Overview of electricity markets and the incorporation of renewable energy sources within them

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Abstract

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Abstract:

The need for an increase in renewable electricity sources brought on by climate targets requires substantial changes in the electricity infrastructure and markets. The Nordic electricity system is an expansive and highly integrated system, with many stakeholders and components. One component, the electricity market is itself made up of several parts, all designed to complement each other and provide stability and electricity security to all stakeholders. An increase in renewable electricity sources will require new innovations, such as energy storage, and new practices in the markets, such as shorter imbalance periods. Furthermore, the predictability of future renewable production will also increase in importance when the renewable share increases, as it is one of the stone pillars in the renewable integration process.

In this thesis data from Denmark is used to perform wind power prediction using proven time series modelling approaches and models, such as Box-Jenkins ARIMA and ARIMAX models in addition to LSTM neural network models. This thesis showed that the more complex LSTM model outperformed the simpler ARIMA and ARIMAX models on several occasions, indicating that model complexity plays a significant part in the ability to model a stochastic process as wind power. Likewise, it was also shown that the autoregressive component in wind power is vital in the wind power forecasting models to produce accurate predictions. The findings in this thesis are supported by similar research on wind prediction.

Models used for wind power prediction are far more complicated than those used in this thesis, consisting of several more modelling steps than I employed, and utilising far more accurate data for the prediction. The consensus in the field of renewable electricity integration is that more flexibility is required by all stakeholders. Through an open and competitive market, stakeholders can be incentivised for their contributions, propelling us towards a greener, more sustainable energy future.

Keywords:
Nordic Electricity Markets, Wind Power forecasting, Renewable Energy, LSTM, ARIMAX, Time series forecasting

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Introduction

To keep global warming to a less than a two-degree increase from before industrialisation, the European Commission has created a roadmap for achieving the needed changes by 2050. The European Commission (2011) estimates that this goal requires an 80-95% reduction below 1990s levels in greenhouse gas (GHG) emissions by 2050. Industry, agricultural, electricity and the heating and cooling sectors are key areas where decarbonisation needs to take place, as they make up a large part of the EUs carbon emissions (Gerres, Ávila, Llamas, & Román, 2019)
In 2017, the energy sector emerged as the primary contributor to GHG emissions, accounting for approximately 25% of the total emissions in the EU. Transport and industry followed closely behind, representing 19% and 18% of the emissions, respectively. (European Environmental Agency, 2019) To achieve the required emission targets and adhere to the Paris Climate agreements the European Commission has introduced the binding Renewable Energy Directive to propel the member countries towards lower energy emissions. The most recent revision to the directive establishes that by 2030, 42.5% of the energy composition must be sourced from renewable sources. Notably, Sweden, Finland, and Latvia surpassed this noteworthy achievement well ahead of schedule, attaining 63%, 43%, and 42% of their consumed energy from renewable sources as early as 2021 (European Commission, 2023). Finland has set its own even more ambitious renewable energy target, at 51% of the total energy consumed by 2030. This target is a significant part of the greater aim of carbon neutrality Finland has set for 2035, surpassing the EUs carbon neutrality target by a decade and a half, as the EU's carbon neutrality target sits at 2050. (Ministry of Economic Affairs and Employment of Finland, 2022)

The Commission (2011) highlights that with the increasing availability of renewable energy sources, carbon reduction in the energy sector can be achieved, in contrast to other sectors where complete decarbonisation might not be as attainable. Thomaßen, Kavvadias, & Navarro (2021) highlights the potential of lower total carbon emissions by transitioning the energy sector to use electricity as the energy carrier, while continuously reducing the carbon intensity of electricity generation by introducing more renewable electricity sources. The transition to electricity as an energy transport medium would for example be if buildings were to switch out their old fossil fuel-based heating systems to electrically driven heat pumps. The researchers advocate the use of heat pumps as they can provide up to five times as much heat energy as they require in electrical energy, making them up to 500% efficient in converting electrical energy to heat. This over 100% efficiency is achieved by moving heat from the outside, instead of directly generating it by burning fossil fuels or resistive heating (Thomaßen, Kavvadias, & Navarro, 2021). The switch to heat pumps and geothermal heating is a top priority in the Finnish 2035 national climate and energy strategy to reduce the climate impact of heating during winter (Ministry of Economic Affairs and Employment of Finland, 2022).

Gerres, Ávila, Llamas, & Román (2019) estimates that electrification can easiest be achieved in auxiliary and low-temperature industrial applications, but in high-temperature application, such as steelmaking, additional technologies are required for reducing the carbon footprint, for example, carbon captures solutions. Industry electrification is also a highly capital-intensive process, as many existing systems are built to run on fossil fuels, and a switch might take a long time to be economically advantageous (Gerres, Ávila, Llamas, & Román, 2019). In instances where direct electrification might not be suitable for energy-intensive settings, some experts in the field propose employing Hydrogen as the energy carrier. Hydrogen can be produced using renewable electricity and can either be used directly or transformed into methane to supply energy for various applications (Dawood, Anda, & Shafiullah, 2020).

This immense decarbonisation of the energy system and switching to electricity as an energy transport medium will require many changes to the European electrical system, which is the world's largest interconnected and partially synchronised electric grid. The Interconnected European grid spans from the Gibraltar Strait in the south to the Arctic Ocean in the north and from the Irish Atlantic coast in the west to Ukraine in the east, as of 2022 (ENTSOE-E, 2022). The European Network of Transmission System Operators for Electricity (ENTSOE-E) is an association consisting of 39 transmission system operators (TSO) from 35 countries. ENTSOE-E is the main organisation for coordinating and cooperating within the interconnected grid in Europe. ENTSOE-E also creates guidelines and frameworks for developing Europe's electrical grid and markets to be more sustainable, flexible, and reliable.

ENTSOE-E (2022) propose a clear pathway to achieving the needed decarbonisation of Europe's electricity system. This entails the switch from fossil-fuel-based power generation to carbon-free generation. Carbon-free power comes in many forms, some time-tested sources such as hydro and nuclear power, as well as more recent biomass, wind, and solar power. Wind and solar power have shown great technical and economic potential, even compared to more traditional and polluting energy sources, while producing no ongoing emissions. However, both wind and solar power are entirely weather-dependent and therefore can be challenging to integrate into the existing electricity system due to their intermittent nature.

Background to the Electrical Grid

The national grid system's main function is to connect power producers to power consumers. In the Nordic region, this is achieved with a connected network of power lines and substations operated by national transmission system operators (TSOs). In Finland, the transmission system operator is Fingrid, which is responsible for maintaining the Finnish main transmission grid, whereas, in Denmark, the TSO is Energinet, which also operates the Danish transmission system for natural gas.

Figure 1

Northern European main power transmission grids.

https://www.svk.se/en/national-grid/map-of-the-national-grid/

National TSOs are responsible for the day-to-day operations of the national transmission grid. This includes everything from ensuring that the electricity market participants follow regulations and standards to ensuring that the grid frequency remains within the operational bounds. Working alongside the national TSO, we also have local Distribution System Operators (DSO) who are responsible for electricity distribution grids. Distribution grids are often lower-voltage grids that connect individual buildings to the national grid system. However, some large industrial complexes are directly connected to the national transmission grid. In Finland, DSOs are usually tied to one operating region, such as Turku Energia Oy in the city of Turku, although there are also DSOs with more spread-out distribution areas, such as Caruna Oyj (Fingrid Oyj, 2023).

The Finnish main grid is a part of the synchronous inter-Nordic system, which incorporates the main grids of Norway, Sweden, Finland, and eastern Denmark. All of these grids are synchronized with each other through a set of AC interconnections. The synchronisation of the national grids comes with the benefit of higher rotational inertia of the power system, as there are more power plants connected to the same system. This helps in the event of any large disturbances in the frequency. As the frequency is synchronised any disturbance is detected almost instantly across the synchronised area, and reserves can thereby automatically be triggered if needed. Another benefit is the division of the reserve requirements amongst the connected TSOs, as these resources can be shared. (Fingrid, 2023)

Need to Balance Production and Consumption

Due to the nature of electrical energy, it must be produced in the same instance as it is consumed. On a grid scale, this balance in production and consumption is indicated by the frequency of the alternating current (AC). The frequency of AC power is the number of times an AC sine wave flips per second and is displayed in hertz (Hz) (Dale & Frado, 2008). European national grids have a nominal frequency of 50 Hz, and one of the main responsibilities of TSOs is to maintain this frequency at 50 Hz to ensure an operational electrical grid. Any large deviation from the nominal frequency causes damage to the electrical equipment connected to the grid.
When an electric system experiences an increase in load without a corresponding rise in generation, its frequency decreases. Conversely, if there's excess generation and demand remains stable or falls, the frequency increases. If the frequency deviates too much from the nominal frequency in either direction damage to the system can occur.

In a national grid, frequency fluctuation is smoothed out by the rotational mass of the generation turbines, also known as the inertia of the grid. Inertia allows for constant, small changes in supply and demand, without a significant change in frequency. In practice, one can see this as the convenience of not having to call up one's electrical provider to ask for more generation whenever the oven or sauna is turned on, which draws quite a bit of power for a single consumer, but on a grid scale, draws practically nothing.

During normal operation, the frequency of the Finnish grid is allowed to fluctuate between 49.9 and 50.1 Hz. If the frequency swings outside this range, action must be taken to correct the frequency back to the nominal value of 50 Hz. In general, there are two approaches to balancing a grid if the 49.9 or 50.1hz threshold is breached. First, and foremost, balancing of the grid can be done with the help of the reserve market, where large electricity producers and consumers can offer the ability to increase production or voluntarily decrease consumption when needed through different types of reserve products. Secondly, if the reserve market is not sufficient to stabilise the frequency, there is the option of large cuts in demand using load shedding, where the TSO demands local DSOs to shed a specific amount of the load on the energy grid. This is generally achieved by large-scale rotating blackouts, which can be very disruptive to everyday life. (Fingrid Oyj, 2022)

Predicting Renewable Energy Production

The increasing integration of weather-dependent electricity sources in our grids introduces a unique set of challenges. Since weather conditions can be highly unpredictable, this unpredictability extends to the power generation of sources like wind and solar power. This variability can significantly impact the stability and reliability of the entire electricity system, particularly when these sources constitute a substantial portion of the energy mix (Thomaßen, Kavvadias, & Navarro, 2021). Due to this challenge, it is increasingly important to be able to predict renewable power output on different time horizons. These predictions are required to ensure everything from the stable operation of the electricity system to long-term energy storage planning (Soman, Zareipour, Malik, & Mandal, 2010). To date, there is a wide array of modelling approaches used for forecasting wind and solar power generation, and they employ a range of different prediction models, from physical models to Artificial Neural Networks (Hanifi, Xiaolei, Zi, & Lotfian, 2020). The use of publicly available data to investigate the effectiveness of various forecasting methodologies remains an underexplored area in this field of research.

This thesis comprises of two main segments. The initial section delves into an in-depth examination of the Nordic electricity market. It addresses key inquiries concerning the prevailing market structures, the spectrum of production methods employed in the Nordic region, and prospects for the future of the electricity market. This analysis is approached through the lens of renewable energy, focusing on its seamless integration into the existing electricity infrastructure.

The second segment focuses on the application of established time series prediction methods to forecast wind power production. This involves utilising publicly accessible data on renewable energy production alongside weather data for empirical testing and comparison of these methods.

My main research questions are to explore the prevailing structures of the electricity market, from the perspective of renewable energy, and to explore time series techniques and models for predicting wind power generation. Subsequently, I will conduct an analysis of the advantages and drawbacks associated with the selected techniques and models. Furthermore, I will examine the real-world applications of these methods in the current electricity system and explore their integration with today's energy infrastructure.

Electricity Markets

When electricity came to Finland in the late 1800s, it was mainly a local affair. Where a local power producer sold electricity to mainly industrial customers in the area. This continued until 1929 when the first cross-country main connection was set up. From the Imatra hydroelectric power plant to Vyborg, Helsinki, and Turku. This 560km powerline, colloquially known as the "Rautarouva" The Iron Lady, became the first component of the country-spanning main grid we have today (Fingrid Oy, 2023). The electrification of Finland and the grid grew steadily and simultaneously throughout the decades, with the public sector being responsible for most of the infrastructure and power plants. However, in the mid-1980s it was noticed the public ownership of the electricity system had led to an expensive and inefficient system, which lacked competition. In 1995 with the new Electricity Market Act the generation of electricity was slowly deregulated and opened to a free and competitive market, while the electricity transfer pricing remained highly regulated, due to its natural monopoly. Finally, in 1998, all electricity customers were able to freely operate on the free electricity market. With the new 1995 regulations, many electricity producers were privatised to Limited Liability Companies, giving them greater freedom on the markets (Kopsakangas-Savolainen, 2002). The state-owned Fingrid Oyj was also established in 1995 and took responsibility for the Finnish main grid, which is still today sometimes called The Iron Lady (Fingrid Oy, 2023). The current electricity market is divided into two main segments: the wholesale market, which comprises various smaller markets where participants trade electricity, and the retail or consumer market, where individual consumers purchase electricity from these larger wholesale market participants. (Fingrid Oyj, 2022)

Futures Market

As with many other commodities, electricity also has a futures market that helps market participants with hedging and risk management. The NASDAQ commodities market in Stockholm Sweden operates the electricity futures market in the Nordic region. Here, market participants can trade futures on different timescales, from weeks to years ahead, to manage their electricity pricing risks. Future contracts are not delivered in energy but instead in cash settlements between the participants on the expiration day. With electricity futures, market participants can lock in the prices they buy and sell their consumption and production. The futures market also usually works as an indicator of the direction in which prices will develop in the future, and how uncertain the market is in general. (Svenska Kraftnät, 2022)

Day-ahead Market

The Nordic day-ahead market is where most of the electricity trading occurs between market participants. Approximately 70% of the traded volume of electricity took place in day-ahead markets in 2021[1]. The day-ahead market is set up as a separate auction for every one-hour time block in the next day. Both producers and consumers place bids on the market for their estimated consumption and generation for the specific time blocks. Bids must be submitted by 13:00 Finnish time. The auction algorithm aggregates the supply and demand for each time interval to form a curve and runs the auction based on supply and demand principles, resulting in the day-ahead price being set at the equilibrium point of the supply and demand curve. (Fingrid Oyj, 2022). This auction ensures that there always is a balance in supply and demand under normal operating circumstances, adhering to the electrical grid's need for equal generation and consumption.

These auctions occur in every European bidding area, also known as bidding zones. The individual countries' TSOs decide how many bidding areas each country is divided into based on the available transfer capacity between the areas. For example, Finland is considered a single bidding area, while Sweden is divided into four distinct areas, due to restrictions in transfer capacity between zones. (Nord Pool, 2023).

[1] According to the Energy Authority 2021 yearly report (The Finnish Energy Authority, 2021)

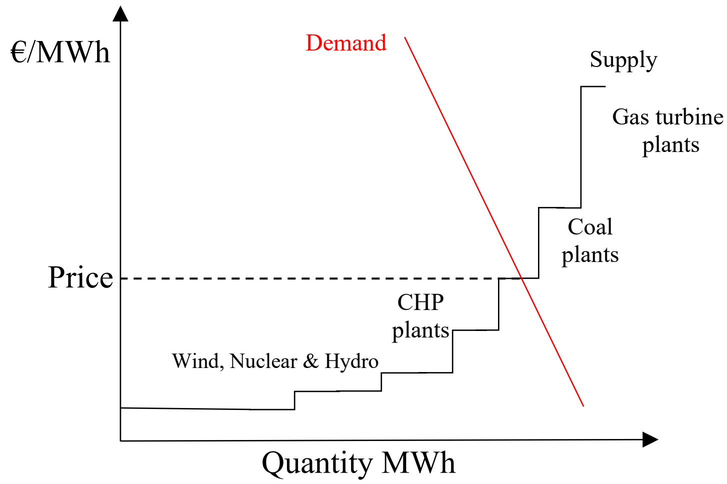

Figure 2: Representation of the supply and demand curves of the Day-ahead Market.

Congestions/Transfer Pricing

According to the free market principles in the European Union, the goal of connected electricity systems is to create a single market within the European Union. This would also mean equal pricing between EU countries when electricity buyers and sellers can operate on a single market. Currently, it is not feasible due to limitations in transfer capacity among various bidding areas, leading to varying prices across these areas. Each country's TSO is accountable for the interconnections within its own country, while interconnections between countries are managed collaboratively by neighbouring TSOs. Some interconnectors are AC connectors, which allow frequency synchronisation between grids; for example, the 440 kV connection between Finland and Sweden near Torneå in north-western Finland. DC interconnectors also exist between bidding areas. For example, EstLink 1 and 2 cables that run between Finland and Estonia. (Fingrid, 2023) The transfer price is determined by combining the individual bidding zones' supply/demand curves into a new aggregated curve, where the transfer price is once again set at the equilibrium point (Nord Pool, 2023).

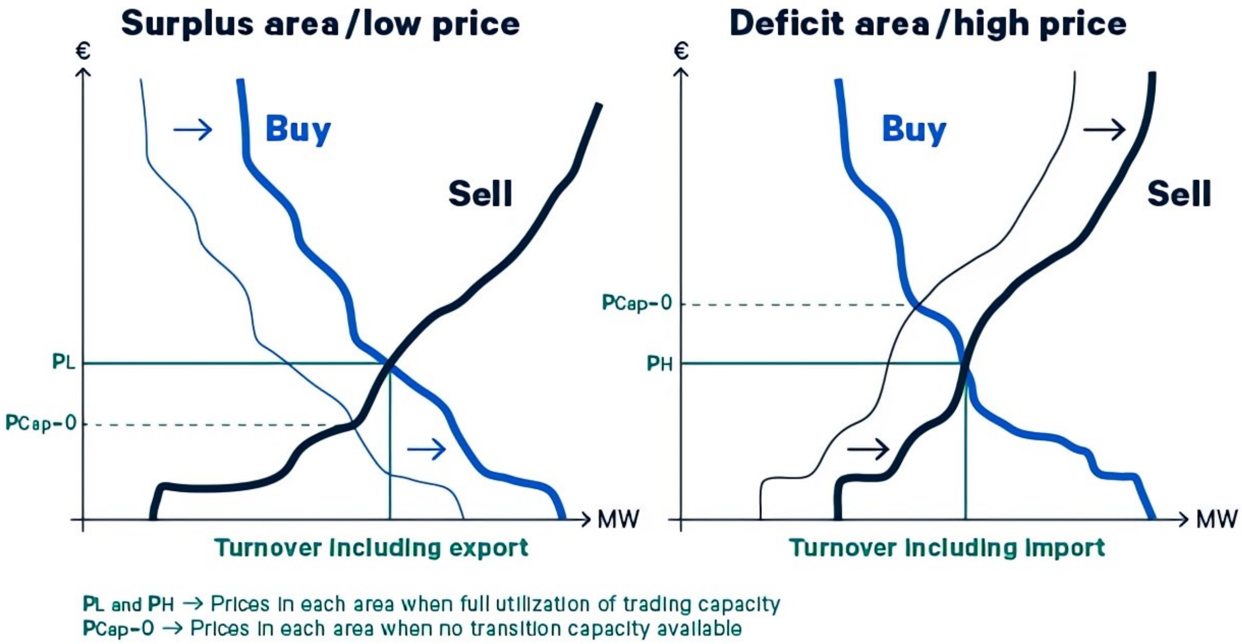

Figure 3: Illustration of transfers effect on bidding zone prices.
Source: https://www.nordpoolgroup.com/en/trading/Day-ahead-trading/Price-calculation/

Intraday Market

Even though the generation and consumption prices and volumes have been calculated in the day-ahead markets, changes can still occur before the agreed physical delivery hour starts. For example, these changes can be unexpected failures in some generation equipment or the weather taking a sudden turn, resulting in lower renewable energy production or increased consumption due to heating requirements. Market participants can participate in the intraday electricity market to deal with these types of changes. Contrary to the day-ahead market, the intraday market does not involve any kind of auction. Instead, it uses a first-come, first-serve principle, where buy and sell offers are matched directly up until the delivery hour. The delivery blocks can range from a 15-minute delivery block to hourly blocks, increasing the flexibility of the market. (Nord Pool Group, 2023)

Balancing and Reserve Market

Thus far, all markets covered have worked on accurate planning in advance. However, when we step into the delivery hour, the laws of physics take over. As discussed previously, the electricity grid must be maintained at a stable frequency to ensure the operation of the entire electric system. In the European electric system, the nominal frequency is 50 Hz. To ensure the stability of the grid frequency and address any deviations from the plans, each national TSO operates a balancing and reserve market. The market is divided into different reserve products to handle different situations that may occur during the grid operation. (Fingrid Oyj, 2023)

The fastest-acting reserve product is the Fast Frequency Reserve (FFR), which consists of varying amounts of very fast capacity, between 0 and 60 MW. The FFR is procured only for the required hours when the rotational inertia of the grid is low. Because the electric system must not see a frequency drop below 49 Hz, the system must have sufficient inertia to compensate for a potential dropout of a powerplant. If this is not the case, the TSOs are responsible for having sufficient FFR reserves to counteract this. The speed at which the FFR is activated is below a second after a frequency change over 0.1 Hz, which is allowed in normal operation. (Fingrid Oyj, 2023) Because of the speed needed for this reserve, it usually consists of different kinds of energy storage means and not direct generation equipment. The producers of FFR products, which Fingrid buys, are compensated based on the reserved capacity for the hour in question. The highest procurement rate is paid to all of the producers. (Fingrid Oyj, 2023)

As the second fastest product, we have the Frequency Containment Reserve for Normal Operation (FCR-N) and the Frequency Containment Reserve for Disturbances (FCR-D). The FCR-D product is also a fast-acting reserve used when there is a sudden disturbance in the frequency and consists of 290 MW capacity. FCR-D is similar to FFR, with only a slightly slower activation requirement at 50% capacity at 5 seconds after a disturbance and full capacity after 30 seconds. This product serves a dual purpose, being utilised for both up-regulation and down-regulation scenarios. In the case of up-regulation, FCR-D is employed when there is a sudden drop in frequency, which can occur when a significant power plant disconnects from the grid. Conversely, in down-regulation, FCR-D comes into play when there is a rapid increase in frequency caused by surplus production, such as when a large exporting transmission cable disconnects.

