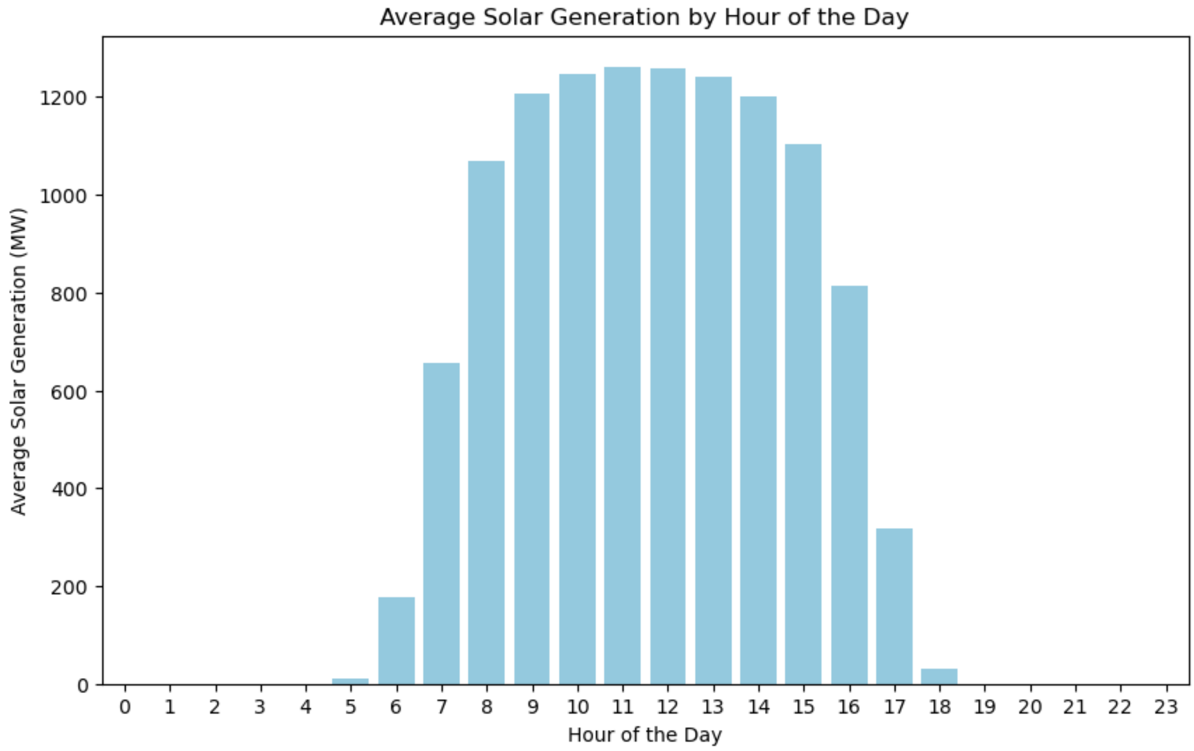
From the correlation plot, we can see that total demand and total generation have high positive correlation, which is accurate since high demand always has high generation (and high dispatch) to ensure supply demand balance. Price is slightly correlated with generation and demand, which also is accurate, since high demand increases price and so does dispatching higher priced generators. However, price has a small negative correlation with solar generation, which shows that even minorly solar does decrease price. Similarly, solar generation is negatively correlated with demand, showing higher solar output often aligns with slightly lower demand, perhaps due to daytime demand loss. Interconnector values is also correlated with demand, showing high demand has high electricity transmission through the interconnectors. Interconnector is also inversely correlated with solar generation, again possibly due to daytime demand loss.



The above chart displays that price currently is highly dependent on demand at previous time interval, and as time increases, the correlation becomes lower.

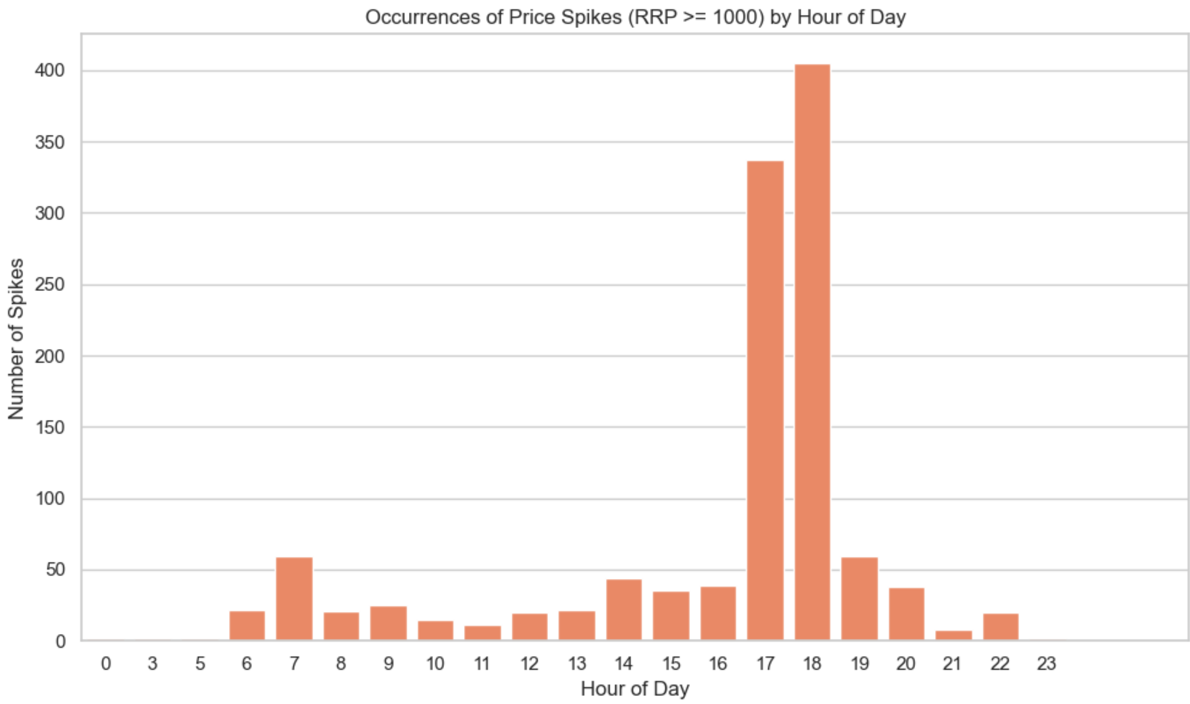


Calculating the amount of solar generation per total generation over time, we can see that solar contribution fluctuates between roughly 15% and 30%, which indicates that solar is a high percentage of total generation but is affected by external factors such as seasonal changes, daylight availability and so on.



Solar generation is the highest during the hours of 10 am to 2 pm on average. Solar generation can start from 6 am normally and ramps up around noon. Similarly, solar generation reduces with sun set around 5 pm with 6 pm generation on particularly sunny days on perhaps summer months.

Analysis on spike occurrence shows that 2021 had 93 spikes, 2022 with 742 spikes, 2023 with 174 and 2024 till June had 114 spikes. Spikes are defined as RRP values over 1000. Similarly, 2021 had 1969 instances of prices being negative, 2022 with 4717, 2023 with 14236 and finally 2024 till June having 4986 negative price instances. When considering average price over the years, 2021 had AUD 97.221459, 2022 had a general increase in average price with AUD 205.141686, 2023 with 90.668314 and finally 2024 with 109.341672.



While there is no set time in which price spikes were observed, a majority of the price spikes occurred during the hours of 5 and 6 pm. This time generally signifies when people return home from their jobs, along with factories closing down. This time also coincides with the time when solar in particular stops generating electricity, and the household electricity generation also stops. All these factors lead to demand imbalance along with demand increase, and coupled with other factors (no wind generation that particular day, no renewable to balance demand) can lead to massive price spikes.

Coming to the modelling part, the prospective models were divided into short term forecasting and long-term forecasting models.

5.4 Modelling and Storytelling

5.4.1 Short Term Forecasting

To ensure the project selects the best forecasting model overall, numerous models were run to gauge their effectiveness in understanding the various relations between the exogenous variables with price, and price's own time-based trends. Since short term forecasting focuses on forecasting electricity price of smaller horizons, 6 such horizons were selected. These horizons include 30-minute forecast, 1 hour forecast, 3-hour forecast, 6-hour forecast, 1 day forecast and 2-day forecast. Time further than 2 days was not considered to ensure short term forecasting, and 2 days in particular was selected to allow the solar farms to use the pre-dispatch forecasted demand data in model calculations.

Before moving on to actual model performance, it is important to determine the metrics on which all models will be gauged. These metrics are important, as they serve not only as a measure of model performance based on error but can also give an idea of how different models are performing with the same training data on the same forecasting period.

Since the major aspect of model forecasting and the project as a whole is to forecast the prices in NEM, metrics that calculate the error in predicted price vs actual price were used. However, the trend of predictions is also important. A model that can successfully predict the future trend, i.e., whether the prices are going to increase, or decrease is more important in this project than a model that can predict with low error. Hence, the metrics used in the project include.

1. Root Mean Square Error - RMSE
2. Mean Absolute Error - MAE
3. Symmetric Mean Absolute Percentage Error - sMAPE
4. Mean Directional Accuracy – MDA

Root Mean Squared Error (RMSE) is the square root of the average of the squared differences between the actual and forecasted values. RMSE gives more weight to large errors, as it squares the error values before averaging. Since RMSE is sensitive to outliers, any case when errors are huge will be flagged, with lower RMSE values indicating better model performance.

Mean Absolute Error (MAE) is the average of the absolute differences between the actual and forecasted values. MAE represents the average absolute error in the forecasts. It treats all errors equally, without placing extra weight on larger deviations.

Symmetric Mean Absolute Percentage Error (sMAPE) is a percentage-based metric that measures the average absolute percentage error between the forecasted and actual values, adjusted symmetrically to prevent skewness. This allows sMAPE to display errors as a percentage. And lastly,

Mean Directional Accuracy (MDA) measures the proportion of times the model correctly predicts the direction of change (i.e., increase or decrease) in the target variable. The higher the MDA, the more then model predicts the direction of change accurately. Since trend forecasting is particularly important for solar farms, this metric will be valuable.

1. ARIMA and ARIMAX model

ARIMA (AutoRegressive Integrated Moving Average) is one of the most widely used models for time series forecasting. ARIMA is adept at understanding the patterns and trends in historical data and uses these to make predictions. ARIMA uses manipulation of 3 main parameters to ensure the model fits. These include:

- **p (AutoRegressive Order)**: Number of lag observations in the model.
- **d (Degree of Differencing)**: Number of times the data is differenced to achieve stationarity.
- **q (Moving Average Order)**: Number of lagged forecast errors in the prediction equation.

Pmdarima library was used to fit the best model on the dataset. The auto_arima function fits multiple models on the dataset of varying p, d and q values and uses the AIC metric to find the best fit. The lower values of AIC, the better the model is. To ensure that auto_arima also uses the independent variables, the exogenous variables were used in calculation. auto_arima function identified ARIMAX(5,1,0) as the best model with the lowest AIC value of 2746077.337, with runner up models 4,1,1 and 3,1,1. However, since AIC only measures goodness-of-fit relative to model complexity, we cannot solely rely on it. Hence the top 5 models by AIC were run and tested using RMSE metric for ARIMAX, which resulted in ARIMA(X) (3,1,1) as the best model overall.

However, on training the model and then evaluating the results based on actual vs predicted values, ARIMA result was a straight line. This meant ARIMA was unable to grasp the various trends in the data and hence was unable to accurately predict the values. While even a straight-line prediction can have metrics, they are not worth evaluating. However, ARIMAX results were better, and the model performed well in mid-range forecasting rather than 30 minute and 1 hour forecasting. On average, ARIMAX (3,1,1) results had

Forecast Horizon	RMSE	MAE	sMAPE	MDA
30 minutes	17.58	16.4	19.85%	0.4
1 hour	26.87	24.89	31.64%	0.55
3 hours	51.81	47.92	69.40%	0.66
6 hours	60.1	57.21	91.01%	0.58
1 day	82.67	73.43	104.04%	0.57
2 days	93.76	80.97	106.60%	0.55
Average	55.8	50.47	70.09%	0.55

2. GARCH models

Since the electricity data contains varying about of volatility at all times, GARCH models or Generalized AutoRegressive Conditional Heteroskedasticity models can be used. These models can adapt the periods of high and low variance and learn the trends by modelling the variance of residuals from a mean-based model. In this project, ARIMA GARCH will be used, which has been used in numerous literature reviews as well. The common GARCH(1,1) model was used, which defined the forecasted variance depending on previous volatility and errors. To check the results of GARCH and to offer a new look at the data as well, extensions of GARCH like EGARCH and GJR-GARCH were also used.

EGARCH is an extension of GARCH models that can focus on asymmetry in volatility, allowing it to react differently to positive and negative volatility. Similarly, GJR-GARCH, another extension of GARCH was used as well. GJR-GARCH further changes GARCH where negative shocks have a different impact on the model's ability to understand volatility than positive shocks, even if the positive and negative shocks are of the same magnitude. Here, since negative prices or price drops are more important (since solar farms need high prices to successfully compete and ensure deployment) than price spikes, GJR-GARCH model was expected to outperform GARCH and EGARCH model and emerge as best.

Model	Average RMSE	Average MAE	Average sMAPE	Average MDA
ARIMAX (3,1,1) + GARCH	42.75	36.92	48.86%	0.55
ARIMAX (3,1,1) + EGARCH	42.31	36.52	46.10%	0.55
ARIMAX (3,1,1) + GJR-GARCH	42.8	36.76	47.97%	0.55

As seen in the evaluation table of averaged metrics across the 6 forecasting horizons, all models have equal MDA score. However, EGARCH performed better than regular GARCH and GJR-GARCH model in all other metrics, albeit slightly. This shows that EGARCH, which is adaptive to extreme changes performed better than GJR-GARCH, which is adaptive to negative changes more than positive changes.

3. ETS (Error, Trend, Seasonal) Holts Winter Smoothing

The Holts Winter model is a Bayesian type of model which uses exponential smoothing to calculate the trend and seasonal components in time series forecasting. Since SARIMA models could not be explored in the project due to SARIMA being extremely memory extensive for large datasets, ETS model which can incorporate seasonality was extremely useful. The model is made of

- Error (E): The residual component representing random noise or fluctuations in the data.
- Trend (T): The long-term movement or direction in the data, which can be upward, downward, or even cyclical.
- Seasonality (S): The repeating patterns at fixed intervals, capturing predictable changes associated with seasons or cycles.

ETS can dynamically adjust to changes int trend and seasonality but is however unable to use exogenous variables. Even without exogenous variables, ETS can accurately account for short term and long-term predictions due to its sensitivity to fluctuations and seasonal patterns.

Forecast Horizon	RMSE	MAE	sMAPE	MDA
30 minutes	8.41	6.79	7.14%	0.8
1 hour	8.07	6.89	7.21%	0.64
3 hours	11.5	10.12	9.94%	0.46
6 hours	20.5	17.77	16.88%	0.46
1 day	38.06	29.51	50.01%	0.52
2 days	50.7	38.5	62.57%	0.5
Average	22.54	18.26	25.63%	0.56

The metrics show that ETS model is one of the best model (along with Prophet). ETS was particularly good for short term forecasts, achieving high metrics on 30 minute and 1-hour forecasts. However, as the horizons got longer, the models accuracy dropped, showing long-term volatility challenge. Graphically, ETS model was one of the best at following the actual predictions accurately, much better than ARIMA GARCH models.

4. Prophet Model

Facebook's Prophet model was the best model overall. This open-source forecasting model is designed to handle time series data that contain large amount of seasonality present. Prophet offers in built seasonalities but also allows the building of custom seasonalities. For this project, to allow more Fourier orders, I decided to use custom seasonalities along with an additive model. Prophet, which not having seen widespread use as other models for electricity data price was the best model in terms of accuracy of trend and other metrics.

Hyperparameters such as changepoint prior scale and seasonality prior scale were tuned to find the best values. These hyperparameters allowed me to identify how much leeway the model should have considering changes in trends and changes in seasonality.

Forecast Horizon	RMSE	MAE	sMAPE	MDA
30 minutes	12.15	10.77	13.44%	0.6
1 hour	10.34	8.38	10.68%	0.73
3 hours	9.16	7.9	10.45%	0.77
6 hours	12.48	10.75	13.47%	0.75
1 day	40.3	28.28	42.07%	0.6
2 days	65.77	43.06	54.99%	0.57
Average	25.7	18.19	24.52%	0.67

As evident from the metrics, prophet shows strong performance in short to mid term horizons. It also has a consistent MDA, showing it can show changes in trend well, which is something solar farms can greatly benefit from.

5. AutoRegressive Distributed Lag Model

ARDL model is a subtype of regression model which is used to capture short-term and long-term relationships between exogenous variables and dependent variable which is price. ARDL model does this by adding lags of all the variables used and then using these lags to show the relationship. Since past values of demand and other exogenous variables are important to predict price, ARDL model is a potentially useful model.

To avoid explicitly overfitting, a parameter grid format of finding the best lags was used with lags going till Lag 7. Through this, the best lags for all the exogenous variables were found to be {'TOTALDEMAND': 2, 'METEREDMWFLOW': 2, 'SCADAVALUE': 2, 'is_holiday': 0, 'TOTAL_SCADAVALUE': 2} which meant apart from holiday Boolean column.

Forecast Horizon	**RMSE**	**MAE**	**sMAPE**	**MDA**
30 minutes	55.55	54.98	46.13%	0.4
1 hour	59.02	58.51	47.93%	0.55
3 hours	64.74	63.75	49.50%	0.43
6 hours	76.05	74.38	55.68%	0.39
1 day	82.17	66.75	50.60%	0.44
2 days	77.88	64.08	69.48%	0.41
Average	69.9	63.41	53.55%	0.44

The ARDL model displays a moderate performance, with a high RMSE and sMAPE across the forecast horizons. While the model captures general trends, as seen in the **Mean Directional Accuracy (MDA)** values, it has difficulty accurately predicting sharp fluctuations in electricity prices. The model performs better in shorter horizons (30 minutes to 1 hour), where it can track changes in prices.

6. State Space Models (Kalman Filter)

The Kalman filter is a recursive algorithm used in datasets that are particularly noisy. In particular, state space models are so called because they refer to the state of the data, which means the exogenous variables that define the system at any given point of time. Kalman filter is used in datasets that are frequently updated, which in this case is beneficial as with pre-dispatch price updates solar farms need models that can adapt to changes in this state.

The Kalman filter predicts the values in two steps. First comes the prediction step, in which model will predict the next state based on the current state. Then, when the actual observation occurs, the model will compare its predictions based on the current state. This is called measurement residual, and the model will train itself by adjusting the predictions for the state in the future.

Forecast Horizon	RMSE	MAE	sMAPE	MDA
30 minutes	83.84	83.54	62.67%	0.6
1 hour	74.51	73.57	56.70%	0.55
3 hours	67.35	66.37	51.10%	0.6
6 hours	67.65	66.62	51.71%	0.62
1 day	77.24	61.22	44.87%	0.5
2 days	75.27	62.3	66.51%	0.47

Average	74.64	68.27	56.26%	0.54

The Kalman filter has a moderate performance on the dataset. Even with hyperparameter tuning and adding ElasticNet, the model was unable to achieve a forecast as good as Prophets. This shows the immense role seasonality has on the models. Kalman filter is unable to aptly capture the volatility in price.

7. Support Vector Machines

Like ARIMA models, SVR models are also one of the most popular models used for all types of forecasting. SVR is a type of ML model which is based on support vector machines and is designed for continuous prediction of values. SVMs find a linear function that can best fit the data alongside allowing a margin of error, thus providing a better forecast compared to others. This margin, called the margin of tolerance alongside the penalty parameter can be tuned. At first, SVM on CPU was run using the dataset, however due to extensively long computation times, GPU based SVM was used through Colab notebooks. To further avoid long computation and since linear model was best, LinearSVR was used.

Forecast Horizon	RMSE	MAE	sMAPE	MDA
30 minutes	33.87	33.69	31.16%	0.4
1 hour	30.46	30.04	27.95%	0.55
3 hours	24.97	23.79	22.07%	0.69
6 hours	25.43	24.29	22.81%	0.65
1 day	35.56	28.12	36.15%	0.57
2 days	49.87	37.31	58.47%	0.55
Average	33.36	29.87	33.10%	0.57

LinearSVR post tuning also shows good performance across all metrics, particularly for 3- and 6-hour period. SVM’s RMSE, MAE values remain steady across the different horizons, with sMAPE following suit except for 2 days prediction. Altogether, with 0.57 MDA value, LinearSVR is also good at forecasting change in direction.

8. LightGBM

LightGBM or Light Gradient Boosting Machines are a form of decision tree models. These models generate numerous decision trees which act as learners of the patterns. Slowly, these random learners are optimized in a sequential way to increase the prediction accuracy. Between all decision tree models, LightGBM is one of the fastest in speed and efficiency, which is required by solar farms to receive up-to date predictions with changes in pre-dispatch values.

Forecast Horizon	RMSE	MAE	sMAPE	MDA
30 minutes	67.06	46.23	40.16%	0.4
1 hour	47.42	45.02	38.60%	0.27
3 hours	48.5	44.81	36.75%	0.51
6 hours	54.53	49.39	40.18%	0.37
1 day	55.67	44.01	36.66%	0.41
2 days	53.13	44.95	56.29%	0.43
Average	54.72	45.4	41.11%	0.4

Overall, even after fine tuning, LightGBM only had average performance. While the RMSE was lower compared to other ARIMA models, its MDA values being lower than most is not something to be desired. Even in graph, LightGBM was not able to accurately follow the actual predictions.

9. XGBoost (Extreme Gradient Boosting)

XGBoost is another decision tree-based machine learning algorithm. It offers more flexibility and effectiveness than LightGBM but is more computationally expensive. XGBoost uses decision trees as base learners, combining them iteratively to reduce errors, making it effective in capturing complex relationships in the data. XGBoost main feature is its ability to smoothly handle data with non-linear relationships like SVMs.

Forecast Horizon	RMSE	MAE	sMAPE	MDA
30 minutes	62.75	61.96	50.48%	0.4
1 hour	58.26	57.04	46.87%	0.27

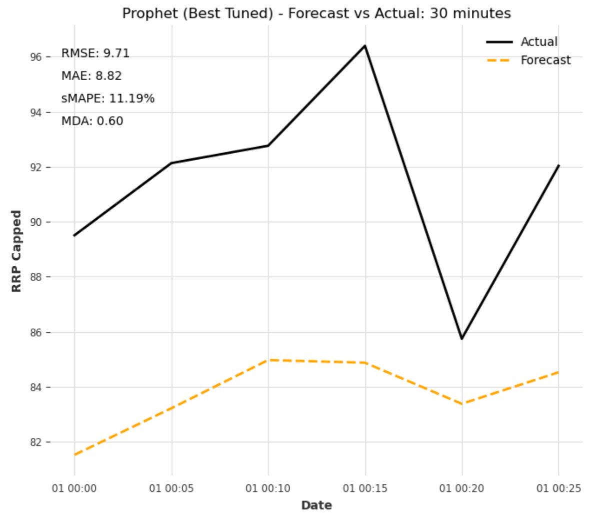
3 hours	51.02	49.56	40.59%	0.6
6 hours	51.93	49.73	41.39%	0.48
1 day	56.45	46.05	38.05%	0.47
2 days	53.84	46.37	57.37%	0.47
Average	56.79	51.12	45.79%	0.45

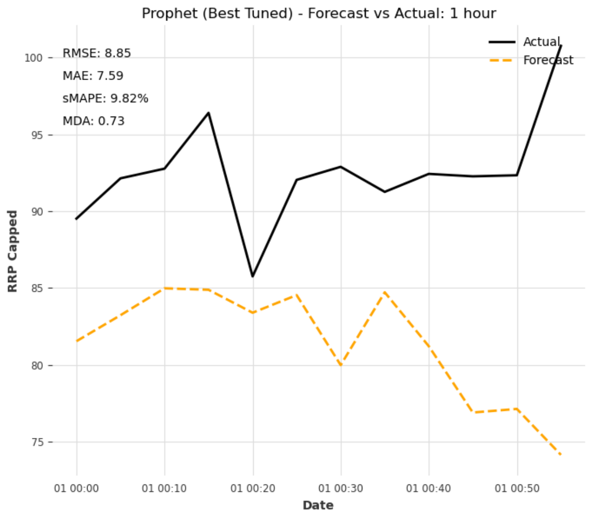
The resultant metrics are slightly worse than LightGBM model. Across RMSE, MAE and sMAPE, LightGBM scores lower values, showing slight outperformance. In MDA, XGBoost has 0.45 which is again slightly better than LightGBM model. XGBoost also offers consistent results across all horizons but will not be considered against Prophet and ETS.

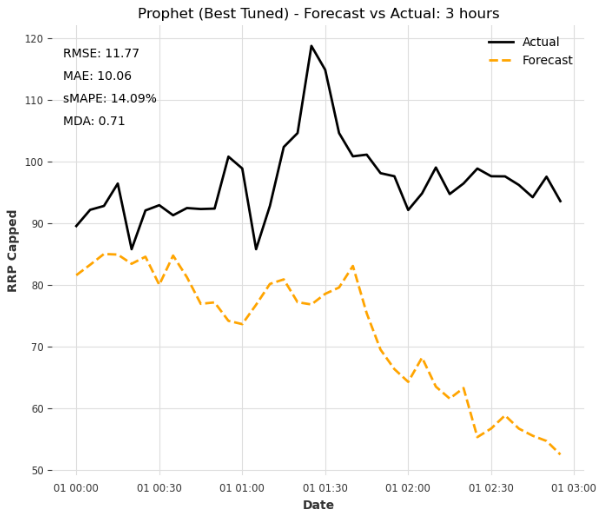
5.3.2 Best Model

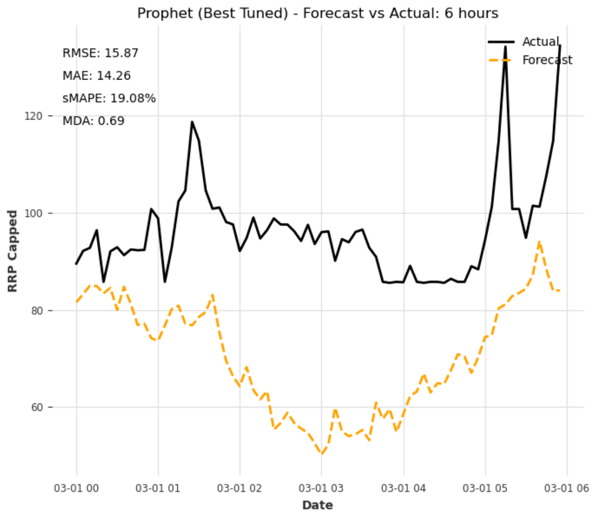
Model	**Average RMSE**	**Average MAE**	**Average sMAPE**	**Average MDA**
Corrected ETS (Holt-Winters)	22.54	18.26	25.63%	0.56
Prophet (Best Tuned)	25.7	18.19	24.52%	0.67
ARIMAX (3,1,1)	56.86	49.9	63.73%	0.52
ARIMAX (3,1,1) + GARCH	41.92	38.21	50.94%	0.49
ARIMAX (3,1,1) + EGARCH	41.6	38	50.77%	0.5
ARIMAX (3,1,1) + GJR-GARCH	41.97	38.35	50.90%	0.5
ARDL	69.9	63.41	53.55%	0.44
State Space Model (Kalman)	74.64	68.27	56.26%	0.54
Linear SVR	33.36	29.87	33.10%	0.57
LightGBM	54.72	45.4	41.11%	0.4
XGBoost	56.79	51.12	45.79%	0.45

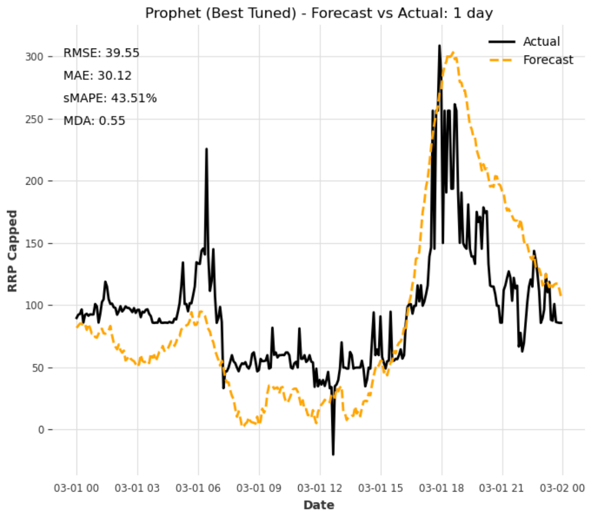
As is evident from the above metrics, Prophet is the best model overall, offering the lowest horizon averaged metrics as well as having the best MDA metric. The closest model is ETS Model which focused on daily seasonality. However, Prophet is better in ETS in two metrics as well, giving the best overall performance.

