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Estimating the Available Energy Flexibility

A case study of Helgeland

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Abstract

This thesis project was commissioned by Cegal and aimed to investigate the potential for demand-side flexibility in the Helgeland region, as well as evaluate forecasting methods for a demand-response system. The future energy situation in the area was analyzed, while the experimental part investigated forecasting methods which can be applied in a demand-response system. Finally, the project investigated the potential of a commercial building to provide demand side flexibility, analyzing the financial aspects of such participation.

The research findings indicate that the energy and load balance in the Helgeland region may decrease in the coming years, potentially leading to tight load balance conditions.

LSTM and XGBoost has been the investigated forecasting methods in this study, where both models showed promising results, though further improvements are recommended.

The commercial building investigated had the capacity to provide 23.87 KW flexibility, and the financial analysis suggested that the consumer would benefit from participating in a demand response system, depending on the needs of flexibility.

This thesis project contributes to the development of a demand-response system and highlights the areas for further research on forecasting methods and potential asset providers in the Helgeland region.

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Contents

List of Figures

List of Tables

1 Introduction

In this chapter, the background and significance of the thesis will be discussed. The problem statement will be highlighted, along with the importance of the project. Additionally, relevant theories and previous research related to the topic will be presented. A description of the project will be provided, along with theories related to the task.

1.1 Introduction

This thesis is initiated by Cegal [1], a global tech company specializing in the energy domain, which aims to develop a tool for efficient grid usage. They want to create a system that can provide flexibility to the energy system. A key factor for the system is the ability to predict future energy demand accurately. This project will investigate different machine learning algorithms to predict energy demand and explore the future energy situation in the Helgeland region to determine the need of flexibility in the region. Furthermore, a portion of the thesis will focus on examining the capability of an individual consumer to offer flexibility.

1.2 Background

This section will go through the motivation and necessity behind having flexibility in the energy system as well as research related to flexible energy.

1.2.1 Motivation

Reducing emissions is a target for Norway's green transition. This will require electrification of different sectors. As part of the electrification, there is a need for a well-developed and efficient use of the power grid. Upgrading the transmission grid is costly, and according to [2], there is anticipated that the upgrade will cost more than NOK 4 billion yearly up to 2030. The electrification of Norway is expected to cause higher peak load which in turn will require more optimal use of the grid capacity. By taking advantage of demand-response technology a more efficient use of the grid can be accomplished.

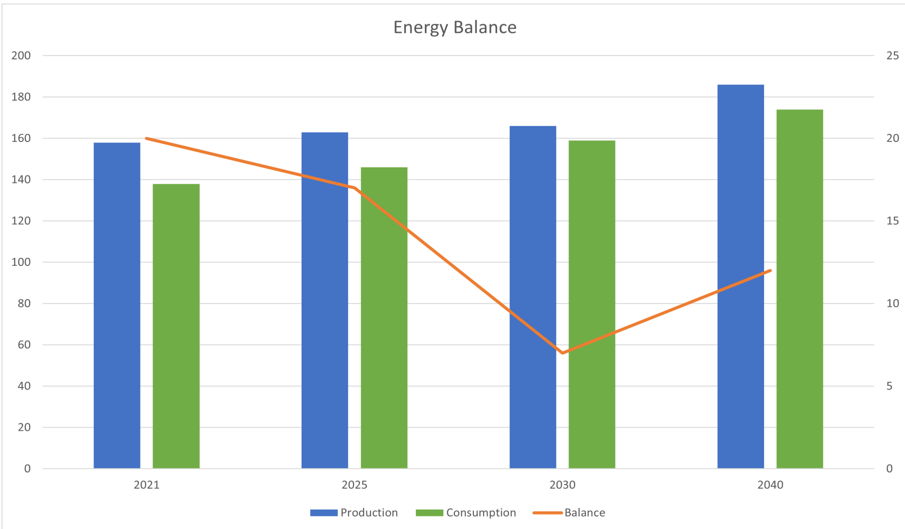


Figure 1.1: Illustration of the anticipated changes in energy production, consumption, and balance. The vertical axis on the right side represents the energy balance, while the left side correspond to production and consumption, both in TWh. Numbers from NVE's long-term analysis [3].