The FCR-N reserve is used in daily operations and has a capacity of approximately 120 MW. The FCR-N is tasked with making the necessary adjustments to keep the grid frequency within the range of 49.9 to 50.1 Hz. This is crucial due to the continuously fluctuating nature of both generation and consumption, requiring frequent small adjustments. Similar to the FFR, the FCR-D and FCR-N producers are compensated for the reserved capacity, and the FCR-N producers are also compensated for the electricity they provide. (Fingrid Oyj, 2023)

All three products, FFR, FCR-D, and FCR-N, are activated automatically based on different frequency thresholds. All producers have their own measuring equipment and automation to achieve the fast speeds needed to keep the electricity grid stable during normal operation or a disturbance. A centralised control system would act too slowly if the grid were to experience a large disturbance. (Fingrid Oyj, 2023)

The second class of products that TSOs acquire is Frequency Restoration Reserves. These products are used to restore the grid's frequency to a nominal value of 50 Hz when needed. The Automatic Frequency Restoration Reserve (aFRR) consists of approximately 50 MW and is procured only for certain hours. The aFRR works on a signal basis, from the TSO to producers and consumers, to increase or decrease their production and consumption. Producers of aFRR have five minutes to activate their capacity when a request is received from the TSO, and this is usually done automatically. (Fingrid Oyj, 2023)

Finally, we come to the slowest reserve, the Manual Frequency Restoration Reserve (mFRR), which also incorporates the balancing energy market into the reserve products. Participants in the balancing market are obligated to leave either up-regulation or down-regulation bids to the market that the TSO maintains and operates. The TSO can then manually activate the required capacity from the bids, and the producers have 15 minutes to make the changes in their production or consumption. The producers are compensated for the reserved capacity and the energy generated if the need arises. To ensure the continued operation of the grid if a major disturbance occurs, the mFRR must have a large capacity. In Finland, it consists of a varying amount between 900 and 1300 MW of generation capacity. This includes power plants that are owned or leased by Fingrid solely for the purpose of providing enough generation in the event of a major disturbance, such as a large powerplant disconnecting from the grid (Fingrid Oyj, 2023).

To ensure the reliability and availability of different reserve products when needed, Fingrid places strict technical requirements on anyone wanting to participate in the reserve or balancing markets. The participants undergo tests and intense integration before being allowed to produce any kind of reserve. Participants are also required by contract not to use the contracted reserve capacity for regular power generation to ensure its availability when needed. The procurement of these products also has some restrictions. Most of the products are procured on a unified Nordic Market with the other Nordic TSOs and can be produced in different countries if the transmission capacity and type allow for it.

The main reason for the large number of reserve products the TSOs procure is the ability to have additional up-regulation or down-regulation capacity available on different capacities and timescales, from very fast products to slower ones. The planned order of events if a powerplants suddenly disconnects is that the FFR is able to almost instantly provide generation to the grid, while the FCR-D is getting its generation up to speed to be able to take over the lost generation as the FFR depletes its energy reserves. After this, the TSO activates either the aFFR or mFFR bids to provide the lost amount of generation, while the FCR-D is freed up to be able to react if any additional disturbances occur. The whole reserve market is built with redundancy in mind to prevent a large-scale failure of the main grid, as a startup from a dead grid would require a lot of time and be very disruptive (Fingrid Oyj, 2023).

A summary of the Reserve products acquired by Fingrid can be found in Appendix 2.

Balance services

After the production hour has been completed, there is a need to know who has done what. Because production and consumption can vary from the initial plan, there is a need to keep track of actual electricity generation and consumption for each market participant. Nordic TSOs have equal ownership over eSett Oy, which provides imbalance settlement for many market participants in the Nordics. The balancing service is designed such that each participant receives less compensation or must pay more if their electricity deliveries or consumption deviates from the planned value in the day-ahead and intraday markets. This is done to incentivise participants to make precise predictions of their production and consumption. (Fingrid Oyj, 2023)

The Consumer Market

Thus far, among the markets discussed, only the day-ahead market has a direct interaction with consumers, as the prices determined in the day-ahead market are used to establish electricity prices in consumer contracts that directly follow the market. This is commonly known as a spot-price contract. In addition to the spot price, there is usually a margin for the seller as well as the value-added tax to constitute the final price for the consumer. In 2019, approximately 9% of Finnish households had an electricity contract that directly followed spot market prices[2].

The alternative option available to consumers is to arrange an electricity contract with an electricity seller. In Finland, consumers have the freedom to purchase electricity from any licenced electricity seller in an open market, fostering competition among electricity sellers to provide the most competitive prices to consumers. However, there are instances where consumers are unable to directly purchase electricity from sellers, such as when the responsibility for electricity contracts rests with landlords or housing cooperatives.

Consumer electricity contracts typically fall into two categories: fixed-term and ongoing contracts. As of 2021, 54% of households held fixed-term contracts, while the remaining 37% had ongoing contracts[2]. In contracts established directly with electricity sellers, it is the responsibility of the sellers to supply electricity to the consumer. This supply can be achieved either through self-generation or by procuring electricity from the Futures, Day-ahead, or Intraday markets. (Energy Authority, 2023)

[2] According to the Energy Agency's statistics (Energy Authority, 2023)

Production means in the Nordics.

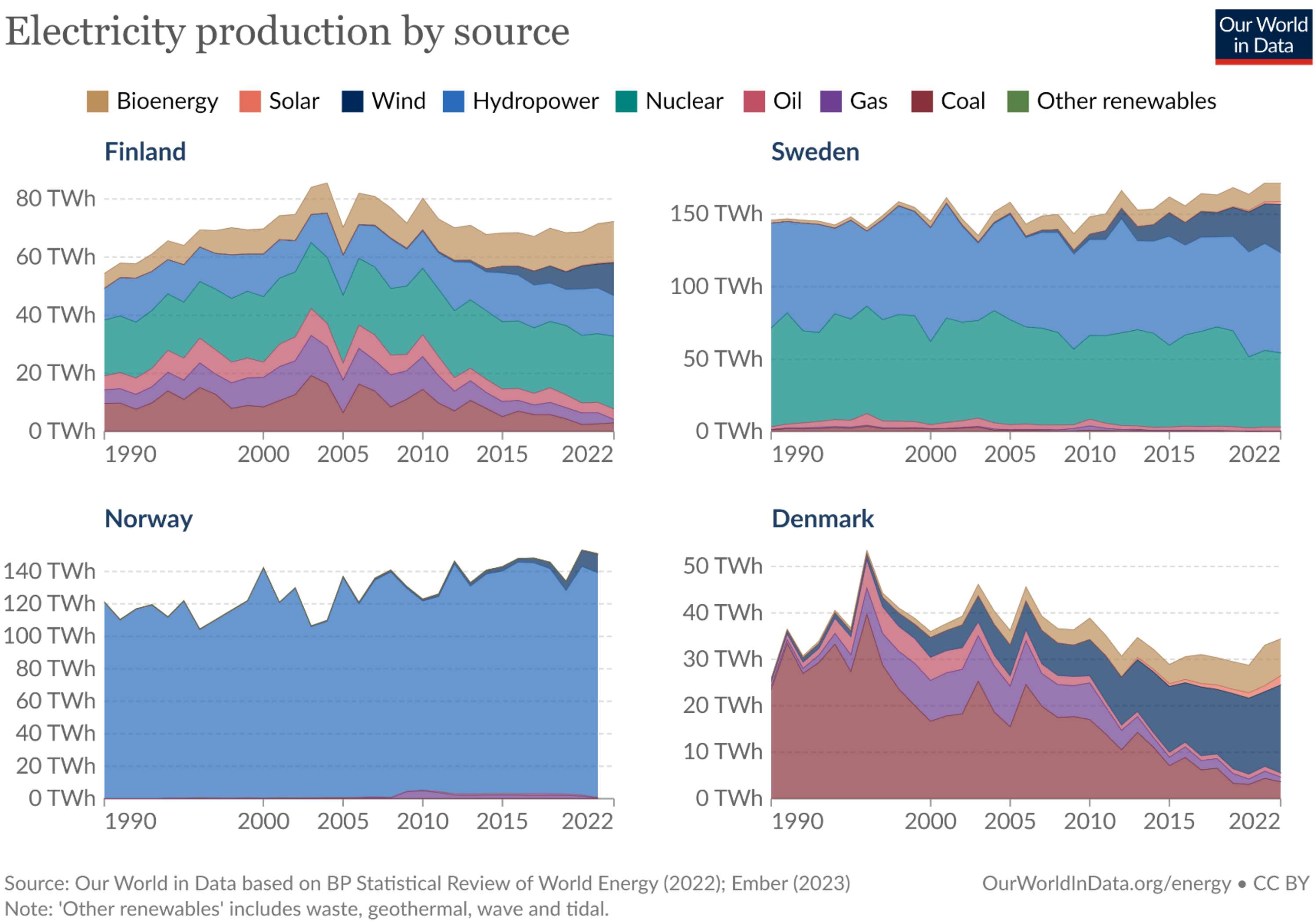

Figure 4: The composition of electricity generation by source.
Source: https://ourworldindata.org/electricity-mix

Although the Nordic countries are very similar in many aspects, their electricity generation differs considerably from each other. This is mainly due to differences in geography and politics related to the use of nuclear energy. Both Sweden and Norway have a large amount of hydroelectric power thanks to their mountainous geography, with a large amount of snow and rainfall in the Scandinavian mountains. Hydropower is responsible for generating approximately 90% of the total electricity in Norway, whereas hydropower accounts for approximately 40% of the total electricity generated in Sweden. To supplement energy requirements, Sweden, in the 20th century has invested a fair amount in nuclear energy, which today constitutes approximately 30% of the country's total generation. (Our World in Data Org, 2023)

Finland and Denmark, both characterised by flat topography, have faced the challenge of diversifying their electricity generation due to limited access to hydroelectric power resources. In Finland, this need for diversification has been addressed by adopting a mix of nuclear, biomass, and wind power, each contributing to the generation in roughly equal proportions, accounting each for around 15-30% of the total electricity generated. Given the winter heating requirements, Finland has also implemented a significant number of combined heat and power generation plants (CHP). These plants serve the dual purpose of producing electricity and generating heat for district heating systems. The CHP plants operate primarily during the winter season when there is a higher demand for heating (Finnish Energy, 2023)

Denmark made a significant decision in 1985 by passing a law that prohibited the construction of new nuclear power plants. Consequently, the country's three existing nuclear reactors were decommissioned in the early 2000s (World Nuclear Org, 2023). The absence of nuclear power, coupled with the oil crisis of the 1970s, prompted Denmark to invest heavily in wind power during the 1990s. Denmark's relatively small electricity demands and favourable geographical location, characterised by flat terrain alongside the windy North Sea, facilitated the growth of wind power. Presently, wind power accounts for approximately 55% of the total electricity generation in Denmark. The remaining portion of the electricity mix is sourced from biomass, solar, coal, and gas power generation. (Our World In Data, 2023)

The Nordic Energy Market has a long and rich history, being one of the first to allow free cross-border electricity trading between countries, beginning with Norway and Sweden in 1995. Finland and eastern Denmark joined the market later in 2000 to encompass the area we still have today. Due to its successful history, deep integration, and functional cooperation, the Nordic Energy Market is seen as a forerunner in the world. (Nord Pool, 2023) The cross-border grid connections and free electricity trade within the Nordic Market have enabled each country to optimise its electricity generation and focus on its competitive advantages.

For the past three decades, Finland has consistently functioned as a net importer of electricity. Mainly importing inexpensively produced hydropower from northern Sweden, where there has been a surplus of hydropower due to transmission restrictions between northern and southern Sweden. Inexpensive imports from both Sweden and Russia have contributed to the underdevelopment of electrical generation capacity in Finland. This is most problematic on very cold and windless winter days when electricity consumption is the highest due to heating requirements (Electricity Authority, 2021). This was even further emphasised as a challenge during the 2022-2023 winter when transmission connections with Russia were closed for imports and electricity shortages were predicted. Nevertheless, the predicted electricity shortages never occurred due to the mild and windy winter of 2022-2023. Finland's energy sector achieved a significant milestone in the spring of 2023 when the third nuclear reactor, Olkiluoto 3 (OL3), with a capacity of 1600 MW, was successfully brought online. This achievement transformed Finland into a net exporter of electricity when weather conditions are favourable, with Estonia being one of its primary recipients. (Hiilamo, 2023)

Sweden and Norway have been net exporters of electricity due to their abundant hydropower. Sweden exports to Finland, Germany, Lithuania, and Denmark, whereas Norway has large undersea transmission cables to the UK, the Netherlands, and Denmark. Denmark exports excess wind power to Germany and the Netherlands under favourable weather conditions. (Fingrid, 2023)

When discussing the GHG emissions of the different power generation sources it is often advised to consider the lifetime emissions of the different types, as they have very different technical lifetimes and ongoing emissions. For example, power plants utilising natural gas are relatively cheap to produce, but have high ongoing GHG emissions, while nuclear power plants produce a lot of emissions in the construction phase but have low ongoing emissions while operating. (Amponsah, Troldborg, Kington, Aalders, & Hough, 2014)

Looking at the lifetime emissions of electricity sources doesn't however get any easier, as there are vast differences in power plant sizes, construction methods, and even in the fuel used, and the values are constantly changing, and vary between countries. Some research also takes externalities into account when considering the lifetime emissions of electricity sources, for example, onshore wind farms might alter the natural landscape causing additional GHG emissions. (Amponsah et al., 2014). The researchers Scarlat, Prussi, & Padella (2022) looked at the GHG emissions of electricity generated within the EU27 countries and created the following graph of the average estimated grams of CO2 equivalent/KWh of produced electricity. This gCO2eq/KWh is a standard metric for measuring the carbon intensity of electricity.

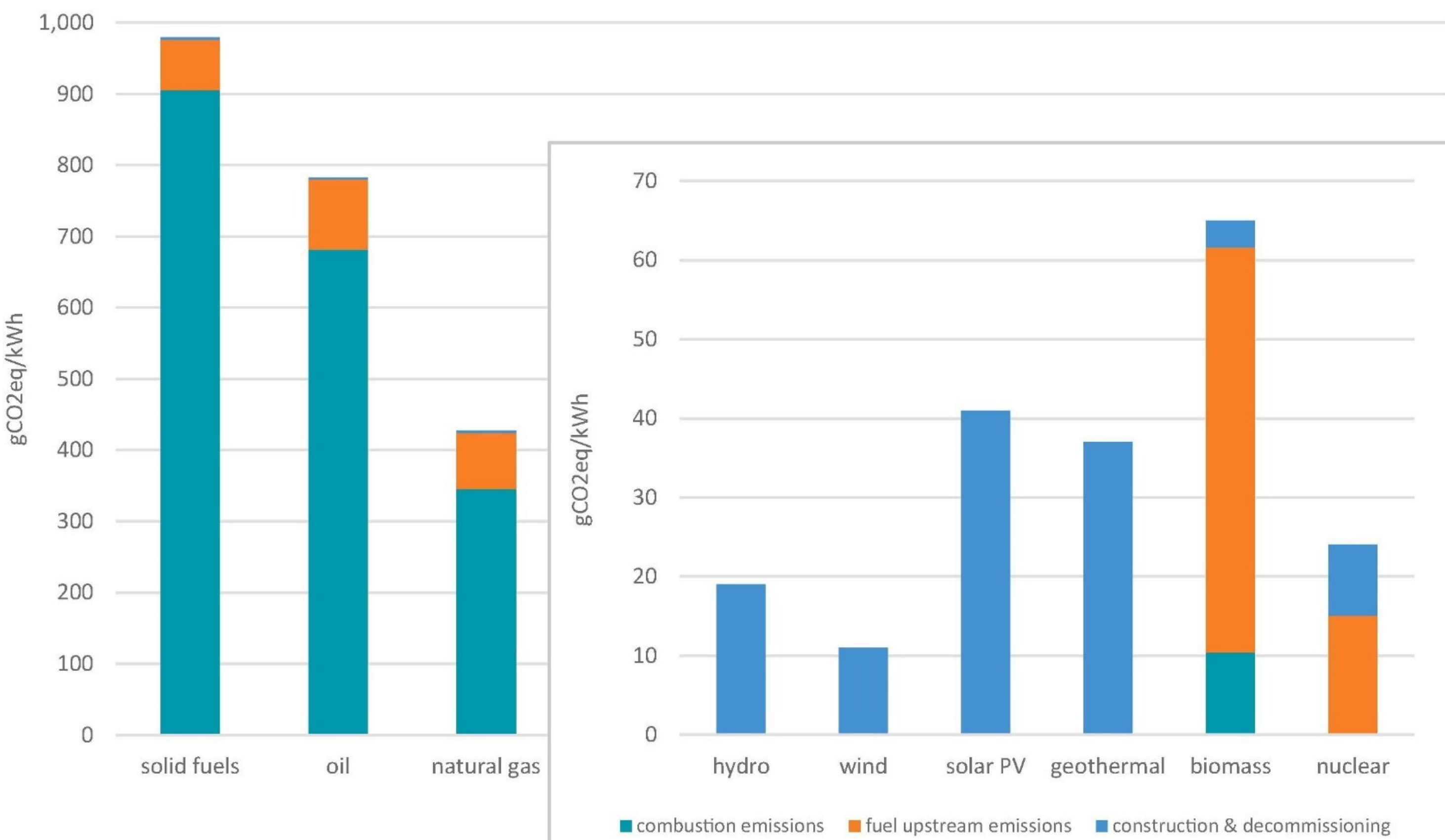

Figure 5: Average GHG emissions by electricity source in the EU27.
Source: https://www.sciencedirect.com/science/article/pii/S0306261921012149

From the Graph, one can clearly see that the renewable electricity sources have vastly lower lifetime GHG emissions than traditional fossil-fuel-based electricity sources, even when considering construction emissions. This is simply because the renewable electricity sources do not have any, or very small ongoing emissions from combustion. In this study, CO2 emissions generated from burning biomass are discarded, as they are not considered to add to the atmosphere's CO2 levels as the biomass has previously captured the same CO2. The writers of the research paper do acknowledge the lack of thorough research on the construction emissions of the various electricity sources, especially on the older power plants (Scarlat, Prussi, & Padella, 2022).

Future of the Nordic Grid

While it may seem like a common statement to acknowledge that we are currently experiencing one of the most rapid periods of transformation in the energy sector, it is undeniably true. Brought on by the increasing need to decarbonise our societies due to climate change, the energy sector is one of the most important factors in CO2 emissions. This is because the energy sector affects almost every part of our daily lives. Approximately 73% of the world's CO2 emissions are estimated to be generated by the energy sector. Of course, this incorporates all kinds of different emission sources, such as industry, transportation, and energy use in buildings, which are very large emitters of greenhouse gases (Ritchie, Roser, & Rosado, 2020). All these subcategories use a mix of either different kinds of carbohydrates, such as oil, coal, or natural gas, as fuels for energy or some low-carbon sources of energy, such as renewable electricity generation, or thermal energy for heat. The exact percentage of low-carbon sources in the energy sector is hard to estimate, but approximately 40% of the electricity produced today originates from low-carbon sources (Low Carbon Power Org, 2023).

Fortunately, the energy sector has a very large potential for decarbonisation by utilising low-carbon energy sources. This can be achieved by increasing the use of geothermal or nuclear energy for heating or by using renewable electricity sources, such as wind and solar energy.

Many energy-intensive industries such as transportation and industrial production, that directly use carbohydrates today, can also be converted to use low-carbon electricity as an energy source (Dawood, Anda, & Shafiullah, 2020).

At the time of writing this thesis, in 2023, we still have an ongoing war in mainland Europe, which has had a significant effect on many people's lives in Europe and has thrown many future energy plans and policies up in the air. Despite the ongoing war, one can see some general changes in the future. One of the biggest consequences of the war for the average European citizen is the drastic increase in energy and electricity prices we have seen in 2022, due to the cut-off from Russian-supplied gas (Osička & Černoch, 2022). In public opinion, we have seen a general doubling down on the green transition to renewable energy sources, not only for the sake of the environment but also to increase energy security in Europe and decrease reliance on outside energy providers. Renewable sources offer a distinct advantage over traditional power plants in that they tend to be more decentralised and smaller in scale. This minimises the potential points of failure in the grid in the event of interference with generation. (Osička & Černoch, 2022)

The ongoing war has posed a challenge to the EU's climate targets, as it has resulted in a higher reliance on energy sources that produce greater quantities of greenhouse gases compared to natural gas, such as coal. It has also hindered the decommissioning of older, more polluting power plants, due to the need for energy. This shift has occurred at a time when the EU is actively transitioning towards greener and more sustainable energy sources. The current energy crisis has further compounded these issues, making it imperative to navigate the delicate balance between addressing immediate energy needs and ensuring progress towards a cleaner and more environmentally friendly energy system. (Osička & Černoch, 2022).