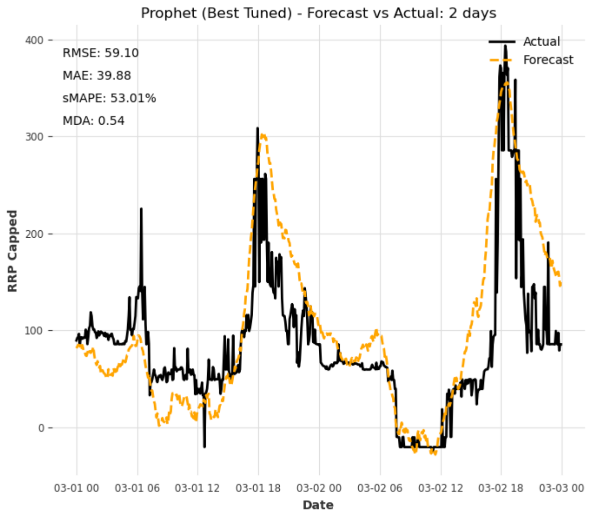


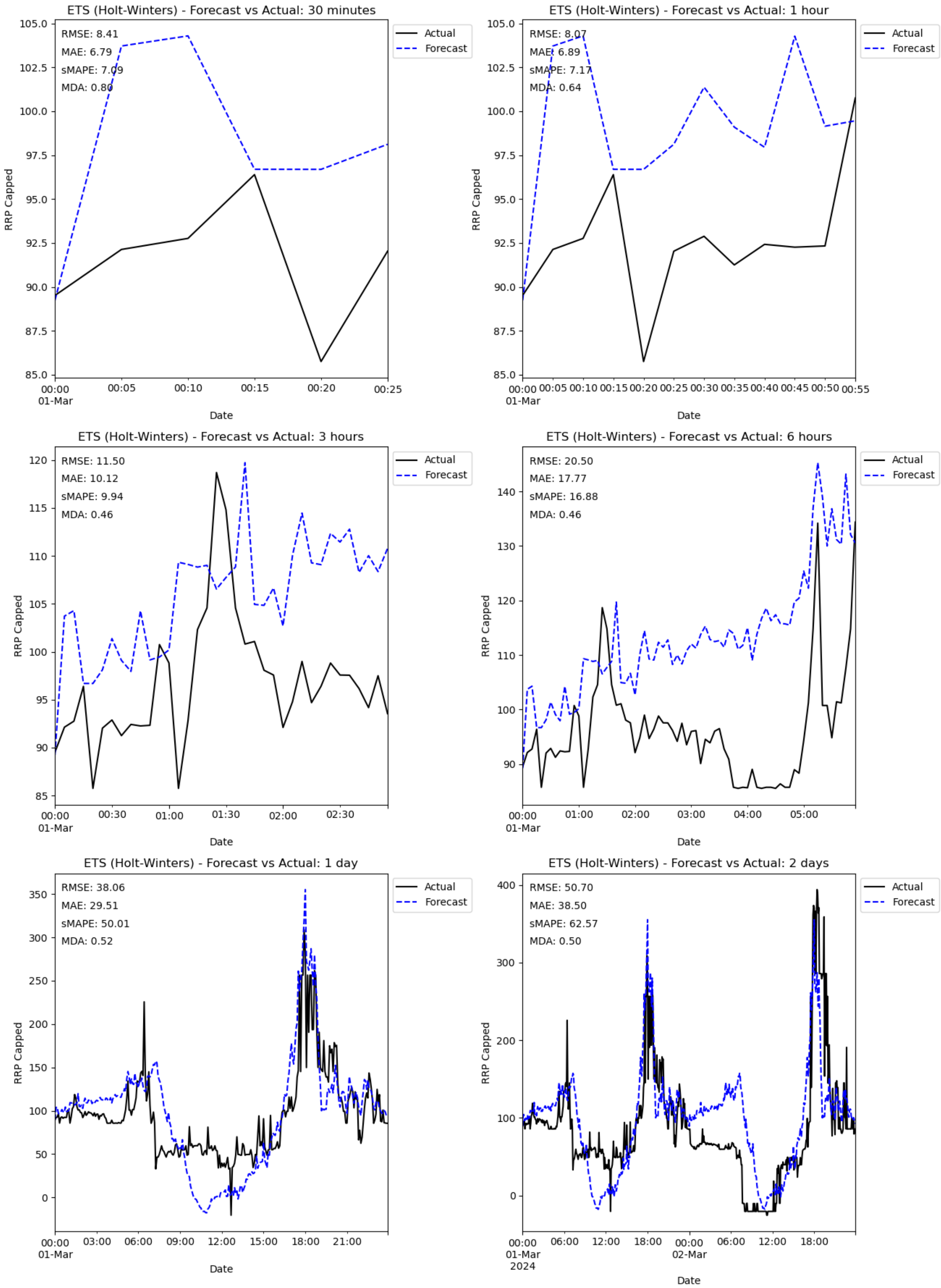








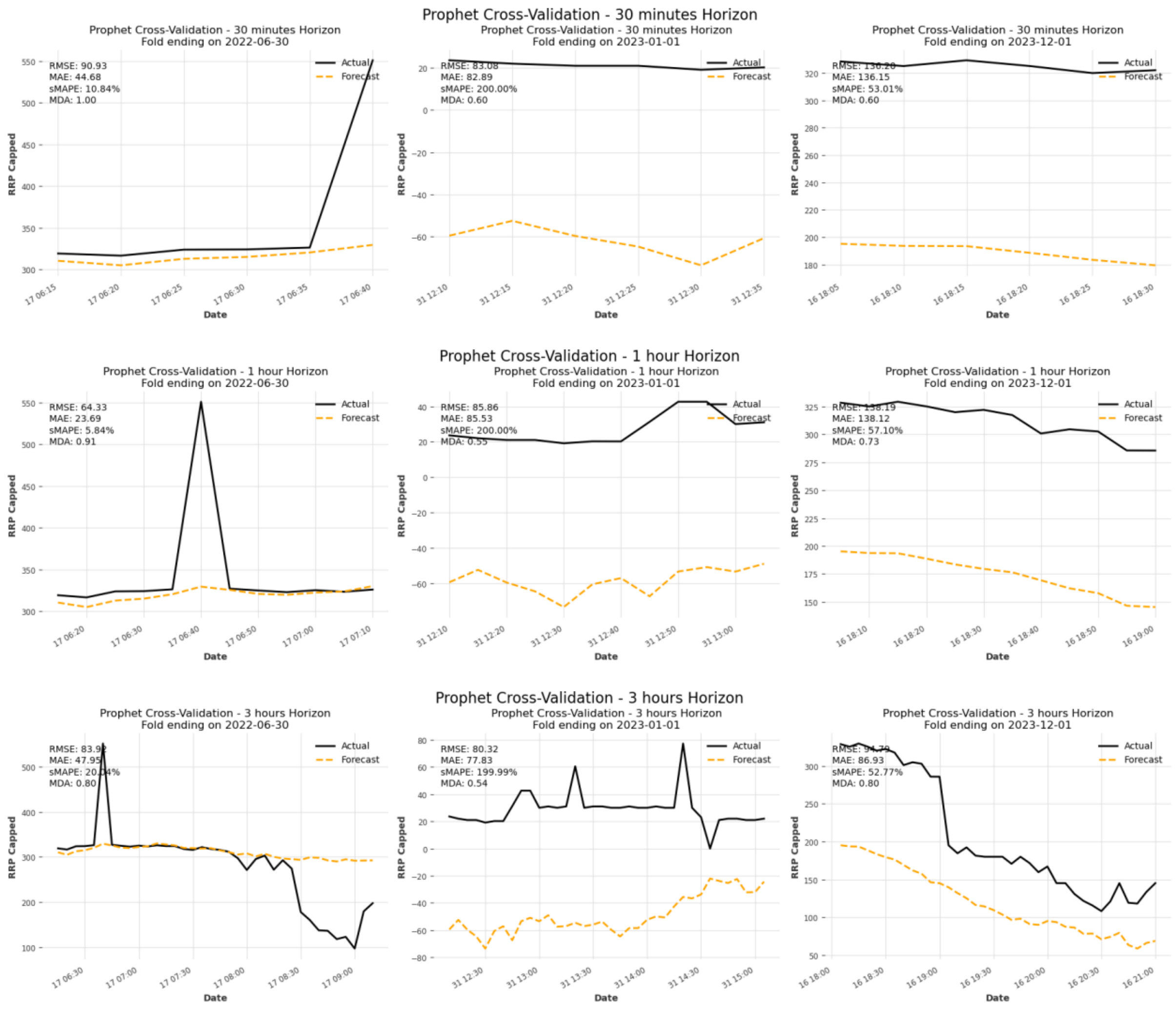


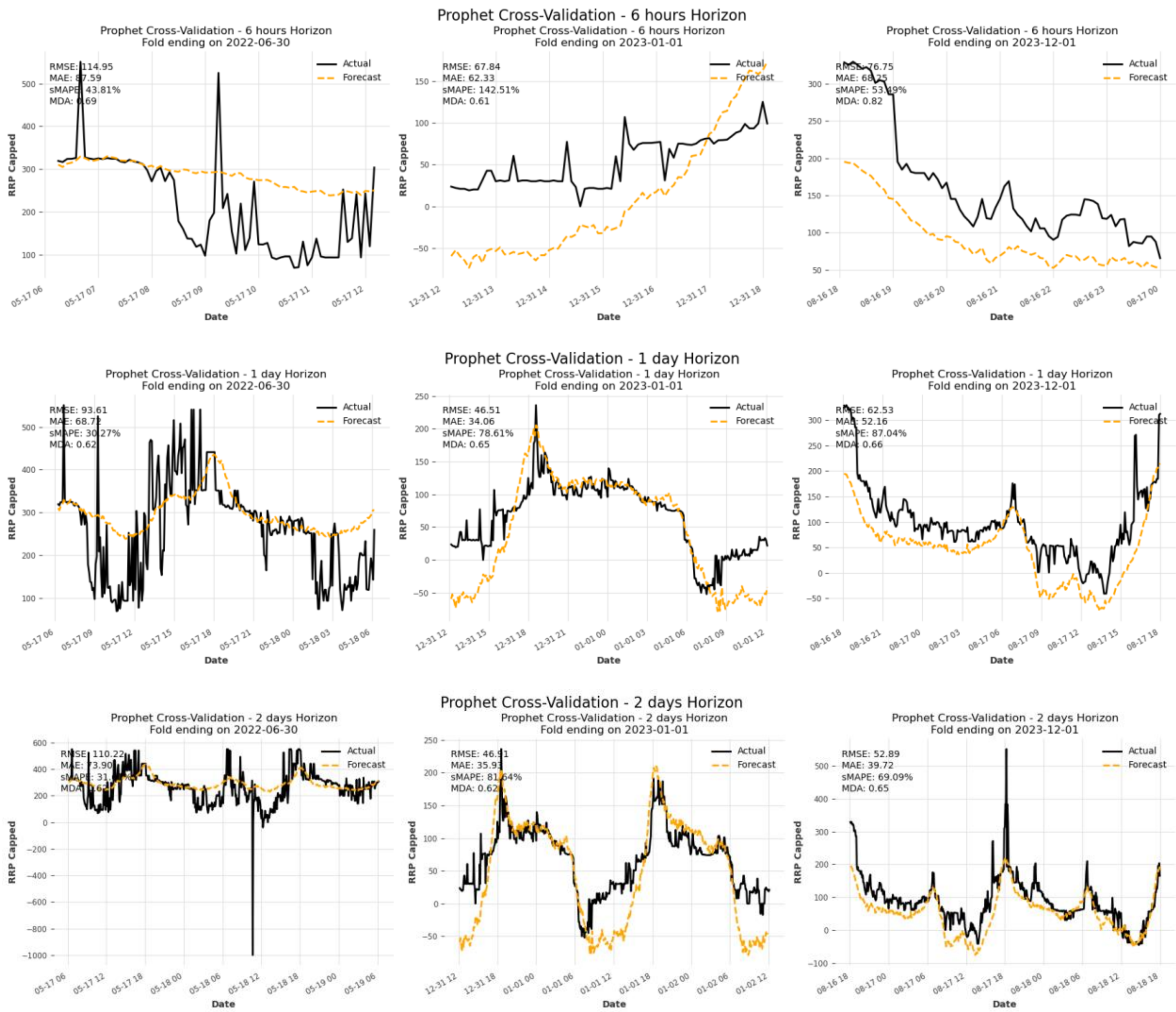


The graphs of the remaining models can be found in Appendix 2.

To ensure Prophet model was performing well across the dataset, time series cross validation was performed. Time series cross validation splits the time series data into numerous folds, with the model training on first fold and then forecasting on the next fold. In the next step, the model will train on the first two-fold and forecast on the third fold. In the next step and so on, models will continue to increase training on folds and forecast on the fold ahead until the end of dataset is reached or the number of folds were exhausted. This is useful in time series modelling since it gives an idea how the model will react to different training datasets, and how does it predicts based on its training. This can also mimic how real-life data works, with the model forecasting into the future, and once the future data is available, the model will retrain with the actual data and then forecast again.

For Prophet, 3-Fold Cross Validation was performed, with results



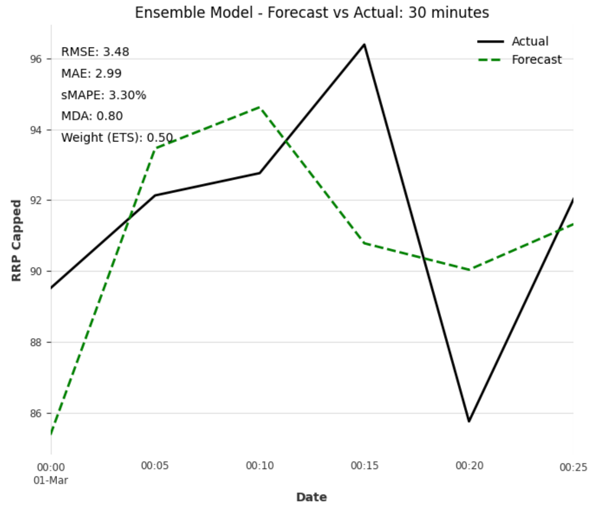


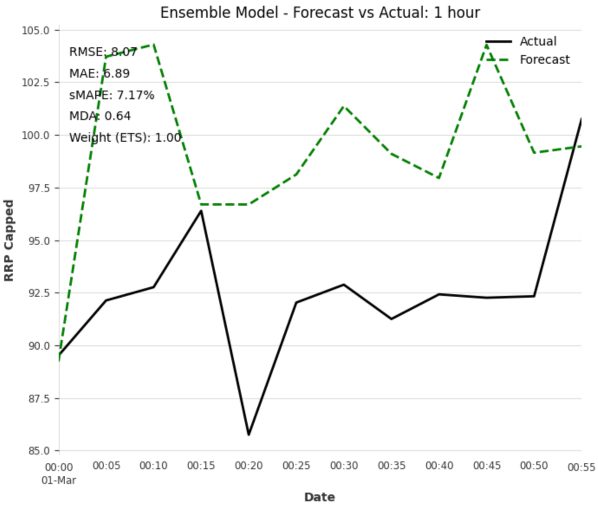
The Prophet model shows good metric values across the dataset for different timeframes, showcasing excellent prowess in prediction.

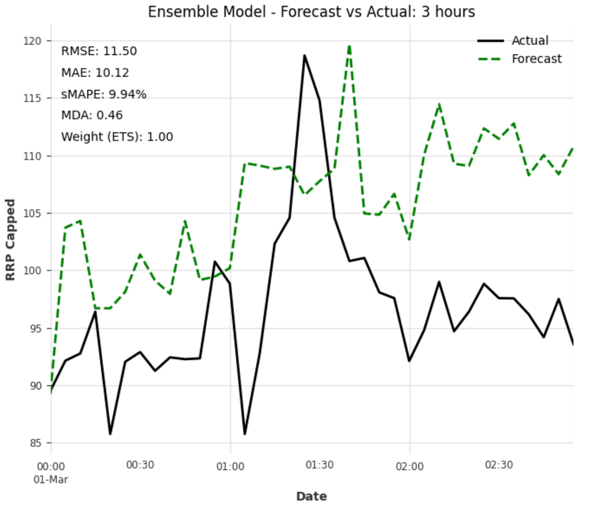
While further feature engineering can be performed for more exogenous variables for all models, this project does not explore them due to feasibility. The models explored are made to run in the shortest time possible while exploring factors such as seasonality and best parameters for models while also running in short amount of time for solar farms to create and set a pipeline. This will allow the models to run numerous times with updated data, ensuring that the predictions made are accurate. However, feature engineering can be performed which will increase the models forecasting to a degree, with features such as lags (for models like Prophet, SVM, Decision Tree models), slope, volatility (for non GARCH models) and more on.

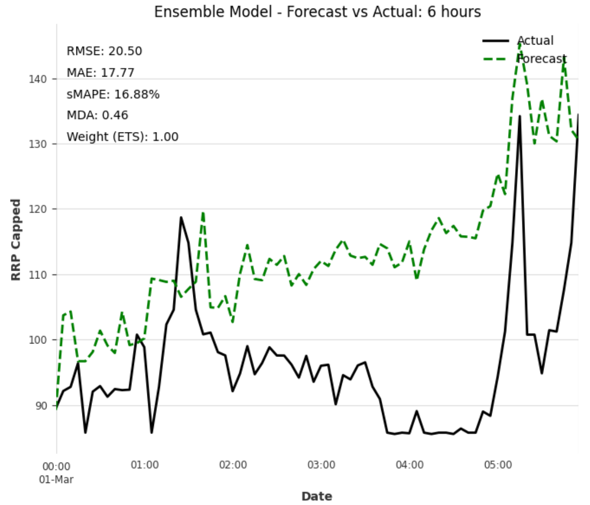
Ensemble Model

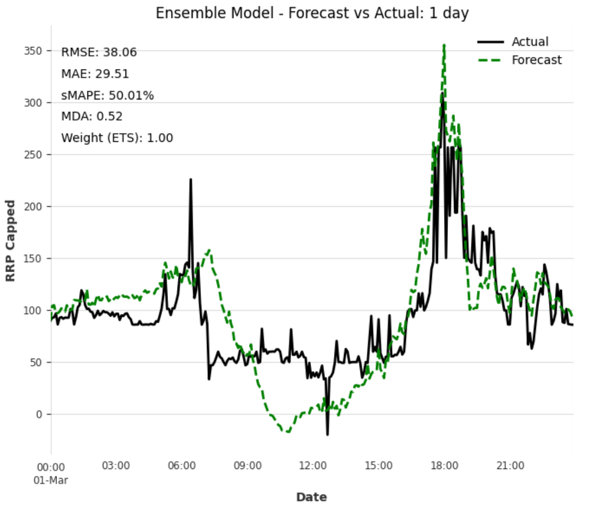
Since ETS and Prophet both had comparable results, a weighted model could be created and tested to see if it could enhance the forecasting ability of both the constituent models.

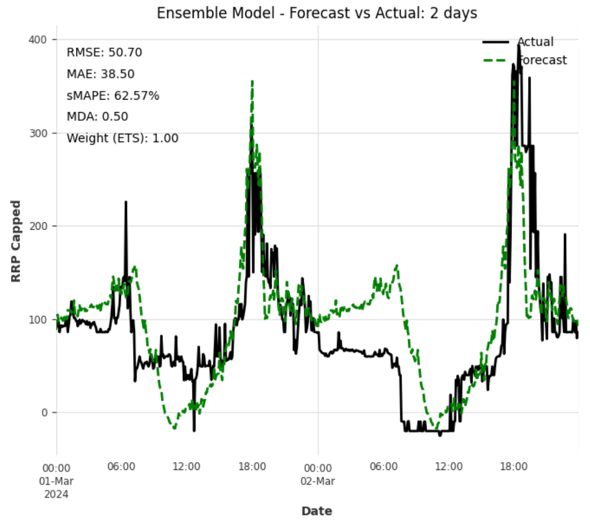












As shown in the results above, the resultant ensemble model does not perform as good as either of its constituent models. Further weight tuning was performed to see if results changed, however the above graph, with ETS having 60% weightage with Prophet's 40% was the best overall ensemble. Hence, Prophet standalone model is still the best model for forecasting.

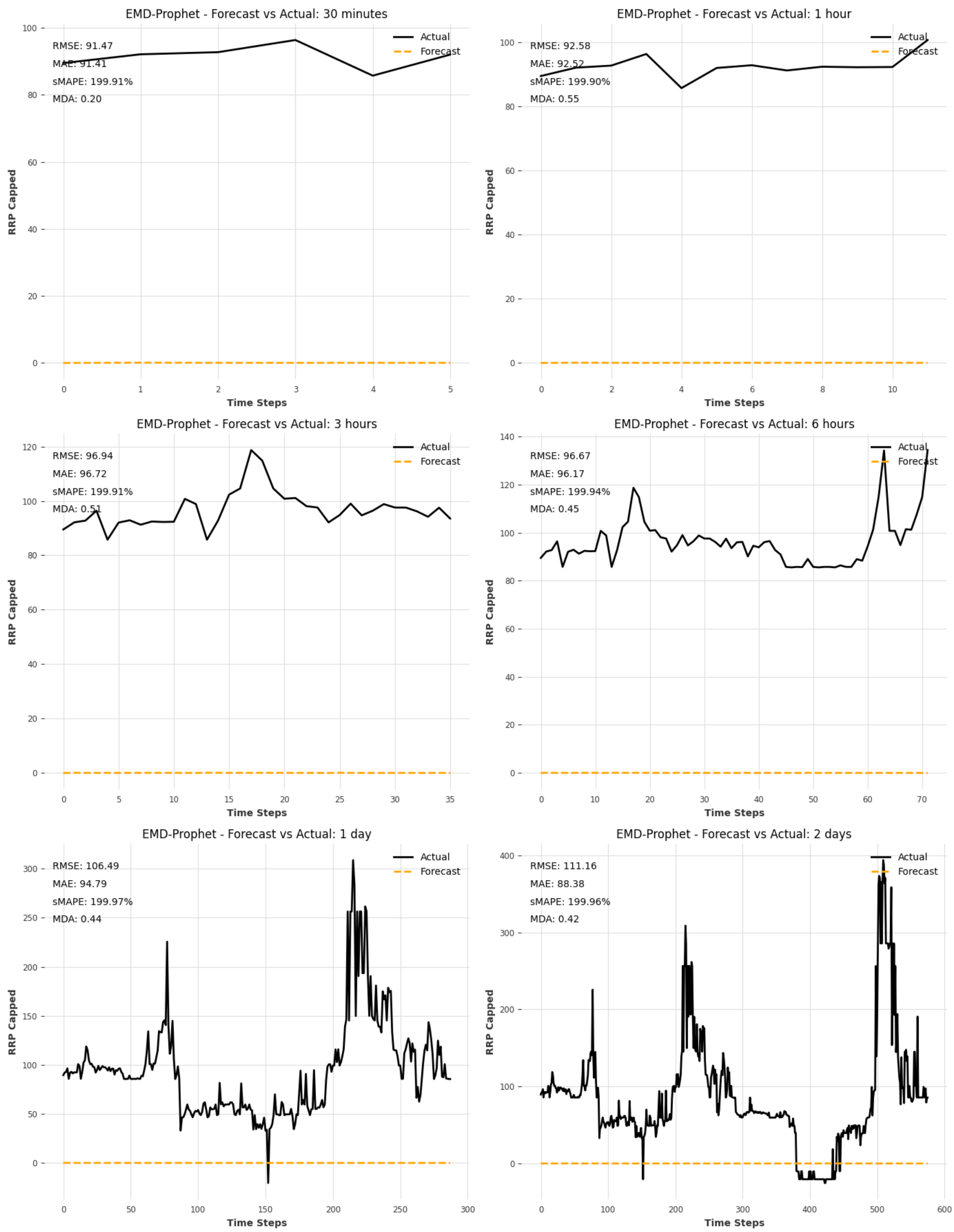
Wavelet Decomposition and Empirical Mode Decomposition Prophet

One of the explored additions to a model covered in the Literature Review is wavelet decomposition and empirical mode decomposition. Both are techniques that are used for analyzing and decomposing time series data before feeding the data to a model for training. Hence, this prior analysis often increases the model's ability to understand the nuances and patterns in a dataset, increasing the accuracy of the model.

Empirical Mode Decomposition breaks down the dataset into a set of simpler components called Intrinsic Mode Functions (IMFs). EMD, for a given data period calculates the maxima and minima points and draws lines that connect these maxima and minima. Then, through these lines, EMD calculates an average curve which is the Intrinsic Mode Function of the data period. Hence, EMD can break down the various patterns making it easier to analyze each component individually.

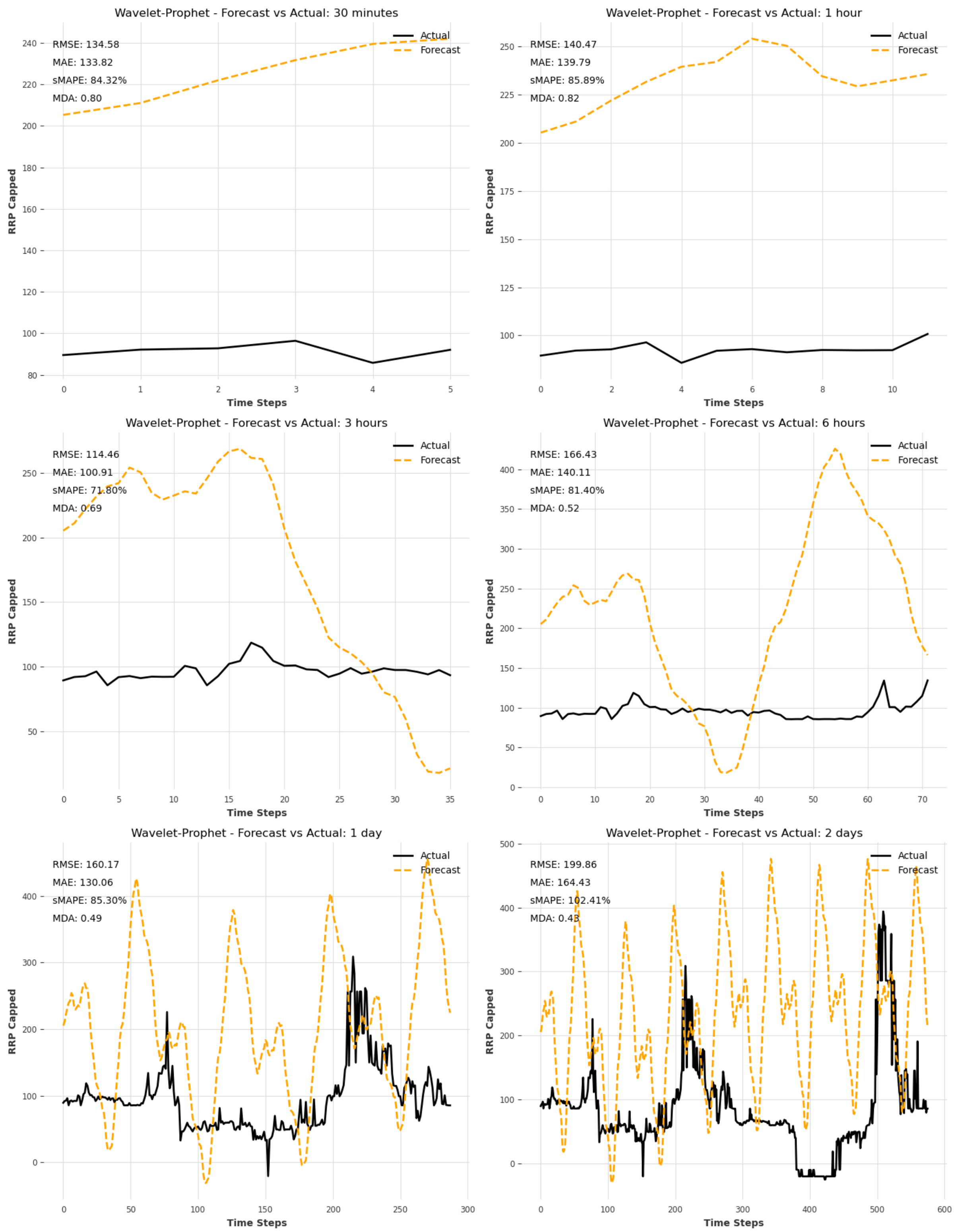
On the other hand, wavelet decomposition creates a sample template wave which it uses to analyze the signal. The function adjusts the template wavelet, also called the mother wavelet to make it fit better on the original dataset. By stretching the wavelet, the function can focus on different scales of patterns. For example, a stretched wavelet might capture a broad, slow-changing trend, while a compressed wavelet can capture short, fast fluctuations.