In 2021 The Norwegian Directorate of Water Resources and Energy (NVE) published a report analysing the long-term power marked [3]. In the report they are considering the future energy production and consumption. They are basing their analysis on that a significantly amount of new developments in energy production is going to come from wind and solar power. In Norway today, 89% of the energy production is produced by hydroelectric power plants [4] where some of them have water reservoirs, making it possible to regulate the energy production, which in turn adds flexibility into the energy system. However, wind and solar power is not possible to regulate and is highly dependent on the weather. According to NVE's estimations of 2040, there will be periodes in future Europe where high energy demand coincides with low amount of sunlight and wind, which can be challenging if the periodes are long-lasting. NVE suggest that the energy system requires significant flexibility to address the aforementioned challenges. NVE also evaluates the future energy balance in Norway, which is predicted to decline. In Figure 1.1 their estimations of the future energy balance can be observed together with the estimated energy production and consumption. From the figure it can be observed that in 2021 Norway had an annual energy surplus of 20 TWh. However, NVE projects that this surplus will reduce to 7 TWh in 2030 due to a rise in energy demand and low increase in production. The energy commission released their report about the long-term perspective of Norwegian energy politics this year [5]. The energy commission's estimation aligns with NVE's regarding the future energy balance, but they anticipate a potential energy shortage of 35 TWh in dry years by 2030. It has to be noted that the numbers illustrated in Figure 1.1 is based on years with normal weather conditions. Dry years referes to years where the amount of influx to the water reservoirs is low. Dry years occurring after one another can cause uncertainty in the energy supply. The largest reservoir in Norway has a capacity of 7,8 TWh which corresponds to three years of normal influx. However, the reservoir can be emptied in 7-8 months with full production [6]. The energy commission proposes solutions such as importing energy, building more multi-year reservoirs, or implementing demand side flexibility to address this challenge. They also suggest making the energy system more efficient and flexible to cope with the challenges. NVE has also researched the connection between the energy balance and the energy price [7]. According to their findings, a positive energy balance in Norway can lead to lower energy prices in the country when energy prices in Europe are high. For instance, if the energy balance in Norway is very high, say 40 TWh, the energy produced in the country will stay within its borders, leading to low energy prices.

The electrification of different sectors in Norway is expected to cause higher peak loads presenting challenges in load balancing. Load balance refers to the balance between energy production and consumption during peak load hours. NVE conducted an analysis on Norway and the Nordic countries' load balance up to 2030 [8]. The report concludes that Norway can currently manage the highest peaks with its energy production, but the combined Nordic countries are experiencing energy shortages during peak load hours. By 2030, there are concerns about having a negative load balance even with a moderate increase in consumption. The report suggests that an increase in demand-side flexibility can be a determining factor in ensuring a positive load balance in

2030. Additionally, grid reinforcements and better utilization of the grid can contribute to solving local load issues.

The challenges previously discussed are also highlighted in Statnett's 2023 long-term market analysis [9]. The report indicates that the most cost-effective approach to achieving green transmission targets is through a combination of renewable energy production and flexibility. This is in line with the findings of a committee established to evaluate measures for developing the Norwegian electricity grid [10], which recommends flexible resources as a viable solution for addressing short-term overloads and reducing the need for new grid development.

In spite of having a positive energy balance and being able to manage high peak loads, some areas in the Norwegian grid are experiencing insufficient capacity to cater to new industries or cope with the electrification of various sectors. ASKO Vestby is one such example where they wanted to replace their fossil-fuel trucks with electric ones, but the grid lacked the capacity to support the additional demand for electricity. To resolve this, they opted for a non-firm contract, allowing the local grid operator to disconnect the charging station during times when the demand is too high for the grid [11]. Similarly, industries in Lofoten were denied connection to the grid due to the same issue [12]. In [13], the authors support this problem by stating that 40 connection applications to the grid were turned down. This issue is not unique to Norway as other countries such as Ireland are also grappling with it. For instance, Microsoft and Amazon's plans to construct data centers have been hampered by grid connection permissions in Ireland [14].