The switch to higher electricity consumption and renewable generation will require significant changes in European electricity markets and physical infrastructure. In general, the main goal is to incorporate the whole EU into a single market, where producers and consumers are free to trade with each other, and the TSOs and power exchanges, for example, the Nordic Nord Pool, are neutral partners that only facilitate trade and transfer capacity (Gomez, et al., 2019). The already deeply integrated Nordic market is seen as a forerunner in a European context and already facilitates electricity trade without many restrictions, except for the transmission capacity between bidding zones (Fingrid Oyj, 2022). In ENTSOE-E's ten-year development plan, there is a huge emphasis on doubling the cross-border transfer capacity in the European grid system. The largest area of interest is developing the North Sea area, with offshore wind farms as well as abundant transmission connections to the surrounding countries. The Baltic region is also a key area of focus, in the Baltic countries' quest to reduce their energy dependence on Russia and move to cleaner electricity generation. This would for example include additional transmission capacity between Finland and Estonia. Finland would also see increased transmission capacity with northern Sweden and Norway to take advantage of their abundant hydropower. (ENTSOE - E, 2020)

One of the main changes in the Nordic market is the change to a 15-minute imbalance settlement period, which would allow the intraday and balance markets to operate at a higher resolution than the present 60-minute imbalance settlement period. This change will occur in 2023 and has been brought on by the need to increase flexibility in the electricity system brought on by the increase of intermittent generation methods, such as wind and solar. These changes will also be implemented later in the day-ahead market and even potentially in the direct consumer markets, as some electricity contracts directly follow the day-ahead price. (Svenska Kraftnät, 2023). The change in the imbalance settlement period will also allow for greater demand-side management of the power grid. Traditionally, demand-side management has been present for large industrial electricity consumers, such as the steel or chemical industries operating directly on the electricity market. However, with the coming changes, aggregators will be able to participate more effectively as well, thus increasing the efficiency of the electricity market. These aggregators combine many small-scale consumption centres, such as commercial buildings or even private residences, to create sufficient adjustable capacity to be able to participate in the balancing and reserve markets (Fingrid Oyj, 2023). In practice, this could look like an aggregator that would combine smart buildings, in which systems could be operated remotely and automatically adjust their electricity consumption, for example, by shutting down their heating for 15 minutes, which would not necessarily be noticed in the building, thus reducing the load on the grid by a significant amount. This could also work on the electricity generation side where buildings backup generators and installed renewable electricity sources could be aggregated to provide up-regulating balance and reserve products for the electricity market, however, generation would be more difficult to implement due to the strict requirements for participating in the market (Celik, Roche, Suryanarayanan, Bouquain, & Miraoui, 2017)

When it comes to the infrastructure side, Fingrid has estimated some trends for the Finnish electricity grid, that are also in line with the EU's general guidelines on energy development. One of the major trends is an increase in local power, which includes everything from small-scale solar power installations to small nuclear modular reactors (SMRs). Ever-cheaper solar panels have allowed even individual consumers to integrate them into their houses and even sell excess electricity back to the grid. The price for photovoltaic, commonly known as solar systems has reduced by an astounding 90% from 2009 to 2019 and has become one of the cheapest sources of electricity on the market (Our World In Data, 2023). SMRs are currently in the early stages of development and regulatory processes. However, if fully realised, they have the potential to be integrated with district heating systems, effectively supplying both heat and electricity to entire cities. (Fingrid Oyj, 2022)

Another estimated trend is the use of hydrogen as a storage and transport medium for green energy production. Due to the variable and intermittent nature of renewable electricity sources, there is an increasing need for energy storage on different time scales, from hourly and daily storage to longer periods, such as seasonal storage (Dawood, Anda, & Shafiullah, 2020). Traditional large-scale energy storage methods, such as pumped hydroelectric storage, are highly geographically dependent and cannot be implemented everywhere. These systems are also highly capital-intensive (McDonagh, Wall, Deane, & Murphy, 2018). In research, it is estimated that renewable power penetration could reach up to 50% of the total electricity mix before any grid storage mediums are required, with the rest of the electricity mix coming from highly flexible sources. Until around 80% of renewables penetration, small but highly efficient storage mediums would be favourable over larger long-term and seasonal storage. These estimates were for the

German grid and the authors acknowledged the importance of geography for the need for electricity storage (Weitemeyer, Kleinhans, Vogt, & Agert, 2015).

Hydrogen can be used as a storage medium to address these issues. Hydrogen is still mostly produced using fossil fuels, often natural gas, and thus, cannot be considered a zero-carbon energy source. Hydrogen derived from fossil fuels is often referred to as grey or blue hydrogen, depending on whether the CO2 generated during the process is captured (Dawood, Anda, & Shafiullah, 2020). Hydrogen can also be produced by electrolysing water to produce hydrogen and oxygen. If electrolysis is performed using zero-carbon electricity, the resulting hydrogen is considered carbon-free or green (McDonagh, Wall, Deane, & Murphy, 2018).

$$H_2O \rightarrow H_2 + O_2$$

Equation 1: Chemical equation of electrolysis

Hydrogen, whether stored or transported through pipelines, can be utilised in various ways. One approach involves harnessing its potential by employing hydrogen fuel cells, which efficiently convert hydrogen and oxygen into electricity and water. Additionally, pure hydrogen can be combined with carbon dioxide through a process called the Sabatier reaction, resulting in the production of methane and water.

This methane can, in turn, be used like natural gas is used today, as it is the largest component of natural gas. If green hydrogen is used for this purpose, the produced methane is considered a third-generation biofuel and can be used in the heavy transport sector where direct electrification can be difficult. The entire process of converting electricity to gas is known as a power-to-gas system (McDonagh, Wall, Deane, & Murphy, 2018).

To achieve renewable energy production requirements to be able to generate hydrogen in addition to normal electricity consumption, a drastic increase in grid-scale renewables is needed. Due to Finland's northern latitude, this in practice means an increase in wind production, as grid-scale solar power would be very limited in the winter season. Added wind energy would be derived from an expansion of onshore wind farms nationwide, as well as the establishment of additional offshore wind parks along the western coast of Finland, particularly in the vicinity of Ostrobothnia, which holds significant potential for increased wind power production (Fingrid Oyj, 2022). To aid with the increase in wind power, we have also observed a drastic reduction in the price of onshore wind power during the last decade, with a reduction of 70% from 2009 to 2019 (Our World In Data, 2023). Around 60% of the total lifetime cost of onshore wind farms comes from the construction stage, and operation & maintenance cost accounts for about 12-20% of the lifetime costs. For offshore wind farms construction costs and the proportion of operational cost are a bit higher than onshore wind farms (Liu, et al., 2023). The small proportion of operational cost contributes to the marginal cost of energy production for windfarms are basically non-existent. The very low marginal cost allows wind farms to utilise all of their capacity for the same cost.

The economic viability of electricity sources is often compared to each other using the levelized cost of electricity (LCOE), which is a measure of the average net present cost of electricity generation for the generator over its lifetime. The LCOE is often measured in currency per MWh of electricity produced. (Badouard, Moreira de Oliveira, Yearwood, Torres, & Altmann, 2020)
In a report published by the European Commission Directorate-General for Energy, it was extrapolated that in 2018 onshore wind power already had the lowest LCOE of all sources examined. I have summarized the report’s findings in the table below. (Badouard et al., 2020)

Table 1: The LCOE of various power generation methods

Electricity source	Levelized cost of electricity (LCOE)
Onshore wind	59 €/MWh
Hydropower	69 €/MWh
Nuclear (estimated based on US & China)	75 €/MWh
Offshore wind	84 €/MWh
Coal	90 €/MWh
Natural gas	95 €/MWh

This report highlights the potential economic savings that could be made by increasing the amount of renewable sources in the electric mix, especially when considering the increased price of natural gas from 2018 to 2023 (Osička & Černoch, 2022). Badouard et al. (2020) acknowledge the challenge of accurately determining the true LCOE for nuclear power. This difficulty arises from the limited completion of new nuclear power plants in recent decades, particularly in Western countries. Furthermore, those that have been completed have exhibited a wide range of expenses and cost overruns.

According to Fernández-Guillamón, Gómez-Lázaro, Muljadi, & Molina-García (2019), one major drawback in introducing additional renewable energy sources to the grid is the decrease in grid inertia. Many of the renewable sources are connected to the grid through electronic inverters, which do not have a rotational mass such as traditional powerplants and thus do not contribute to the grid inertia. Denmark, for example, has seen a decrease in its power systems inertia of approximately 60% between 1996 and 2016 (Fernández-Guillamón, Gómez-Lázaro, Muljadi, & Molina-García, 2019). As mentioned earlier, a low inertia system is inherently less stable and more prone to failure if any fault occurs in the grid. According to Ahmed et al. (2023), there are many ways of combatting low inertia. For example, grid operators can procure sufficient reserves to help stabilise the grid in low inertia situations. In the Nordics, this reserve is called the FFR reserve and has already been introduced in the markets. Another way of providing stability is the use of synchronous condensers, which simplified, are rotational masses connected to the grid with the aim of providing voltage and frequency stability in the system. Such condensers have for example already been successfully employed in the Danish grid (Ahmed, et al., 2023). Fingrid has also identified the possibility of using similar synchronous condensers in areas with high renewable penetration, such as Ostrobothnia (Fingrid Oyj, 2022).

Farahmand, Jaehnert, Aigner, & and Huertas-Hernando (2015) explore the scenario of using the abundant hydropower in Norway and Sweden as energy batteries in a scenario where wind generation is expanded. The researchers highlight the ability to store and adjust the hydropower production and thus the ability to compensate for the shortfalls of the intermittency in wind power production. Farahmand et al. (2015) emphasises the need to expand the interconnections between the Nordic countries and continental Europe as well as the British Iles to increase the efficiency of such an approach, as flexibility is also needed around the North Sea.

In a vector autoregressive study by Spodniak, Ollikka, & Honkapuro (2021) they found significant granger causality between the pricing spreads in the Nordic Day-ahead and Intraday electricity markets and the wind power forecast errors, in the bidding zones that had a high wind power penetration. In layman's terms, this suggests that the uncertainty in the electric markets with high enough wind penetrations is largely driven by the uncertainty in wind production. Furthermore, the researchers observed that as the share of renewables in the energy mix increased, the significance of the Intraday market grew as the producers found it necessary to adjust their initial bids in response to changing forecasts. Consequently, the spreads in the Intraday market narrowed, reflecting a reduction in forecast uncertainty compared to the Day-ahead forecast (Spodniak, Ollikka, & Honkapuro, 2021).

With the green transition and the increasing amount of renewable power in our electricity systems, there is also an increasing need to be able to accurately predict future generation due to the intermittency of renewable power. The accurate prediction helps TSOs to keep the electricity system stable and operate the reserve markets to ensure future stability as well (Fingrid Oyj, 2023). High-accuracy predictions are also vital for many of the new innovative technologies, such as power-to-gas, and energy storage systems to function and become economically sustainable. The higher the share of intermittent renewables in an electricity system the more important accurate predictions and operation plans become (Madsen, 2023).

In the context of renewable energy integration, the realm of wind power prediction has gained substantial prominence. This heightened focus is driven by a dual imperative; market participants within the electricity sector are increasingly pursuing higher prediction accuracies for economic optimisation, while TSOs are pursuing this increased accuracy to strengthen their grid stability planning. The evolution of wind power prediction has transitioned from localised and rudimentary models to expansive systems that employ real-time meteorological data derived from multiple wind farms, and several different climate models that provide numerical weather forecasts (Stathopoulos, Kaperoni, Galanis, & Kallos, 2013). This all has been led by advancements in meteorological research as well as advancements in time series forecasting.

Methodology

In this thesis, I will focus on wind energy, as it is the most applicable type of renewable energy generation on a grid scale in countries far from the equator, such as the Nordic countries.
In my research on wind power prediction, I focus on understanding the factors that need to be considered when conducting forecasts for wind generation. Additionally, I investigate the analytical methods and models commonly employed in the field of wind power forecasting.

The first thing one must consider when choosing a model for wind power prediction is the time horizon on which one will make the predictions (Hanifi, Xiaolei, Zi, & Lotfian, 2020). Predictions can often be divided into a handful of time horizons, where the predictions have different uses. Hanifi et al. (2020) summarised the uses and lengths of these horizons in the following table:

Table 1. Prediction horizons in wind power forecasting.

Table 2: Summary of the different wind prediction time horizons and their applications.

Source: (Hanifi, Xiaolei, Zi, & Lotfian, 2020)

Time Horizon	Range	Applications
very short-term	few minutes to 30 min	regulation actions, real-time grid operations, market clearing, turbine control
short-term	30 min to 6 h	load dispatch planning, load intelligent decisions
medium-term	6 h to 1 day	operational security in the electricity market, energy trading, on-line and off-line generating decisions
long-term	1 day to a month	reserve requirements, maintenance schedules, optimum operating cost, operation management

The second factor that must be considered is the type of model used for the forecast. Different types of models perform better for different time horizons. The very short-term models are applicable to internal wind farm operations such as turbine control or regulating transformers, depending on the wind turbine in question. Some of the most frequently used models for this task are known as Persistence models. These models assume that the windspeed is the same at time "*t + 1*" as it is at time "*t*"; in other words, the wind remains the same as before. This persistence presumption is partially made because numerical weather prediction (NWP) data, which are often incorporated in wind power forecast models, do not have sufficiently high granularity and are often given on a larger geographical area than single wind turbines or farms (Soman, Zareipour, Malik, & Mandal, 2010).

The short-term models can be integral to operating the intraday electricity market. Wind farms can place correcting bids based on their previous day-ahead market bids to reflect the actual generation capacity of their wind turbines. TSOs can also plan and prepare different reserve products based on short-term wind predictions. As the imbalance settlement period decreases to 15 minutes, the shorter horizon predictions will become even more important to operate in the intraday market (Svenska Kraftnät, 2023). Moving into the short-term models, we begin to see different types of physical models. Physical models are complex mathematical models that incorporate the physical aspects of wind turbines and farms, as well as factors such as the surrounding terrain and the wake effect of other turbines to produce a windspeed prediction. This prediction is then fed into the power curves of the wind turbines to obtain a power generation estimate. As the models use physical real-time data it doesn't need to be trained on historical data (Hanifi et al. 2020).

In the realm of wind energy production, the medium-term time horizon is very important. It becomes crucial for operators to have precise predictions when submitting electricity bids to the day-ahead market, which is the primary trading platform for most of Europe's energy transactions (Gomez, et al., 2019). When the actual energy production differs from the electricity bids submitted, operators may face penalties in the balancing market. These penalties can take the form of reduced payments for surplus energy or increased payments for insufficient production. (Fingrid Oyj, 2023). As this time horizon is central to wind power operators, a variety of prediction models have been developed. In addition to physical models, there is a host of statistical models in use. Statistical models are typically categorised into two main groups. The first group consists of models that focus on modelling the characteristics of time series data. These models include autoregressive (AR) models, moving average (MA) models, and combinations of these two, known as autoregressive moving average (ARMA) models. These models capture the patterns and dependencies within the time series data itself. ARMA models can further be modified to use exogenic variables, such as NPW data to improve prediction (Soman, Zareipour, Malik, & Mandal, 2010).

The second category of statistical models falls under the umbrella of machine-learning models (MLMs). These models harness computational power to tackle intricate mathematical challenges. A wide array of MLM models is available, each tailored to address specific problems. Examples include various types of regression models and support vector machines. Within MLM models, we also have Artificial Neural Networks (ANN), which apply weights to a set of connected neurons to produce an output. ANN have a mix of different architectures and functions to suit different tasks. One of the biggest advantages of ANN models is their ability to use a large amount of input data and find relationships with the output, which would be difficult for a human to detect (Hanifi, Xiaolei, Zi, & Lotfian, 2020).

Returning to the time horizons, as the final one, we have the long-term horizon. This incorporates all predictions which are made + 1 day to months ahead in time. These types of forecasts can be utilised for everything from estimating the generation within the coming week to planning turbine maintenance and even calculating the expected cash flow of the power plant, based on monthly or seasonal forecasts. The longer the prediction horizon is, the more NWP-dependent it is. As with NWP models the further you go in the future with wind production, the more uncertain they become and the error term increases, as the weather is partially a stochastic process, which cannot be exactly predicted (Hanifi, Xiaolei, Zi, & Lotfian, 2020).

For my thesis, I am going to explore some traditional statistical models as well as some Machine Learning approaches to forecasting wind power generation on data I have obtained myself. The empirical part will be performed in an exploratory manner, where I will apply some of the methods and approaches used in time series forecasting and compare them to each other.

Box-Jenkins Methodology

The Box-Jenkins methodology is a time series analysis method that is used for modelling and forecasting future observations of a univariate time series. This methodology was developed by George Box and Gwilym Jenkins in the 1970s and has since become a widely used approach for time series analysis. The method involves a series of steps including stationarity testing, determination of the appropriate model structure, estimation of model parameters, and model diagnostic checking. (Bowerman, O'Connell, & Koehler, 2005)

A stationary time series is one where the mean and the variance stay constant throughout time. While a non-stationary time series displays either local or global trends or a constantly changing variance throughout.

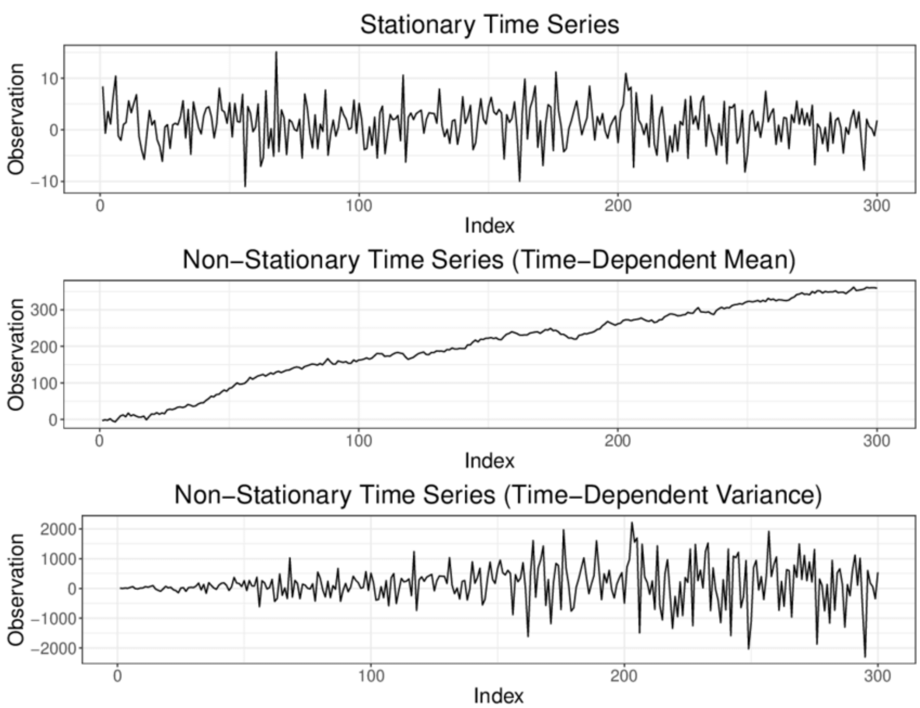

Figure 6: Example of a Stationary and non-Stationary time series. Source:https://www.researchgate.net/publication/348592737_Automated_Hybrid_Time_Series_Forecasting_Design_Benchmarking_and_Use_Cases

To generate a stationary series from a non-stationary series one can take the first difference of the non-stationary series. By taking the difference one converts the time series to one that displays the changes between two data points instead of the absolute value. In the ARIMA model the "I" stands for integrated, which tells us how many times the time series in the model has been differenced. In the ARIMA (p,d,q) model explanation the differencing is represented by the letter "d". The equation for differencing is the following.

Equation 2: Equation for the differencing of a time series

$$Z_t = Y_t - Y_{t-1}$$

After one has determined that a series is stationary, one must find a model that fits the data. Bowerman, O'Connell, & Koehler (2005) advocate using the Autocorrelation function (ACF) and the Partial Autocorrelation Function (PACF) to find a suitable model. The ACF measures the linear relationship between the time series observation separated by *k* lags time units.

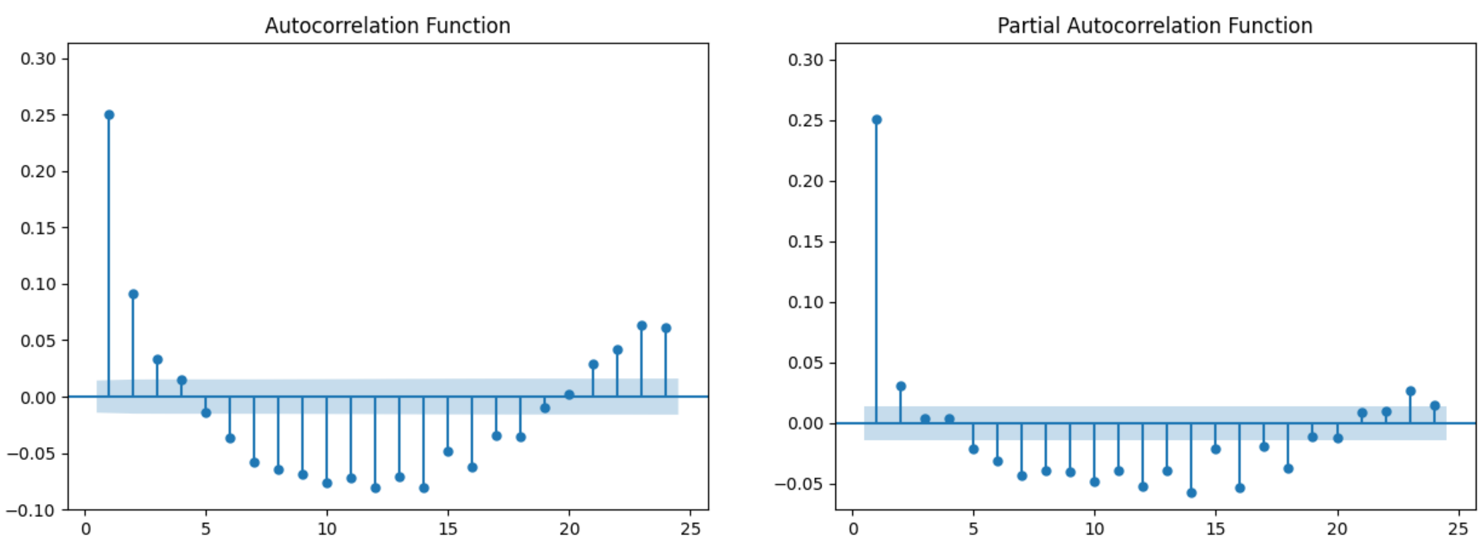

Figure 7: ACF and PACF graph of the differentiated average wind speed in an area.