Both the results of EMD and Wavelet Decomposition were fed to Prophet model to check if the response was better than normal:

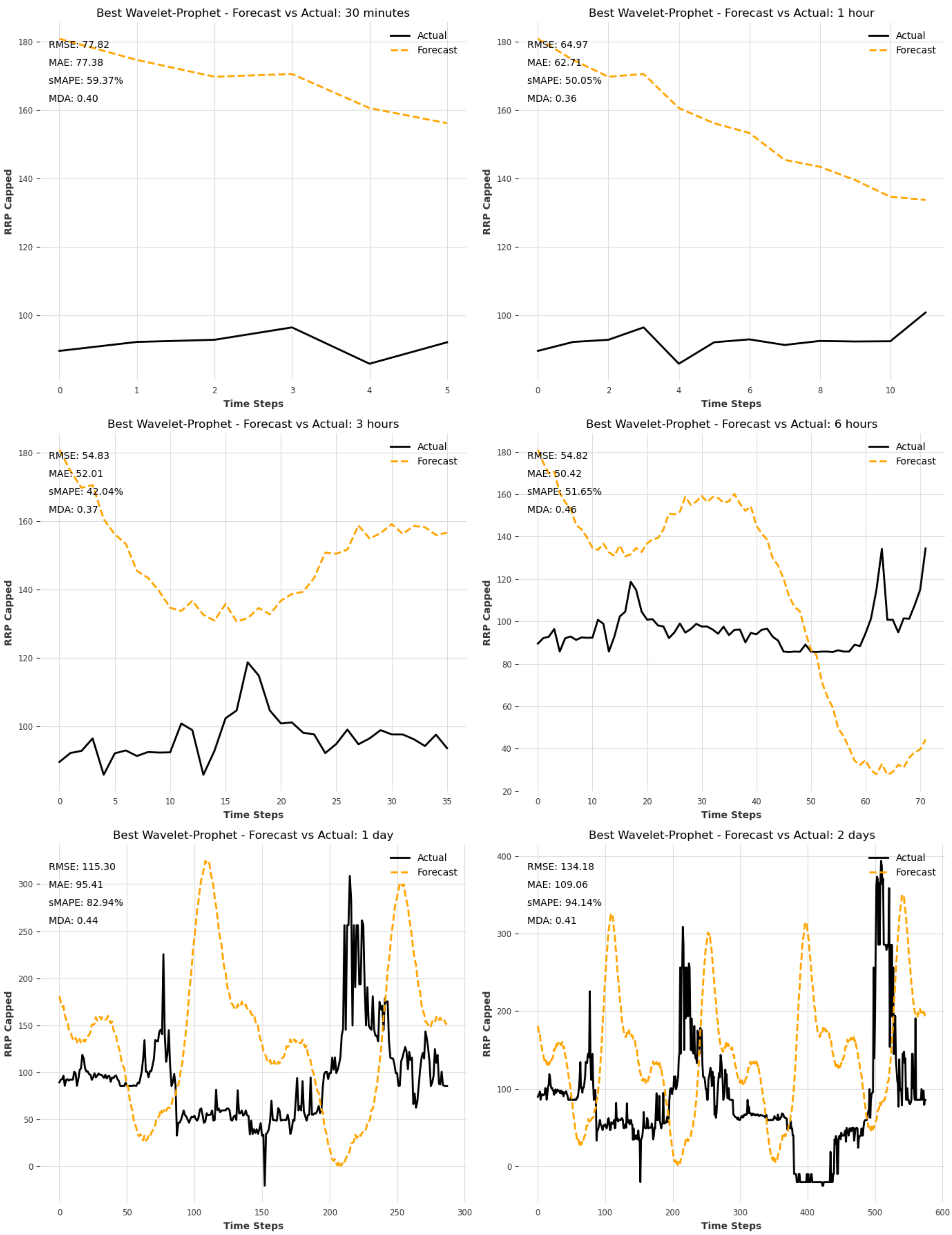


EMD Prophet was unable to capture the trends in the data, producing result at 0. Maybe the model is not fitting the EMD results, or another possible result could be Prophet is not the best model for EMD decomposition.

However, for Wavelet decomposition



The resultant forecasts followed a seasonal cyclic prediction style, which meant that while the wavelet decomposition had been able to break down the seasonality aspect of the dataset, which lead to Prophet over-forecasting on this trend. However, wavelet decomposition could be still fine-tuned to give a better forecast, and post that:



While the limit of predictions was lessened to fit the data better, there is still cyclic nature present. This implies that wavelet decomposition (and EMD) could be better for models such as ARIMA GARCH which only model based on mean and volatility, imparting a seasonal nature to those predictions.

5.4.2 Long Term Forecasting

For long-term forecasting, all the models were trained from 1st October 2021 till 31st December 2023. The months of January, February and March of 2024 were used as evaluation months. These 3 months gave a better understanding of how the models would be able to forecast over time, and how much did their forecast deteriorated with time. Models were used with the same hyperparameters as short-term forecasting. The same evaluation metrics were used for long-term forecasting as well. The same exogenous variables of exogenous variables of demand, holiday, interconnector metric, solar generation and total generation were used.

1. ARIMA and ARIMAX

The same ARIMA (3,1,1) and ARIMAX (3,1,1) with the same metrics and exogenous variables. Like last time, ARIMA model once again gave a straight-line prediction, showing that basic ARIMA is unable to fit properly to the data. However, ARIMAX was able to perform well, with metrics below.

Model	**Month**	**RMSE**	**MAE**	**sMAPE**	**MDA**
ARIMA (3,1,1)	Jan-24	119.47	56.25	52.25%	0.16
	Feb-24	102.45	52.18	51.38%	0.14
	Mar-24	56.51	38.57	52.46%	0.12
ARIMAX (3,1,1)	Jan-24	100.62	68.14	77.84%	0.6
	Feb-24	89.93	63.73	77.45%	0.6
	Mar-24	78.35	64.02	96.10%	0.62

Averaged over the 3 months.

Model	**Avg RMSE**	**Avg MAE**	**Avg sMAPE**	**Avg MDA**
ARIMA (3,1,1)	92.14	49.67	52.03%	0.14
ARIMAX (3,1,1)	89.63	65.96	83.80%	0.61

2. GARCH models

To learn the volatility in the dataset, like before GARCH models were used in conjecture with ARIMA models. ARIMA GARCH, ARIMA EGARCH and ARIMA GJR GARCH were used. Their metrics are as below

Model	**Month**	**RMSE**	**MAE**	**sMAPE**	**MDA**
ARIMAX (3,1,1) + GARCH	Jan-24	102.77	69.54	68.89%	0.6
	Feb-24	91.81	63.84	68.65%	0.6
	Mar-24	74.45	59.04	80.10%	0.62
ARIMAX (3,1,1) + EGARCH	Jan-24	102.83	69.6	68.83%	0.6
	Feb-24	91.87	63.89	68.61%	0.6
	Mar-24	74.45	59.02	79.90%	0.62
ARIMAX (3,1,1) + GJR-GARCH	Jan-24	103.01	69.78	68.64%	0.6
	Feb-24	92.05	64.07	68.50%	0.6
	Mar-24	74.45	58.95	79.49%	0.62

Averages Across the Three Months

Model	**Avg RMSE**	**Avg MAE**	**Avg sMAPE**	**Avg MDA**
ARIMAX (3,1,1) + GARCH	89.68	64.14	72.55%	0.61
ARIMAX (3,1,1) + EGARCH	89.72	64.17	72.45%	0.61
ARIMAX (3,1,1) + GJR-GARCH	89.84	64.27	72.21%	0.61

Overall, all three GARCH models nearly perform the same across metrics. All the models can be said to be average in long term forecasting. The GJR-GARCH model, which provides a higher impact on negative shocks showed slightly better handling of downside volatility, resulting in a marginally lower sMAPE, while EGARCH's capacity to manage asymmetry helped it respond effectively to sharp fluctuations, especially in months with higher volatility spikes. The traditional GARCH model provided a steady baseline performance, particularly suited to periods with consistent volatility patterns. Directional accuracy (MDA) was similar across all models, further supporting their comparable predictive capabilities.

3. Exponential Smoothing (Holts Winter)

Daily Seasonality was considered again akin to short-term forecasting for the ETS model.

Model	**Month**	**RMSE**	**MAE**	**sMAPE**	**MDA**
ETS	Jan-24	109.38	62.52	74.95%	0.47
	Feb-24	89.42	57.71	68.61%	0.49
	Mar-24	66.91	56.89	70.86%	0.5
Average		88.57	59.71	71.47%	0.49

The ETS model evaluated across the three months shows an average RMSE of 88.57 shows a moderate level of prediction. The average MAE of 59.71 and sMAPE of 71.47% highlight the model's relative accuracy over this period, with some limitations in adapting to the high variability of electricity prices. The MDA average of 0.49 suggests that the model's ability to predict the correct directional changes is limited even when compared to base ARIMA GARCH and its extensions.

Unlike short term forecasting, ETS in long term forecasting is very limited in its prediction prowess, which is understandable considering it is only smoothing the historical patterns that too for a single seasonality without any exogenous variables.

4. AutoRegressive Distributed Lag Model

Keeping the same hyperparameters, the ARDL model for long term forecasting provided an average forecast.

Model	**Month**	**RMSE**	**MAE**	**sMAPE**	**MDA**
ARDL	January	93.31	61.05	59.27%	0.56
	February	88.84	65.92	60.71%	0.58
	March	73.07	59.34	66.29%	0.59
	Average	85.74	62.1	62.09%	0.58

5. Kalman Filter

Model	Month	RMSE	MAE	sMAPE	MDA
Kalman Filter	January	95.76	62.53	57.37%	0.46
	February	90.08	67.32	62.11%	0.48
	March	72.99	60.37	66.17%	0.5
Average		86.94	63.41	61.22%	0.48

The State Space Model with Kalman Filter performed worse than other models. Its MDA metric of 0.48 is the lowest yet, showing that its forecast for trend is worse than a coin toss. The Kalman Filter is effective in environments with noise and varying dynamics as it estimates the state of data by minimizing the mean square error through current and future state. However, it struggles with rapid price fluctuations which are present in the dataset.

6. Support Vector Machine

Model	Month	RMSE	MAE	sMAPE	MDA
Linear SVR	January	101.24	50.47	51.33%	0.56
	February	84.66	48.73	52.35%	0.57
	March	48.1	39.35	56.91%	0.58
Average		78.67	46.18	53.53%	0.57

SVM is the second-best model for long term forecasting. Linear SVR is effective at handling linear relationships and shows good stability in its error metrics across the three-month period. While LinearSVR is not as good at capturing volatility in data as GARCH models are, it sometimes misses these volatile price jerks and gives a smoother response. However, since it's consistent in its forecasting and when compared to other models is much better when comparing metrics, LinearSVR is a solid model for long-term forecasting.

7. LightGBM and XGBoost

Model	Month	RMSE	MAE	sMAPE	MDA
XGBoost	January	93.88	58.25	53.27%	0.47
	February	91.92	59.63	54.77%	0.48
	March	75.48	55.06	61.91%	0.48

LightGBM	January	93.28	57.37	52.35%	0.46
	February	93.74	60.18	54.62%	0.46
	March	78.3	55.82	62.14%	0.47

Model		**RMSE**	**MAE**	**sMAPE**	**MDA**
XGBoost	**Average**	87.09	57.65	56.65%	0.48
LightGBM	**Average**	88.44	57.79	56.37%	0.46

Based on the evaluations above, both the models are worse than SVM on prediction. XGBoost has moderate metrics overall, but its January and February scores are worse than March. Jan and Feb had more volatile prices than March which can clearly be seen in XGBoost's metrics. Even in March however, it overpredicted price a few times.

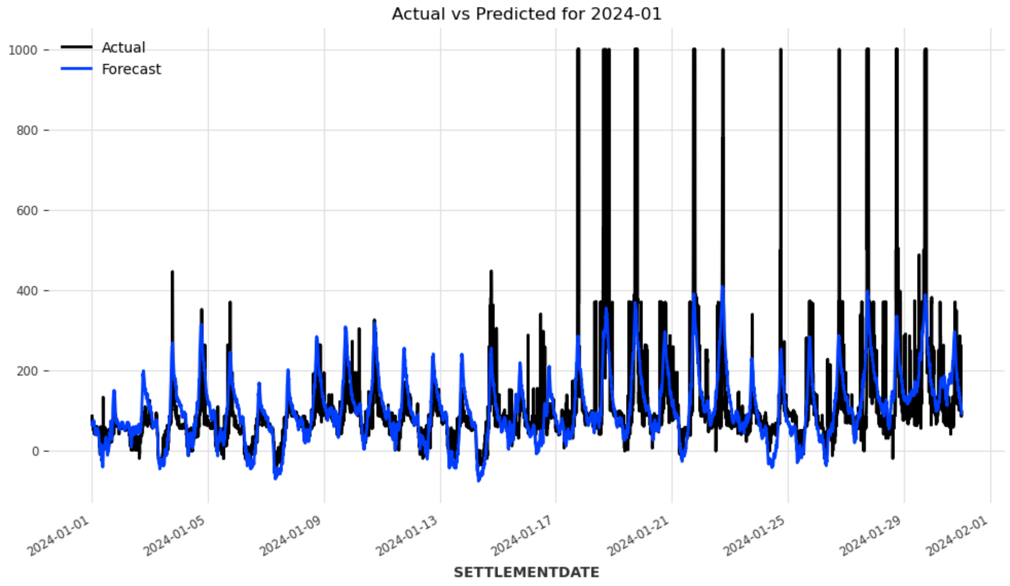
LightGBM is remarkably like XGBoost across metrics. It got worse MDA score than XGBoost consistently across all months, and similar to XGBoost suffered in the months of January and February. Both the models are suitable for changes in trend, but not in highly volatile areas.

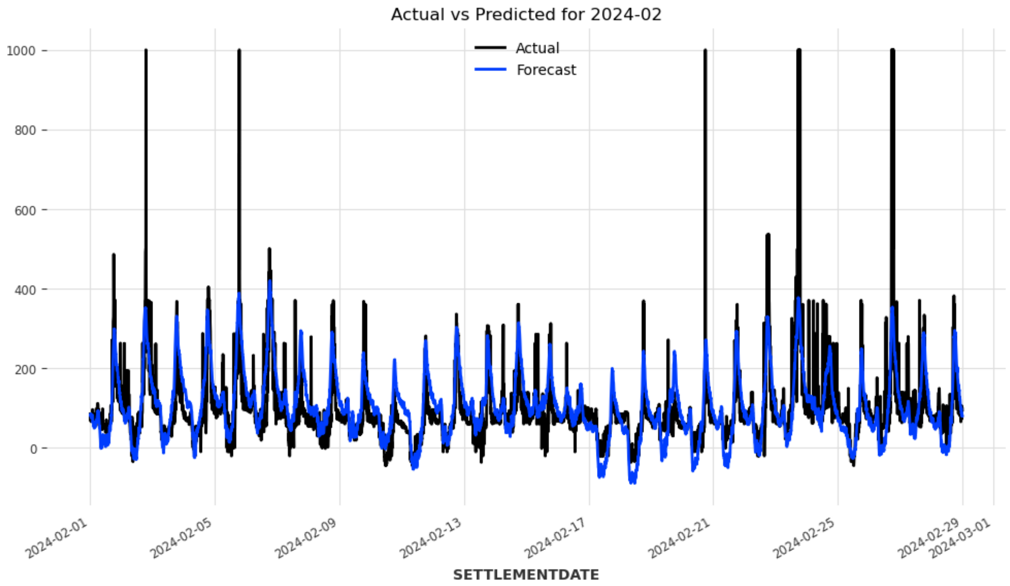
Overall, both models are moderate at prediction with comparatively worse directional accuracies.

8. Prophet

Model	**Month**	**RMSE**	**MAE**	**sMAPE**	**MDA**
Prophet	January	86.31	47.53	52.93%	0.56
	February	70.34	43.67	53.01%	0.58
	March	56.85	44.6	66.17%	0.59
Average		72.22	45.31	57.47%	0.58

Prophet was once again the best model overall for long-term forecasting. Since it is designed to handle trends and seasonality, it excels when compared to other models. While its MDA was not as good as ARIMA GARCH models at 0.61 vs Prophet at 0.58 it is still the second best overall. Prophet was also able to capture the trend and not overshoot the predicted price, which other models failed to perform. Prophet is the best model in this project for both short-term and long-term forecasting.


Actual vs Predicted for 2024-01
Actual
Forecast
SETTLEMENTDATE


Actual vs Predicted for 2024-02
Actual
Forecast
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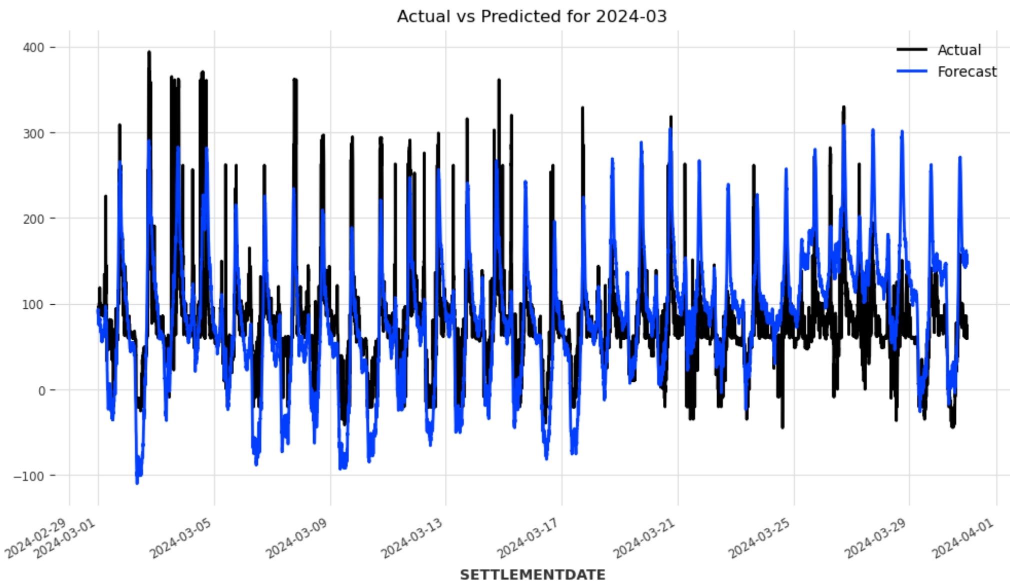
Actual vs Predicted for 2024-03
Actual
Forecast
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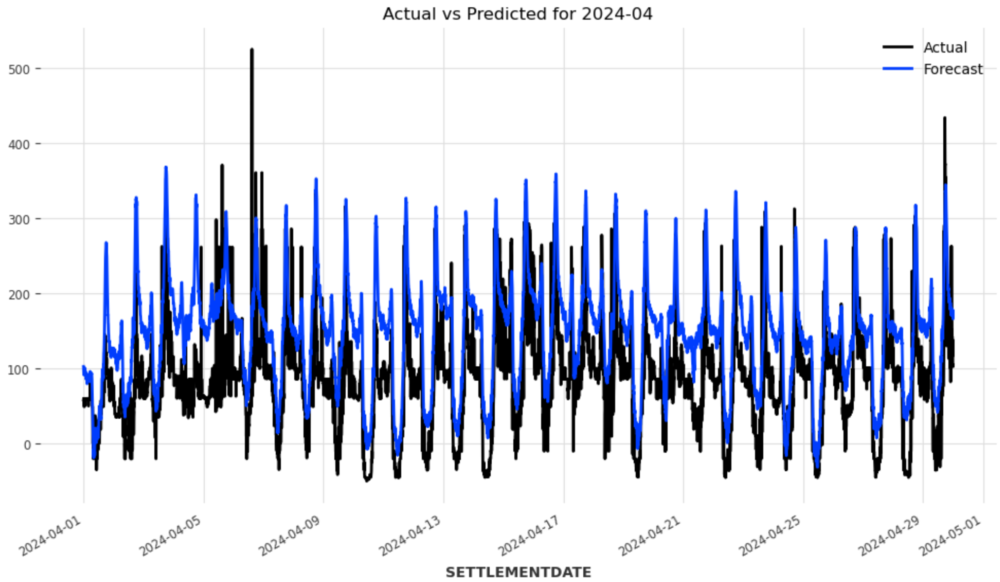
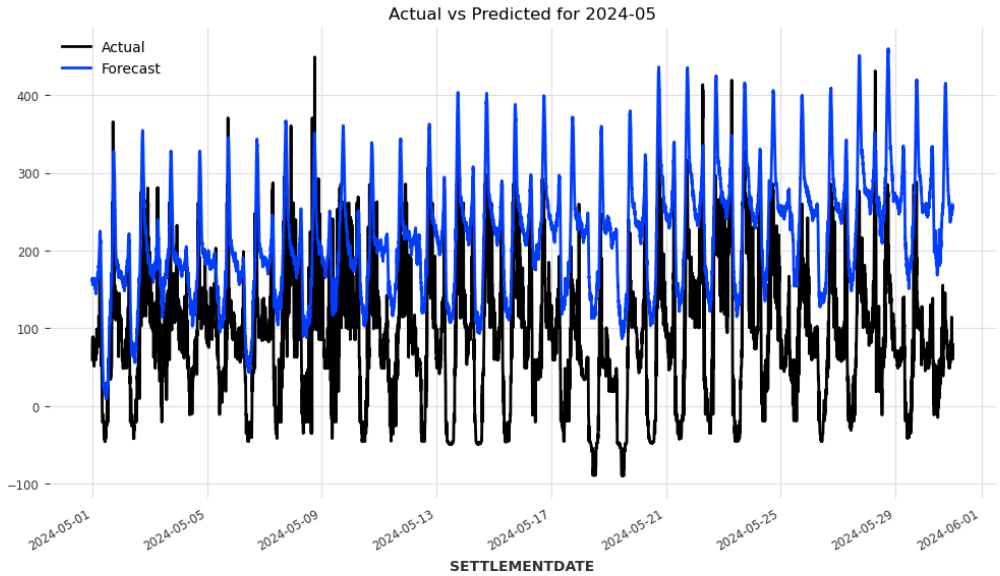
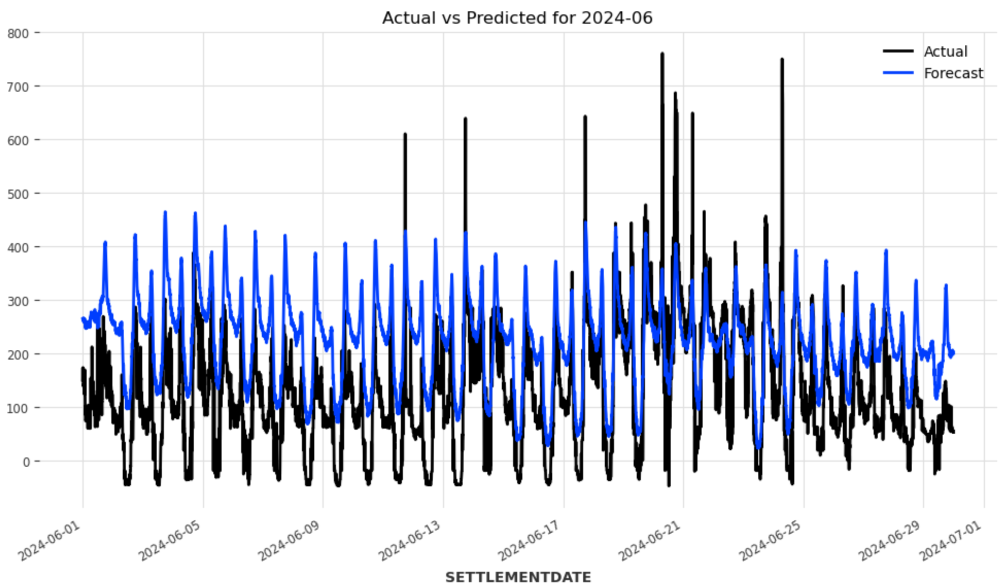
Furthermore, for out of sample validation, prophet again has good metrics







Model	Month	RMSE	MAE	sMAPE	MDA
Prophet	April	74.73	66.72	74.09%	0.57
	May	138.37	128.05	98.23%	0.59
	June	122.06	109.40	83.23%	0.60
Average		115.23	101.69	85.33%	0.585

While Prophet did miss predict the trend alignment, it still had comparatively good graphical results, even if the metrics are a bit high. This goes to show that while there will be errors in long term forecasting, Prophet is still able to understand the trend and nature of data, and with more data Prophet would have better accuracy in predictions.

Performing Walk Forward Cross Validation on Prophet,

Fold	RMSE	MAE	sMAPE	MDA
1	215.66	160.74	85.15%	0.56
2	250.24	235.37	99.37%	0.61
3	95.55	73.75	67.75%	0.62
4	69.46	47.45	61.27%	0.62
5	67.56	44.71	71.96%	0.58
6	94.93	70.88	99.07%	0.59
Overall Average	**132.23**	**105.48**	**80.76%**	**0.59**

6. Future Work

The current approach still contains various prospects which can be improved for a better forecasting model. For the project and for the sake of solar farms, LSTMs and other complex Neural Network models were not used. Traditional models are faster than complex NN models, especially in short term forecasting which is highly beneficial when considering the speed at which market changes in terms of volatility. However, these models when explored properly might outperform the traditional time series networks, and hence can be explored in future. Furthermore, many other exogenous variables can also be explored to be added to the models. In particular, weather data could not be considered due to Queensland being vast with varying weather conditions. However, if models for different areas which host solar farms were considered, an overall model could be made with this varying weather being added as exogenous variables. Renewable penetration rate is also another variable which could not be added since it is calculated daily instead of the highly granular 5-minute data. However, it could be added similar to the Boolean implementation where an entire day shares the renewable penetration rate.

Feature Engineering in detail could also be performed, which includes creating special variables which are modelled after existing exogenous variables and helps the model understand the dataset better. Features such as lags of price, lags of other exogenous variables, slope, momentum, trend and even day of week or additional moving average, weighted moving average, percentage change could be considered and added to the model for better forecasting.

Finally, while the project explores the various market dynamics and government incentives for solar farms and the National Electricity Market in general, these dynamics are also rapidly changing and evolving with time. Hence, repeated market analysis should be performed to ensure that the solar farms are up to date with the current prices, technologies and trends. This ensures that they remain open and adaptive to newer changes in policies, technologies and trends and hence keep maximizing profits.

7. Conclusion

To conclude, this project addresses the challenges solar farms face in the highly volatile National Electricity Market. Through a comparative evaluation, this project recommends the Prophet model for spot price forecasting for the NEM for Queensland. Through proper usage of the Prophet model and other time series-based models this project aims to help solar farms prevent losses and ensure financial stability. Understanding complex relationships within the NEM is essential for solar farms, particularly in relation to demand, price fluctuations, and external factors like holidays and solar generation. Tools like Prophet and Exploratory Data Analysis reveal key patterns, offering insights into these dynamics. Through the use of such predictive models that can forecast short-term and long-term trends, solar farms can make educated bids. Furthermore, information about Green Hydrogen and BESS and FCAS participation can ensure that solar farms have a secondary revenue stream.

The proposed model is still imperfect and suffers from the unpredictability of renewable generation and market conditions. Furthermore, limited historical generation data and the exclusion of real-time weather variables restrict the full potential of the models. Future research should explore the incorporation of additional exogenous factors, such as interconnector flows and weather forecasts, to enhance model precision. While the project does perform an evaluative exploration of market dynamics, it is recommended to regularly perform such analysis due to the ever-changing market. As

Australia continues to strive for 100% renewable penetration and dependencies, the usage of such forecasting models is essential for maximizing revenue, improving stability, and supporting the transition towards renewable energy.