In [15] it was investigated whether Norway is equipped to handle the challenges that has been presented. The authors concluded that the need for flexibility to maintain energy system balance is increasing. They recommended that flexibility resources should be distributed throughout the country in order for the resources to be available where needed. The authors also suggested using alternative flexibility sources, as an increase in the use of hydroelectric power plants is expected to be expensive. Moreover, they advocated for utilizing demand side flexibility from various sources to address peak load challenges.

The reports discussed in the preceding paragraphs all suggest that the Norwegian energy system is confronted with multiple challenges. It appears that a flexible energy system is necessary to address these challenges. In the following section, we will explain the concept of energy flexibility and review relevant research conducted on this topic.

1.2.2 Energy Flexibility

The Norwegian energy system is predicted to face challenges in the near future. To address these challenges, providing more flexibility to the system can potentially help optimize the grid management and serve as an alternative to costly grid development. This section will provide an overview of energy flexibility and its current applications.

Energy flexibility refers to the energy systems ability to adjust supply and demand by using available resources. Flexible resources play a crucial role in ensuring stability in the grid, especially as more unregulated renewable energy is integrated into the energy system. As previously mentioned, hydroelectric power plants provide 89% of the Norwegian energy supply, and some of these plants have water reservoirs that can be regulated. Such reservoirs are considered flexible resources.

Demand side flexibility (DSF) refers to the energy flexibility provided by the end consumers. It allows consumers to either be disconnected from the power grid for short periods of time or to shift their energy consumption from peak load hours to another time of the day. DSF can be divided into two types: implicit and explicit flexibility. The difference between them is related to the motivation behind the offered flexibility. Implicit flexibility is related to the users adjusting their consumption in response to prices, while explicit flexibility has the goal of motivating the consumers to provide flexibility by increasing their earnings. Explicit flexibility can be provided by the end consumer or a service provider that controls the consumers' consumption or production. One type of service provider is aggregators who work as an intermediary between the flexibility provider and the buyer. When an aggregator has multiple flexibility providers, they can obtain flexibility from several resources to sell as one bid [10].

In the previous section, it was mentioned that ASKO faced difficulties connecting their charging stations to the grid and resolved the issue by providing the local grid operator with DSF and making the charging station a flexible resource. However, this was only part of the solution. Together with Smart Innovation Norway, they designed a system which obtained information about grid availability from the DSO. Using this information, the system could use other flexible resources, such as batteries, ventilation systems, and cooling machines, to adjust the demand and prevent disconnection of the entire charging station. This solution was presented during the Smart Innovation Workshop 2022 [11]. However, it was also suggested that a market-based approach, such as the establishment of a local flexibility market (LFM), also could contribute to solving the problem.

There has been a lot of research on developing LFMs in order to address the challenges the energy system is facing. The following section will provide an overview of the theory underlying LFMs, and present some related research on the topic.

1.2.3 Local Flexibility Market

Local flexibility markets are marketplaces operating in a geographical area where energy flexibility provided by prosumers can be bought by flexibility users, commenly the local grid operator (DSO). Figure 1.2 illustrates the basics of a LFM where an aggregator collects flexible resources from various prosumers and sells the flexibility to either the DSO or the balancing responsible party (BRP).

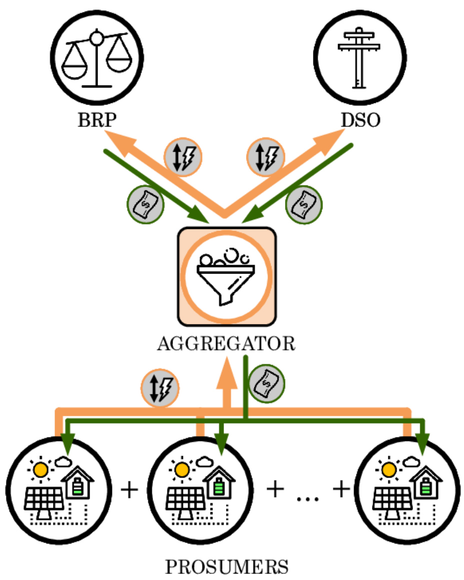


Figure 1.2: Illustration of a local flexibility market [16].