A value close to 1 shows a strong correlation between the value and the k:th lag, while a value close to -1 shows a negative correlation. In general, if a time series has strong positive correlations at the first lags, the series tends to move in the same direction as the previous values. We can also calculate the standard error of the correlation and thereby a t-statistic for determining if a correlation is significant or not. The ACF graph is often used as a visual tool to determine whether a series is stationary and to identify the moving average component of the Box-Jenkins model. A non-stationary time series usually has a slow dying off on the correlation of the lagged values. In contrast, a stationary time series often sees a sharp cut-off at the first lags, after which the correlation can no longer be considered statistically significant. The ACF considers all correlations of the intermediate lags and shows the overall autocorrelation in the series. The MA component is usually represented by q in the ARIMA (p,d,q) model explanation and by the Greek letter theta (θ) in mathematical equations. (Bowerman, O'Connell, & Koehler, 2005)

We can also utilise the PACF graph, which only measures the direct correlation between a time series and its lagged values, controlling for the intermediate lags. A PACF graph is typically used to identify the autoregressive (AR) components of an ARMA model. The AR component is usually represented by p in the ARIMA (p,d,q) model and by the Greek letter phi (Φ) in mathematical equations. (Bowerman, O'Connell, & Koehler, 2005)

$$
\begin{aligned}
y_t^* &= \Delta^d y_t \\
y_t^* &= \mu + \underbrace{\sum_{i=1}^{p} \phi_i y_{t-i}^*}_{\text{AR}} + \underbrace{\sum_{i=1}^{q} \theta_i \epsilon_{t-i}}_{\text{MA}} + \epsilon_t
\end{aligned}
$$

Equation 3; General ARIMA equation with an intercept

Several MA and AR components can be added to the ARIMA model. However, it is not recommended that the components exceed two of either AR or MA if both are used in the model. This is because the addition of many components makes the model unnecessarily complicated. One can also difference the time series several times to make it stationary, however, two times is usually also recommended as a maximum. (Bowerman, O'Connell, & Koehler, 2005)

Despite their versatility in various time series prediction tasks, ARIMA models face a fundamental limitation in their predictive capability due to their univariate nature. Univariate models make predictions on a time series based on previous values of the same time series and the statistical characteristics of the time series; thus, they do not incorporate any new information into the prediction. However, many time series depend on external factors that can significantly influence the time series in question. For instance, in the context of wind generation forecasting, the prediction of wind power heavily relies on the external factor of wind speed. Fortunately, methods exist to address this issue by combining linear regression models with ARIMA models, resulting in dynamic regression models commonly referred to as ARIMAX models. By incorporating the influence of wind speed as an additional variable, ARIMAX models can enhance their predictive capabilities and account for the crucial external factors impacting wind generation time series. (Bowerman, O'Connell, & Koehler, 2005)

Arima Models with Exogenic Variables

The ARIMAX models incorporate multiple linear regression of independent and, in this case, exogenic variables, with the autoregressive and moving average terms of the ARIAM models.

$$\Theta(L)^p \Delta^d y_t = \Phi(L)^q \Delta^d \epsilon_t + \sum_{i=1}^{n} \beta_i x_t^i$$

Equation 4

$General\ ARIMAX\ model\ for\ time\ t, with\ the\ coefficients\ B\ for\ the\ independant\ variables\ x$

By using exogenous variables in the model, one can incorporate information from other sources to improve the accuracy and reliability of the model, as well as rely on future values of the exogenous variables to improve long-term forecasts, where the univariate ARIMA models quickly run out of new information to forecast. (Yerim & Jin, 2019). Essentially, the ARIMAX model can be seen as a type of linear regression model that includes both autoregressive and moving average terms, as well as additional exogenous variables. The model has coefficients (represented by β for the exogenous variables and ϕ and Θ for the autoregressive and moving average terms, respectively) that represent the strength and direction of the relationships between the variables. Additionally, the model may include an intercept term that represents the baseline level of the dependent variable when all other variables are zero. In summary, the ARIMAX model is a regression model with additional time-series components and exogenous variables. The optimal parameter for an ARIMA and ARIMAX model is usually calculated using the

Maximum Likelihood method, which aims to find the parameter values that maximise the likelihood of the observed data given the model. (Bowerman, O'Connell, & Koehler, 2005)

ARIMA Model Diagnostics

As is the case with numerous statistical models, it is always advisable to examine the residuals to assess the model's effectiveness in capturing the characteristics of the series and to detect any anomalies, such as the presence of heteroskedasticity. Additionally, different types of statistical tests can be used to check and compare the fit of the model. One of the most prevalent in ARIMA time series forecasting is the Akaike Information Criterion (AIC), which evaluates a model's performance by rewarding the goodness of fit with the model maximum likelihood function, while also penalising the number of parameters a model has. This ensures that a simpler model with the same goodness of fit will receive a better score and is therefore preferable. This model selection approach creates a good balance between the model's complexity and accuracy and reduces both over- and underfitting (Stoica & Selén, 2004).

Artificial Neural Network Methodology

The inception of artificial neural networks (ANN) can be traced back to the 1950s when they were initially built upon the concept of a perceptron. A perceptron can be described as an artificial neuron that takes multiple binary inputs and generates a single binary output. This function is based loosely on how biological neurons in the wild work and has therefore adopted the name neural network. Each perceptron neuron has weights attached to the inputs, and if a weighted sum of the inputs exceeds a certain threshold, the output would be either 1 or 0.

To adapt the perceptron to a machine-trainable network, the architecture had to be changed slightly while still maintaining the core idea of a biological neuron. Instead of a threshold, a bias is used, which can be thought of as the sensitivity of the neuron to stimuli. Finally, instead of a binary output, a continuous output is preferred because it allows fine adjustments in the network. To achieve a continuous output, the weighted sums of the inputs plus the bias are fed into an activation function that alters the output in the desired manner. A sigmoid activation function is commonly used as an example. The sigmoid activation function is a logistic function that squashes any input into the interval from 0 to 1.

The following is an illustration of a single neuron in a neural network. These neurons can be stacked beside each other, often called units, or in several different layers contributing to the "network" in neural networks. With several layers and units per layer, networks can be created that can model very complex and non-linear problems. (Nielsen, 2015)

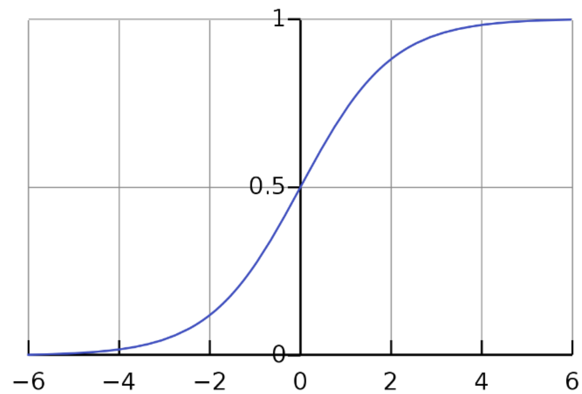

Figure 8: The Logistic Curve of a Sigmoid Function. Source:https://en.wikipedia.org/wiki/Sigmoid_function#/media/File:Logistic-curve.svg

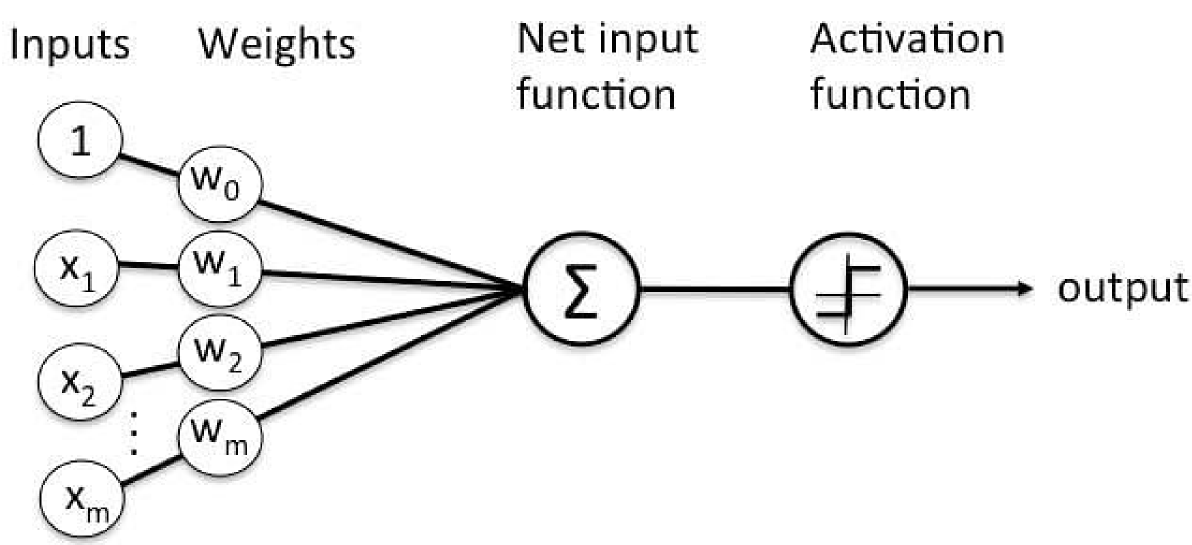

Figure 9: Representation of a linear regression network, where the inputs are summed up, run through an activation function to a single output. Source: https://wiki.pathmind.com/neural-network

To effectively model a problem using a neural network, it's essential to find the right set of network parameters that lead to the desired outcome through iterative adjustment. These parameters, collectively known as trainable parameters, include the weights and biases associated with the network's neurons. The adjustment process is accomplished through a technique called backpropagation, with the aim of minimising the network's cost function via gradient descent.

The cost function serves as a metric for evaluating the prediction errors, and the updates to the neural network's parameters are made in a way that steadily reduces this cost function. The goal is to find the optimal parameter values that minimise this cost function.

During the backpropagation process, the gradients of the cost function with respect to each trainable parameter are calculated using the chain rule from calculus. These gradients provide the direction of the steepest descent in the cost function space. To make these adjustments, a learning rate parameter is introduced, which controls the size of the parameter updates.

In practice, a variant of stochastic gradient descent is often employed. This method involves the computation of the cost function gradient with respect to a randomly selected subset of the training data, referred to as a mini-batch. The parameter updates are determined by this gradient, scaled by the learning rate. The use of mini-batches significantly reduces the computational demands of gradient descent calculations.

The training of a neural network is an iterative process. The parameters continue to be updated using this algorithm until one of two conditions is met: either the cost function converges to a local minimum, indicating that the network is not making any additional progress in minimising the cost function, or a predetermined number of training cycles, known as epochs, is reached. An epoch involves one pass through the entire training dataset. (Nielsen, 2015)
Neural Networks have been tailored in diverse ways to address a wide range of problems. They encompass various types of layers, activation functions, and optimisation algorithms, all aimed at making the best predictions for a specific problem.

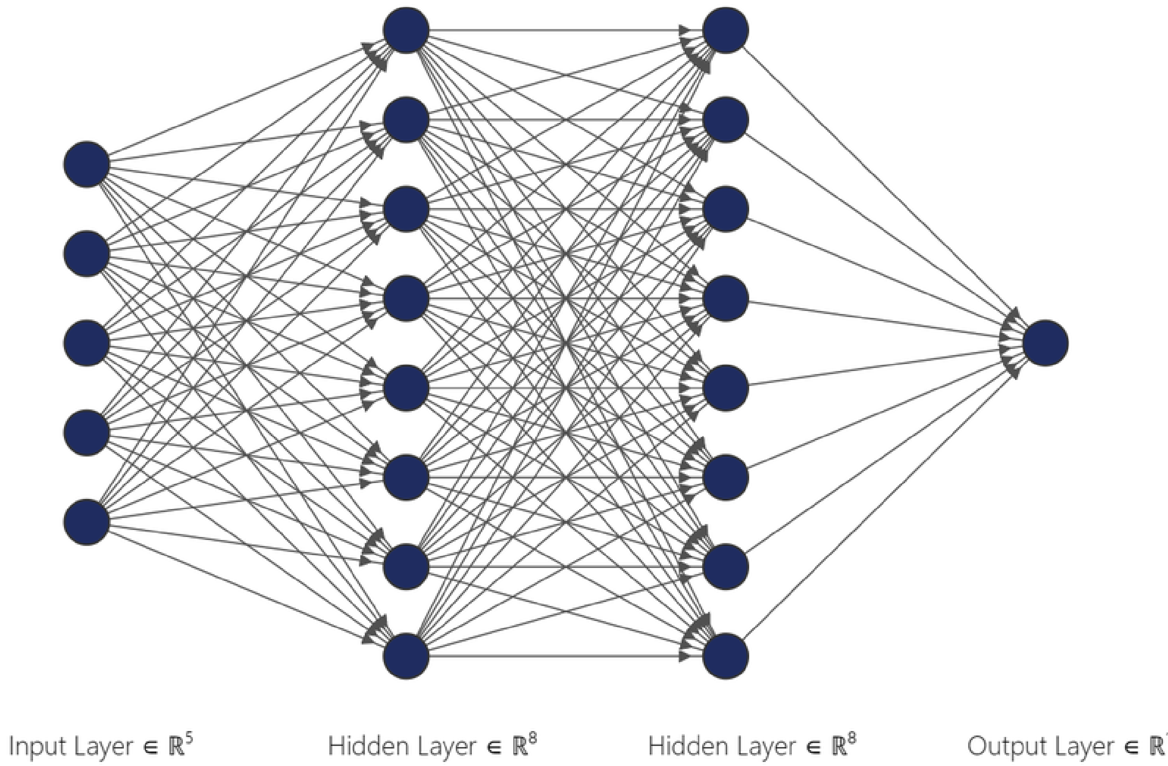

Figure 10: Diagram of a fully connected MLP.

Source: https://www.researchgate.net/publication/369021391_A_Tutorial_on_AI-Enabled_Non-Terrestrial_Networks_in_6G/figures?lo=1

A Multi-layered Perceptron (MLP) is a basic type of neural network with connected neurons arranged in layers. It's good for simpler data, but not ideal for high-dimensional data like images. For images, a Convolutional Neural Network (CNN) is recommended. It uses filters to extract features and simplify the data, making it better at learning complex patterns. Networks where the information only flows in one direction are called "feed-forward networks" (Nielsen, 2015). Another type of neural network architecture commonly used in modelling sequential data, such as time series or natural language processing, is the Recurrent Neural Network (RNN). The RNN architecture allows information to be retained from previous inputs in the sequence, and to carry forward to help with the current prediction. A key advantage of RNNs is their ability to process variable-length data sequences. This is because the same set of weights are applied to each element in the sequence, allowing the network to handle inputs of different lengths. RNNs can be trained using backpropagation through time (BPTT), which is a technique for computing gradients in recurrent networks. The simplest form of an RNN is when the output of the neuron is fed back as an input for the next value in the sequence (Heaton, 2020).

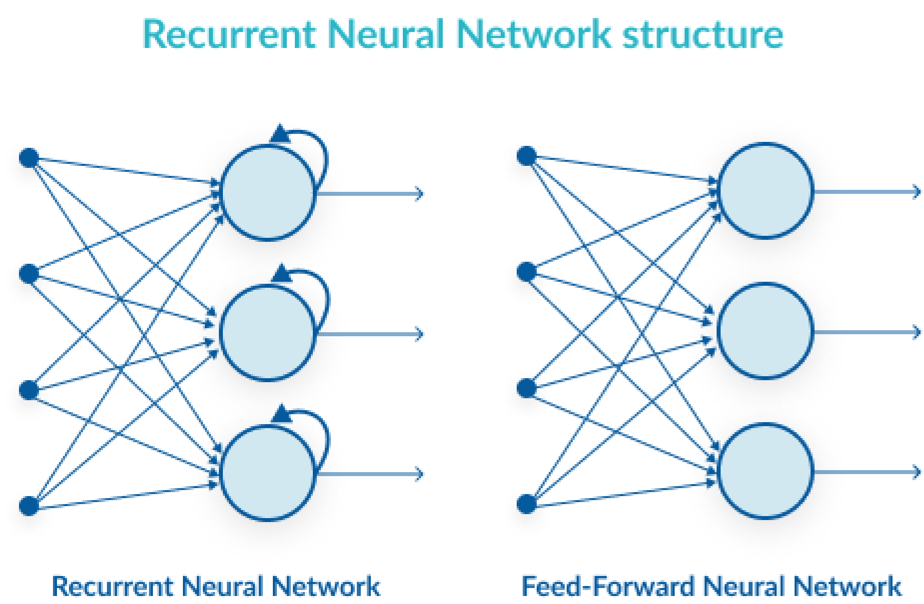

Figure 11: A diagram of the information flow in a simple RNN.

Source: https://machine-learning.paperspace.com/wiki/recurrent-neural-network-rnn

Because RNNs use outputs from previous timesteps as inputs to predict the current output, the backpropagation algorithm used to minimise the loss function must also consider these previous timesteps. Backpropagating through time works by "unrolling" the RNN over time, creating a feedforward neural network that considers all previous timesteps in the sequence. The gradients are then computed using the chain rule, backpropagating the errors back through time to update the weights of the network. However, BPTT can be computationally expensive, especially when processing long sequences, because the gradients must be propagated back through all previous timesteps. The problem of vanishing or exploding gradients can also arise when using BPTT to train RNNs. This is because the gradients must be propagated back through all previous timesteps, which can lead to the gradients becoming either very small (vanishing gradients) or very large (exploding gradients) as they are multiplied over many time steps. In effect, this can lead to difficulties for a simple RNN to model long-term dependencies in the data (Staudemeyer & Morris, 2019).

LSTM Neural Networks

The Long-Short Term Memory (LSTM) neural network architecture is purposely designed to mitigate the problem of vanishing gradients in simple RNNs by introducing a “cell state” that allows information to be carried over and used throughout the sequence. In addition to the cell state, the LSTM architecture also uses the previous hidden state, which is passed along with the current input, to determine the new hidden state and cell state for the current time step. This is why the architecture is called "Long-Short Term Memory", as it can selectively remember or forget information over short and long periods (Staudemeyer & Morris, 2019).

The cell state acts as a kind of conveyor belt, allowing information to be added or removed at each time step based on a set of learned "gates" that control the flow of information. The gates are implemented using sigmoid and hyperbolic tangent functions that can learn to either amplify or dampen the information flow through the cell state, thereby allowing the LSTM to selectively store or discard information based on the current input and current state of the network (Gonzalez & Wen, 2018).

By combining the current input with the previous hidden state and using the different gates to selectively update the cell state, LSTMs can maintain long-term dependencies and avoid the problem of vanishing gradients that can plague simple RNNs. However, with the additional trainable parameters in an LSTM network, we also substantially increase the complexity, and thereby, the computational requirements of the network. The LSTM architecture is designed to consider the time dependence of the sequential data. Therefore, the input data must be organised into a 3D tensor that respects the temporal order of the sequences. (Staudemeyer & Morris, 2019).

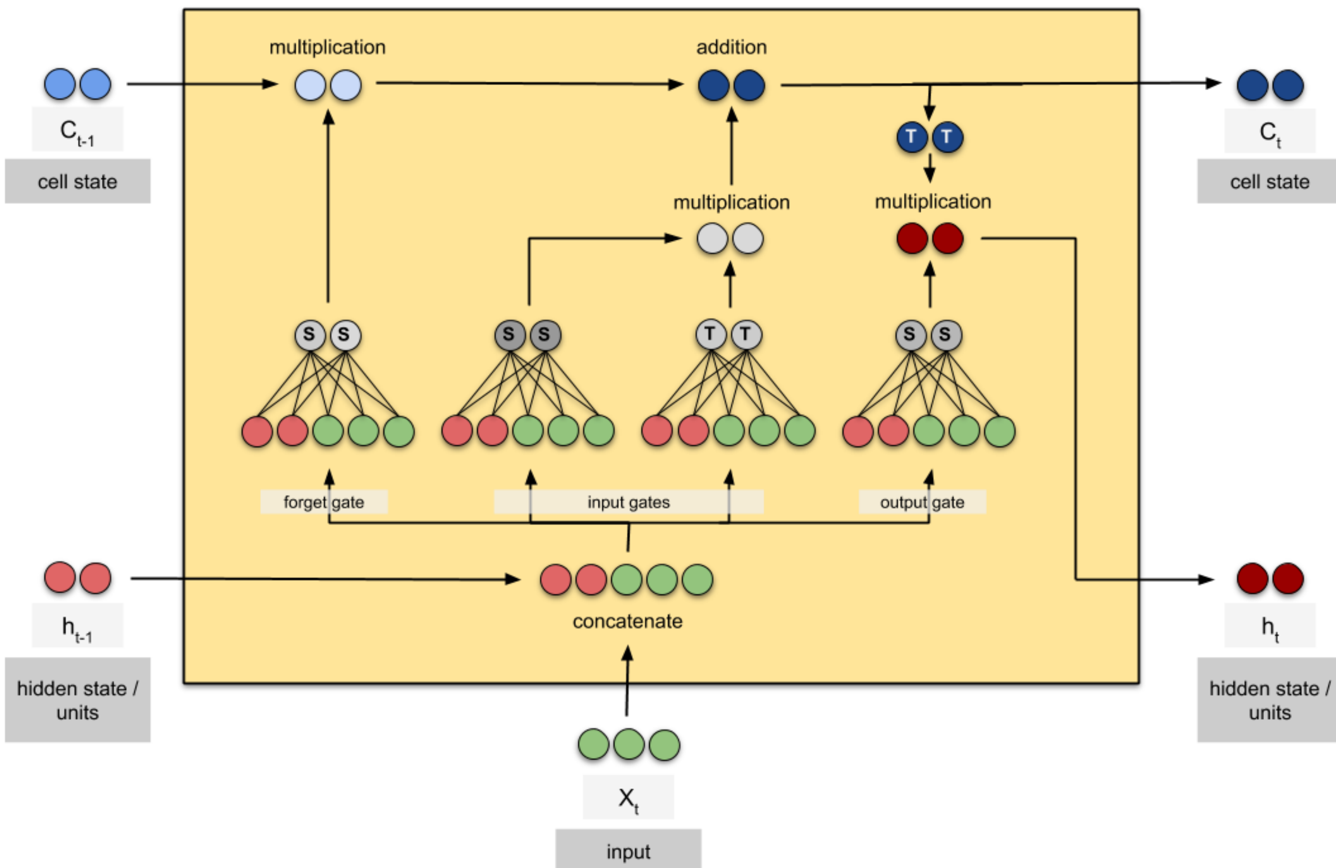

Figure 12: Diagram of a LSTM cell, including the various "gates" utilized.

Source: https://towardsdatascience.com/animated-rnn-lstm-and-gru-ef124d06cf45

In simple terms, tensors are mathematical concepts used in machine learning to represent multidimensional arrays of data. In the case of LSTM, we use 3D tensors to represent time-series data, where each "slice" in the tensor corresponds to a single sample and the rows and columns represent the features and time steps, respectively. While tensors are similar to matrices in that they are composed of rows and columns of numbers, tensors can have any number of dimensions. For instance, a 3D tensor is like a cube, a 4D tensor is like a hypercube, and so on. Tensors are particularly useful in machine learning because they allow for efficient mathematical operations to be performed on large amounts of data. These operations can include matrix multiplication, element-wise multiplication, and other operations that can be used to train and optimise complex neural networks, such as LSTMs (Heaton, 2020).