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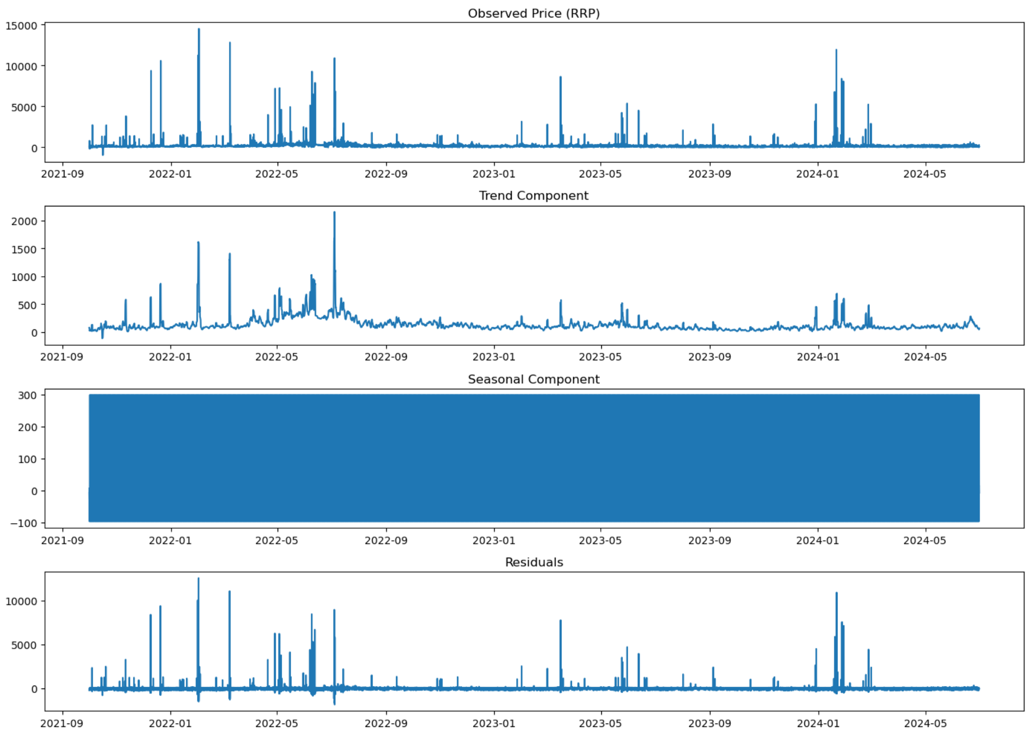
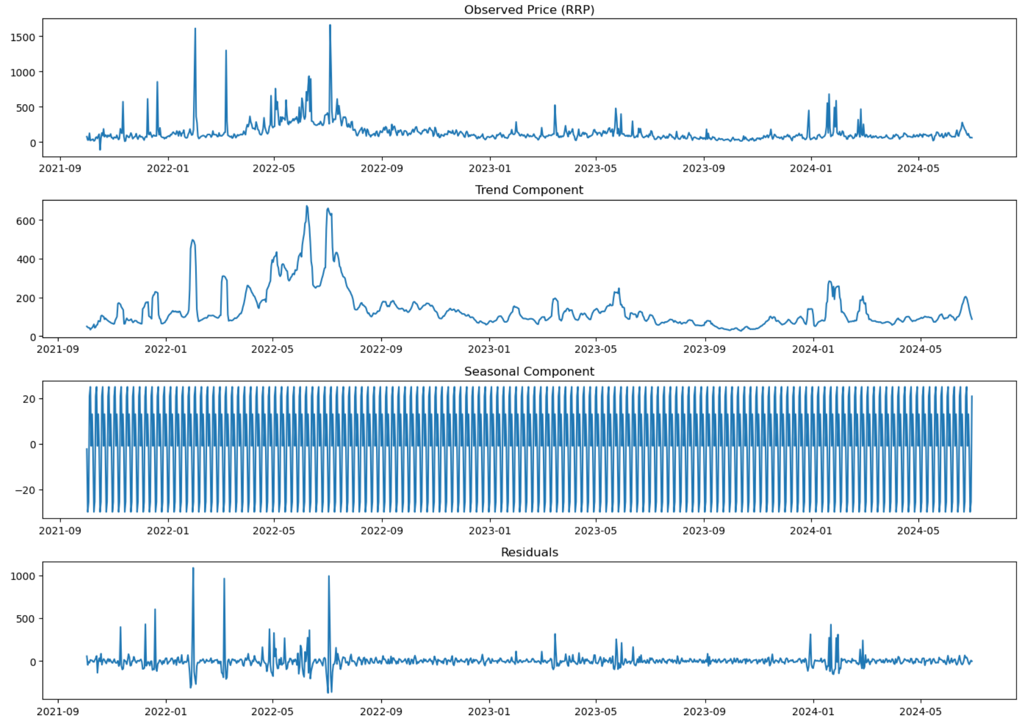
Appendix A – STL Decomposition

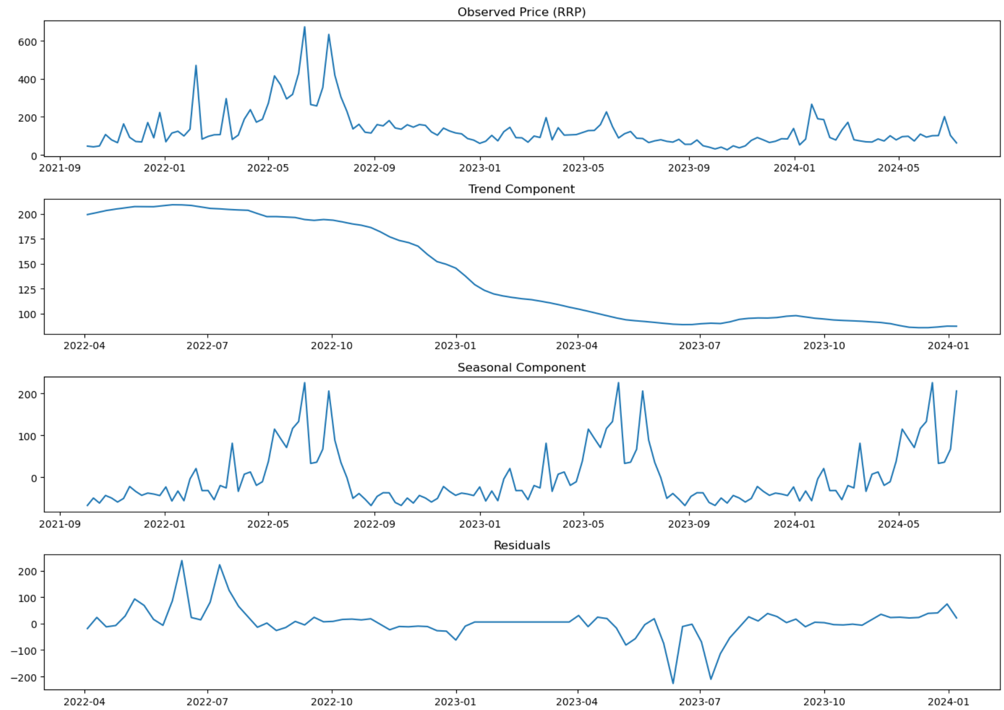
Hourly



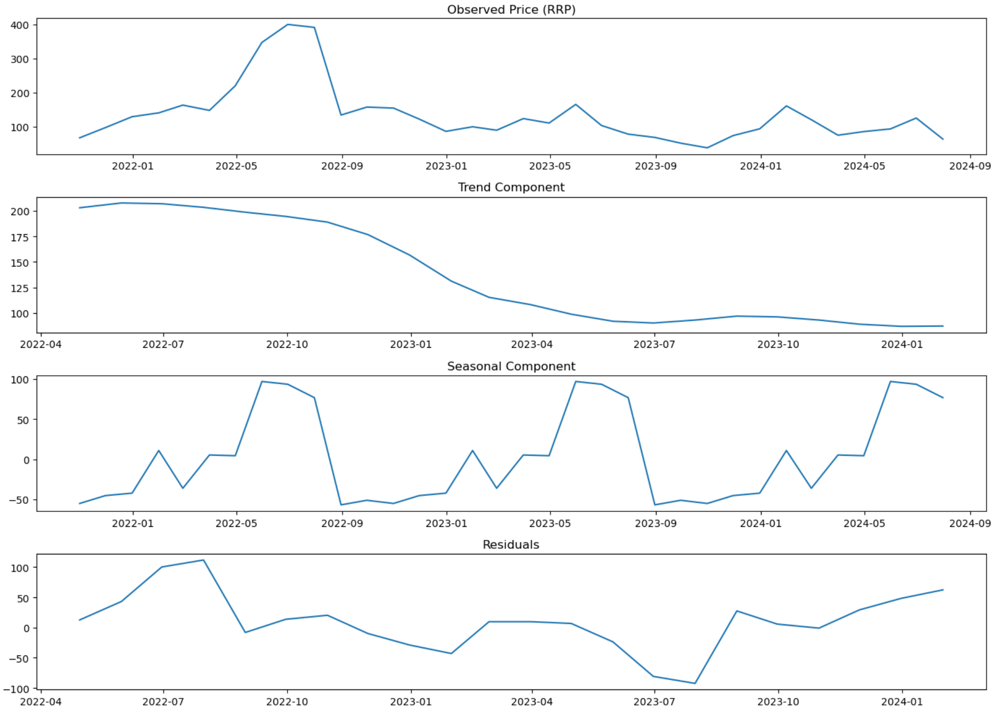
Daily


Observed Price (RRP)
0
500
1000
1500
2021-09
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01
2024-05
Trend Component
0
200
400
600
Seasonal Component
−20
0
20
Residuals
0
500
1000

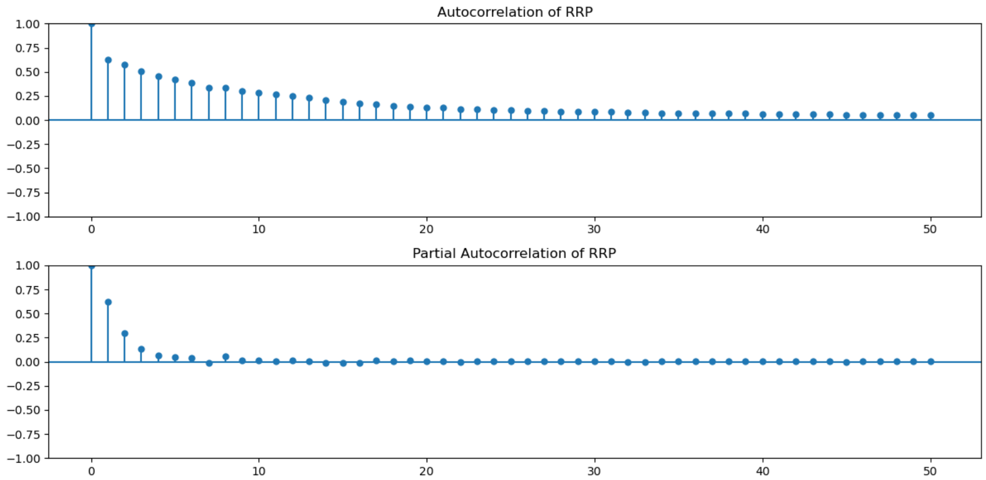
Weekly


Observed Price (RRP)
0
200
400
600
2021-09
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01
2024-05
Trend Component
100
125
150
175
200
2022-04
2022-07
2022-10
2023-01
2023-04
2023-07
2023-10
2024-01
Seasonal Component
0
100
200
Residuals
−200
−100
0
100
200

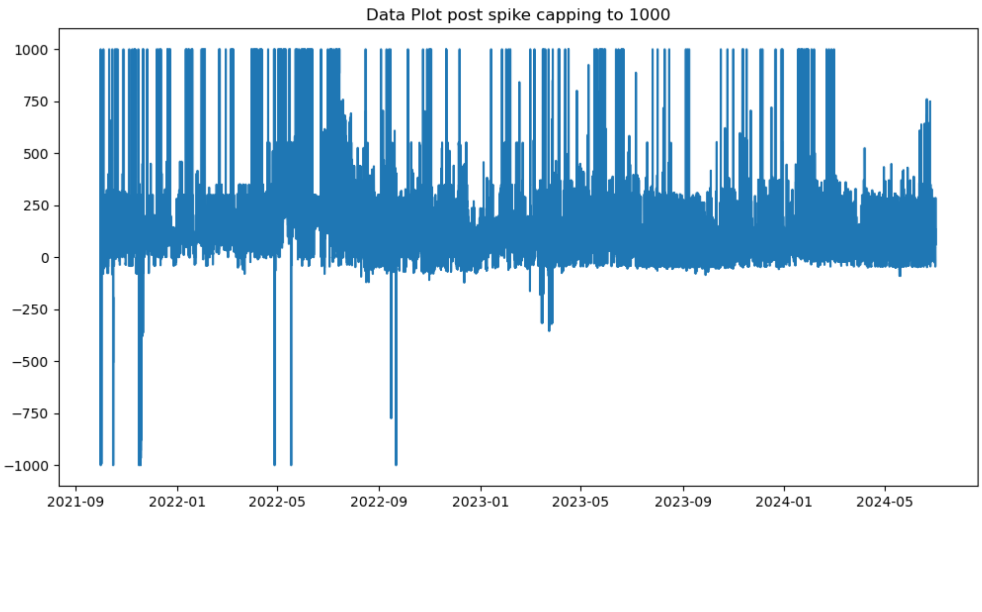
Monthly



Observed Price (RRP)
400
300
200
100
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01
2024-05
2024-09
Trend Component
200
175
150
125
100
2022-04
2022-07
2022-10
2023-01
2023-04
2023-07
2023-10
2024-01
Seasonal Component
100
50
0
−50
Residuals
100
50
0
−50
−100

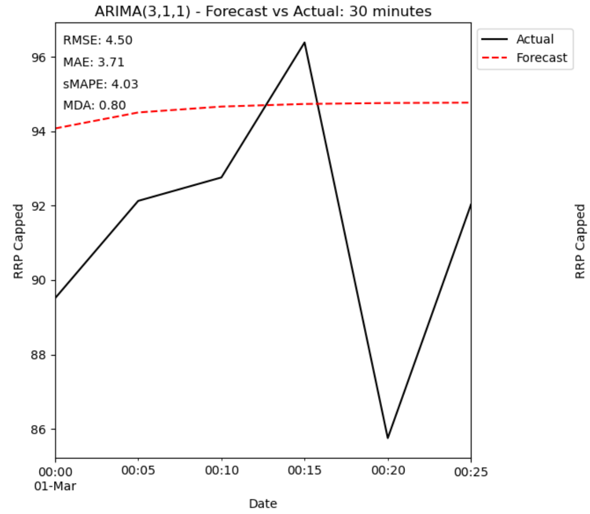


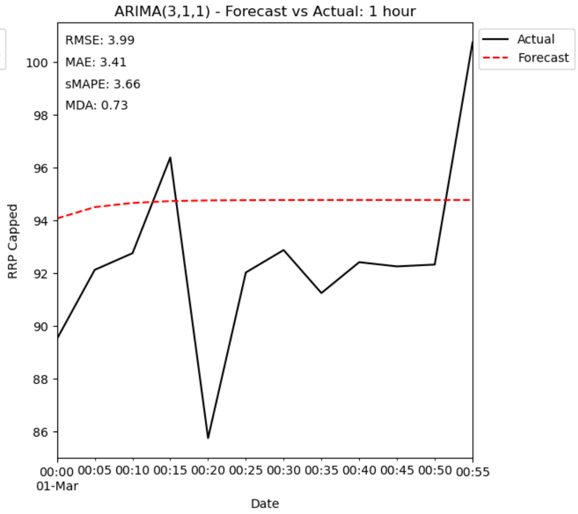
Autocorrelation of RRP
Partial Autocorrelation of RRP
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
10
20
30
40
50

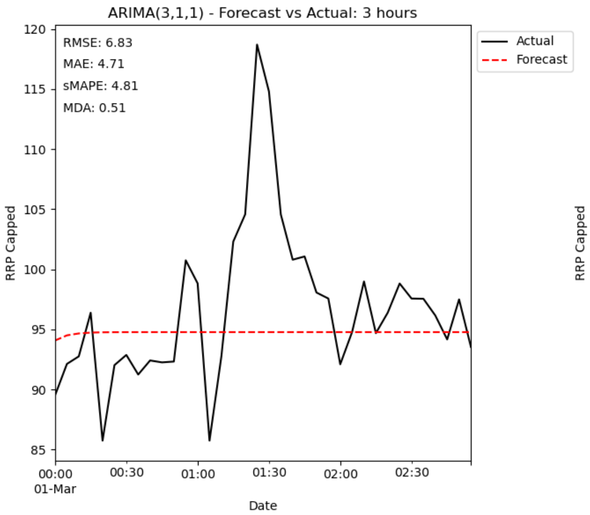


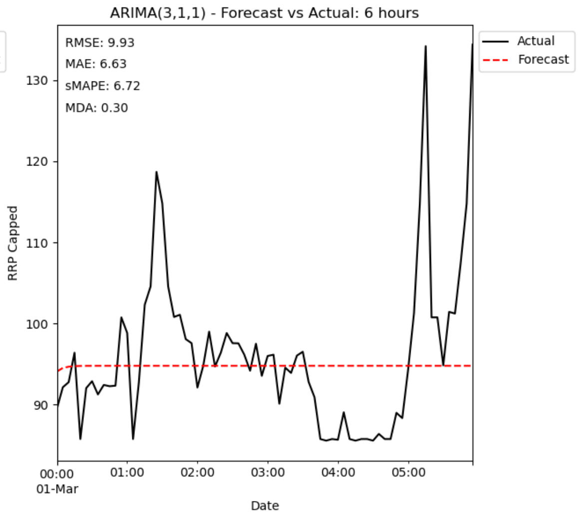
Data Plot post spike capping to 1000
1000
750
500
250
0
−250
−500
−750
−1000
2021-09
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01
2024-05

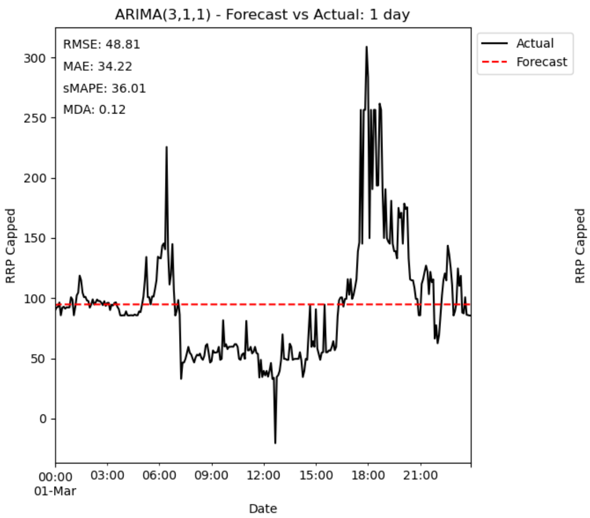
Appendix B – Short Term Forecasting Graphs