In Subsection 1.2.1 the challenges of the Norwegian energy system were highlighted. Nevertheless, these issues are not unique to Norway, and many other countries are facing similar challenges. As a result, there has been a significant amount of research on implementing LFMs globally. In [17] it was investigated how to make power systems more flexible by aggregating distributed resources through aggregator companies in the Netherlands. In [18] it is presented a method to create a local flexibility market in Northern Germany to prevent grid congestions. In the UK there has been developed a marketplace, Piclo Flex, for trading energy flexibility [19] and in Italy there is a flexibility project called RomeFlex [20].

The INVADE project is trying to create better energy services in order to increase the amount of energy flexibility. They are researching the use of cloud-based flexibility management system integrated with electric vehicles (EVs) and batteries together with existing infrastructure at the pilot sites in Bulgaria, Germany, Spain, Norway and the Netherlands [21]. In Norway they are investigating the use of vehicle-to-home (V2H) technology, enabling a two-way flow of electricity. According to their project description this can be a win-win situation where the end user can save money if they can avoid high loads at times where the prices are high, and the DSO can potentially postpone grid investments [22].

Another project in Norway, the NorFlex project, has investigated the potential of having a local flexibility market where demand side flexibility is provided to both the DSO and the transmission system operator (TSO), which in Norway is Statnett. NorFlex is a collaboration between Agder Energi, Glitre Energi, NODES and Statnett. Flexibility was provided by rapid charging facilities, commercial buildings, schools, sports facilities, nursing homes and horticultures. Agder Energi and Glitre Energi as DSOs bought flexibility through the marketplace NODES and resources which were not bought by the DSOs were aggregated and made available to the TSO as a resource in the balancing market. The goal of the project was to create a solution which could benefit all participants, and demonstrate how flexibility can be used by DSOs to increase efficiency of grid operations, increase grid capacity and postpone grid investments. Flexibility providers benefited by earning money when offering their flexibility assets [23] [24] [25] [26].

The NorFlex project used the marketplace NODES for trading energy flexibility. However, NODES is involved with several projects which involves unlocking demand flexibility. In Norway they are involved in NorFlex, SmartSenja, CINELDI, FlexLab and Engene. They are also involved outside Norway, including IntraFlex and sthlmflex. The latter is a project in Sweden where they are investigating a TSO/DSO coordination, where the regional DSO can buy flexibility from the neighbouring DSO. IntraFlex is a project in the United Kingdom which is looking into the impact of flexibility activation on the balancing responsible parties. NODES role is to provide a place where the buyer and the sellers can agree on a price [11].

In this section, we have discussed LFMs and summarized some of the existing research on the subject. We have learned that the buyers in these markets are the balancing responsible party and the local grid operator. The next two sections will focus on these buyers, describing their roles and responsibilities in the Norwegian energy system.

1.2.4 Transmission system operator

Norway has three grid levels: transmission grid, regional grid and distribution grid. The transmission grid is operated by the transmission system operator (TSO) which in Norway is Statnett. The grid transports electricity on a national basis. The TSO is responsible for keeping the production and consumption in balance [27] [28]. In order to keep the grid in balance there exists several markets to buy energy reserves. There are different types of reserves depending on the time of need. Frequency Containment Reserves (FCR) [29], automatic Frequency Restoration Reserves (aFRR) [30], manual Frequency Restoration Reserves (mFRR) [31] and Fast Frequency Reserves (FFR) [32]. The mFFR-market is the last reserve which is activated. It has to be activated within 15 minutes after the unbalance occurred and has a minimum duration of one hour. The reserves for the mFRR-market includes both reserves in the form of production and reduction in consumption.