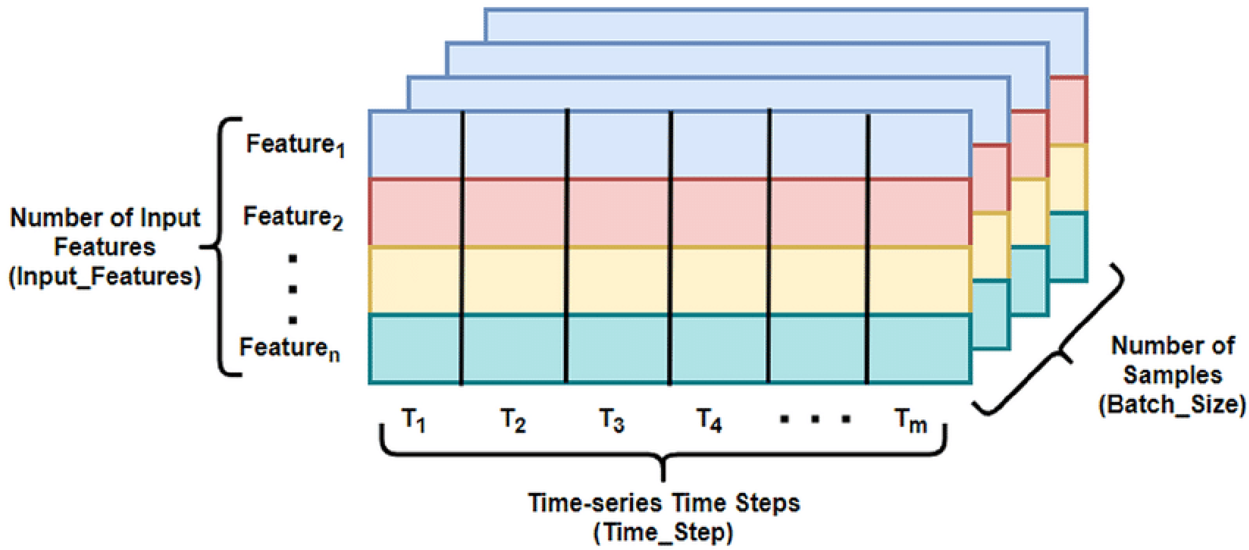

Figure 13: A schematic diagram of a 3D array for LSTM networks.

Source: https://www.researchgate.net/publication/350218060_Designing_a_long_short-term_network_for_short-term_forecasting_of_global_horizontal_irradiance

Error Metrics

In statistics and machine learning, a multitude of error metrics can be employed as cost or loss functions in both training and assessing models, as well as in demonstrating their performance. It's worth noting that some of these error metrics may be more easily understood and interpreted than others.

The simplest error is often referred to as the error and is calculated by subtracting the predicted value from the actual value. It is presented in the same units as the variable of interest and is therefore quite intuitive to understand. The biggest drawback of the simple error is that when it is aggregated over a dataset, the positive errors cancel out the negative errors.

To avoid mutual cancellation of aggregated errors, we can treat both negative and positive errors as equal by calculating the absolute error relative to the actual value. As with the simple error, it has the same unit as the variable of interest and is easily interpreted. The drawback of the absolute error is that its skewness cannot be determined. For example, one cannot determine if the error is systematically above or below the actual value, which could indicate a problem in the model used for the forecast. By calculating the absolute error over a whole dataset och then averaging it to gain the Mean Absolute Error (MAE).

The Squared Error is a commonly employed error metric in various domains, due to its capability to circumvent the issues of negative errors and cancellation of errors. The Squared Error is obtained by squaring the difference between the predicted and actual values, which renders larger individual errors more influential than smaller ones. This is particularly significant when the Squared Error is aggregated into Mean Squared Error (MSE). As MSE is widely adopted as a loss function in machine learning, minimising it helps reduce the impact of large errors, as large errors have a larger impact on the aggregated error than small errors. One of the disadvantages of the Squared Error is that the units are square units of the variable of interest. However, this can be solved by taking the square root of the Squared Error and then obtaining the Root Squared Error. The Root Mean Squared Error (RMSE) is therefore displayed in the same units as the variable of interest and is also widely used in machine-learning contexts (Botchkarev, 2019).

Error Metric	Formula
Error	$E = (y_i - \hat{y}_i)$
Absolute Error	$AE = \lvert y_i - \hat{y}_i \rvert$
Mean Abolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert$
Mean Squared Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{MSE}$

Figure 14: Equations of the error metrics, where y is the actual value and ŷ is the predicted value.

Data Collection

For the empirical research segment of this thesis, I conducted an analysis involving various models to predict renewable energy generation. This analysis was based on data sourced from the publicly accessible datasets provided by Energinet, the Danish TSO[3]. Additionally, I incorporated weather data obtained from the publicly available APIs of the Danish Meteorological Institute (DMI)[4]. The study utilised a dataset spanning a two-year period, specifically from 2021 to 2022.

I chose to use Danish data for my thesis because of its availability and precision. The electricity generation data is aggregated on a municipality level and thus provides information on electricity generation in a fairly compact geographical area. The generation data also has a resolution of one hour, meaning that the data consists of the total amount of generated electricity within an hour's interval. I decided to utilise historical weather data for both training and testing the model, as I could not find any available historical weather forecast data that was easy to work with.

The weather data sourced from the DMI comprised of precise weather observations collected from multiple weather stations distributed throughout Denmark. Initially, the weather data had a 10-minute resolution, but it was resampled to hourly intervals to align with the generation data. Weather stations that did not have a sufficient number of measured variables were discarded from the initial dataset. For example, some weather stations only measured very specific weather events, such as snow depth or rainfall. These types of stations were discarded. Additional geographical information was provided by the Danish Geodata Agency in the form of maps used for this thesis[5].

[3] Production data from the Energinets dataset "Production per Municipality per Hour".
Source: https://www.energidataservice.dk/tso-electricity/ProductionMunicipalityHour

[4] Weather data from DMIs dataset "Meteorological Observations Data"
Source: https://confluence.govcloud.dk/display/FDAPI/Meteorological+Observation+Data

[5] Geodata from the Danish Geodata Agency. Source: https://lab.information.dk/

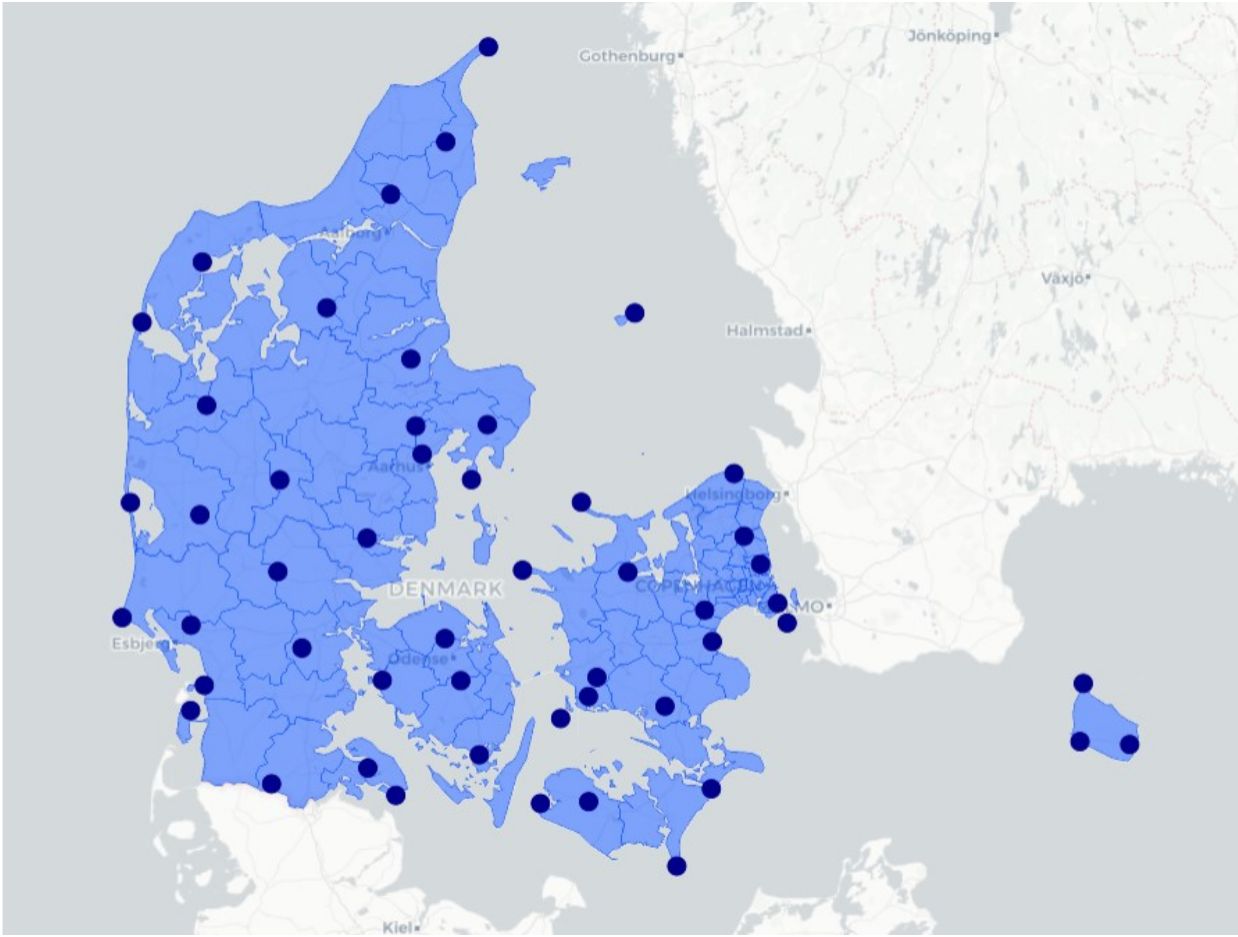

Figure 15: Representation of the municipalities and weather stations.

Data Pre-processing

As the generation data was aggregated on a municipality level, I could not determine the exact location of the wind turbines within each municipality. Therefore, I calculated the central point of the municipality using the polygons of the geographical maps. By calculating the central points of the municipalities, I found the three closest weather stations for each municipality based on distance. The distance mapping was performed using the k-nearest neighbour methodology, with the Haversine distance as a metric. The Haversine formula is a widely employed method for computing the shortest distance between two points on a sphere, primarily using their longitude and latitude coordinates. To apply the Haversine formula to Earth, a typical radius of 6,367.45 kilometres is used. It's important to note that the Haversine distance does not account for geographical variations such as hills or valleys and is not perfectly accurate due to

Earth's non-spherical shape. Nevertheless, it remains a popular choice for distance approximation due to its simplicity and ease of use (Maria, Budiman, & Taruk, 2020).

Equation 5: The equation for the Haversine distance

$$d = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)$$

Where *d* is the distance, *r* represents the radius of the earth, and ($\varphi 1$, $\lambda 1$) and ($\varphi 2$, $\lambda 2$) are the latitude and longitude coordinates of the two points, respectively.

The mean distance from each municipality's central point to the closest weather station was approximately 19 kilometres, and the mean distance to all three closest stations was 31 kilometres.

After the three closest weather stations per municipality were identified, averages of overlapping weather variables were computed to derive an area-wide average. To elaborate, when weather measurements were recorded by all three weather stations, a new dataset was created by averaging the readings from each station. On the other hand, if a measurement was only recorded by two of the closest stations, an average value was computed from those two readings. Any missing values were disregarded, and instead, the mean of the measurements from other stations was utilised. This approach effectively mitigated the issue of not all stations measuring the same variables, and some of the data being missing from the stations. Additionally, this data averaging introduced some variability into the weather measurements, which can simulate weather forecast data quite effectively, as it is not often very precise over small geographical locations or longer time horizons.

Some missing values were also present in the generation data, and even after the weather data had been aggregated, certain gaps remained. To address these gaps, linear interpolation was employed to estimate the missing data points using the datapoints before and after the missing values. This approach was necessary because some of the machine learning models utilised in this thesis do not allow for any missing data.

Equation 6: Equation of the Linear Interpolation

$$y = y_1 + \frac{(x - x_1)(y_2 - y_1)}{x_2 - x_1}$$

Data Selection

To limit the scope of this thesis, I chose to perform time-series modelling on only one of the municipalities in the data. To find suitable candidates, I correlated the onshore wind production data with the mean wind speed data from the three closest weather stations. From the municipalities with the highest correlation, I selected the municipality that had the highest average wind generation. This gave me a robust dataset with sufficient variation and a high correlation with the mean wind speed of the area to work with.

Tønder, the selected municipality is situated in the southern region of the Jutland Peninsula, bordering Germany, and featuring a coastline along the North Sea. As of July 2022[6], the municipality had a total of 337 onshore wind generators that could generate up to 176 MW of electricity. In the years 2021-2022, the mean onshore wind power generation of the municipality was approximately 34 MW per hour. This power generation was found to have a high correlation coefficient of 0.86 with the mean wind speed.

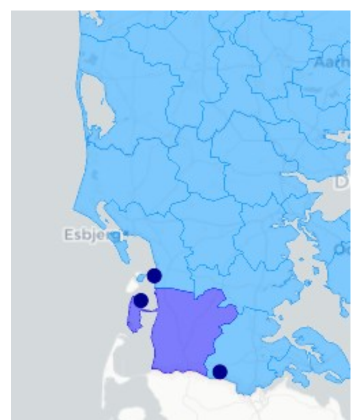

Figure 16: Tønder, and the closest weather stations.

[6] Based on data from Energinet.
Source: https://www.energidataservice.dk/tso-electricity/CapacityPerMunicipality

To ensure consistency in my modelling approach and enable meaningful comparisons between models, a specific data division strategy was implemented. Given the dataset's two-year timeframe, the final five months of 2022 were exclusively reserved for testing the models. This partitioning allowed for the assessment of a wide range of weather conditions and the potential capture of any seasonal patterns present in the data. Overall, I believe that this split provided a well-rounded testing environment for model evaluation.

For all the models, the same dataset division approach was employed. The initial 60% of the data was designated for model training, followed by the next 20% for validation, and the final 20% for testing. In cases where models did not use validation, 80% of the data was used for training. Given the nature of modelling a time series, the sequential splitting method was employed to partition the data into consecutive training, validation, and test sets. This approach adheres to established best practices for time series forecasting, as it replicates the linear passage of time (Bowerman, O'Connell, & Koehler, 2005).

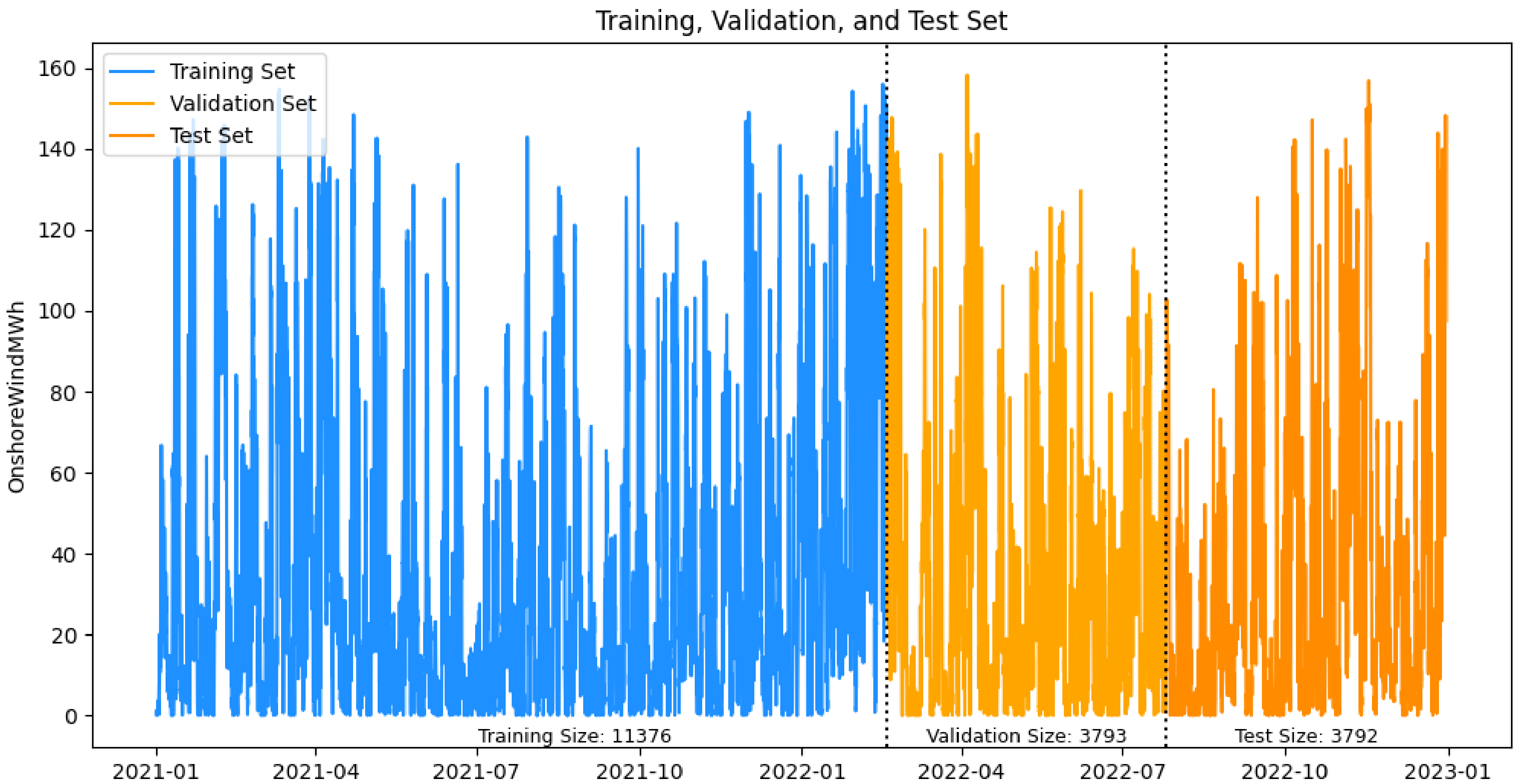

Figure 17: Visualisation of the train, validation, and test split.

I decided to perform a 60/40 split of the data because, in the middle of 2022, there was a significant reduction in wind power generation. If the validation and test sets were smaller, the characteristics of the dataset as mean and standard deviation would differ, and this could introduce errors in the models. With the 60/40 split, all the datasets had very similar characteristics.

Modelling

Univariate Modelling

First, I decided to make predictions solely based on the generation data and test some univariate forecasting approaches. As a baseline model, I chose a very simple Persistence model that assumes that nothing will change from one timestep to another. In this case, with backtesting, the equation of the forecast for period t equals the true value from the past timestep t-1.

Equation 7: The Persistence model equation

$$\widehat{Y_t} = Y_{t-1}$$

To find an ARIMA model for univariate forecasting, I started by determining whether the training set was stationary using the KPSS test. From the KPSS test, I obtained a P-value of 0,01 which is significant enough to reject the null hypothesis that the series is trend stationary. As the ARIMA model requires a trend stationary series, we must take the difference of the time series. Taking the diff of the series, I once again ran the KPSS test, and this time got a P-value of 0,1 or above. This P-value is high enough to fail to reject the null hypothesis and, therefore, determine that one diff is sufficient to make the time series trend stationary.

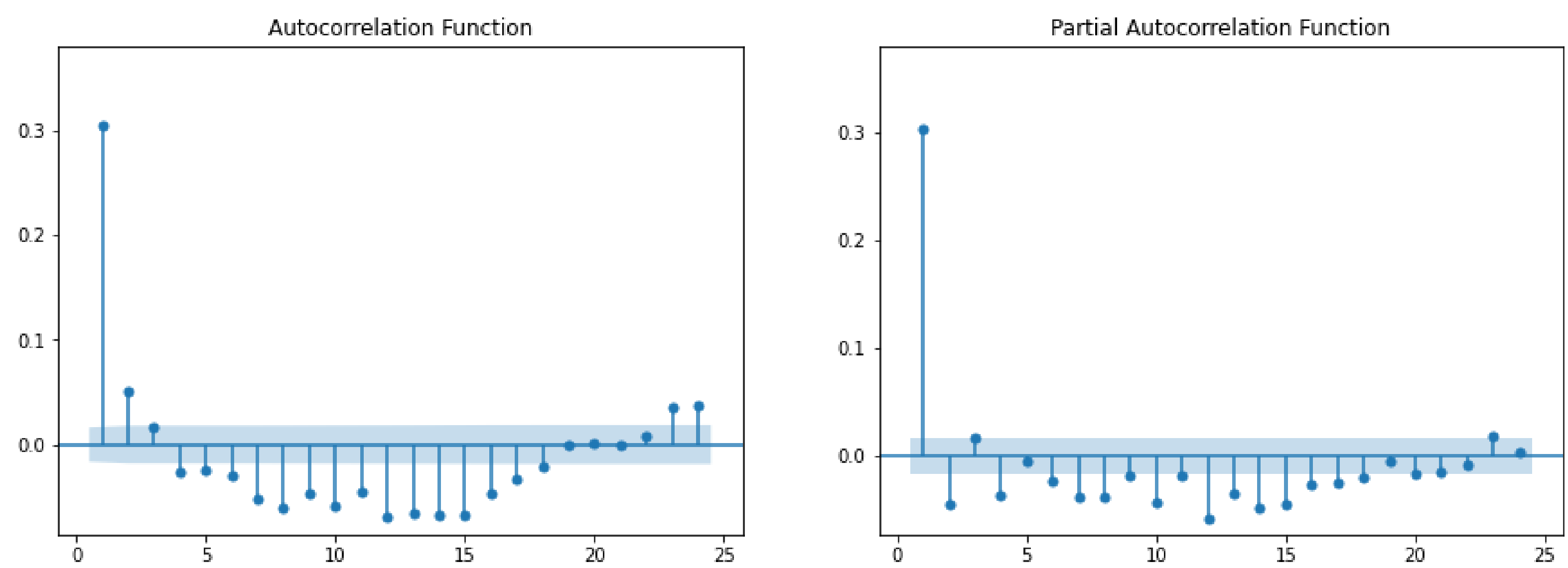

Figure 18: The ACF and PACF graphs after one difference.

Subsequently, I used the ACF and PACF graphs to determine a suitable ARIMA model for the data. In the graphs, the zeroth lag is removed, as it always has a perfect correlation of one. From the graphs, we can see that at least the first lag is significant in both the ACF and PACF graphs. Subsequently, the correlation values become quite small, even though they are still significant according to the two standard error confidence intervals[7]. Observing the graphs, one can imagine that an ARIMA model with 1-2 AR and MA components would be suitable for forecasting. To test the different possible ARIMA models, I used the Python *pmdarima* package, which can be used to train and score several models and choose the best one based on some metric. As a criterion for choosing the model, I used the Akaike Information Criterion (AIC), which scores the maximum likelihood function of the ARIMA models while also disincentivising overly complex models (Stoica & Selén, 2004).