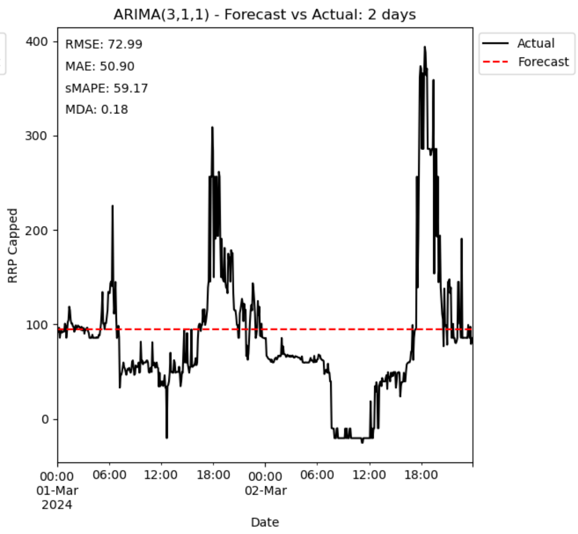


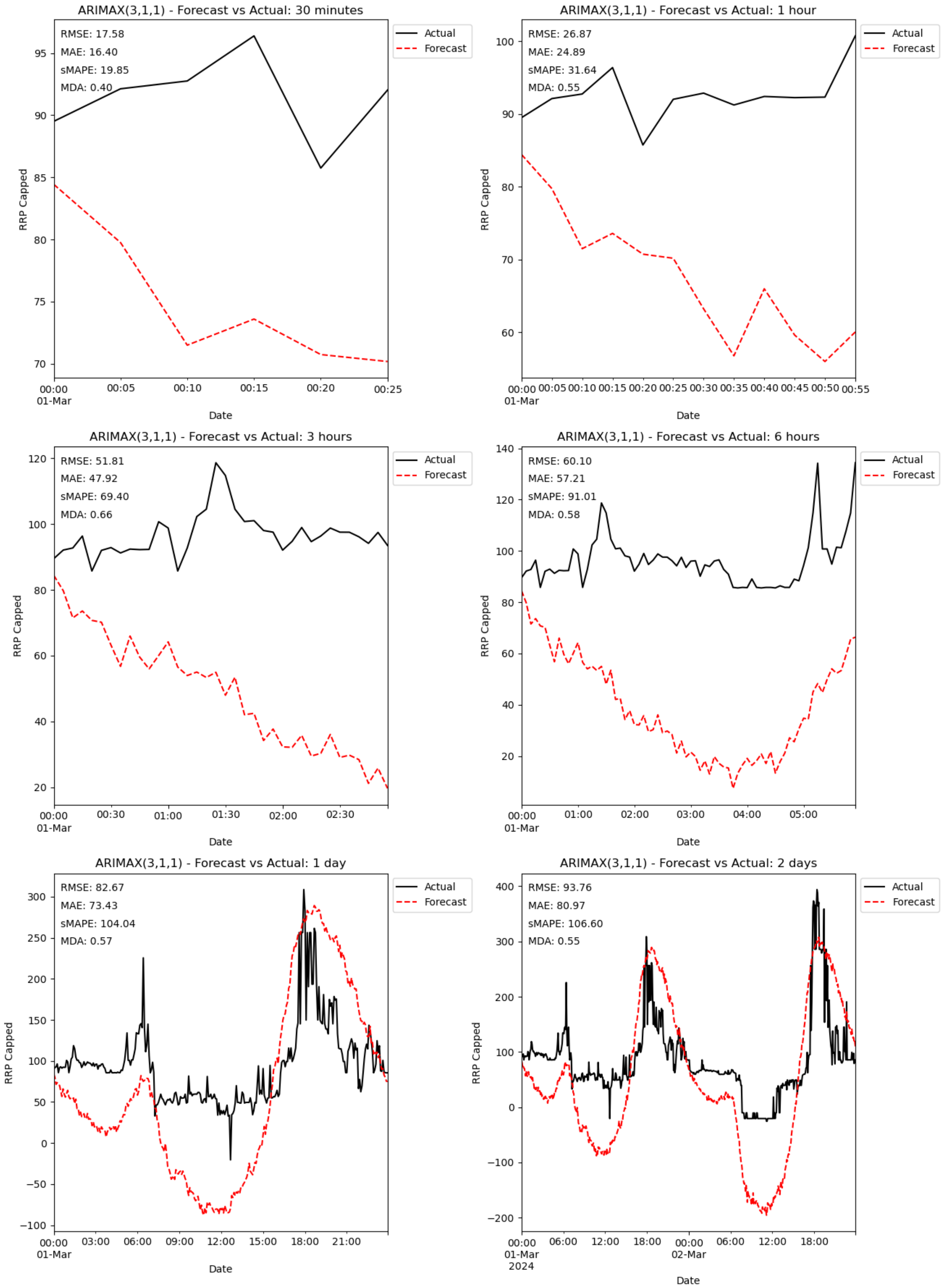


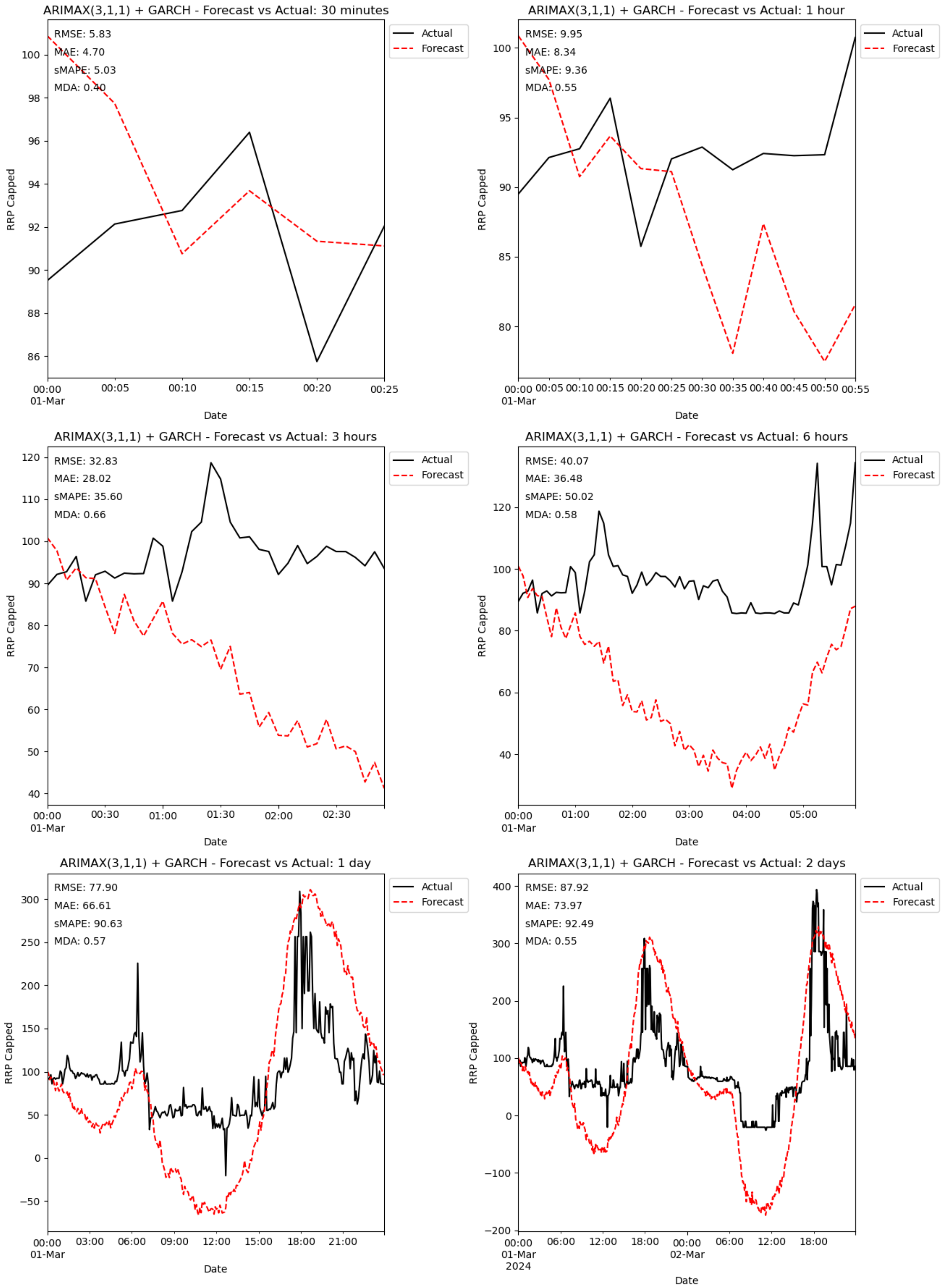


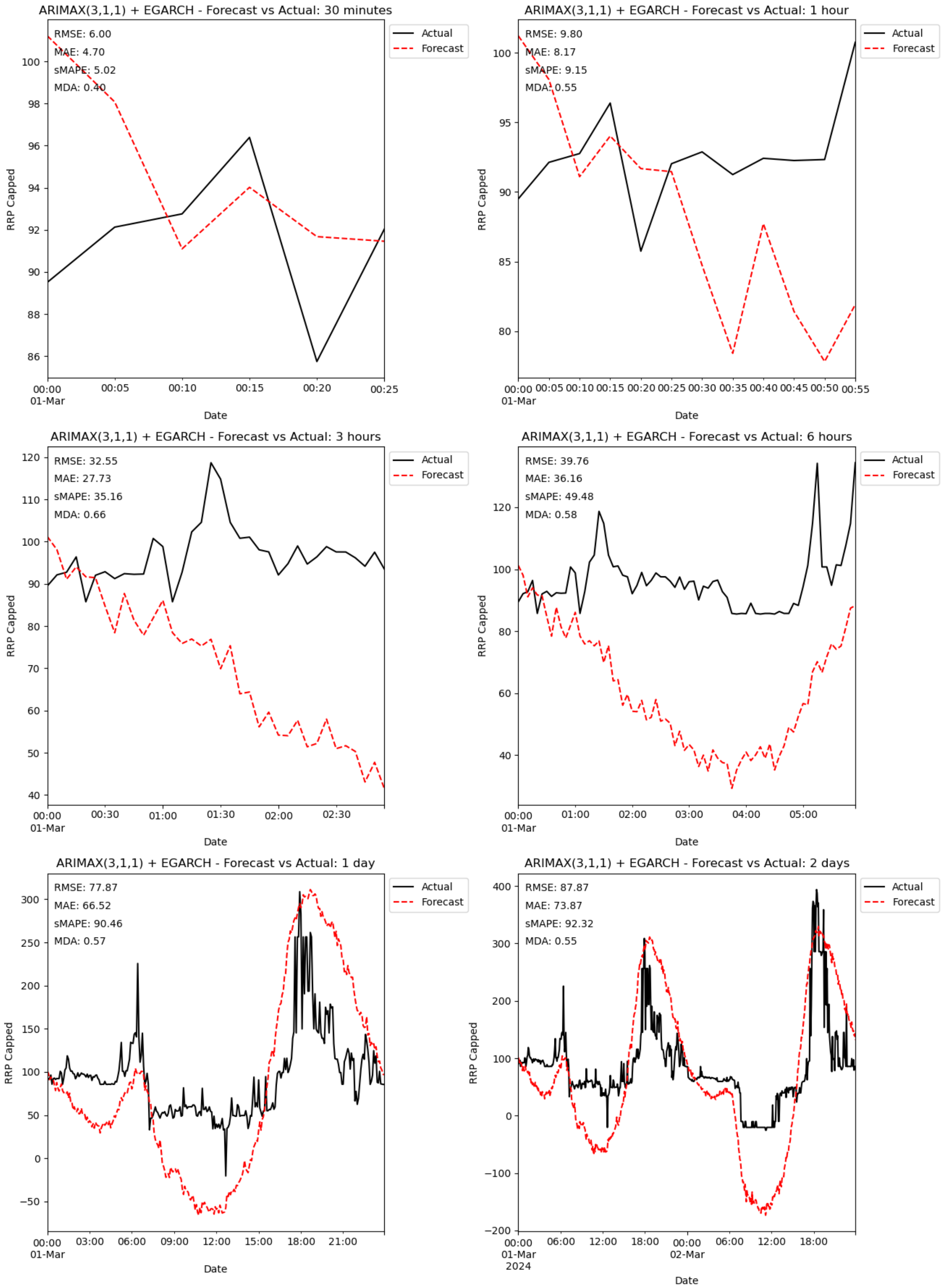


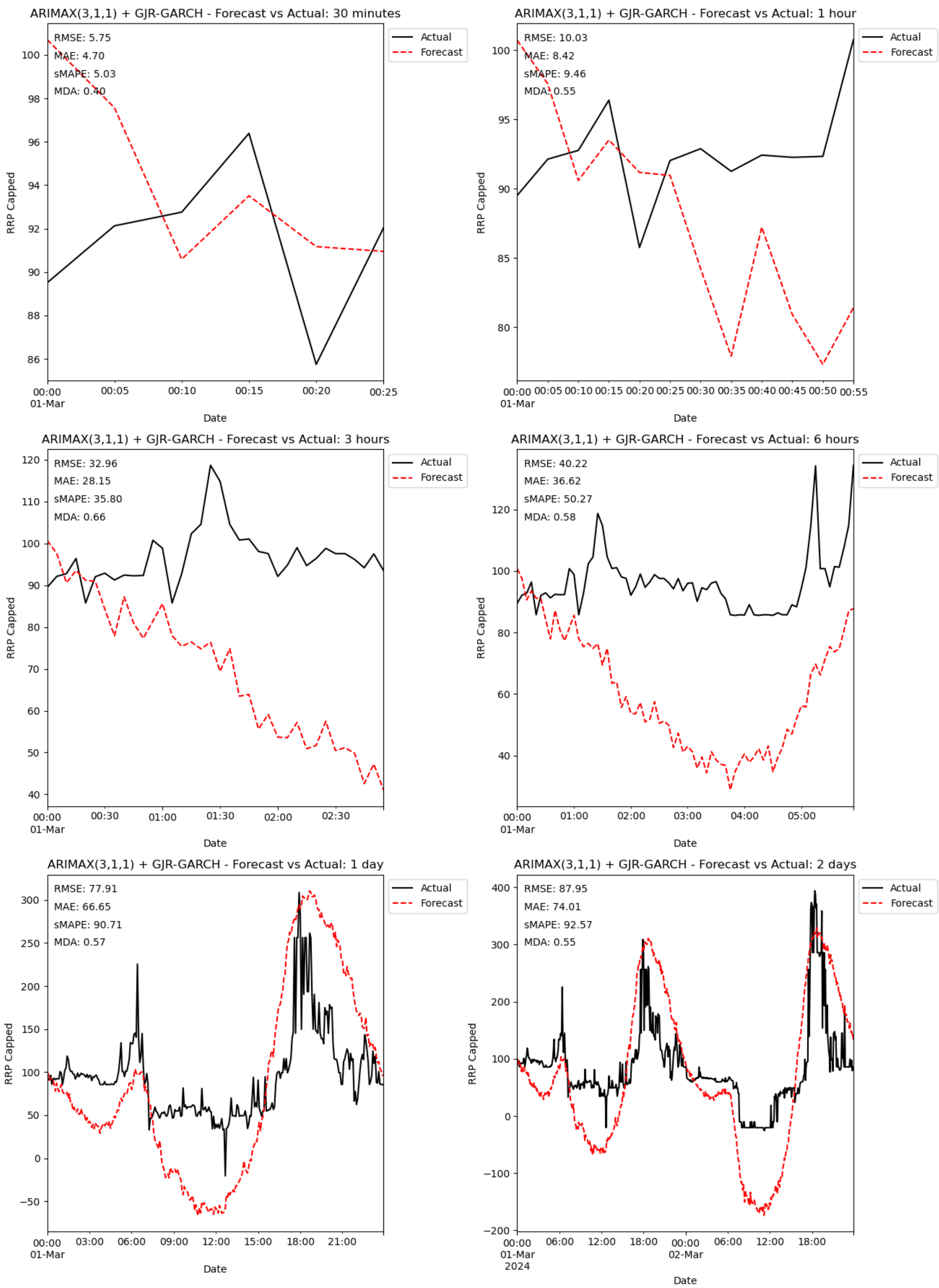


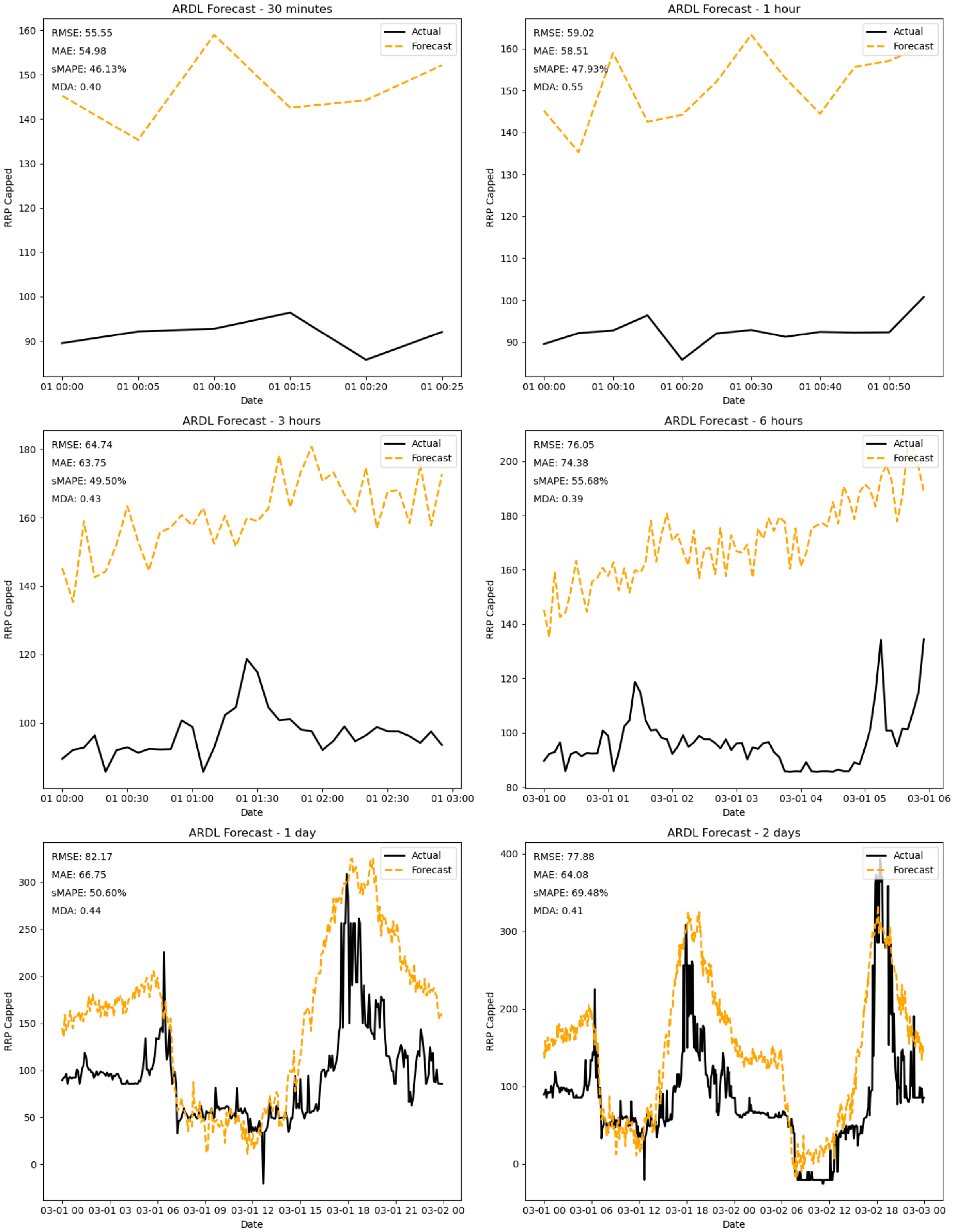


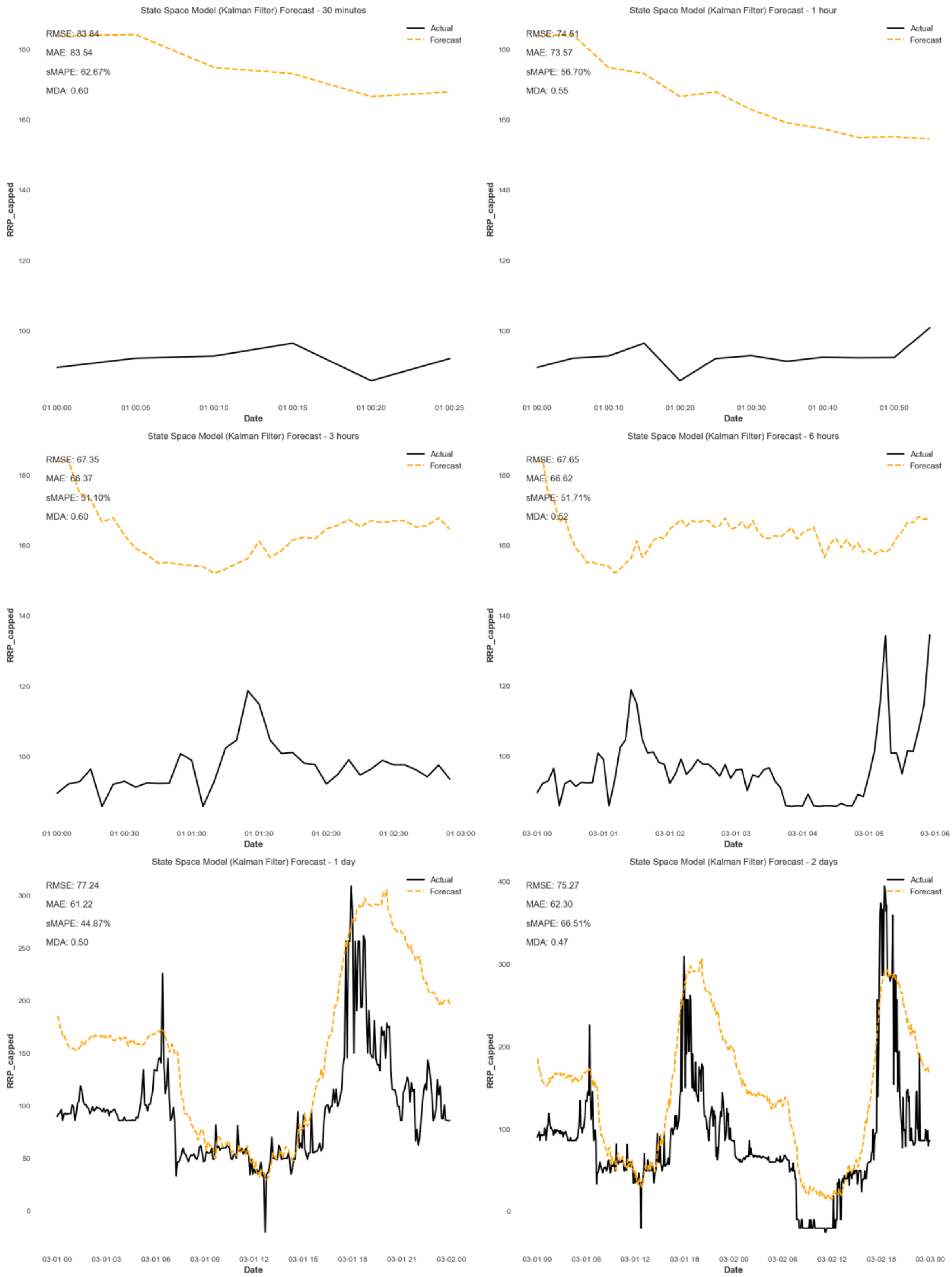

ARIMAX(3,1,1) - Forecast vs Actual: 30 minutes
RMSE: 17.58
MAE: 16.40
sMAPE: 19.85
MDA: 0.40
ARIMAX(3,1,1) - Forecast vs Actual: 1 hour
RMSE: 26.87
MAE: 24.89
sMAPE: 31.64
MDA: 0.55
ARIMAX(3,1,1) - Forecast vs Actual: 3 hours
RMSE: 51.81
MAE: 47.92
sMAPE: 69.40
MDA: 0.66
ARIMAX(3,1,1) - Forecast vs Actual: 6 hours
RMSE: 60.10
MAE: 57.21
sMAPE: 91.01
MDA: 0.58
ARIMAX(3,1,1) - Forecast vs Actual: 1 day
RMSE: 82.67
MAE: 73.43
sMAPE: 104.04
MDA: 0.57
ARIMAX(3,1,1) - Forecast vs Actual: 2 days
RMSE: 93.76
MAE: 80.97
sMAPE: 106.60
MDA: 0.55
Actual
Forecast
RRP Capped
Date
01-Mar
02-Mar
2024

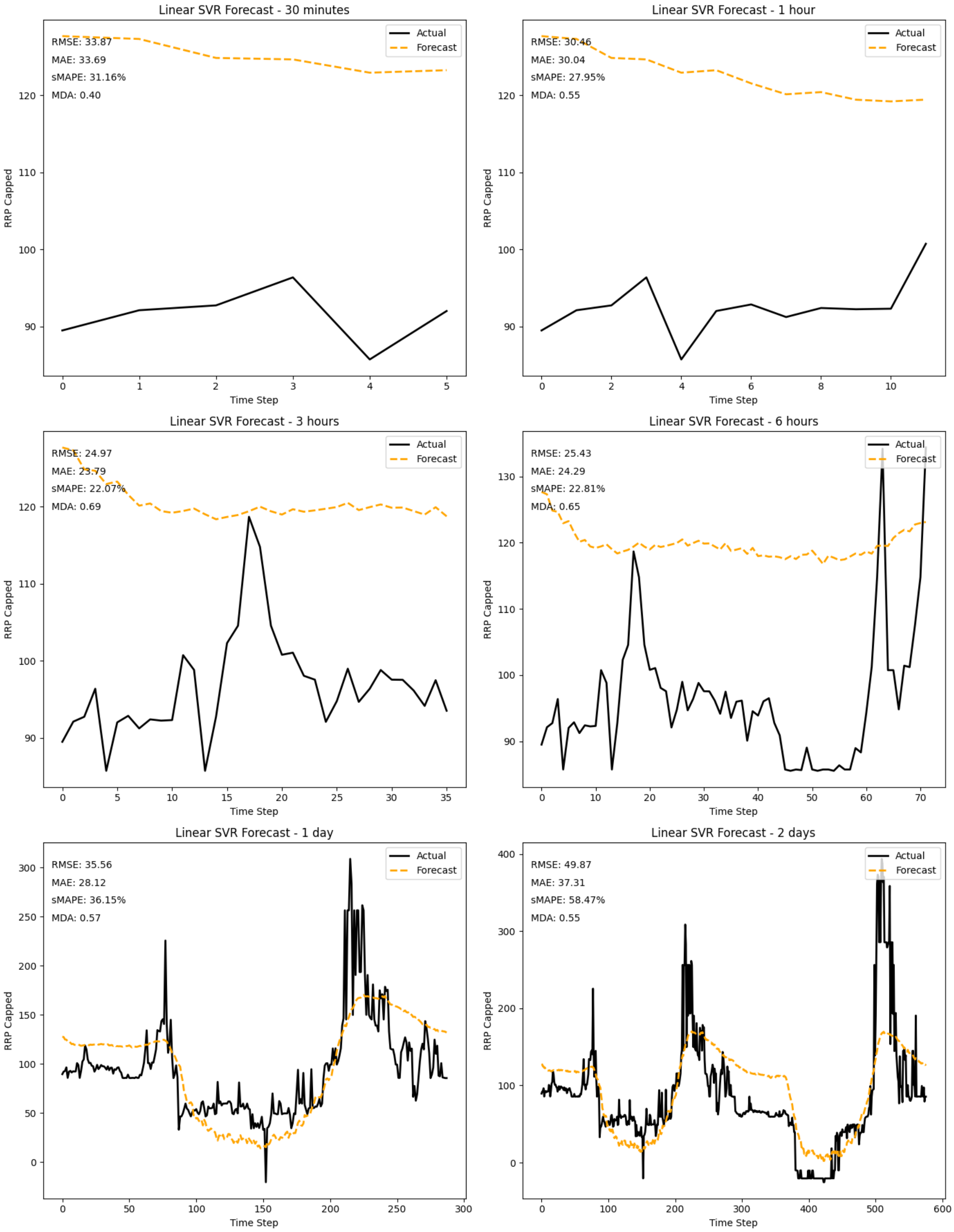

ARIMAX(3,1,1) + GARCH - Forecast vs Actual: 30 minutes
RMSE: 5.83
MAE: 4.70
sMAPE: 5.03
MDA: 0.40
ARIMAX(3,1,1) + GARCH - Forecast vs Actual: 1 hour
RMSE: 9.95
MAE: 8.34
sMAPE: 9.36
MDA: 0.55
ARIMAX(3,1,1) + GARCH - Forecast vs Actual: 3 hours
RMSE: 32.83
MAE: 28.02
sMAPE: 35.60
MDA: 0.66
ARIMAX(3,1,1) + GARCH - Forecast vs Actual: 6 hours
RMSE: 40.07
MAE: 36.48
sMAPE: 50.02
MDA: 0.58
ARIMAX(3,1,1) + GARCH - Forecast vs Actual: 1 day
RMSE: 77.90
MAE: 66.61
sMAPE: 90.63
MDA: 0.57
ARIMAX(3,1,1) + GARCH - Forecast vs Actual: 2 days
RMSE: 87.92
MAE: 73.97
sMAPE: 92.49
MDA: 0.55
Actual
Forecast
RRP Capped
Date
01-Mar
2024
02-Mar

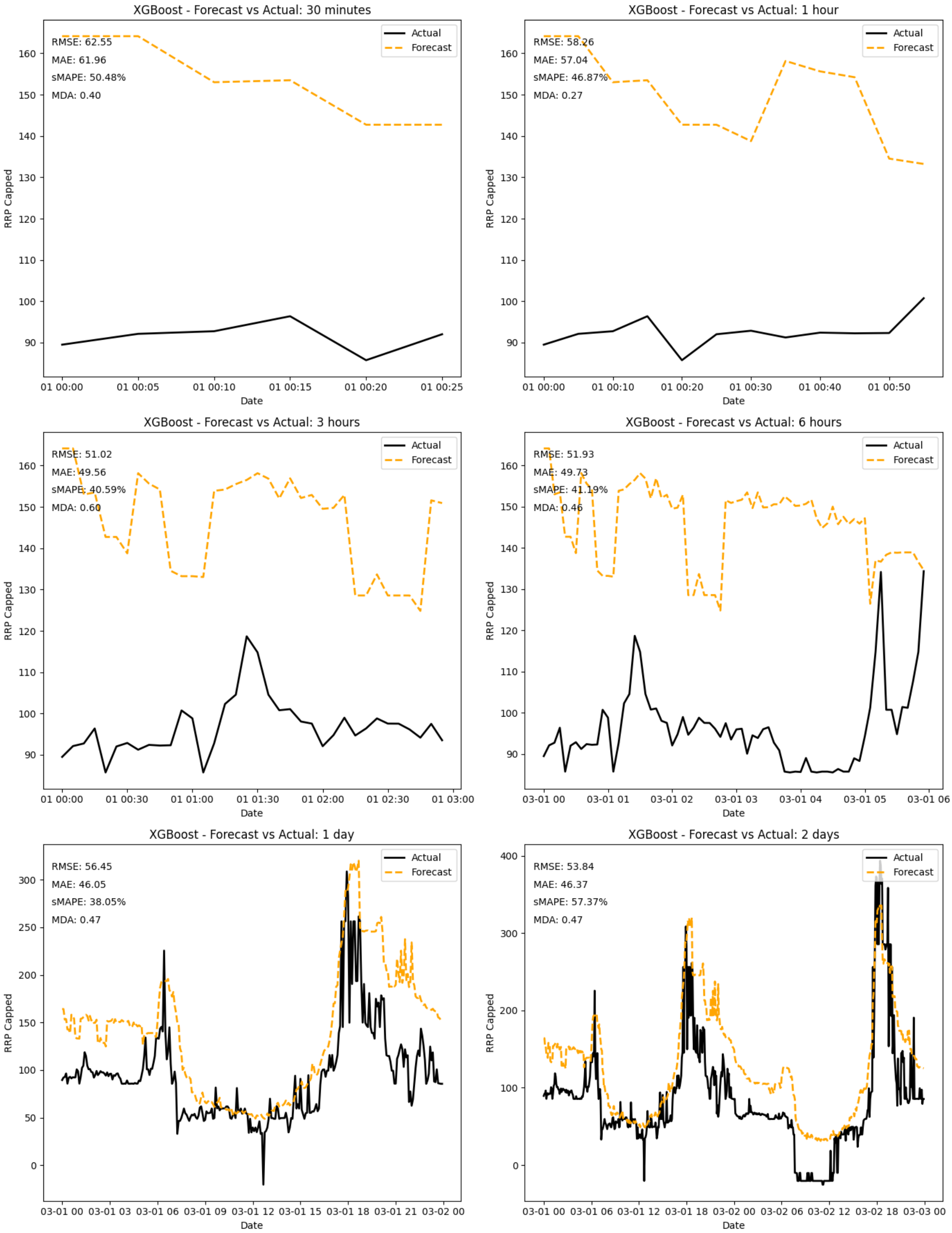

ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: 30 minutes
RMSE: 6.00
MAE: 4.70
sMAPE: 5.02
MDA: 0.40
Actual
Forecast
RRP Capped
Date
ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: 1 hour
RMSE: 9.80
MAE: 8.17
sMAPE: 9.15
MDA: 0.55
Actual
Forecast
RRP Capped
Date
ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: 3 hours
RMSE: 32.55
MAE: 27.73
sMAPE: 35.16
MDA: 0.66
Actual
Forecast
RRP Capped
Date
ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: 6 hours
RMSE: 39.76
MAE: 36.16
sMAPE: 49.48
MDA: 0.58
Actual
Forecast
RRP Capped
Date
ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: 1 day
RMSE: 77.87
MAE: 66.52
sMAPE: 90.46
MDA: 0.57
Actual
Forecast
RRP Capped
Date
ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: 2 days
RMSE: 87.87
MAE: 73.87
sMAPE: 92.32
MDA: 0.55
Actual
Forecast
RRP Capped
Date

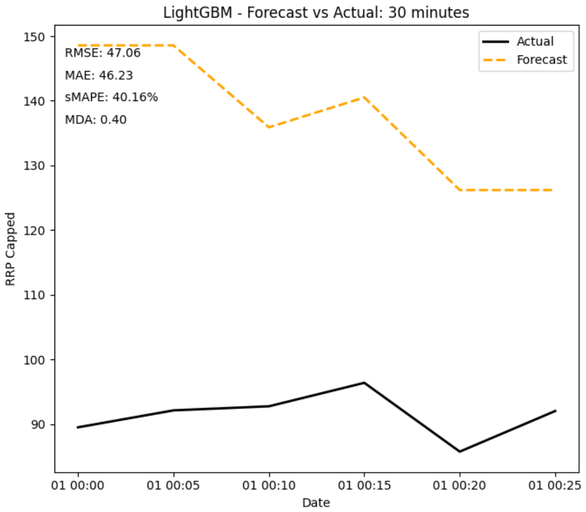

ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: 30 minutes
RMSE: 5.75
MAE: 4.70
sMAPE: 5.03
MDA: 0.40
Actual
Forecast
RRP Capped
Date
ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: 1 hour
RMSE: 10.03
MAE: 8.42
sMAPE: 9.46
MDA: 0.55
ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: 3 hours
RMSE: 32.96
MAE: 28.15
sMAPE: 35.80
MDA: 0.66
ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: 6 hours
RMSE: 40.22
MAE: 36.62
sMAPE: 50.27
MDA: 0.58
ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: 1 day
RMSE: 77.91
MAE: 66.65
sMAPE: 90.71
MDA: 0.57
ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: 2 days
RMSE: 87.95
MAE: 74.01
sMAPE: 92.57
MDA: 0.55

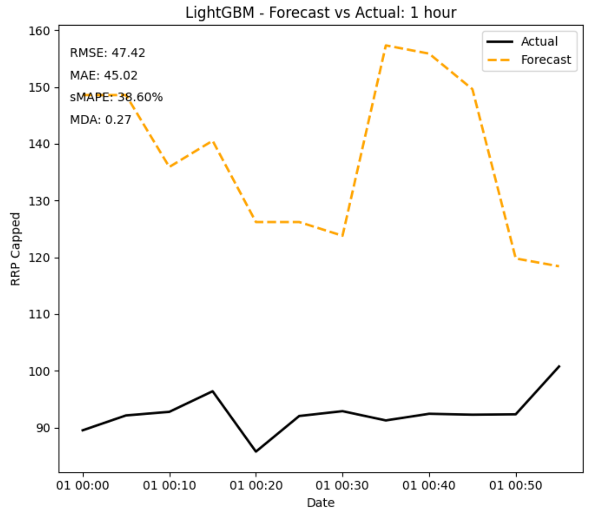

ARDL Forecast - 30 minutes
RMSE: 55.55
MAE: 54.98
sMAPE: 46.13%
MDA: 0.40
Actual
Forecast
RRP Capped
Date
ARDL Forecast - 1 hour
RMSE: 59.02
MAE: 58.51
sMAPE: 47.93%
MDA: 0.55
Actual
Forecast
RRP Capped
Date
ARDL Forecast - 3 hours
RMSE: 64.74
MAE: 63.75
sMAPE: 49.50%
MDA: 0.43
Actual
Forecast
RRP Capped
Date
ARDL Forecast - 6 hours
RMSE: 76.05
MAE: 74.38
sMAPE: 55.68%
MDA: 0.39
Actual
Forecast
RRP Capped
Date
ARDL Forecast - 1 day
RMSE: 82.17
MAE: 66.75
sMAPE: 50.60%
MDA: 0.44
Actual
Forecast
RRP Capped
Date
ARDL Forecast - 2 days
RMSE: 77.88
MAE: 64.08
sMAPE: 69.48%
MDA: 0.41
Actual
Forecast
RRP Capped
Date

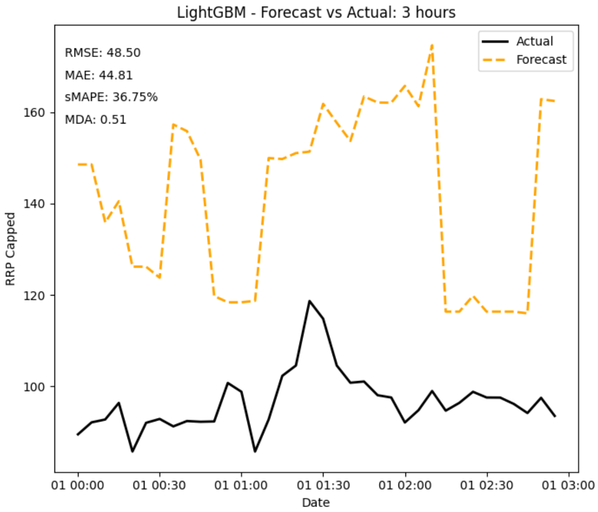

State Space Model (Kalman Filter) Forecast - 30 minutes
RMSE: 83.84
MAE: 83.54
sMAPE: 62.67%
MDA: 0.60
Actual
Forecast
RRP_capped
Date
State Space Model (Kalman Filter) Forecast - 1 hour
RMSE: 74.51
MAE: 73.57
sMAPE: 56.70%
MDA: 0.55
Actual
Forecast
RRP_capped
Date
State Space Model (Kalman Filter) Forecast - 3 hours
RMSE: 67.35
MAE: 66.37
sMAPE: 51.10%
MDA: 0.60
Actual
Forecast
RRP_capped
Date
State Space Model (Kalman Filter) Forecast - 6 hours
RMSE: 67.65
MAE: 66.62
sMAPE: 51.71%
MDA: 0.52
Actual
Forecast
RRP_capped
Date
State Space Model (Kalman Filter) Forecast - 1 day
RMSE: 77.24
MAE: 61.22
sMAPE: 44.87%
MDA: 0.50
Actual
Forecast
RRP_capped
Date
State Space Model (Kalman Filter) Forecast - 2 days
RMSE: 75.27
MAE: 62.30
sMAPE: 66.51%
MDA: 0.47
Actual
Forecast
RRP_capped
Date

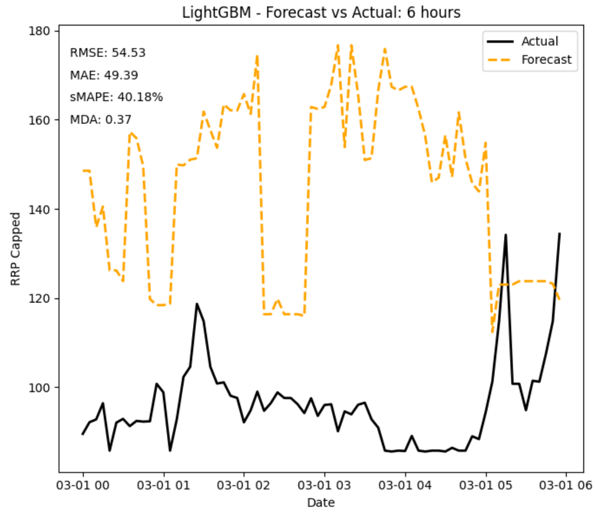

Linear SVR Forecast - 30 minutes
RMSE: 33.87
MAE: 33.69
sMAPE: 31.16%
MDA: 0.40
Linear SVR Forecast - 1 hour
RMSE: 30.46
MAE: 30.04
sMAPE: 27.95%
MDA: 0.55
Linear SVR Forecast - 3 hours
RMSE: 24.97
MAE: 23.79
sMAPE: 22.07%
MDA: 0.69
Linear SVR Forecast - 6 hours
RMSE: 25.43
MAE: 24.29
sMAPE: 22.81%
MDA: 0.65
Linear SVR Forecast - 1 day
RMSE: 35.56
MAE: 28.12
sMAPE: 36.15%
MDA: 0.57
Linear SVR Forecast - 2 days
RMSE: 49.87
MAE: 37.31
sMAPE: 58.47%
MDA: 0.55
Actual
Forecast
RRP Capped
Time Step

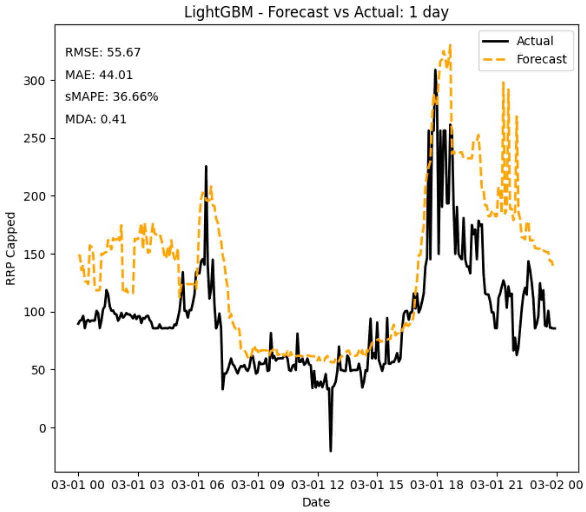

XGBoost - Forecast vs Actual: 30 minutes
RMSE: 62.55
MAE: 61.96
sMAPE: 50.48%
MDA: 0.40
XGBoost - Forecast vs Actual: 1 hour
RMSE: 58.26
MAE: 57.04
sMAPE: 46.87%
MDA: 0.27
XGBoost - Forecast vs Actual: 3 hours
RMSE: 51.02
MAE: 49.56
sMAPE: 40.59%
MDA: 0.60
XGBoost - Forecast vs Actual: 6 hours
RMSE: 51.93
MAE: 49.73
sMAPE: 41.19%
MDA: 0.46
XGBoost - Forecast vs Actual: 1 day
RMSE: 56.45
MAE: 46.05
sMAPE: 38.05%
MDA: 0.47
XGBoost - Forecast vs Actual: 2 days
RMSE: 53.84
MAE: 46.37
sMAPE: 57.37%
MDA: 0.47
Actual
Forecast
RRP Capped
Date

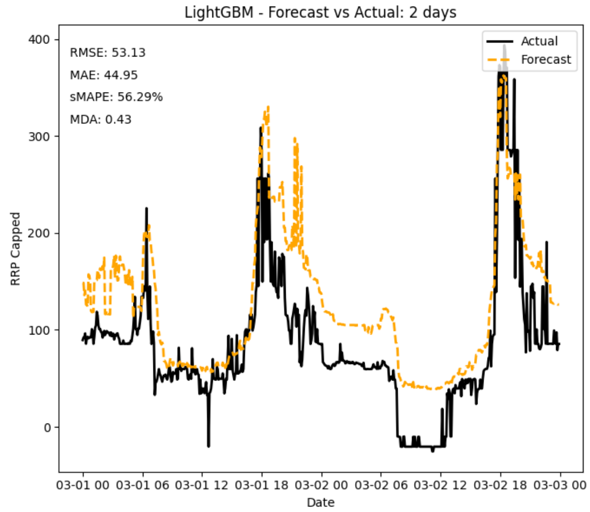




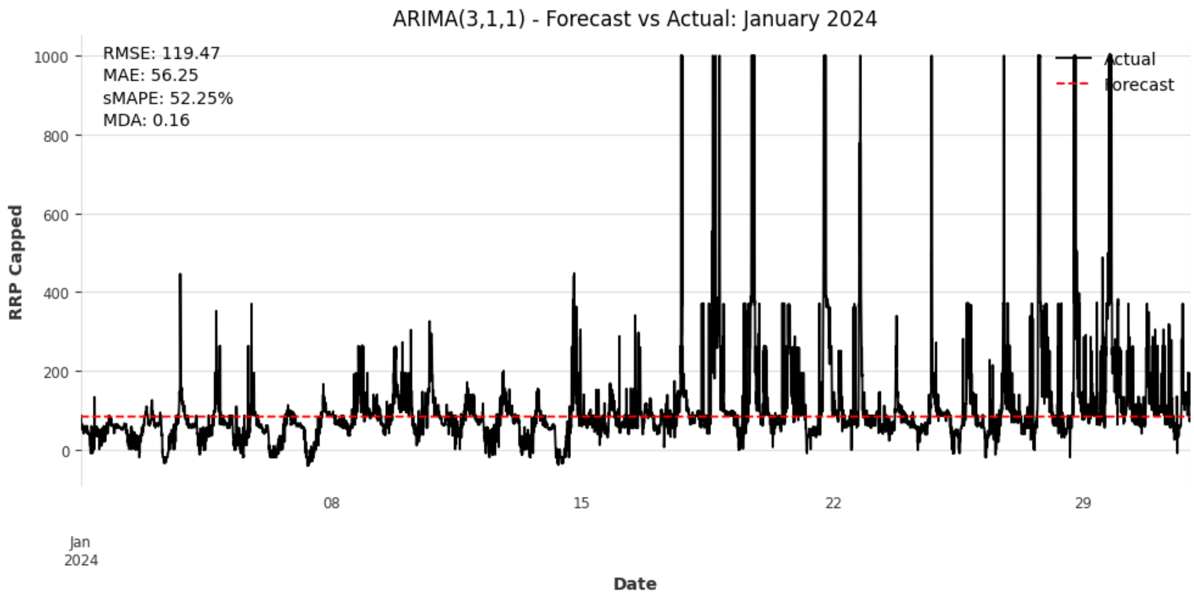


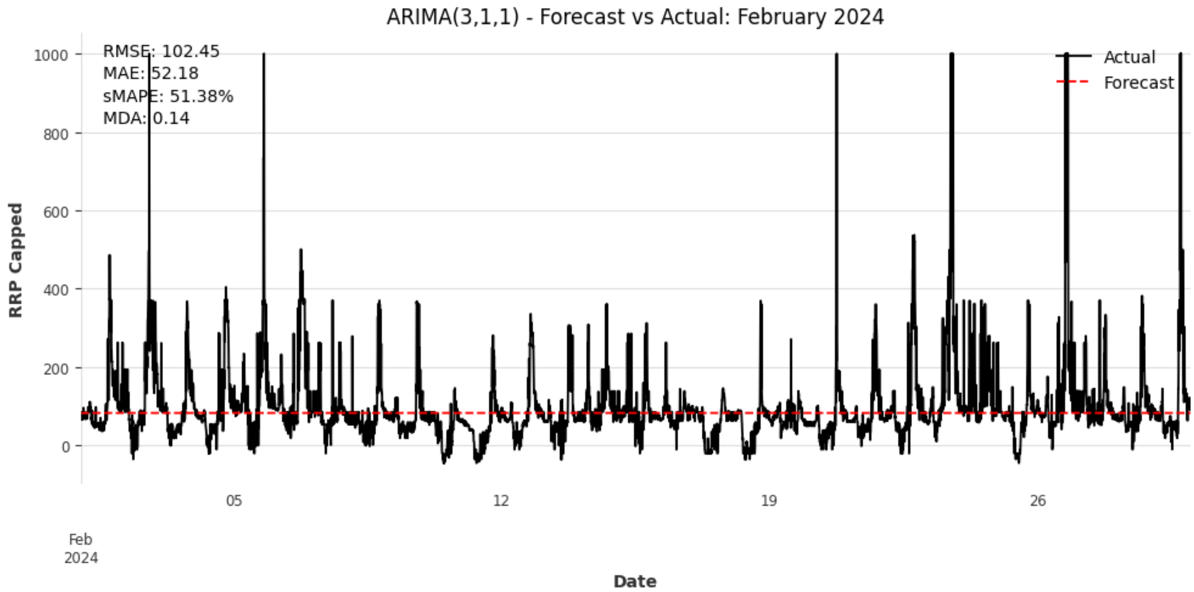


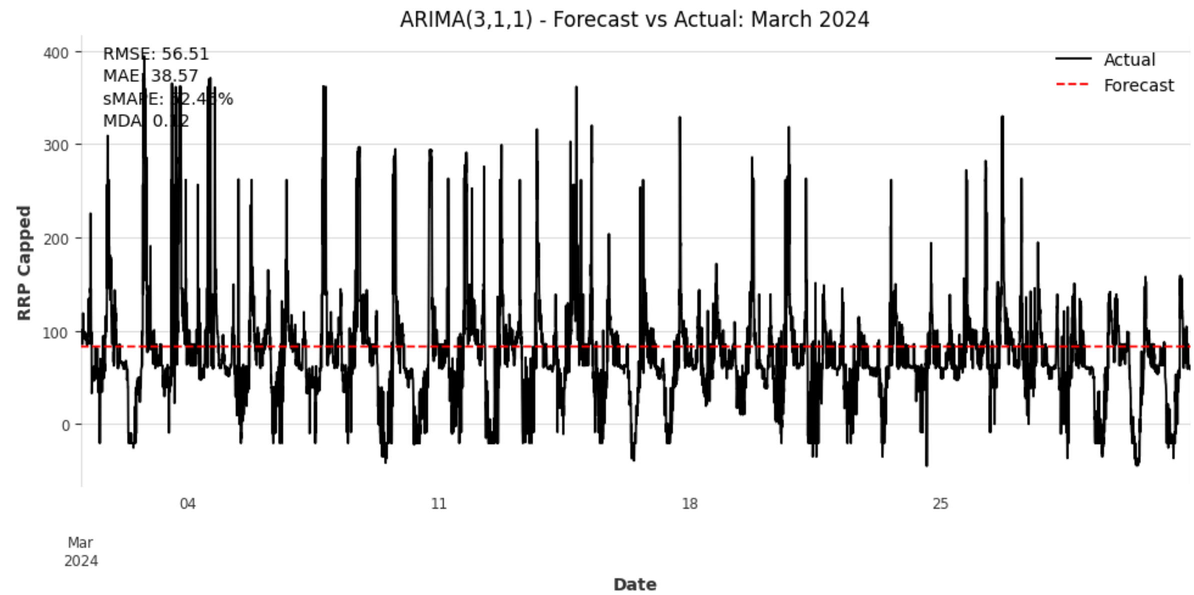


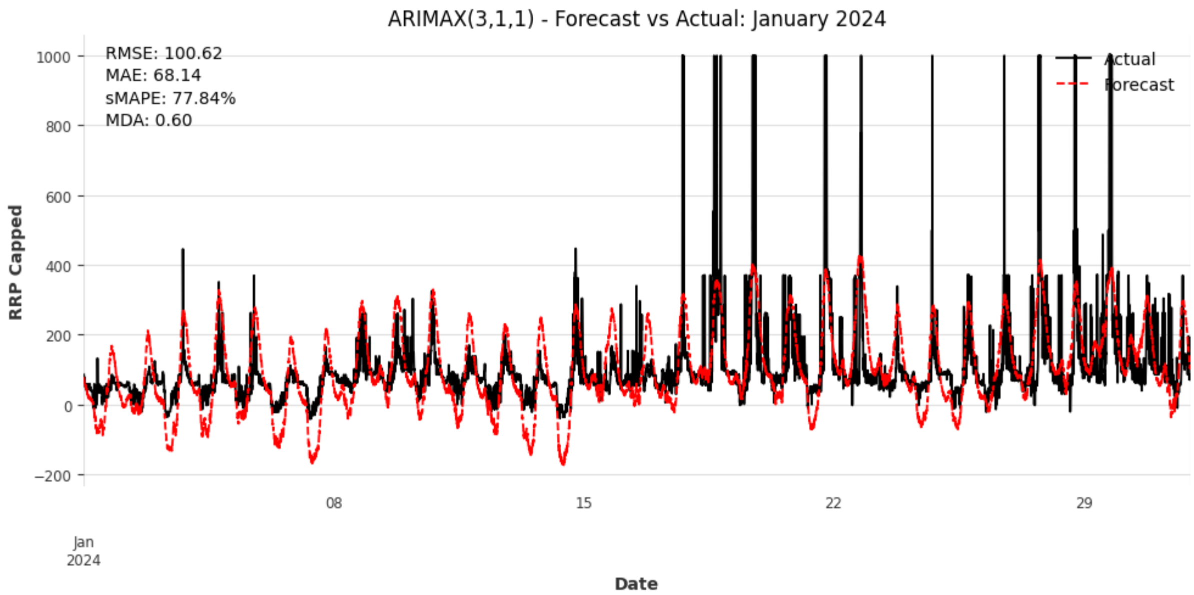


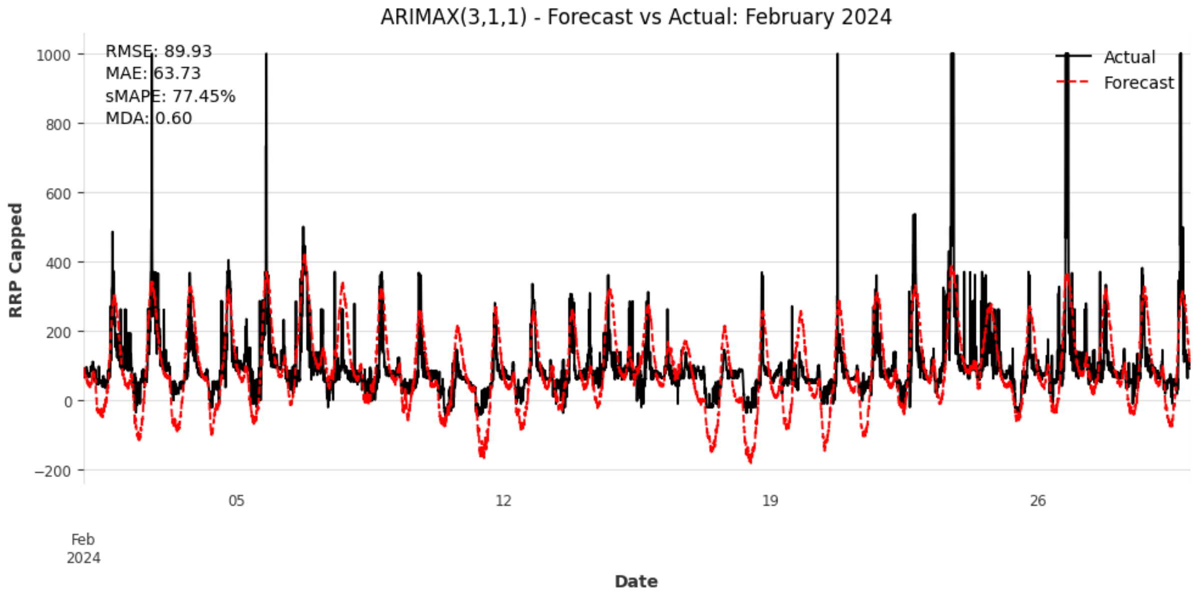
Long Term Forecasting

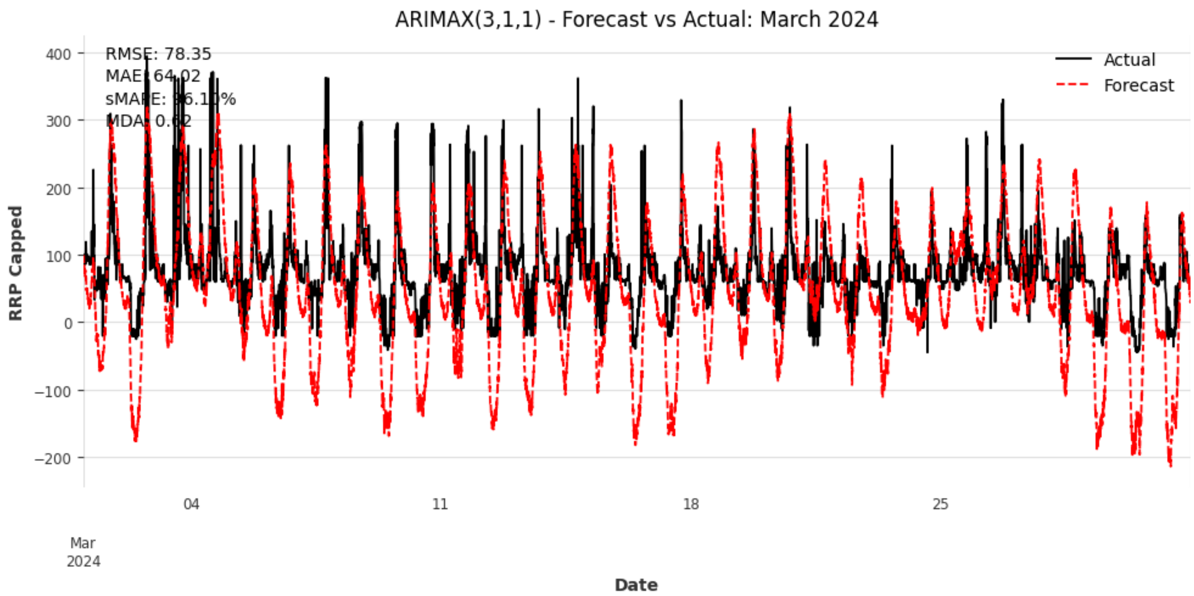

ARIMA(3,1,1) - Forecast vs Actual: January 2024
RMSE: 119.47
MAE: 56.25
sMAPE: 52.25%
MDA: 0.16
Actual
Forecast
RRP Capped
Date
Jan
2024

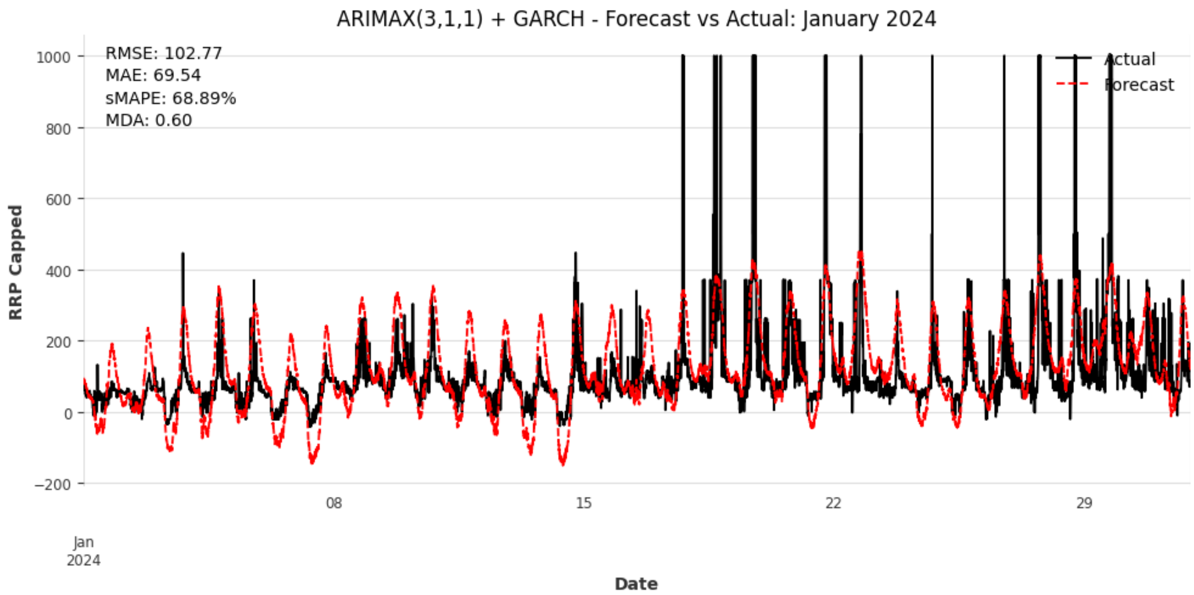

ARIMA(3,1,1) - Forecast vs Actual: February 2024
RMSE: 102.45
MAE: 52.18
sMAPE: 51.38%
MDA: 0.14
Actual
Forecast
RRP Capped
Date
Feb
2024

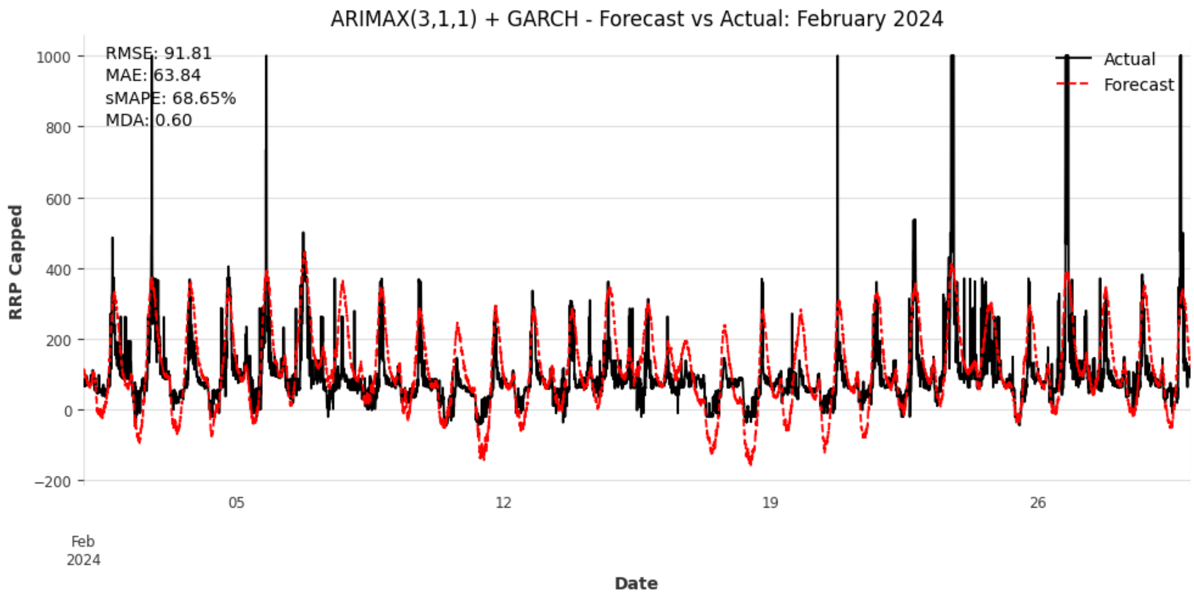

ARIMA(3,1,1) - Forecast vs Actual: March 2024
RMSE: 56.51
MAE: 38.57
Actual
Forecast
RRP Capped
Date
Mar
2024

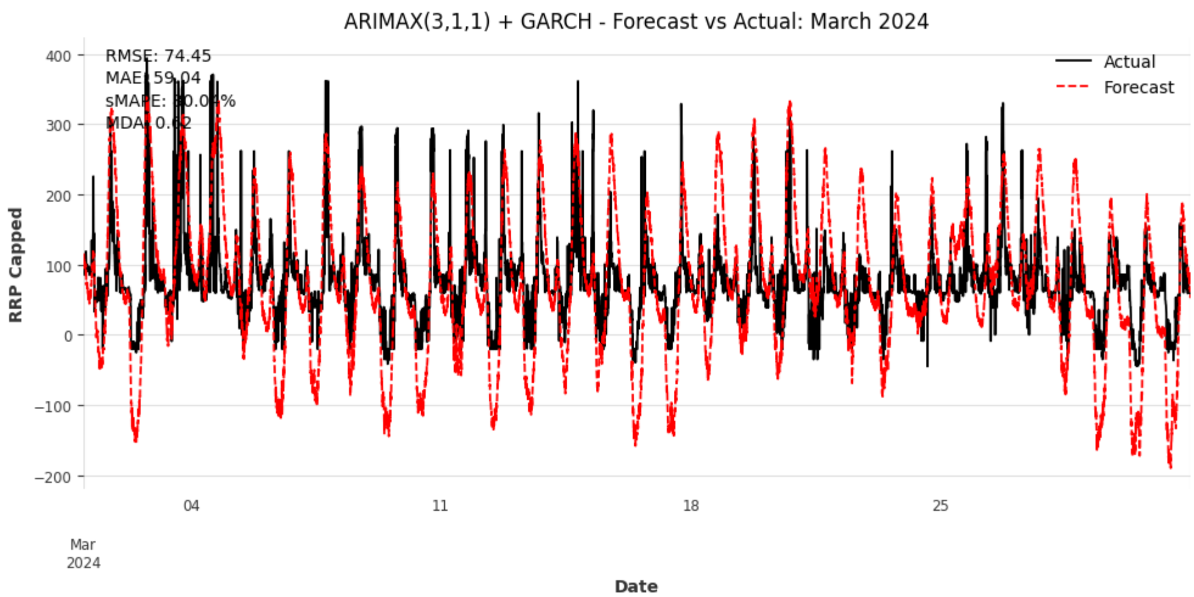

ARIMAX(3,1,1) - Forecast vs Actual: January 2024
RMSE: 100.62
MAE: 68.14
sMAPE: 77.84%
MDA: 0.60
Actual
Forecast
RRP Capped
Date
Jan
2024
08
15
22
29

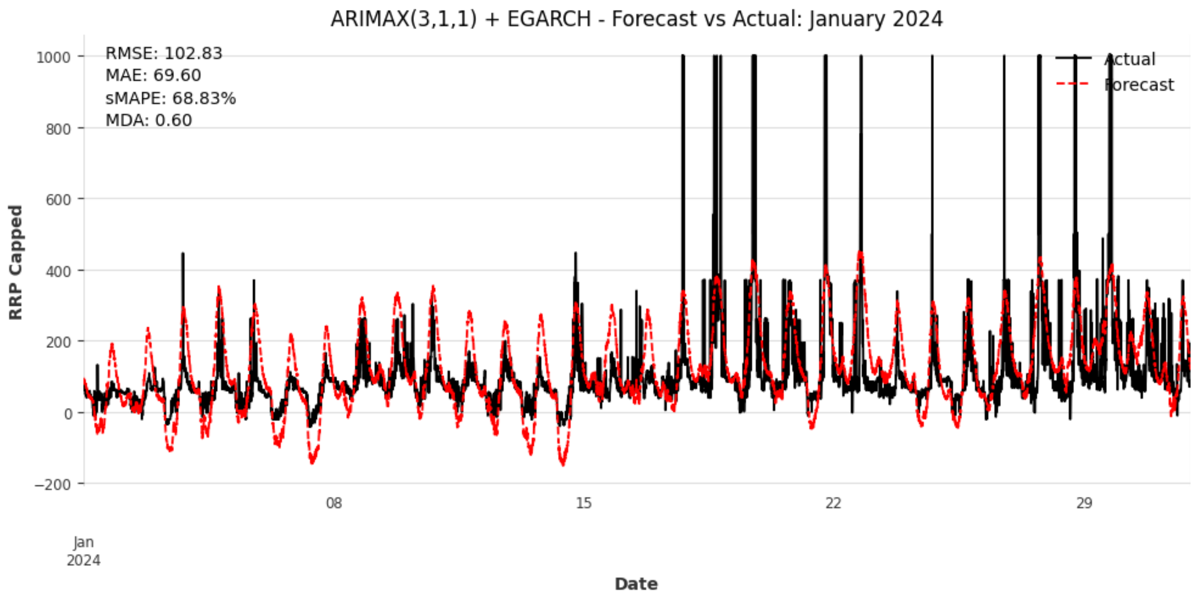

ARIMAX(3,1,1) - Forecast vs Actual: February 2024
RMSE: 89.93
MAE: 63.73
sMAPE: 77.45%
MDA: 0.60
Actual
Forecast
RRP Capped
Date
Feb
2024
05
12
19
26


ARIMAX(3,1,1) - Forecast vs Actual: March 2024
RMSE: 78.35
MAE: 64.02
MDA: 0.62
Actual
Forecast
RRP Capped
Date
Mar
2024
04
11
18
25