[7] Note. The error confidence is quite small in this graph due to a large amount of data in the train set, as it is calculated as 1/sqrt(N) (Statsmodels developers, 2023)

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                14219
Model:                 ARIMA(2, 1, 2)   Log Likelihood              -49451.374
Date:                Wed, 29 Mar 2023   AIC                          98912.749
Time:                        14:26:01   BIC                          98950.560
Sample:                             0   HQIC                         98925.327
                              - 14219
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.3560      0.051     -6.995      0.000      -0.456      -0.256
ar.L2          0.1636      0.018      8.983      0.000       0.128       0.199
ma.L1         -0.3256      0.073     -4.439      0.000      -0.469      -0.182
ma.L2         -0.6744      0.063    -10.727      0.000      -0.798      -0.551
sigma2        61.4153      3.309     18.560      0.000      54.930      67.901
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):             53695.98
Prob(Q):                              0.90   Prob(JB):                         0.00
Heteroskedasticity (H):               1.15   Skew:                            -0.08
Prob(H) (two-sided):                  0.00   Kurtosis:                        12.52
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

Figure 19: Model results of the ARIMA(2,1,2) model, with coefficients.

As one can see from the model summary, the model that had the best fit on the training data was an ARIMA (2,1,2), with all of the parameters being statistically significant. Due to the stochastic nature of wind speeds, it is very difficult to find a model suited for all of the training data. This can be observed in the model's diagnostic plots. In a comparative study predicting windspeed for power production Elsaraiti & Merabet (2021) also observed that an ARIMA(2,1,2) model performed best in predicting windspeed.

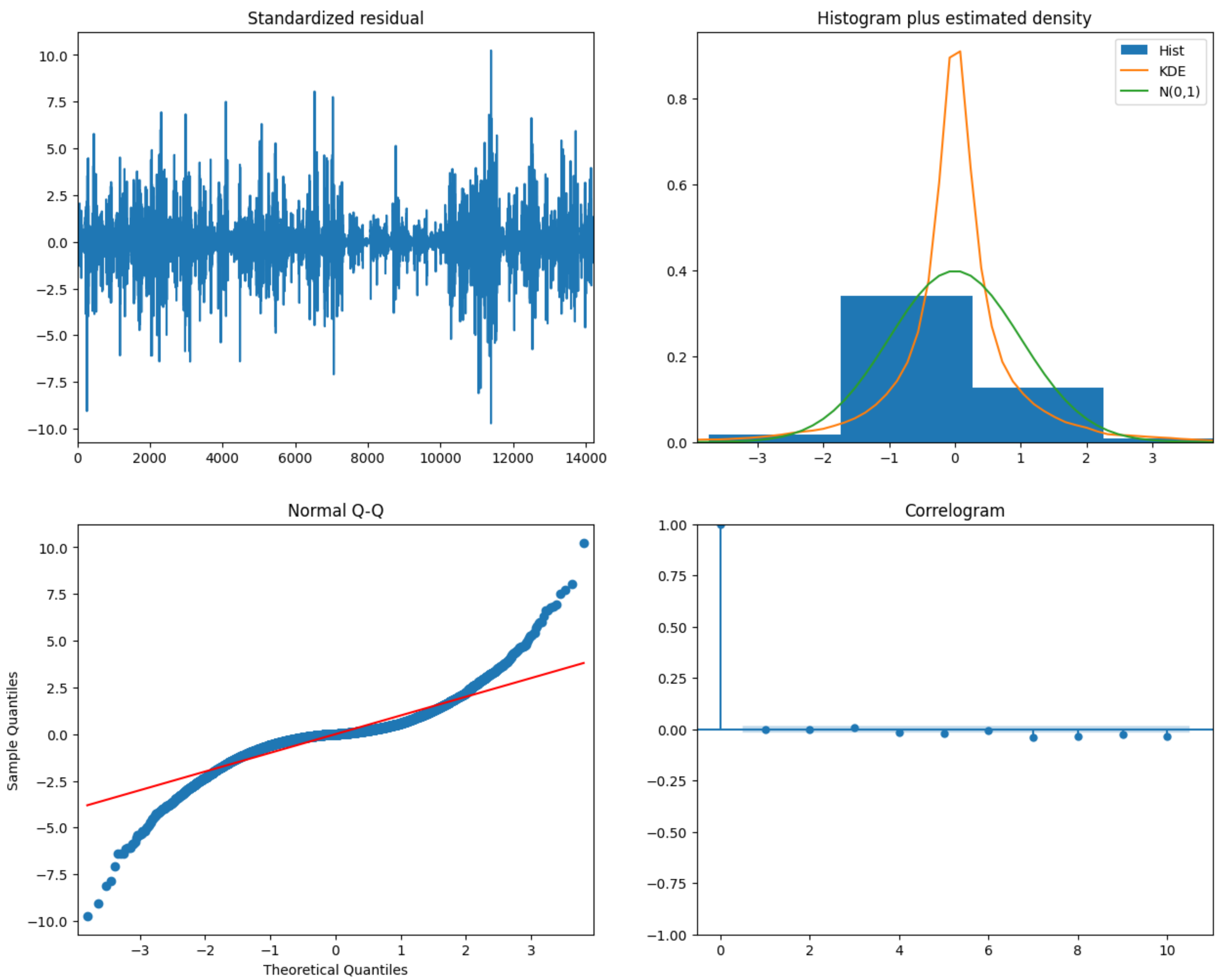

Figure 20: The ARIMA (2,1,2) diagnosis plots.

From the standardised residual plot, it can be seen that the residual does not represent uniform white noise, and some spikes are significantly larger than others. The residual histogram or the Q-Q plot does not either convey that the residuals are normally distributed. However, the Correlogram of the residuals shows no significant correlation between them and their lags. Although not perfect, the selected model performed the best based on AIC compared to the others tested.

One of the drawbacks of univariate forecast models of stochastic processes without any inherent seasonality is that they quickly revert to the mean if no new information is provided.
This is illustrated in the following graph, where the model exclusively relies on the training data and iteratively utilises its past predictions for future predictions without incorporating any new data. As can be seen, the forecast reverts quite quickly to the mean, and the accuracy suffers significantly.

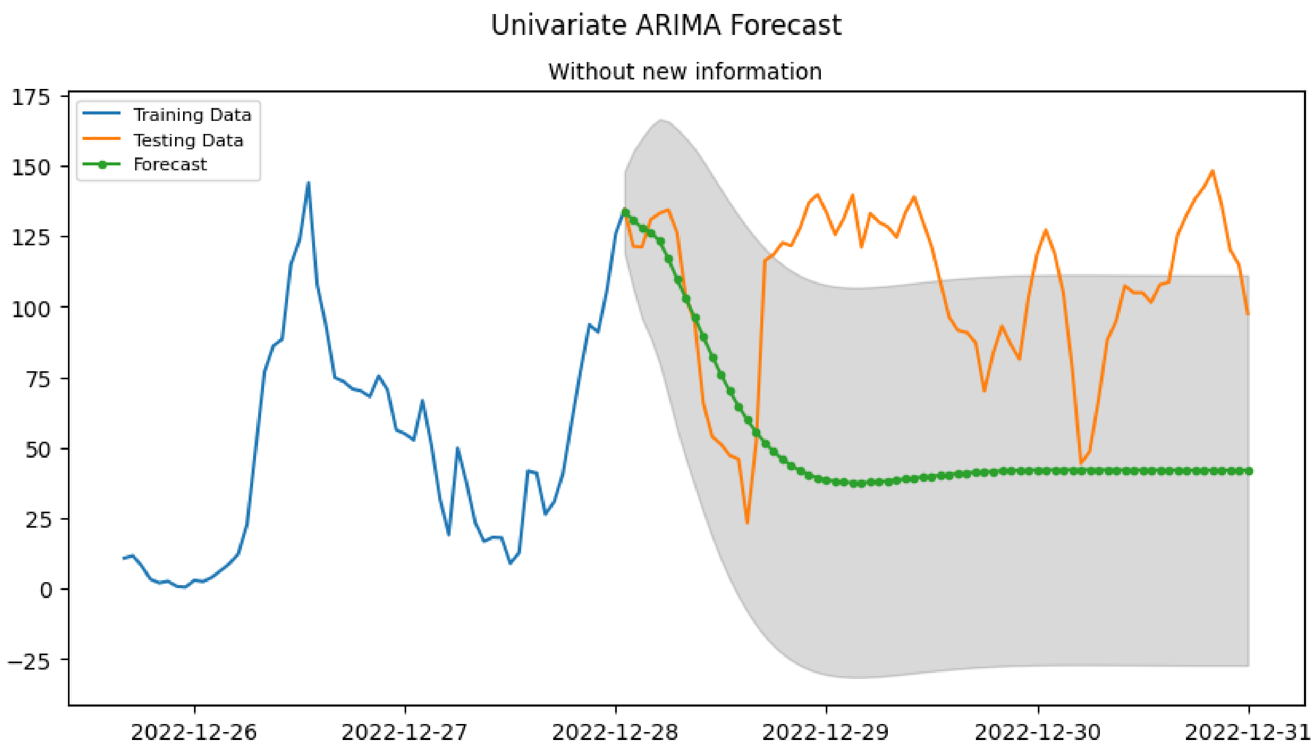

Figure 21: Illustration of the "lack of new information" problem.

To address this problem, it is often recommended to use ARIMA models for very short predictions of up to 1-2 periods ahead. The LSTM neural network also suffers from the same effect if no new information is provided to the network. To solve this problem, I decided to perform only one-step-ahead predictions for the time series models, and after every prediction, the models were updated with the true generation value of that time step.

For the LSTM network, I chose the following network architecture after initially creating a larger and more complex architecture and then gradually shrinking it to the smallest achievable without suffering any significant accuracy loss.

Sample 1		
Time "t"	X - value	y - target
t-10	19	
t-9	18	
t-8	18	
t-7	20	
t-6	25	
t-5	22	
t-4	20	
t-3	30	
t-2	38	
t-1	40	
t		44

Sample 2		
Time "t"	X - value	y - target
t-10	18	
t-9	18	
t-8	20	
t-7	25	
t-6	22	
t-5	20	
t-4	30	
t-3	38	
t-2	40	
t-1	44	
t		45

Figure 22: Visual representation of the 3D tensors.

The model's input is a 3D tensor with 10 past values of the target value to mimic the ARIMA model, which also predicts one timestep into the future. After the input layer, there is an LSTM layer with 16 units, representing the hidden states and output vectors of the LSTM cell. The default tanh function was used as the activation function.

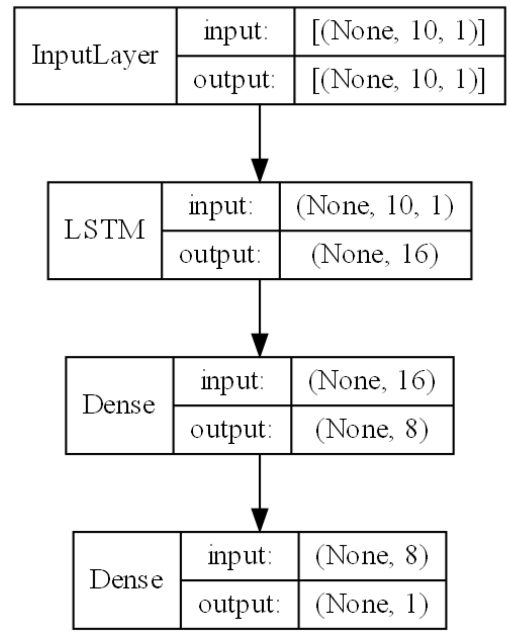

Figure 23: Visual representation of the univariate LSTM model architecture.

After the LSTM layer, a fully connected dense layer with 8 neurons was added to the neural network to facilitate convergence and potentially prevent overfitting. The Rectified Linear Unit (ReLU) was used as the activation function for this layer. ReLU outputs a linear line, but any negative input is returned as 0.

The final layer of the neural network is an output layer consisting of a single neuron. This layer serves as the regression layer and its output represents the result of the regression performed by the network. A linear activation function was applied to this layer, allowing the network to output any number as the result of the regression. As an optimiser for the model, Adam was used, which is an extended version of the stochastic gradient descent and is popular in various neural networks. The final chosen LSTM model had a total of 1297 trainable parameters. Trainable parameters are quite a common universal measurement of the size of a neural network.

Univariate Modelling Results

Due to the linear nature of the regression, there was a possibility that the regression would return negative results. However, because the target variable, Onshore Wind Generation, cannot be negative, all the negative values in the results were changed to 0, meaning there was no power generation.

Table 3: The Univariate modelling results

Model	Mean Squared Error	Root Mean Squared Error	Mean Absolute Error
Persistence model	62.78	7.92	4.98
ARIMA model	54.95	7.41	4.63
LSTM model	53.14	7.29	4.67

Both the ARIMA and the LSTM models performed very similarly in the task of predicting one timestep ahead. The simplest Persistence model performed surprisingly well, with an RMSE of 7.92, only a tad worse than the other models. This result indicates that wind generation is highly correlated with the previous value. The RMSE of the ARIMA models was 7.41 while the LSTM model had an RMSE of 7.29. On average, both models were off the actual value by an absolute value of approximately 4.6 MWh. Considering the 34 MWh average onshore wind production in Tønder, both models were off by approximately 13.5%. The true value was captured 93.88% within the AIRMA model's 95% confidence interval, which is a promising indicator that the model was properly configured.

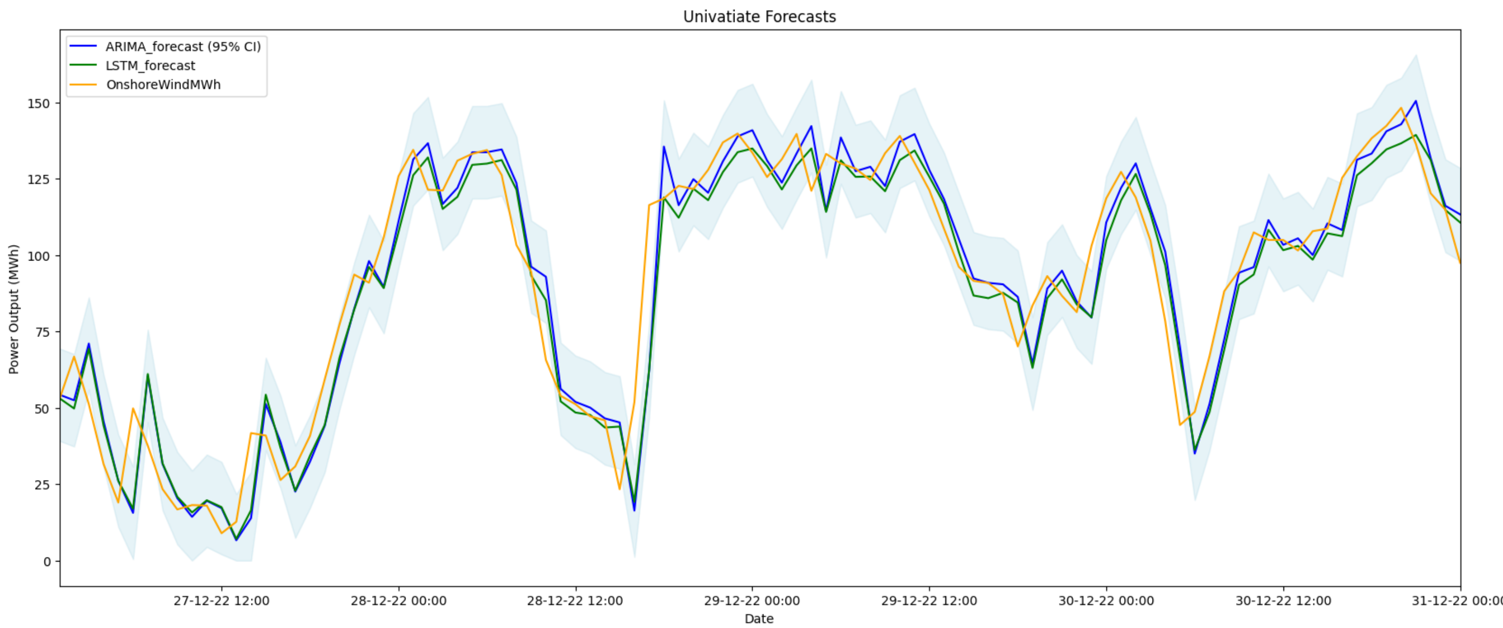

Figure 24: Visualisation of the last four days of testing data.

The models were tested on approximately five months of data, but I have chosen to only visualise the last four days or so to keep the charts clean and readable. The last four days were a good choice for this because there was a varying amount of onshore wind generation, with some highs, lows and quick changes which were typical for the whole testing period.

From the results graph, it can be seen that the two models were very close to each other in their predictions, usually lagging slightly behind the actual value, as expected. The largest deviations from the true value occurred when there was a rapid change in the value, as can be seen when the power generation quickly decreased.

Multivariate Modelling

In multivariate modelling, various methodologies can be explored. The initial approach mirrors univariate modelling, relying solely on historical data to forecast a single step into the future, akin to univariate models. However, in this case, my intention was to examine whether incorporating additional exogenous variables could enhance the forecast compared to the univariate models. By introducing more information into the model, the aim was to assess whether these exogenous variables could improve the accuracy and reliability of predictions.

As exogenic variables, the Mean Wind Speed, Mean Wind Direction, Mean Pressure and Mean Temperature were chosen, because these had the highest absolute correlation with the target variable Onshore Wind Generation. All three variables are commonly obtainable in weather forecasts, meaning that all the models used in this thesis could theoretically be adapted to use real weather forecasts instead of the averaged past weather observations. In similar research to mine, Xie et al. (2021) also used the Pearson correlation value to select external variables for a multivariable LSTM model for windspeed prediction, although they had different exogenic variables available.

Variable	Correlation with OnshoreWindMWh
mean_wind_speed	0.919332
mean_wind_dir	0.178897
mean_temp_dry	-0.077401
mean_pressure	-0.349136

Figure 25: The Pearson correlations of the exogenic variables.

```
                               ARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                15167
Model:                ARIMAX(1, 0, 3)   Log Likelihood              -52403.854
Date:                Sat, 29 Apr 2023   AIC                         104825.709
Time:                        12:19:29   BIC                         104894.351
Sample:                             0   HQIC                        104848.471
                              - 15167
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
x1             1.9777      0.091     21.688      0.000       1.799       2.156
x2            -0.0093      0.003     -2.878      0.004      -0.016      -0.003
x3             0.0152      0.003      5.922      0.000       0.010       0.020
x4             1.0488      0.061     17.128      0.000       0.929       1.169
ar.L1          0.9546      0.003    362.449      0.000       0.949       0.960
ma.L1          0.2499      0.006     42.426      0.000       0.238       0.261
ma.L2          0.0157      0.006      2.807      0.005       0.005       0.027
ma.L3          0.0316      0.005      6.196      0.000       0.022       0.042
sigma2        58.2104      0.315    184.610      0.000      57.592      58.828
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):              46869.87
Prob(Q):                              0.94   Prob(JB):                          0.00
Heteroskedasticity (H):               1.23   Skew:                              0.30
Prob(H) (two-sided):                  0.00   Kurtosis:                         11.59
===================================================================================
```

Figure 26: The multivariate ARIMAX model coefficient.

As with the univariate model, the *pmdariam* package was used to determine the best-fitting model based on the AIC score. From the model summary, we can see that all the exogenic variables have a statistically significant impact on the model with P-values of 0.05 or below. From the model summary, we can also see that the optimal AIRMA parameters are one autoregressive part and three moving average parts. Similar to the univariate modelling, I chose to update the parameters of the models after each timestep prediction to avoid the lack of information problem.

For the LSTM model, I decided to increase the size of the model to capture the complexities from the larger input data more accurately. The data was otherwise similarly structured as in the univariate model, except that instead of inputting one feature, I used five: the previous power generation value plus the exogenic variables. Overall, the model was approximately five times larger than the univariate model, with 5409 trainable parameters.

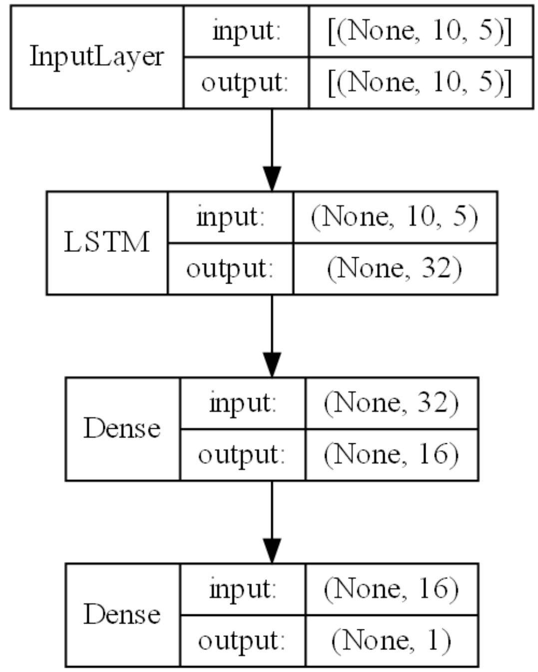

Figure 27: The Multivariate LSTM model architecture.

Multivariate Modelling Results

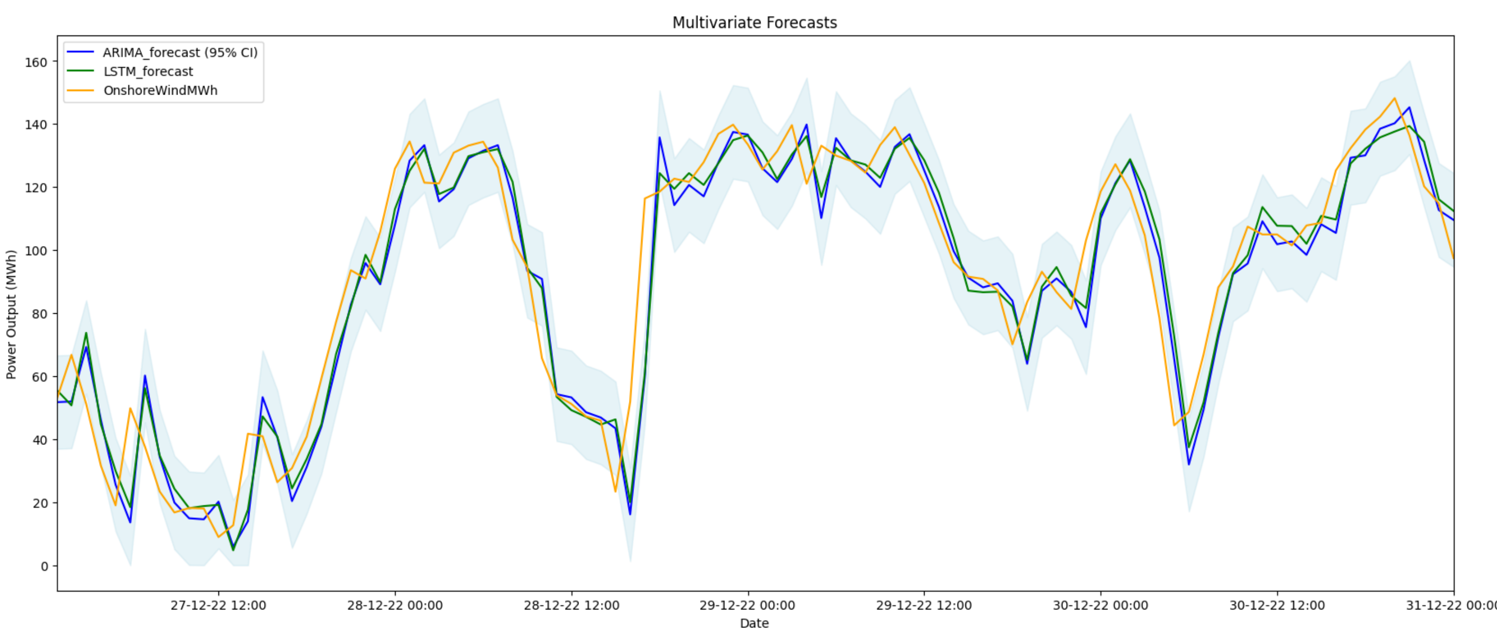

Figure 28: The Multivariate results.

Table 4: The Multivariate modelling results

Model	Mean Squared Error	Root Mean Squared Error	Mean Absolute Error
ARIMA model	53.19	7.29	4.71
LSTM model	55.82	7.47	4.82

When adding additional variables to the models, I saw a slight increase in the accuracy of the autoregressive model, whereas the neural network model showed a slight decrease in accuracy compared to the univariate model.

One explanation is that the additional variables did not provide any additional information for the models to work on or the fact that the RMSE around 7 is already close to the top of the possible accuracy with the available data.

Regression Modelling

Another approach to the forecasting problem is to look at it from a regression point of view, where one uses the predictions from the independent variables to find a relationship with the dependent variable. In the context of this thesis, one could imagine it as having numerical weather predictions for the future and wanting to know the future renewable generation based on the NWP values. This approach does not use the past generation data and thus doesn’t either capture any autoregressive properties in the dependent variable.

As a baseline for the regression model, I chose the Ordinary Least Squares (OLS) multiple linear regression. OLS multiple linear regression attempts to find the best fit by minimising the sum of the squared errors (SSE) between the predicted and actual values of the dependent variable. Specifically, OLS estimates the regression coefficients that produce the minimum SSE over the whole dataset. OLS estimates the regression coefficients that minimise the SSE using a mathematical formula that involves the independent and dependent variables. The resulting equation can then be used to predict the dependent variable based on the values of the independent variables. (Bowerman, O'Connell, & Koehler, 2005)

In the OLS model, the averaged weather data for time t were used to predict the generation of time t, simulating that the weather data would also be used similarly to NWP.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:         OnshoreWindMWh   R-squared:                       0.868
Model:                            OLS   Adj. R-squared:                  0.868
Method:                 Least Squares   F-statistic:                 2.485e+04
Date:                Mon, 17 Apr 2023   Prob (F-statistic):               0.00
Time:                        16:00:29   Log-Likelihood:                -60502.
No. Observations:               15168   AIC:                         1.210e+05
Df Residuals:                   15163   BIC:                         1.211e+05
Df Model:                           4
Covariance Type:            nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
const              41.9769     10.466      4.011      0.000      21.461      62.492
mean_wind_speed    12.4453      0.044    282.883      0.000      12.359      12.532
mean_wind_dir      -0.0447      0.001    -31.839      0.000      -0.047      -0.042
mean_pressure      -0.0602      0.010     -5.853      0.000      -0.080      -0.040
mean_temp_dry      -0.4923      0.017    -29.089      0.000      -0.525      -0.459
==============================================================================
Omnibus:                     1834.765   Durbin-Watson:                   0.304
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            20122.013
Skew:                          -0.058   Prob(JB):                         0.00
Kurtosis:                       8.641   Cond. No.                     1.02e+05
==============================================================================
```

Figure 29: The OLS model coefficients.

For the OLS model fit, we can see that wind speed has the largest effect on the dependent variable; however, all the other variables are statistically significant as well, with p-values near 0. The OLS model had an R2 score of 0.868, indicating a decent overall fit, and the F-statistic was also close to 0, indicating that the independent variables together had a statistically significant effect on the dependent variable.

The LSTM model employed for the regression approach had a nearly identical architecture to the time series models, with one key distinction being the exclusion of past power generation values from the input data. Instead, the model utilised real-time values along with the 10 previous values of weather data as inputs. This can be seen in the input shape which was (11,4) 11 timesteps and 4 features. The LSTM model had a total of 5281 trainable parameters.

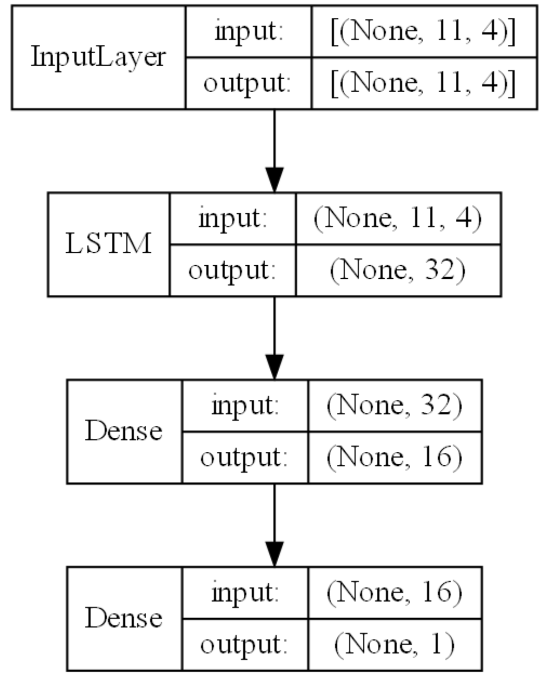

Figure 30: The regression LSTM model architecture.

Regression Modelling Results

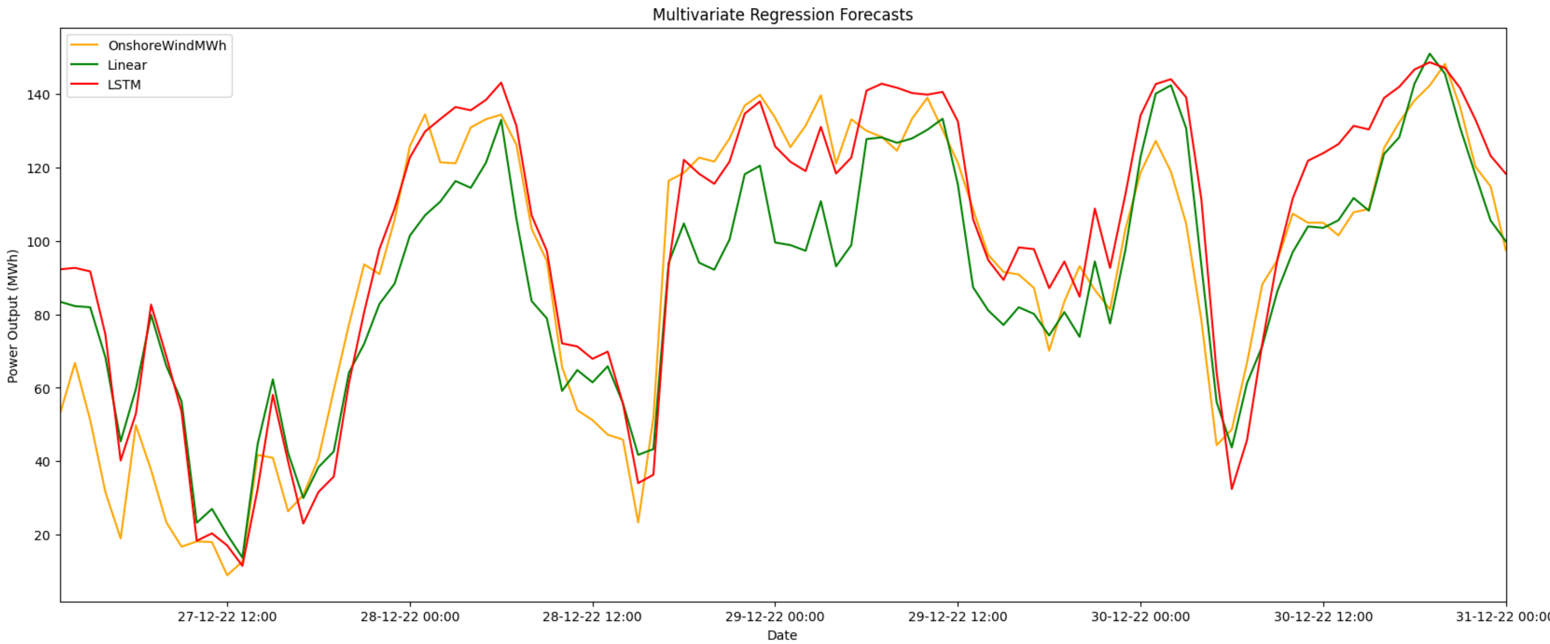

Figure 31: The Regression modelling results.

Table 5: The Regression modelling results

Model	Mean Squared Error	Root Mean Squared Error	Mean Absolute Error
OLS model	190,93	13,82	9,89
LSTM model	144,97	12,04	8,29

Compared to the time series models, with the past generation values, both models performed worse despite the availability of real-time weather data. The RMSE for the models was approximately 12 MWh for the LSTM model, and 14 MWh for the OLS model. The result that the LSTM outperformed the OSL model was not surprising considering that the OLS only models linear relationships, while the LSTM model can incorporate non-linear relationships as well. However, it was surprising to see both from the metric results as well as the visual results that the OLS model was still able to predict the true values fairly well, and even outperformed the LSTM a couple of times, as can be seen in the last 12 hours of the chart.

Hybrid Modelling

The last modelling approach I will touch upon in this thesis is a combination of time series models and regression models, having real-time weather data as well as the past generation values to incorporate into the model. In this way, one might be able to capture the autoregressive characteristics of wind power generation, as well as having current weather variables to use. As with the previous ARIMA models, the best-fitting model was selected based on the AIC score, and this time, an ARIMAX (3,0,0) model with three autoregressive parts was selected.