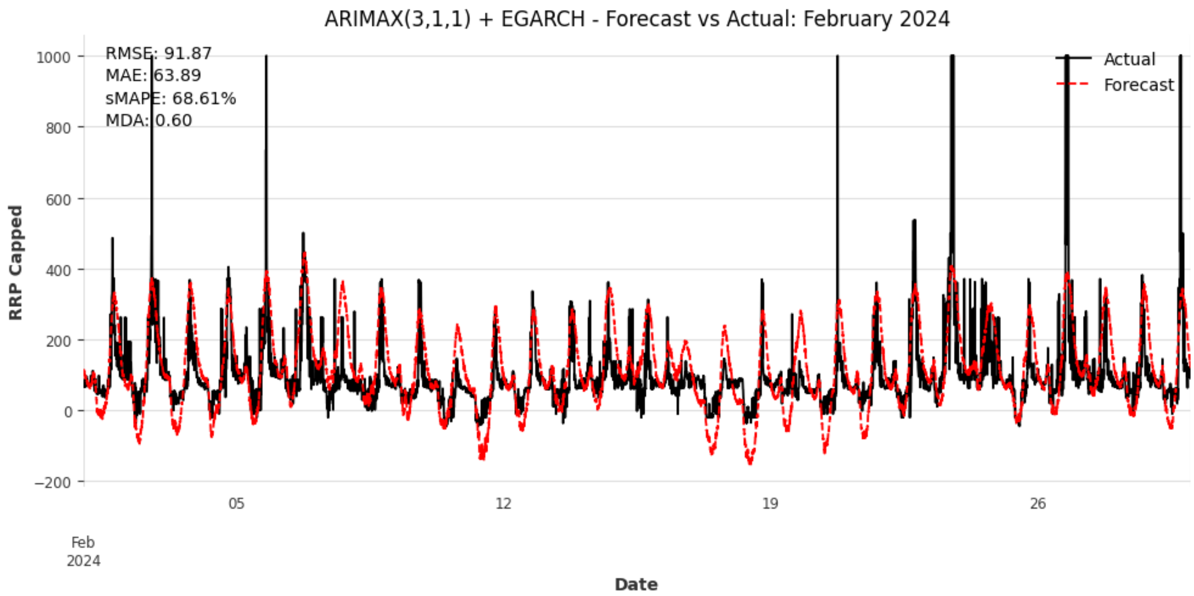

ARIMAX(3,1,1) + GARCH - Forecast vs Actual: January 2024
RMSE: 102.77
MAE: 69.54
sMAPE: 68.89%
MDA: 0.60
Actual
Forecast
RRP Capped
Date
Jan
2024


ARIMAX(3,1,1) + GARCH - Forecast vs Actual: February 2024
RMSE: 91.81
MAE: 63.84
sMAPE: 68.65%
MDA: 0.60
Actual
Forecast
RRP Capped
Date
Feb
2024

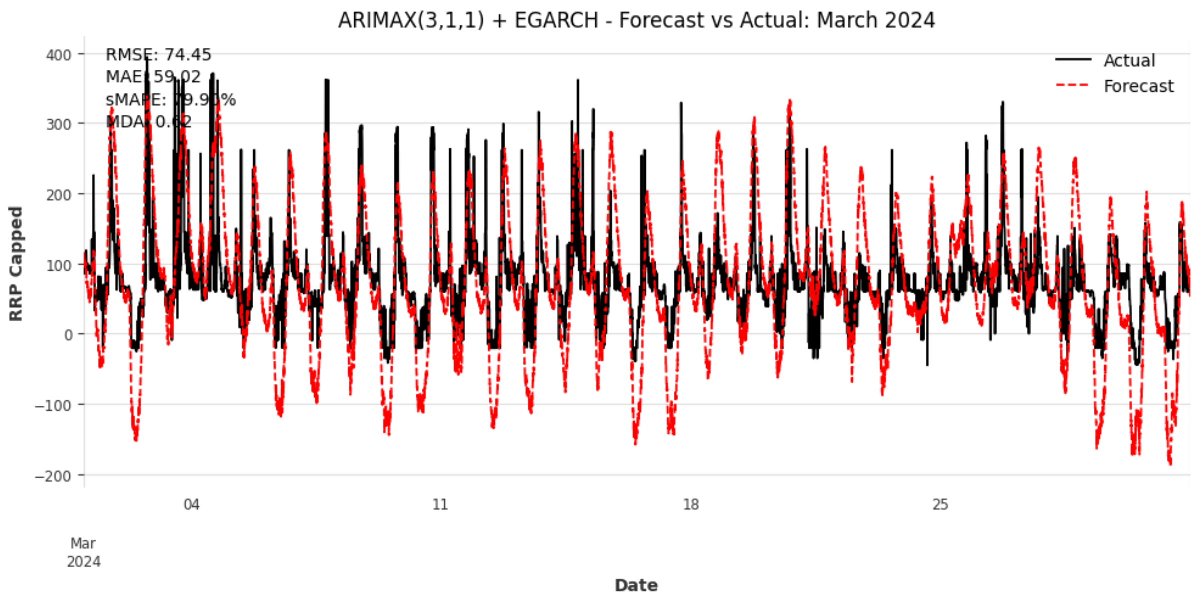

ARIMAX(3,1,1) + GARCH - Forecast vs Actual: March 2024
RMSE: 74.45
MAE: 59.04
Actual
Forecast
RRP Capped
Date
Mar
2024



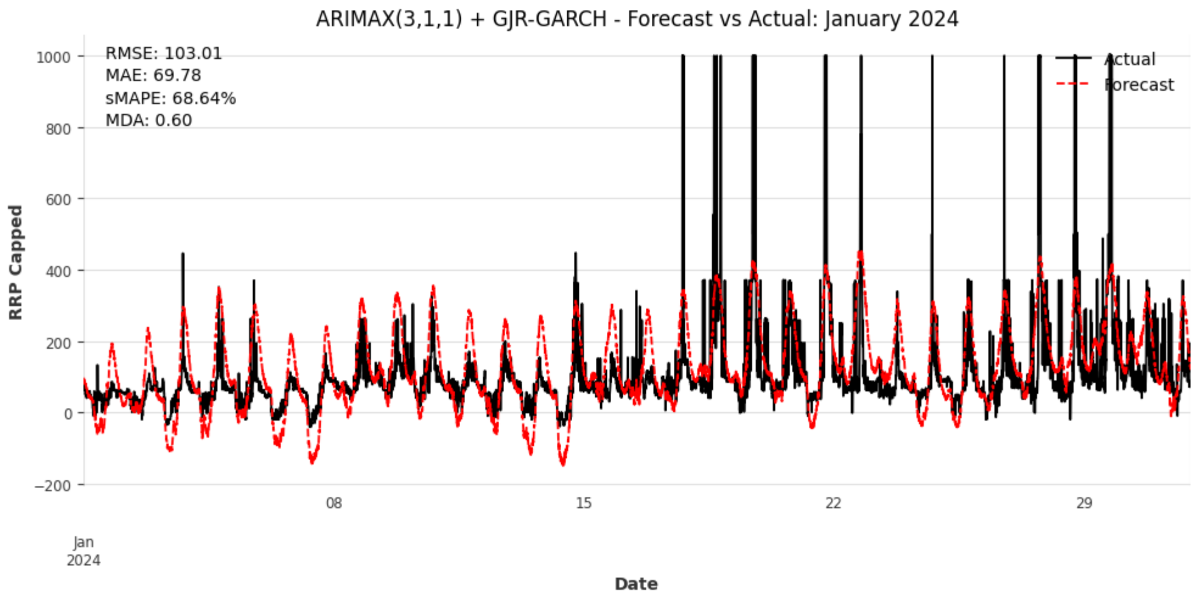
ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: January 2024
RMSE: 102.83
MAE: 69.60
sMAPE: 68.83%
MDA: 0.60
Actual
Forecast
RRP Capped
Date
Jan
2024

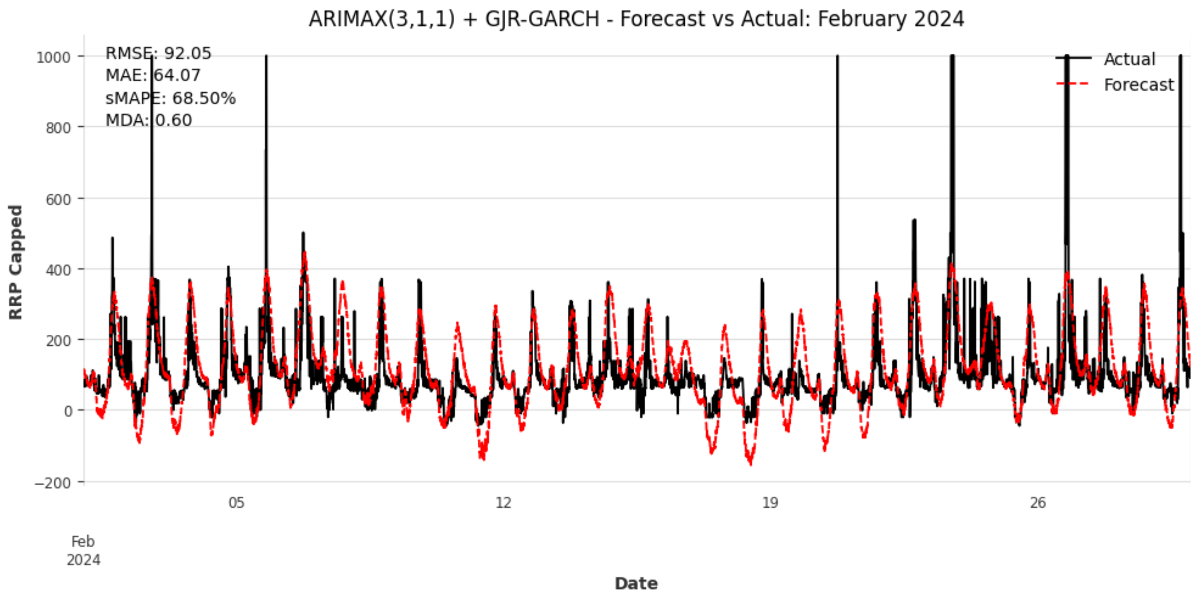


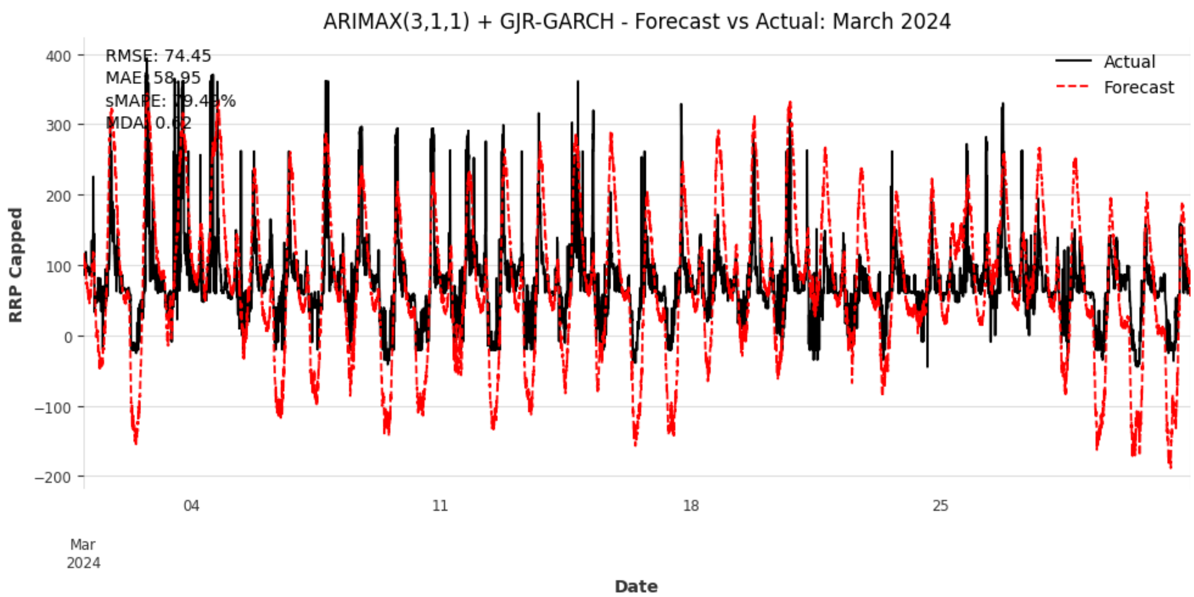
ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: February 2024
RMSE: 91.87
MAE: 63.89
sMAPE: 68.61%
MDA: 0.60
Actual
Forecast
RRP Capped
Date
Feb
2024

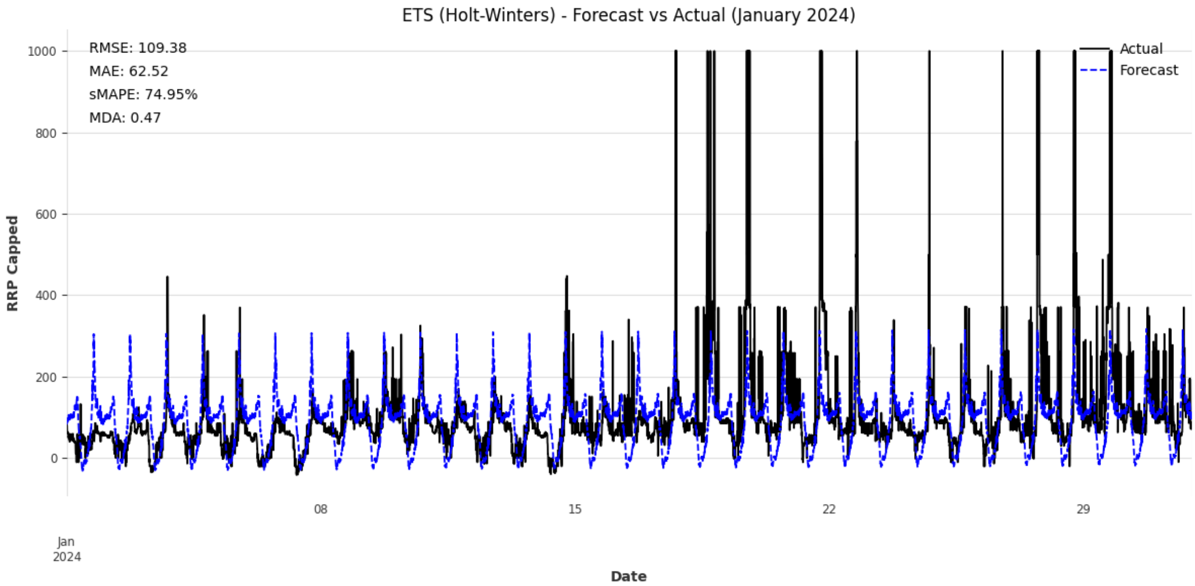


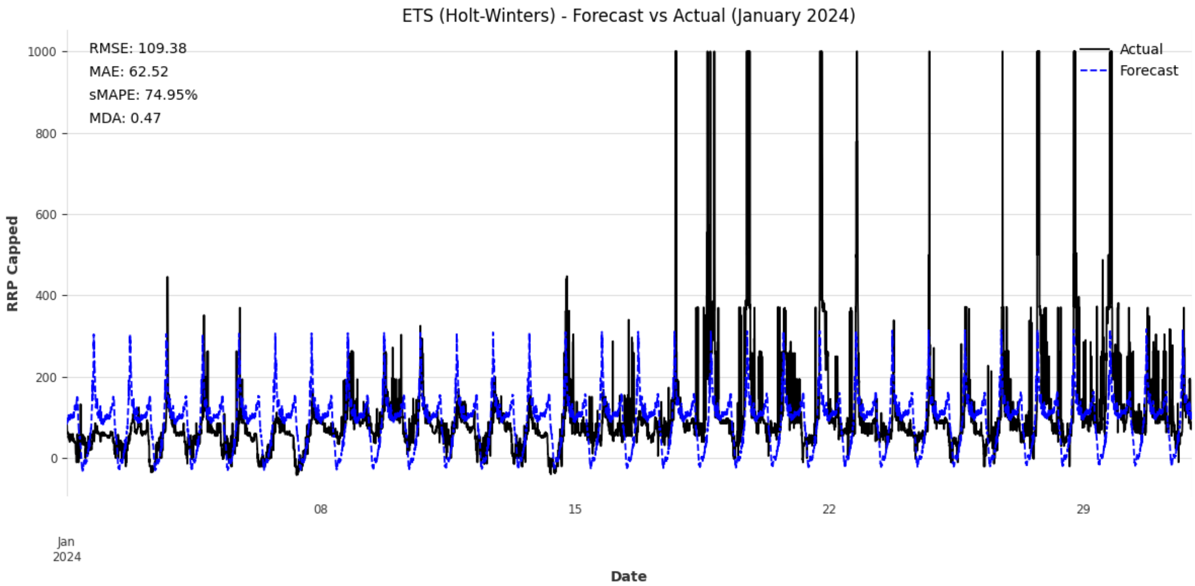
ARIMAX(3,1,1) + EGARCH - Forecast vs Actual: March 2024
RMSE: 74.45
MAE: 59.02
Actual
Forecast
RRP Capped
Date
Mar
2024

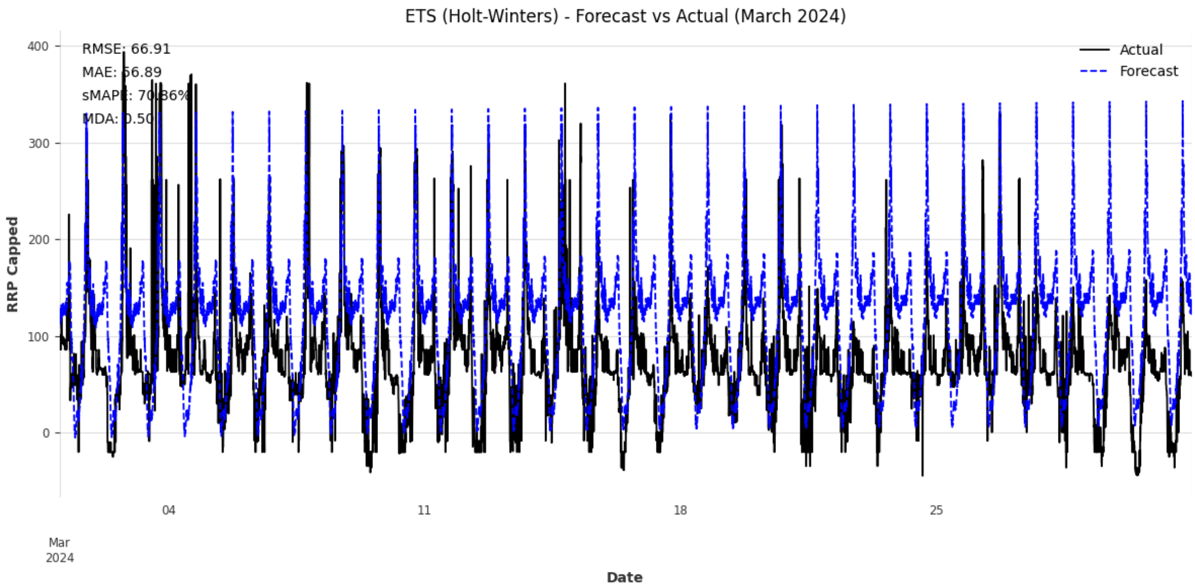

ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: January 2024
RMSE: 103.01
MAE: 69.78
sMAPE: 68.64%
MDA: 0.60
Actual
Forecast
RRP Capped
Date
Jan
2024
08
15
22
29

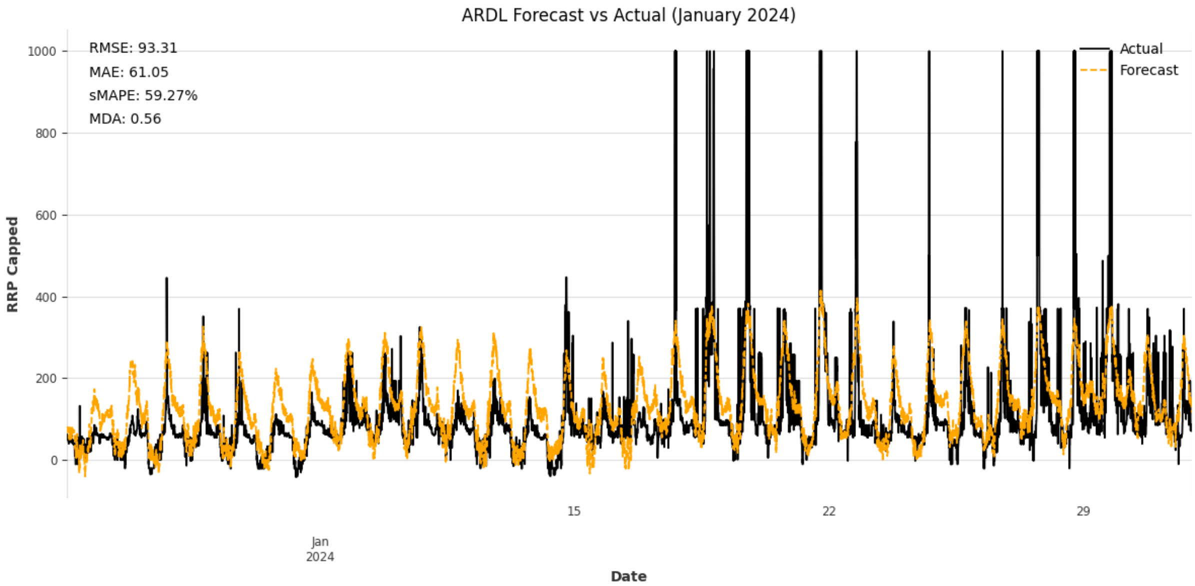

ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: February 2024
RMSE: 92.05
MAE: 64.07
sMAPE: 68.50%
MDA: 0.60
Actual
Forecast
RRP Capped
Date
Feb
2024
05
12
19
26

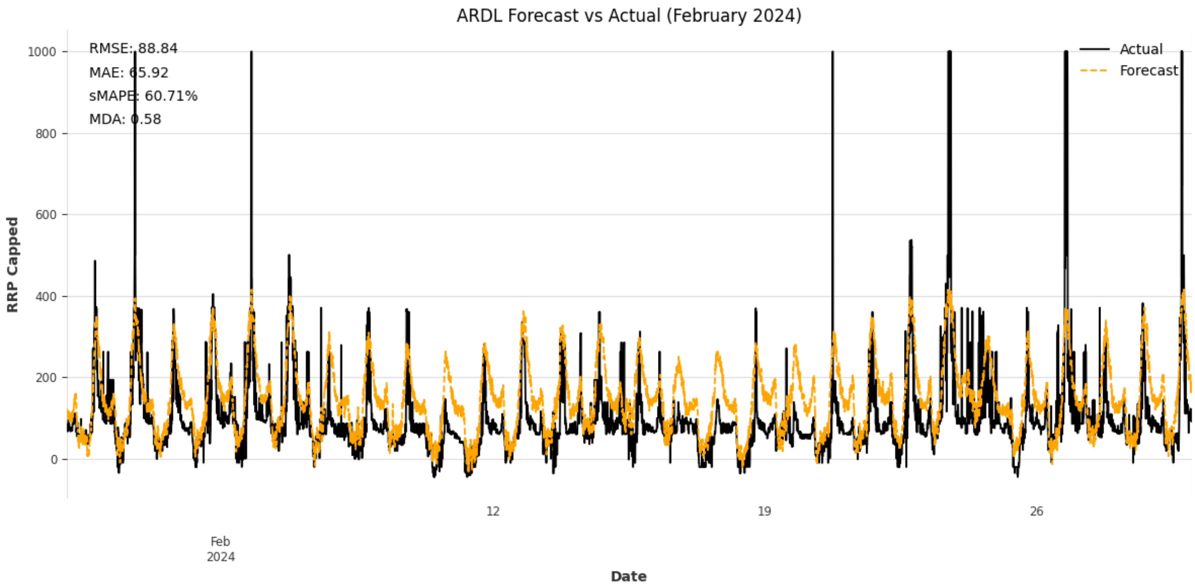

ARIMAX(3,1,1) + GJR-GARCH - Forecast vs Actual: March 2024
RMSE: 74.45
MAE: 58.95
Actual
Forecast
RRP Capped
Date
Mar
2024
04
11
18
25

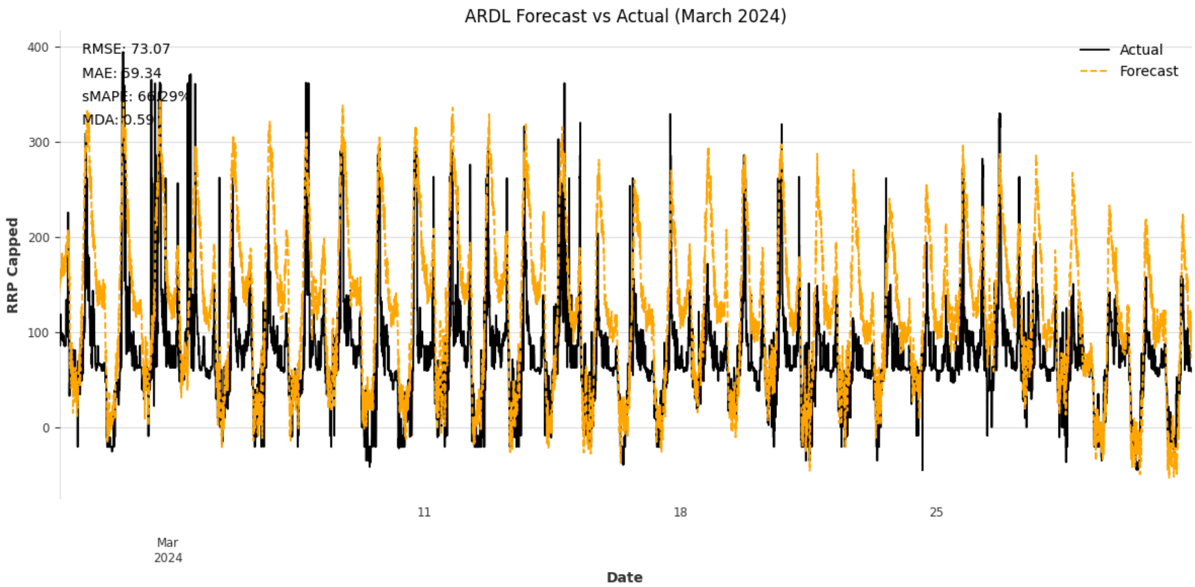

ETS (Holt-Winters) - Forecast vs Actual (January 2024)
RMSE: 109.38
MAE: 62.52
sMAPE: 74.95%
MDA: 0.47
Actual
Forecast
RRP Capped
Date
Jan
2024
08
15
22
29

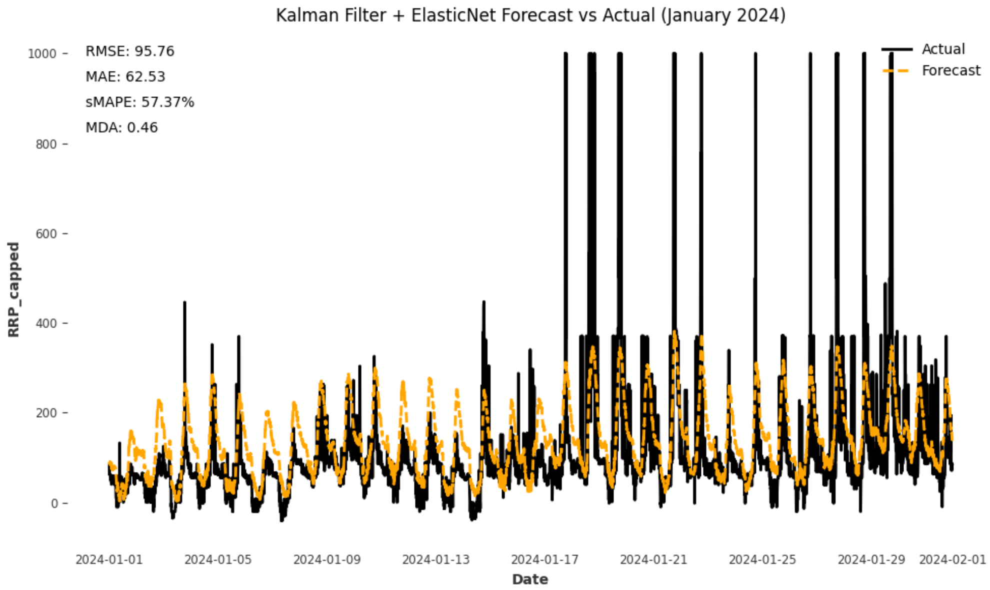

ETS (Holt-Winters) - Forecast vs Actual (January 2024)
RMSE: 109.38
MAE: 62.52
sMAPE: 74.95%
MDA: 0.47
Actual
Forecast
RRP Capped
Date
Jan
2024
08
15
22
29