```
                                ARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                15168
Model:                 ARIMAX(3, 0, 0)   Log Likelihood              -50058.268
Date:                Thu, 11 May 2023   AIC                         100132.537
Time:                        16:33:32   BIC                         100193.552
Sample:                             0   HQIC                        100152.770
                              - 15168
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
x1             8.3939      0.051    163.422      0.000       8.293       8.495
x2            -0.0175      0.003     -6.306      0.000      -0.023      -0.012
x3            -0.0044      0.001     -3.616      0.000      -0.007      -0.002
x4            -0.2594      0.077     -3.384      0.001      -0.410      -0.109
ar.L1          0.9965      0.005    199.643      0.000       0.987       1.006
ar.L2         -0.1138      0.006    -17.808      0.000      -0.126      -0.101
ar.L3          0.0365      0.005      7.707      0.000       0.027       0.046
sigma2        42.9968      0.261    164.452      0.000      42.484      43.509
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):             29489.10
Prob(Q):                              0.99   Prob(JB):                         0.00
Heteroskedasticity (H):               1.19   Skew:                             0.25
Prob(H) (two-sided):                  0.00   Kurtosis:                         9.81
===================================================================================
```

Figure 32: The Hybrid model ARIMAX coefficient.

Similarly, to the ARIMAX model using past data, all exogenous variables were found to be statistically significant based on their p-values.

For the LSTM model, I added 10 past generation values to the input data, making the shape (11,14), 10 timesteps back, 14 features of which 4 were the real-time exogenous weather variables, and 10 past generation variables. Otherwise, the model architecture was kept similar to the others, with 6561 trainable parameters. I experimented with some more complex models, such as stacking two LSTM units after one another and increasing the size of the units, but this did not result in any significant increase in accuracy.

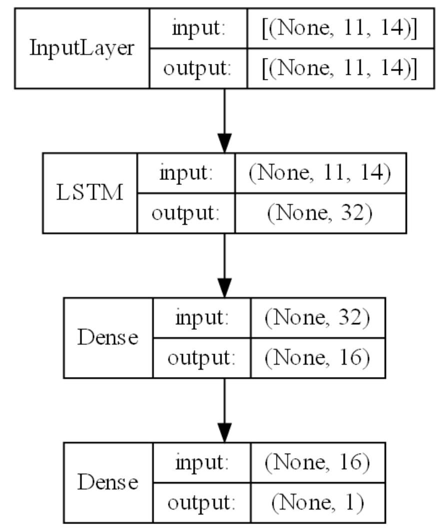

Figure 33: The Hybrid model LSTM architecture.

Hybrid Modelling Results

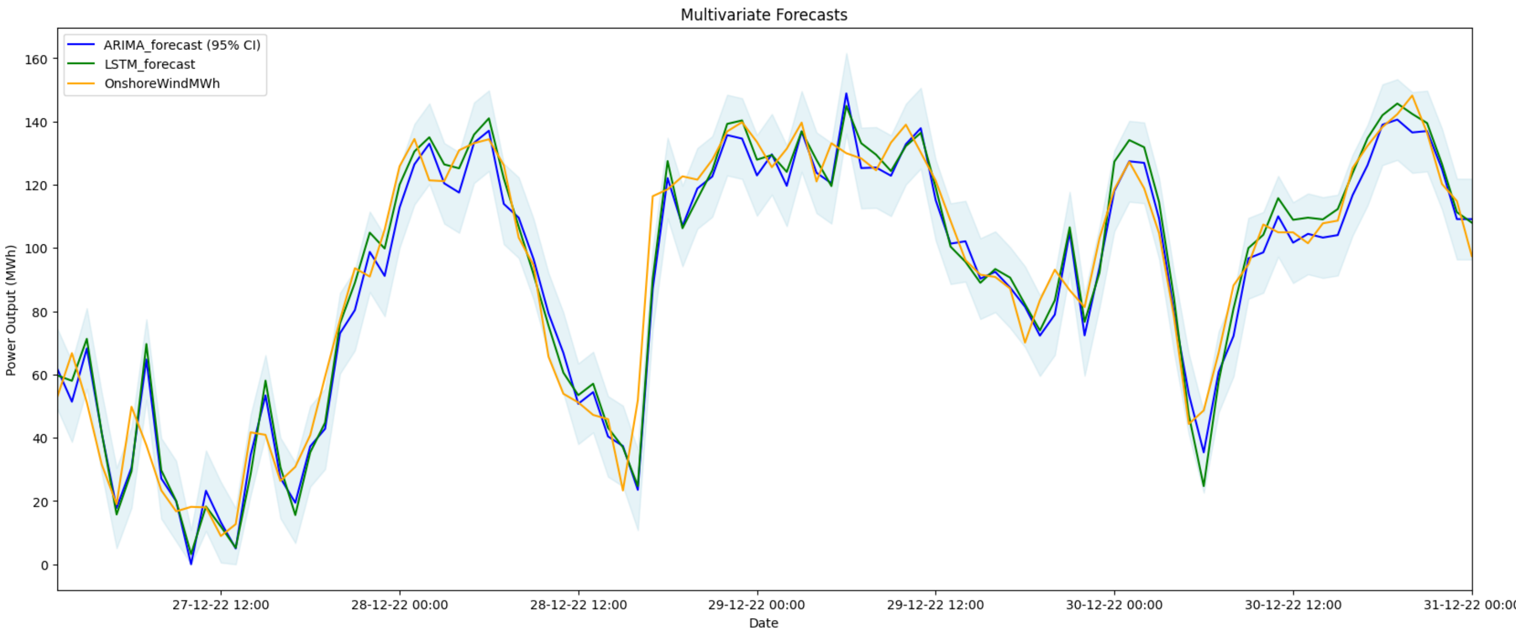

Figure 34: The Hybrid model results.

Table 6: The Hybrid modelling results

Model	Mean Squared Error	Root Mean Squared Error	Mean Absolute Error
ARIMAX model	38,93	6,24	4,33
LSTM model	34,03	5,83	4,02

From the visual as well as the numerical results, it can be seen that this modelling approach was the most accurate, only being off the true values of approximately 4 MWh MAE, which is less than 10% of the mean generation power. The hybrid model is most comparable to the multivariate time-series model in terms of methodology, with the key distinction being that the multivariate time-series models solely utilise past values as inputs. Compared to the multivariate time-series model, the hybrid approach ARIMAX model saw a 14.4% increase, and the LSTM model saw a 22% improvement in the RMSE accuracy when real-time weather variables were added. The 95% confidence interval in the hybrid model was also 13.4% smaller than the time-series result.

Results and Discussion

Table 7: Summary table of the modelling results

Approach	Model	Mean Squared Error	Root Mean Squared Error	Mean Absolute Error
Univariate Time Series				
	Persistence model	62.78	7.92	4.98
	ARIMA model	54,95	7,41	4.63
	LSTM model	53.14	7.29	4.67
Multivariate Time Series				
	ARIMAX model	53.19	7.29	4.71
	LSTM model	55.82	7.47	4.82
Regression				
	OLS model	190.93	13.82	9.89
	LSTM model	144.97	12.04	8.29
Hybrid models				
	ARIMAX model	38.93	6.24	4.33
	LSTM model	34.03	5.83	4.02

The summary table of the results reveals that most of the modelling approaches produced very similar outcomes. However, the regression approach stood out as an outlier, with a nearly 90% increase in the RMSE compared to the other models. One important thing to note is that the regression model did not incorporate previous true generation values when making the predictions.

Taking these results into account and recognising the great performance of the simple Persistence model, it can be concluded that the autoregressive component plays a central role in accurately predicting short-term wind generation within a limited prediction horizon. The inclusion of the autoregressive element allows for the capture of the inherent internal patterns and dependencies in wind generation data.

In addition, it is noteworthy that all models, except the regression models, outperformed the simplest Persistence model. This suggests that increasing the complexity of the models led to a better representation of the complexities within wind generation, which the Persistence model could not fully capture. Therefore, incorporating more sophisticated models becomes crucial for effectively modelling and predicting wind generation dynamics.

Both the univariate and multivariate time series models' performance was very similar, with the ARIMAX benefiting slightly from the extra exogenous variables, and the LSTM performing slightly worse. However, the differences are quite small and can feasibly be explained by the stochastic nature of the optimisation algorithms used in both the ARIMA and LSTM models. As mentioned earlier, accurately predicting the stochastic nature of wind generation solely based on past values is quite challenging. This difficulty is underscored by the fact that the Persistence model performed nearly as accurately as the other time series models.

In my research, I found some advantages and disadvantages of the ARIMA and LSTM models. The ARIMA and ARIMAX models were quite easy to structure and train on the training data, with only slight data manipulation required to make the models work. With regard to backtesting the ARIMA and ARIMAX models on the testing set, which comprises approximately 3800 data points, there's a notable increase in computational requirements. This is primarily attributed to the model's need for incremental parameter updates after each prediction. It's important to note that iterative updating is a highly sequential process, and its efficiency cannot be enhanced through parallelisation, unlike the training of the neural networks used in this thesis.

The ARIMA and ARIMAX models' output encompasses not only the prediction itself but also includes the critical 95% confidence interval. This interval plays a crucial role in gauging the model's confidence level in the prediction, making it an integral part of the evaluation process.

The LSTM models required considerably more data preparation than the ARIMA models, as one needed to reshape the tabular data into 3D tensor blocks to train the model on. The *Keras* Python package, built upon TensorFlow, made it easy and intuitive to build the ANN models. In building the ANN models, I added the functionality that the model was updated by a small amount after each prediction to gain some insight from the newer data, akin to the ARIMA models. Surprisingly, I tended to obtain better results when not updating the model and running the entire test set through the original model trained only on the training set. This also drastically reduced the time required to backtest the models, as all the testing data could be run through the model at once. The LSTM models, while often producing more accurate results, only output the prediction and no confidence interval. Methods do exist for generating prediction or confidence intervals using neural networks, but these require considerable alteration of the original models, such as adding several networks or working with Bayesian statistics (Khosravi et al., 2011).

The Regression approach distinguishes itself from the rest primarily in terms of accuracy, as it solely depends on the correlation between weather variables and power generation, without taking into account the autocorrelation within the generation data. This might seem like a drawback, but it comes with the added advantage of being independent of the sequential nature of wind power and can therefore be easily adapted on longer timescales. However, the pure regression model is highly dependent on the accuracy of the weather data. Any errors present in the NWP data can propagate through and can be amplified in the power prediction.

The hybrid model, which combines the autoregressive nature of wind power with real-time weather data, was shown to be highly effective in this research, surpassing other models by a significant margin. This approach offers the advantages of both autoregressive and regression models and has the potential to deliver more accurate results. However, it is important to note that this model is not immune to errors in wind prediction, which can affect its overall accuracy.

Furthermore, when used for longer time horizons, errors in the initial wind prediction can propagate forward and magnify because the prediction is used as an input for subsequent calculations in the model, which is also known as the propagation of errors.

Elsaraiti & Merabet (2021) found in their study on predicting wind speeds using univariate ARIMA and LSTM models that the LSTM model saw a lower RMSE than the ARIMA model by approximately 8%. While the exact error rates observed by Elsaraiti & Merabet (2021) are not directly comparable to my research, I can concur that the LSTM saw a lower RMSE than the ARIMA models, around 3% on average. Xie, Yang, Chen, Sheng, & Zhang (2021) observed in their study on predicting wind speed one hour ahead, that a multivariate LSTM model, using temperature, pressure, and humidity as external variables outperformed their univariate ARIMA, and LSTM models by around 5-8% lower RMSE. The researchers used past meteorological values, which corresponds to the multivariate time series approach in my study. I, however, did not see an improvement in the performance of the LSTM model when using additional external past variables. Xie et al. (2021) also note that they saw the highest errors when the wind changes rapidly, this phenomenon can also be seen in my study. In a study by Tiboaca, Costinas, & Radan (2021), where they used different kinds of regression algorithms to find the relationship between wind power production and a set of weather variables, they achieved an accuracy with OLS of around 10.72MWh RMSE. This is significantly better than my regression approach, however Tiboaca, Costinas, & Radan (2021) utilised data gathered from a much smaller geographical area, and different weather variables than me, for example, windspeed measurements from different heights and wind gusts. Interestingly, if you compare their results with my multivariate time series ARIMAX model, which is a dynamic regression model, utilising past values of the dependent variable as well as past external variables, we see an accuracy of 7.29 MWh RMSE, which is significantly better than their result. This further emphasises the autoregressive nature of wind power production, and why it is important to implement it in forecast models.

The VTT Technical Research Centre of Finland published a report on wind forecasting errors in Finland, where they calculated the error of an area using the following equation:

Equation 8: Equation of the VTT wind forecasting errors

$$\frac{\text{MAE}}{\text{Total Installed Capacity}}$$

Holttinen, Miettinen, & Sillanpää (2013) calculated that the 1-hour ahead forecast had an error rate between 4-6% MAE divided by Total Installed Capacity depending on the observed area. Note that the areas observed in this report were substantially larger than the area worked with in this thesis. When calculating the equivalent metric for the worst-performing Persistence model, using the installed capacity of 176 MW, an error of 2.83% was achieved. For the best-performing hybrid model, an error of 2.28% was achieved. It is also important to mention that the VTT report calculated the errors on observed areas, that had substantially lower generation capacities than the aggregated municipality area I used.

In this thesis, I have examined various models employed for wind power prediction. As mentioned earlier, a wide array of model types and their variations exist. Based on my research, the prevailing approaches incorporate frequency decomposition and transformation techniques, such as Wavelet or Fourier transformations, on the wind speed variable prior to its integration into the models. This facilitates the capture of wind speed frequencies (Madsen, 2023). Hanifi et al. (2020) advocates for the use of Kalman filtering algorithms for reducing uncertainty in and eliminating systematic errors in the NWP data before it's used for wind power forecasting. Another suggested data preparation method is outlier removal, where extreme values are removed from the data before prediction.

Moreover, a multitude of data preparation steps are essential for producing accurate results, especially when extending the time horizon. The models commonly employed are designed for individual wind turbines or entire wind farms. Single turbine models leverage the specific power curve of the turbine to precisely estimate power output at given wind speeds and directions.

Real-world wind generation models often integrate diverse weather forecasts from various providers to obtain a spectrum of potential forecasts. This enables the creation of more precise prediction intervals or confidence intervals for generation forecasts (Madsen, 2023).

According to Professor Henrik Madsen from the Department of Applied Mathematics and Computer Science at the Technical University of Denmark, an expert in the area of wind power forecasting, many types of wind generation forecasts are used today. Some of the most common are probabilistic forecasts that provide a range of possible forecast outcomes and their respective probabilities. These types of forecasts are often preferred by electricity market participants as they can be used to optimise the profit for the company (Madsen, 2023). As the electricity market is set up in a way that large errors in production forecasts are penalised for the producer, it is often useful to underestimate the forecasted generation to avoid penalties if the actual generation falls short of the forecasted generation. This is because the penalties are often asymmetrical, and a shortfall in production is penalised more than a surplus in production (Madsen, 2023).

Many prominent people in the renewable energy space have a consensus that one of the largest hurdles for the green energy transition is the need for more flexibility on both the supply and demand sides. This is because of the fundamental intermittency of today's renewable energy sources. Not only is there a need to find flexibility from different sources, but there is also a need to find flexibility in spatial and temporal plains (Kondziella & Bruckner, 2016).

Supply-side generation flexibility mainly originates from traditional combustion and hydroelectricity power plants, where the generation can be controlled to a high degree. Of these, hydropower is considered the best option, but it is quite geographically limited, and the potential new locations for hydroelectric plants are limited. In the combustion category, biomass power generation is considered the best, as it has lower GHG emissions compared to fossil-fuel plants. However, biomass also comes with drawbacks, including the substantial need for pre-processing of the biomass before combustion (Kondziella & Bruckner, 2016). The need for increasing flexibility also takes centre stage in the Finnish government's national climate and energy strategy for 2035, where an increase in digitalisation and market participation is highly sought after to allow more participants to economically benefit from their flexibility (Ministry of Economic Affairs and Employment of Finland, 2022).

As mentioned earlier, demand-side flexibility in today's market is predominantly managed by large industrial electricity consumers who possess the capability to temporarily reduce their production to ease the burden on the electricity grid. Some demand aggregators have also gained traction lately for facilitating smaller consumers to also participate in the electricity markets with their flexibility (Fingrid Oyj, 2023).

Finally, some methods combine both the demand and supply sides of the equation. Of these, pumped hydro storage is the most established, in which excess or cheap electricity is consumed to pump water to a body of water at a higher elevation. This process can later be reversed to function as a normal hydroelectric power plant. Some new ideas, such as power-to-gas or compressed-air systems, are also being explored and developed (Kondziella & Bruckner, 2016).

Currently, existing flexibility in the market is primarily incentivised through the balance and reserve markets, which are administered by national TSOs. In these markets, companies have the opportunity to bid on contracts, either on the supply or demand side, to contribute to maintaining the stability of the electricity grid. Moreover, flexibility is also rewarded in the day-ahead and intraday markets, where participants can strategically withhold or offer additional supply or demand at a price that maximises their profits.

Flexibility is also needed on different time horizons, as renewable energy can have gaps of varying sizes in their production. Very short-term flexibility is going to increase substantially when the imbalance settlement period is decreased from one hour to fifteen minutes. This transition enables fine-grained supply-side flexibility, allowing for more precise adjustments. On the demand side, the shorter settlement period enables the participation of a larger number of market participants. Many consumers may have the ability to modify their demand for periods shorter than one hour, and this adjustment allows them to actively engage in the market directly or through an aggregator (Fingrid Oyj, 2022).

To allow the needed flexibility in the electricity infrastructure and markets, continuous improvement in renewable power prediction is needed to give the market participants the confidence to actively operate in the market. As the proportion of renewable energy increases in our national grids, so does the importance of accurate predictions as well. Hanafi et al. (2020) highlight the importance of using more accurate and numerous NWP data in the prediction models. They also advocate for the adoption of newer hybrid approaches, that incorporate traditional statistical models with modern neural network variants, to enhance predictive accuracy. With a high proportion of renewables powering the grid, any large errors in the generation predictions can cause significant instability and a potential need for load shedding. Thankfully, the TSOs are highly aware of the risk brought on by the increased renewable integration and can plan accordingly, using a variety of tools, including reserve procurement, that they have at their disposal.

Conclusions

In conceptualising this thesis, my primary objectives were to enhance my understanding of the electricity market and to effectively communicate this knowledge to the reader. This stemmed from a recognition of the significant impact that renewables and the 2022 energy crisis had on electricity prices. Additionally, I aimed to refine my data analysis skills, making it a natural progression to delve into the predictability of renewable energy. This area is particularly noteworthy in the energy sector, where analytics and machine learning play a pivotal role.

Thanks to an abundance of information from national TSOs and various other sources, consolidating data on electricity markets and their functionalities into a unified package was a relatively straightforward process. Given the contemporary importance of climate change, many of these sources already approached the grid with a focus on the increasing adoption of renewable energy sources.

The primary lessons drawn from the integration of renewable energy into our national electricity grids underscore the critical need for increasing flexibility in both consumption and production. On the consumption side, flexibility can come in the form of integrating smart homes and buildings into the grid. On the production side, extra generation can come when needed from increased energy storage solutions. Energy storage has emerged as a pivotal advancement in the energy market, encompassing traditional sources like pumped hydro and newer hydrogen-based technologies. To facilitate the needed flexibility the electricity infrastructure and markets also must continually improve, allowing more participants to join the free market, and thus incentivising and enabling the green transition towards a more sustainable energy system.

For the empirical part of this thesis, I originally imagined using actual weather forecasts to build the predictive models on. This however did not materialise, due to the lack of available historical forecasts to use, and current forecast would have been difficult to adapt to models trained on historical weather data. Most of the existing theory and research in the area of wind power prediction, also used custom datasets, with much higher data resolution and more accurate geographic areas than I had available. Because of these limitations I had to invent my own direction, testing different modelling approaches and models on the data available, and assessing the models' strengths and weaknesses.

Despite the data I utilised having quite a bit worse resolution than comparable research, one could still observe the general tendencies of more complex models outperforming simpler models. One improvement I could have implemented was normalising the data before training the machine learning models as data normalisation has shown in research to benefit the training of for example Neural Networks, because the input variables are squashed to a specific range, and thus simultaneously reducing the impact of outliers.

From the empirical part of the thesis, the most important lesson is perhaps the fact that a problem can have multiple approaches one can take in solving it, and all of the approaches come with their own advantages and drawbacks. One of the lessons I personally learned is that although the most complex models might result in the highest accuracy, it is not always advisable to spend an ever-increasing amount of time chasing marginal improvements in accuracy, when most problems in machine learning are inherently unsolvable, due to the stochastic nature of the world.

In closing, I hope the reader of this thesis has gained some knowledge and insight into the workings of the electricity market and its challenges as well as its opportunities moving forward. I also hope I was able to open the door to some of the methodologies and approaches when it comes to forecasting time series. By honing our ability to accurately predict and incorporate renewable energy sources into the grid, we are not only reducing our reliance on fossil fuels but also paving the way for a future powered by clean, renewable resources. This shift promises not only environmental benefits but also economic advantages and increased energy security. Together, these efforts propel us towards a future where our energy needs are met with minimal impact on the planet, creating a more promising and resilient world for all.

Swedish Summary- Sammanfattning på svenska

De ambitiösa utsläppsmålen fastställda av EU-kommissionen kräver omfattande förändringar inom energisektorn. Denna sektor står för en betydande del av dagens utsläpp och har en betydande potential för avkarbonisering i jämförelse med andra sektorer som också har en stor klimatpåverkan (European Commission, 2011). I EU driver organisationen ENTOSE-E, som inkluderar alla EU-länders stamnätsoperatörer och ett antal operatörer från närliggande områden, en stor del av elsektorns utvecklingsarbete. ENTSOE-E hävdar att avkarboniseringen i det europeiska elnätverket ska ske genom bland annat genom utvidgningen av förnybara energikällor, som sol- och vindkraftverk (ENTSOE-E, 2022). Expansionen av förnybara energikällor i det nuvarande elnätet ytterligare betonar vikten av att kunna prognostisera den varierande elproduktionen på ett pålitligt sätt över flera tidshorisonter, eftersom vind- och solkraftverks elproduktion är helt och hållet väderberoende (Hanifi et al., 2020).

Examensarbetet är uppdelat i två delar; den första är en kartläggning av den nordiska elmarknaden ur ett förnybarhetsperspektiv. Den andra delen är en explorativ djupdykning i tillvägagångssätt och modeller som tillämpar sig för prediktion av vindkraft med hjälp av väderdata. I examensarbetet har jag använt offentligt tillgängliga data med avsikten att hitta för- och nackdelar med de olika tillvägagångsätten och modellerna som presenteras.

Fysikens lagar tvingar elproduktionen och elkonsumtionen att ständigt vara i balans. I Europa är frekvensen på elnätet 50hz och hela elsystemet har uppkommit och utvecklats runt denna inbyggda frekvensbegränsning. Om frekvensen skulle öka över eller falla under en viss tröskel skulle det orsaka stora skador i elnätet och leda till elavbrott för många människor. Elsystemets svängmassa bestämmer hur snabbt frekvensen ändras då produktionen och konsumtionen hamnar i obalans. I Norden har Finland, Sverige, Norge och östra Danmark kopplat sina elsystem till det sammanlänkade och synkroniserade nordiska elnätet genom gränsöverskridande sammankopplingar. Det hopslagna nordiska elsystemet tillåter större svängmassa i systemet och möjliggör en fri nordisk elmarknad, där aktörer som producerar samt aktörer som konsumerar fritt kan handla på marknaden (Fingrid Oyj, 2022). I praktiken betyder det att konsumenter är fria att konkurrensutsätta flera elproducenter då de ingår elavtal, och denna konkurrens sporrar producenterna att sänka sina priser. I största delen av världen är elöverföringen antingen statsägd eller starkt reglerad på grund av den naturliga monopolställningen som infrastrukturen ger (Fingrid Oyj, 2022).

Sammantaget är elmarknaden uppbyggd av förhandsmarknaden, där aktörer kan säkra priset på kommande produktion eller konsumtion genom olika terminskontrakt som sträcker sig från månader till år i framtiden. Sedan kommer dagen före-marknaden, där största delen av elhandeln äger rum. Dagen före-marknaden fungerar genom en daglig auktion, där det sista produktionsanbudet som överskrider de aggregerade konsumtionsanbuden ställer priset för elen i ett specifikt tidsintervall. För tillfället hålls auktionen för varje entimmesintervall under dygnet Figur 2 exemplifierar prissättningen på dagen före-marknaden. Handeln på dagen före-marknaden kan senare kompletteras och justeras på intradagsmarknaden, där direkta konsumtions- och produktionsanbud paras ihop ända till början av leveranstimmen. Komplettering och justering kan förekomma på grund av oförsedda förändringar i produktionen eller konsumtionen. Slutligen kommer reservmarknaden och balansmarknaden som upprätthålls av varje lands stamnätsoperatör för att säkerställa att tillräcklig upp-och nedregleringskapacitet finns tillgänglig om det skulle behövas och för balansräkningen efter elleveransen (Fingrid Oyj, 2022).

Elproduktionen i de nordiska länderna har under olika tider varierat relativt mycket från varandra, främst på grund av geografi och politik. Norge och Sverige har länge utnyttjat sina rikliga tillgångar av vattenkraftverk, medan Finland och Danmark har tvingats komplettera sin elproduktion med andra produktionsmedel. Finland och Sverige har introducerat en del kärnkraftverk i produktionsmixen, medan Danmark och Norge har satsat på vindkraftverk (Our World In Data, 2023). Tack vare sin stora produktionsförmåga har även Norge och Danmark haft möjlighet att exportera överloppsel till grannländerna, medan Finland och Danmark ofta varit importerande länder (Fingrid, 2023). ENTSOE-E:s mål är att bygga ut tillräckligt med överföringskapacitet mellan de europeiska länderna så att elpriset skulle bli enhetligt i stora delar av området (ENTSOE-E, 2022).

För både elinfrastrukturen och elmarknaderna kommer det att krävas förändringar för att uppfylla de krav som avkarboniseringen ställer. Gällande infrastrukturen intresset ökat för flera typer av el- och energibatterier, samt möjligheten att utnyttja väte i olika processer. Vätgas kan produceras genom elektrolys då det finns överflödig elproduktion. Dessa framsteg bygger på förmågan att noggrant kunna prediktera framtidens elproduktion, speciellt då den blir allt mera varierande och väderberoende (Hanifi et al., 2020). Beträffande elmarknaden går utvecklingen mot att öka flexibiliteten på marknaden samt att tillåta flera aktörer att delta, till exempel genom att slå ihop mindre konsumtionsställen (Fingrid Oyj, 2022).

När det gäller prediktion av vindenergi spelar prediktionshorisonten en stor roll i valet av prediktionsmodell. Det finns korta kontinuitetsmodeller (Persistence model), som antar att produktionen är den samma vid tidpunkt *t* som i tidpunkt *t-1*. På längre sikt används också klassiska tidsseriemodeller och slutligen komplexa artificiella neuronnät (Soman et al., 2010).

I examensarbetet använde jag mig av Box-Jenkins metodologi, som utforskar de statistiska sambanden inom en tidsserie och försökte genom dessa prediktera följande värde i sekvensen. Som modeller använde jag ARIMA-modellen som enbart utnyttjar tidigare värden av den beroende variabeln. Utöver det använde jag mig av ARIMAX-modellen som är en dynamisk regressionsmodell som använder externa exogena variabler i samband med den beroende variabeln för prediktionerna (Bowerman, O'Connell, & Koehler, 2005).

I undersökningen använde jag mig även av LSTM-neuronnät, som är en specialvariant av neuronnät som är specifikt utvecklat för att bearbeta längre sekvenser och kunna utnyttja information från en längre tid bakåt i sekvensen för nästa prediktion (Staudemeyer & Morris, 2019).

Jag använde modellerna för att utforska om tillagd extern väderinformation kan förbättra prediktionen för elproduktionen en timme framåt. Data jag använde var produktionsdata som aggregerades på kommunnivå och aggregerade väderdata från Danmark. Tillvägagångssätten jag utforskade var att enbart använda historiska produktionsdata, att använda historiska produktionsdata och historiska väderdata, att använda enbart externa väderdata och slutligen att använda historiska produktionsdata inklusive aktuella väderdata. I arbetet använde jag mig av historiska väderdata, men i verkligheten kunde man ersätta det med väderprognoser för att få prediktioner för framtiden.

Som förväntat presterade de mera komplicerade modellerna allmänt bättre i min undersökning. Resultaten är sammanfattade i tabell 7. Fördelen med Box–Jenkins ARIMA- och ARIMAX-modellerna är att de kräver relativt lite datamanipulation innan man matar in den i modellen. Modellerna anger även ett konfidensintervall utöver prediktionen, vilket indikerar hur säker modellen är på prediktionen. Fördelen med LSTM-modellerna är att de producerade allmänt noggrannare resultat jämfört med de andra modellerna. LSTM-modellen är även betydligt snabbare att köra än Box-Jenkins-modellerna, då man kan parallellisera tränandet och testandet av modellen medan Box-Jenkins-modellerna måste tränas och testas ett steg i taget.

I verkligheten används mycket mera komplicerade modeller i vindenergiprediktion, som ofta utnyttjar väderprognoser från ett flertal meteorologiska institut. Man måste dock notera att fel i väderprognoserna också tar sig igenom till elproduktionens prediktion. Modellerna som används i verkligheten är oftast också inriktade på att prediktera produktionen på mycket mindre geografiska områden (oftast enskilda vindturbiner- eller farmer) än vad min undersökning omfattade (Madsen, 2023).

Framtidens elsystem och elmarknad kommer att kräva mera flexibilitet från alla håll, då produktionen kommer att variera i högre grad. Det ökade kravet på flexibilitet medför att såväl producenter som konsumenter måste spela en mera aktiv roll i elsystemet - och genom den öppna elmarknaden kan aktörerna belönas för deras flexibilitet (Arbets- och näringsminiseriet, 2022). Tillsammans kan dessa insatser och förbättringar driva oss framåt i den gröna omställningen mot en mera miljövänlig energisektor och därmed en mera hållbar framtid.

Abbreviations in Text

ACF = Autocorrelation Function

AIC = Akaike Information Criterion

ANN = Artificial Neural Networks

AR = Autoregressive

ARIMA = Autoregressive Integrated Moving Average

BPTT = backpropagation through time

CHP = Combined heat and power generation plants

DMI = Danish Meteorological Institute

ENTSOE-E = The European Network of Transmission System Operators for Electricity

EU = European Union

FCR-D = Frequency Containment Reserve for Disturbances

FCR-N = Frequency Containment Reserve for Normal Operation

FFR = Fast Frequency Reserve

GHG = Greenhouse gas

LCOE = Levelized cost of electricity

LSTM = Long-Short Term Memory Neural Network

MA = Moving Average

MLM = Machine Learning Model

NPW = numerical weather prediction

OLS = Ordinary Least Squares Regression

PACF = Partial Autocorrelation Function

RNN = Recurrent Neural Networks

SMR = Small Modular Reactor

SSE = Sum of Squared Errors

TSO = Transmission system operator

aFRR = Automatic Frequency Restoration Reserve

mFRR = Manual Frequency Restoration Reserve

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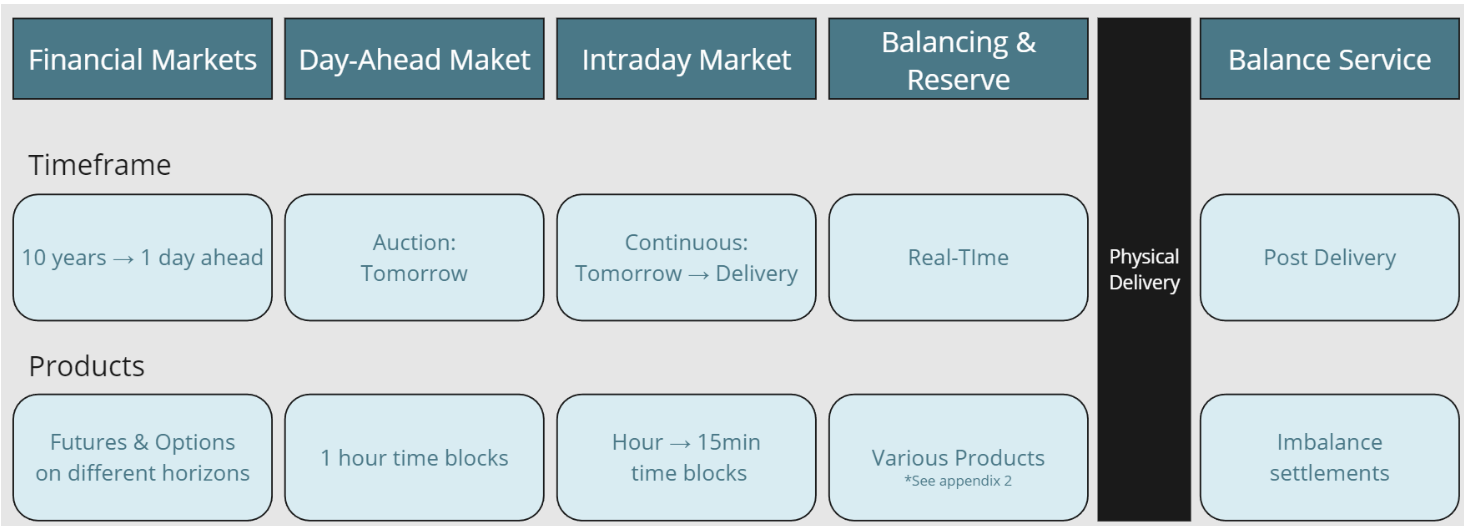
Appendices



Appendix 1: Summary of the Electricity Market

Source: https://www.fingrid.fi/sahkomarkkinat/markkinoiden-yhtenaisyys/johdanto-sahkomarkkinoihin/

Appendix 2: Summary of the Reserve Products

Source: https://www.fingridlehti.fi/en/lots-of-news-on-the-reserve-front/