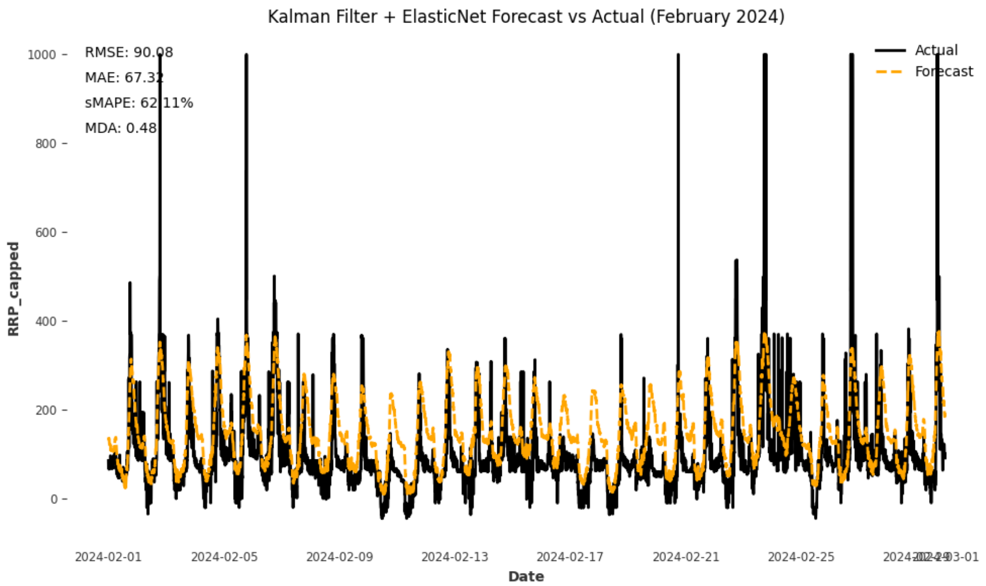

ETS (Holt-Winters) - Forecast vs Actual (March 2024)
RMSE: 66.91
MAE: 56.89
sMAPE: 70.86%
MDA: 0.50
Actual
Forecast
RRP Capped
Date
Mar
2024
04
11
18
25

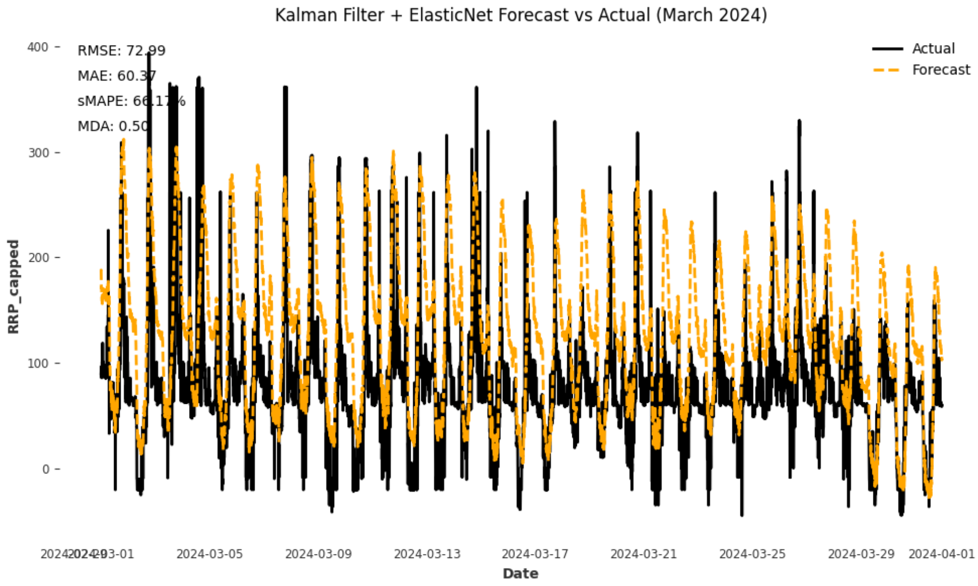

ARDL Forecast vs Actual (January 2024)
RMSE: 93.31
MAE: 61.05
sMAPE: 59.27%
MDA: 0.56
Actual
Forecast
RRP Capped
0
200
400
600
800
1000
Jan
2024
15
22
29
Date

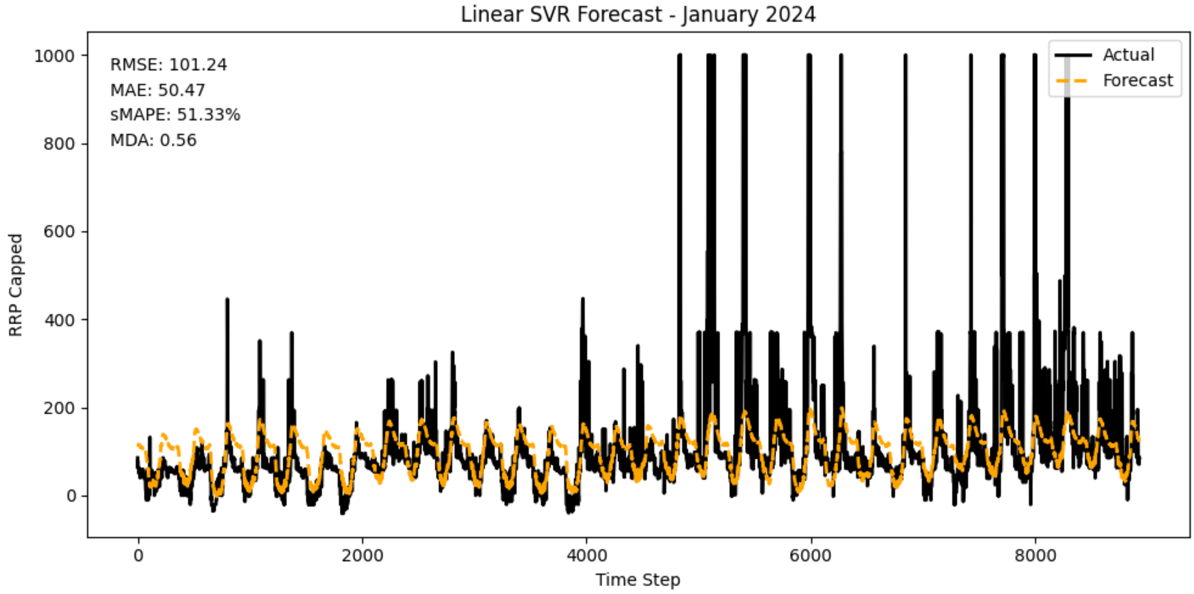

ARDL Forecast vs Actual (February 2024)
RMSE: 88.84
MAE: 65.92
sMAPE: 60.71%
MDA: 0.58
Actual
Forecast
RRP Capped
0
200
400
600
800
1000
Feb
2024
12
19
26
Date

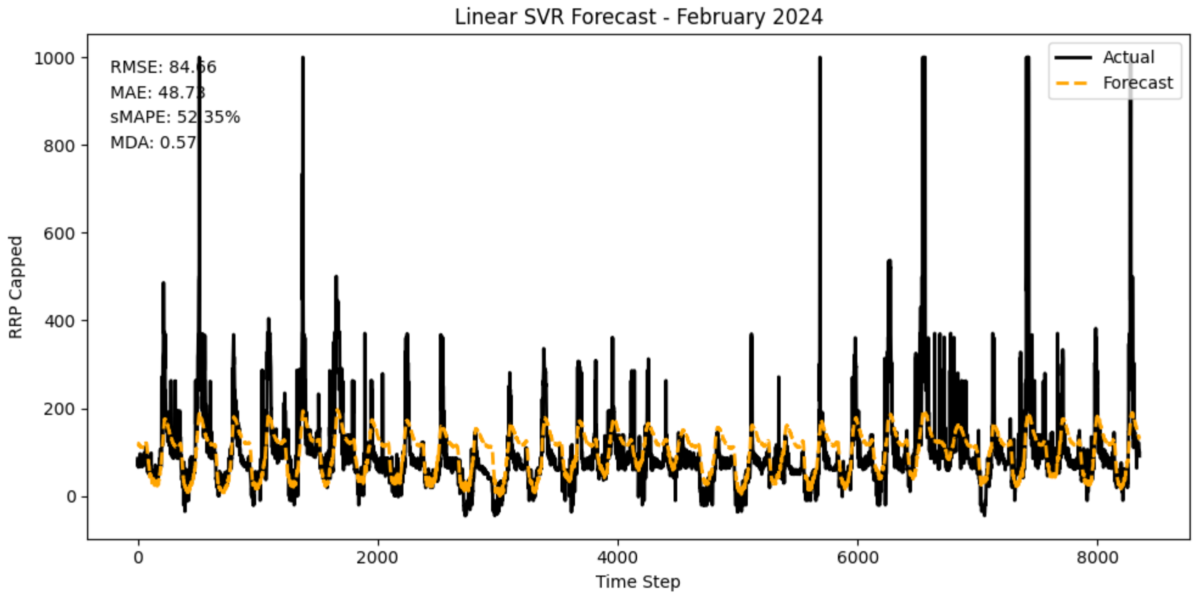

ARDL Forecast vs Actual (March 2024)
RMSE: 73.07
MAE: 59.34
MDA: 0.59
Actual
Forecast
RRP Capped
0
100
200
300
400
Mar
2024
11
18
25
Date

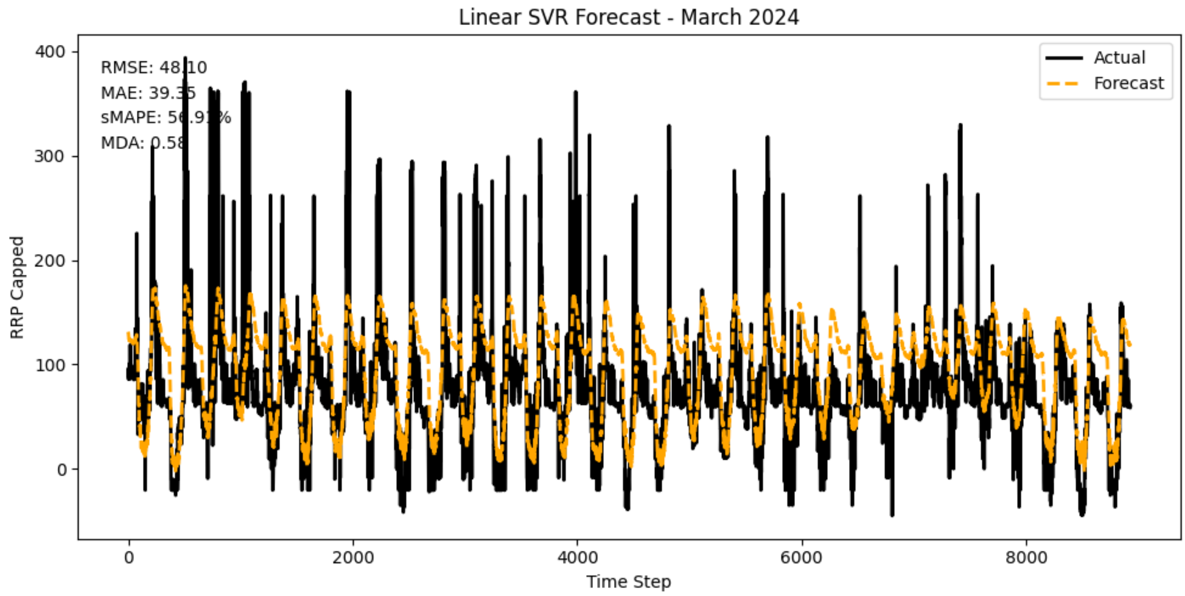

Kalman Filter + ElasticNet Forecast vs Actual (January 2024)
RMSE: 95.76
MAE: 62.53
sMAPE: 57.37%
MDA: 0.46
Actual
Forecast
RRP_capped
Date
1000
800
600
400
200
0
2024-01-01
2024-01-05
2024-01-09
2024-01-13
2024-01-17
2024-01-21
2024-01-25
2024-01-29
2024-02-01

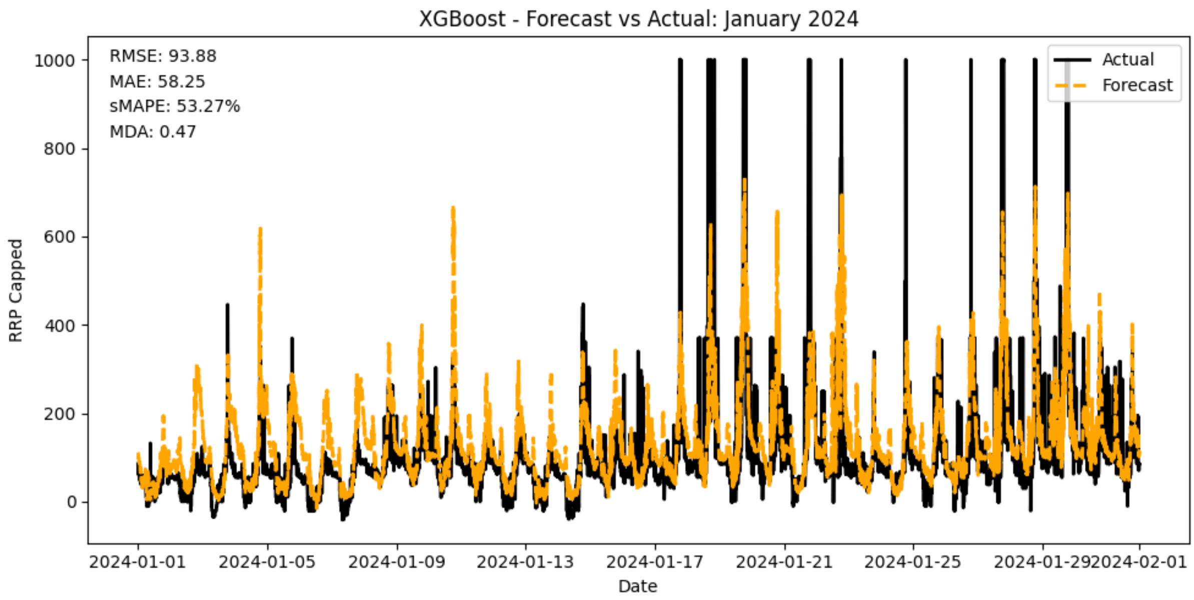

Kalman Filter + ElasticNet Forecast vs Actual (February 2024)
RMSE: 90.08
MAE: 67.32
sMAPE: 62.11%
MDA: 0.48
Actual
Forecast
RRP_capped
Date
1000
800
600
400
200
0
2024-02-01
2024-02-05
2024-02-09
2024-02-13
2024-02-17
2024-02-21
2024-02-25
2024-02-29
2024-03-01

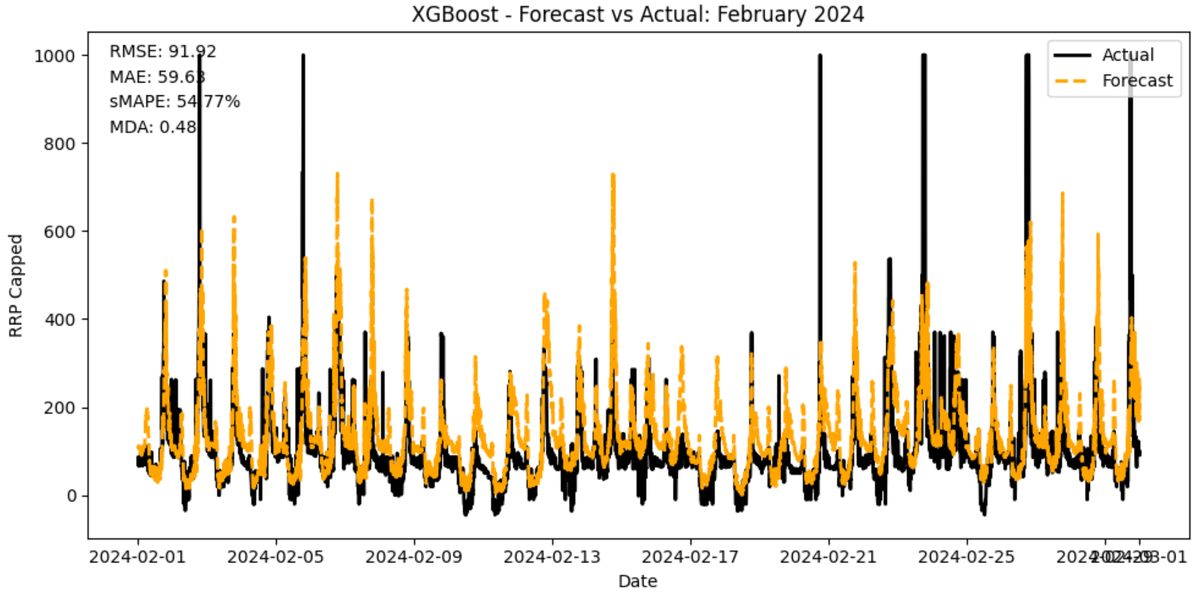

Kalman Filter + ElasticNet Forecast vs Actual (March 2024)
RMSE: 72.99
MAE: 60.37
sMAPE: 66.17%
MDA: 0.50
Actual
Forecast
RRP_capped
400
300
200
100
0
2024-02-29
2024-03-01
2024-03-05
2024-03-09
2024-03-13
2024-03-17
2024-03-21
2024-03-25
2024-03-29
2024-04-01
Date


Linear SVR Forecast - January 2024
RMSE: 101.24
MAE: 50.47
sMAPE: 51.33%
MDA: 0.56
Actual
Forecast
RRP Capped
Time Step
0
200
400
600
800
1000
0
2000
4000
6000
8000


Linear SVR Forecast - February 2024
RMSE: 84.66
MAE: 48.73
sMAPE: 52.35%
MDA: 0.57
Actual
Forecast
RRP Capped
Time Step
0
200
400
600
800
1000
0
2000
4000
6000
8000


Linear SVR Forecast - March 2024
RMSE: 48.10
MAE: 39.35
sMAPE: 56.91%
MDA: 0.58
Actual
Forecast
RRP Capped
Time Step
0
100
200
300
400
0
2000
4000
6000
8000


XGBoost - Forecast vs Actual: January 2024
RMSE: 93.88
MAE: 58.25
sMAPE: 53.27%
MDA: 0.47
Actual
Forecast
RRP Capped
Date
0
200
400
600
800
1000
2024-01-01
2024-01-05
2024-01-09
2024-01-13
2024-01-17
2024-01-21
2024-01-25
2024-01-29
2024-02-01


XGBoost - Forecast vs Actual: February 2024
RMSE: 91.92
MAE: 59.63
sMAPE: 54.77%
MDA: 0.48
Actual
Forecast
RRP Capped
Date
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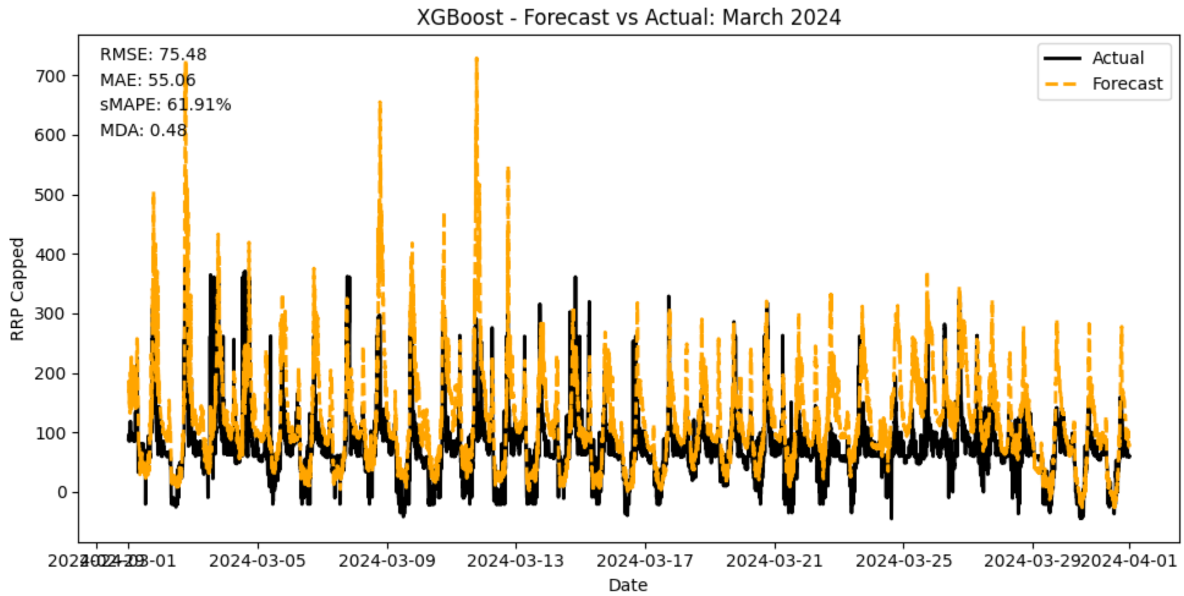
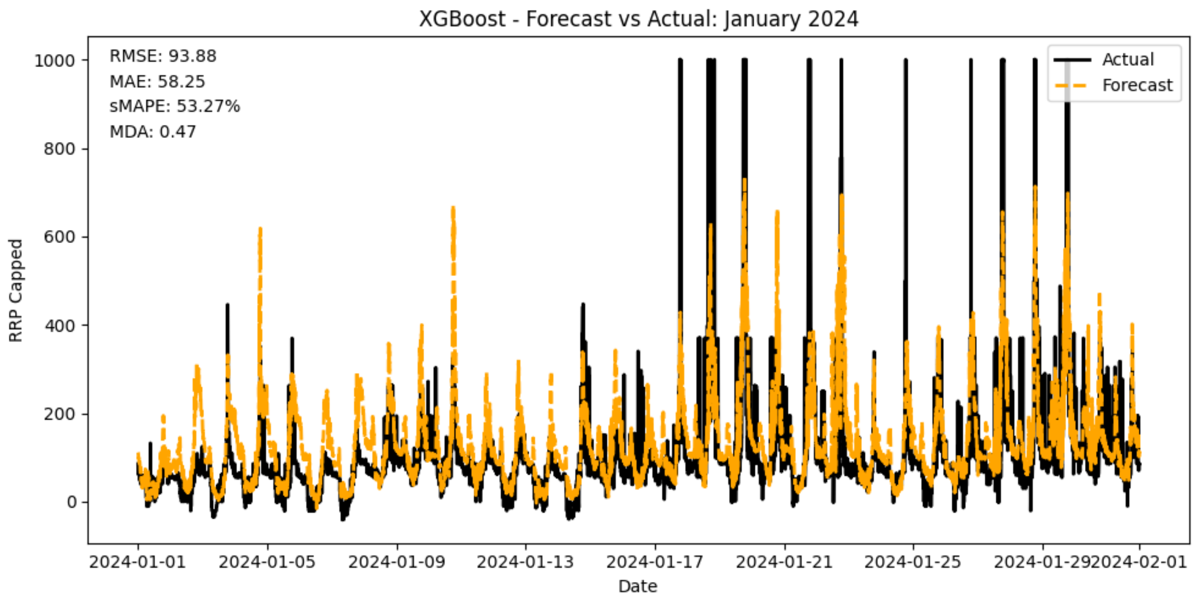
2024-02-01
2024-02-05
2024-02-09
2024-02-13
2024-02-17
2024-02-21
2024-02-25


XGBoost - Forecast vs Actual: March 2024
RMSE: 75.48
MAE: 55.06
sMAPE: 61.91%
MDA: 0.48
Actual
Forecast
RRP Capped
Date
0
100
200
300
400
500
600
700
2024-03-05
2024-03-09
2024-03-13
2024-03-17
2024-03-21
2024-03-25
2024-04-01


XGBoost - Forecast vs Actual: January 2024
RMSE: 93.88
MAE: 58.25
sMAPE: 53.27%
MDA: 0.47
Actual
Forecast
RRP Capped
Date
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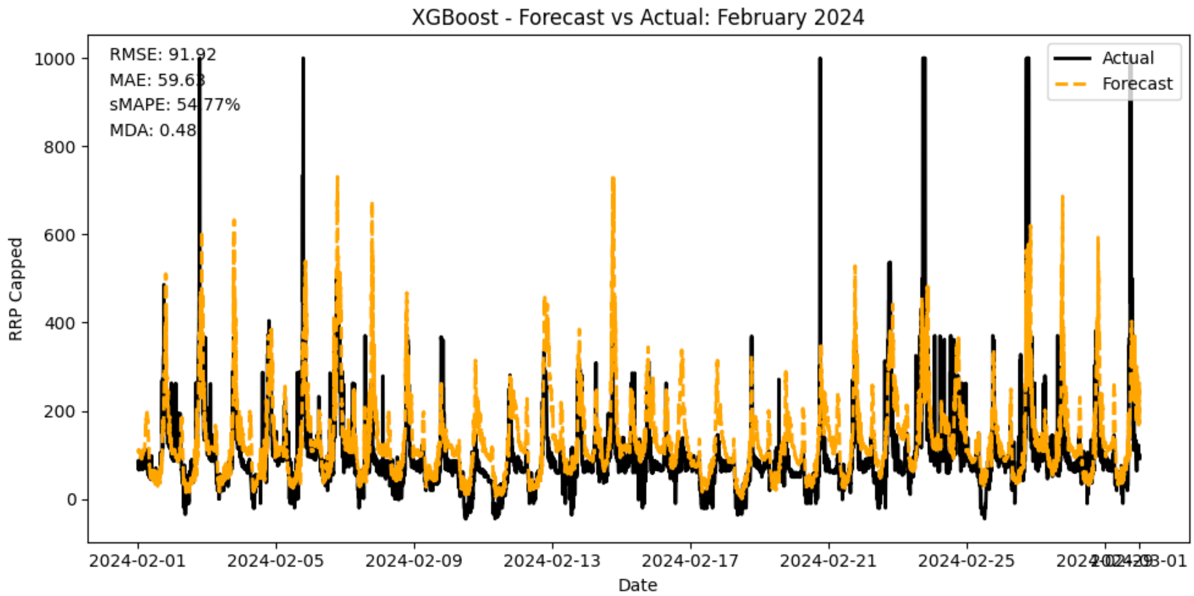
1000
2024-01-01
2024-01-05
2024-01-09
2024-01-13
2024-01-17
2024-01-21
2024-01-25
2024-01-29
2024-02-01


XGBoost - Forecast vs Actual: February 2024
RMSE: 91.92
MAE: 59.63
sMAPE: 54.77%
MDA: 0.48
Actual
Forecast
RRP Capped
Date
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600
800
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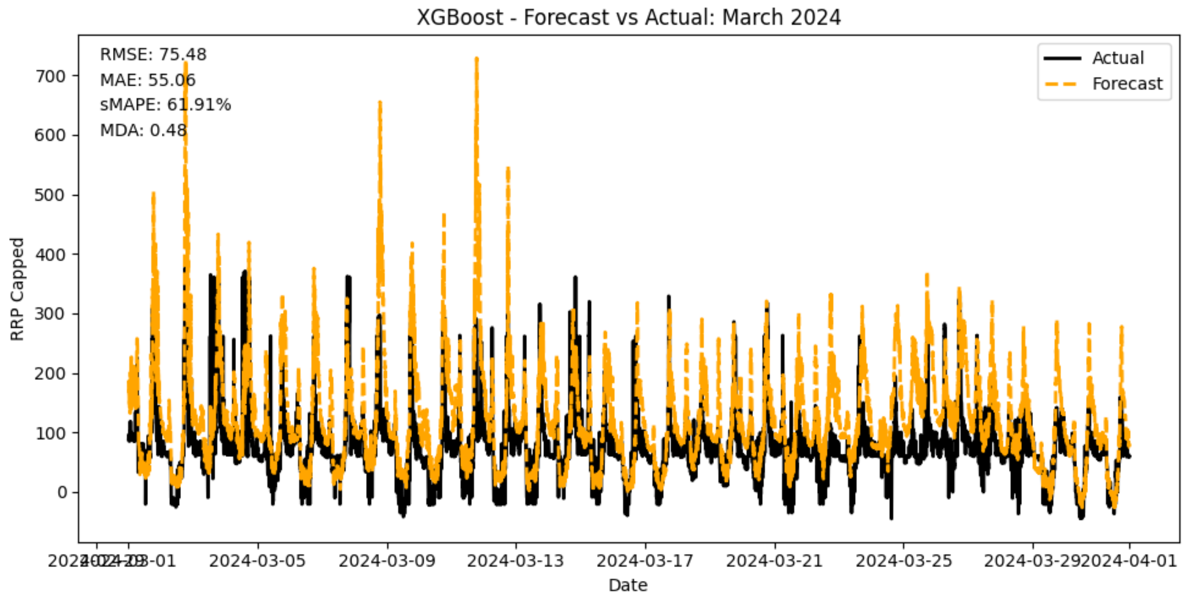
2024-02-01
2024-02-05
2024-02-09
2024-02-13
2024-02-17
2024-02-21
2024-02-25
2024-03-01


XGBoost - Forecast vs Actual: March 2024
RMSE: 75.48
MAE: 55.06
sMAPE: 61.91%
MDA: 0.48
Actual
Forecast
RRP Capped
Date
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400
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600
700
2024-03-01
2024-03-05
2024-03-09
2024-03-13
2024-03-17
2024-03-21
2024-03-25
2024-03-29
2024-04-01