At a workshop hosted by Smart Innovation Norway in 2022, NVE presented some limitations of balancing markets [11]. According to the presentation, the minimum bid size in the market is currently 10 MW, which is considered quite high in the context of DSF. The market also lacks automated solutions, which makes it difficult to manage multiple bids. The presentation suggested implementing automated solutions to optimize the market and reduce the bid size. Additionally, it was stated that changes are expected in the Nordic balancing markets within the next 1-2 years, where the market processes will be fully automated, the bid size reduced to 1 MW, and the time resolution reduced to 15 minutes.

In 2019/2020, the eFleks project [33] tested the use of demand side flexibility in the mFRR-market in Norway. The project involved collaboration between Statnett, Tibber, Entelios, Enfo, and Siemens. Tibber and Entelios provided DSF, with Tibber using panel heaters and electric vehicles with a size of 1 MW and Entelios providing 4 MW from a portfolio of industrial loads and 1.37 MW from commercial buildings. The project report suggests that lowering the minimum bid size was essential in using demand side flexibility in the mFRR-market.

1.2.5 Distribution system operator

The regional grid connects the distribution and transmission grid, with the distribution grid being the link between the regional grid and the end consumer. The distribution and regional grids are owned and operated by the local grid operator, also known as the distribution system operator (DSO). In Norway, each area has a designated DSO responsible for the distribution and regional grids. The DSO is in charge of maintaining, utilizing, and operating the grids they own. Customers using the grid must pay a grid tariff to the local DSO, in addition to their electricity consumption. The income generated from the grid tariff covers the DSO's costs, which include the transportation of electricity, efficient operations, and the development of the grid [34]. Therefore, if the DSO needs to expand the grid to increase capacity, customers may experience an increase in the grid tariff.

The grid tariff consists of two parts: a fee for the electricity consumption per kilowatt hour and a fixed monthly fee. Starting from July 1st, 2022, the grid tariff has been updated to encourage consumers to distribute their energy consumption throughout the day. The fixed monthly fee is now based on the capacity needs of each customer, and the cost for the first part of the grid tariff can vary depending on the time of day and year. Using electricity during off-peak hours, such as at night or on weekends, can be cheaper. The purpose of these changes is to incentivize consumers to use the grid more efficiently, which can lead to cost savings for both consumers and the local grid operator [35].

As presented in Subsection 1.2.1, there are several examples of where the grid is almost utilized and new industries wanting to establish either gets declined or has to agree on a non-firm contract. Which is the case at Innlandet, where new grid customers has to either wait until the grid is reinforced or agree on a non-firm agreement in order to connect to the grid [36]. The non-firm agreement is a contract which allows the DSO to disconnect the grid customer in case of operational problems.

1.2.6 Helgeland

A part of this theis aims to investigate the future energy situation at Helgeland in order to see if there is a viable opportunity of establishing a LFM in the area. The historical and current energy situation in Helgeland will be presented further.

Helgeland is a region in the southern part of Nordland county which is within price area NO4 Figure 1.3. Statnett is currently investigating different actions that is needed concerning the grid capacity in several regions in Norway. In Nordland it is expected major industrial investments which can lead to change in the energy balance in the area if no new production is added. They are planning to increase the capacity in the grid. Today the grid can handle an increase of 2200 MW in demand in NO4. However, an increase in demand of 2200 MW without an increase in production will increase the probability of disconnection in dry years [37].

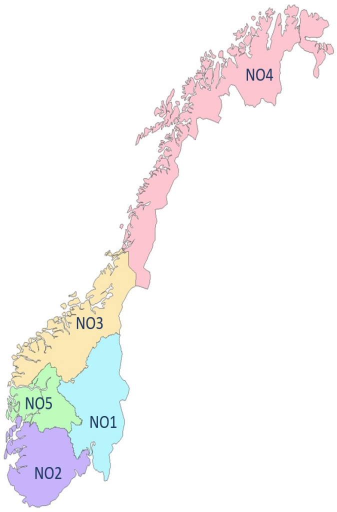


Figure 1.3: Energy price areas from NVE [38]

Linea owns the distribution grids at Helgeland and according to Linea's power system report from 2022, 79% of the electricity consumption at Helgeland in the last 10-year period is from power-intensive industry [39]. The electricity production in the region the last 10-year period has been at approximately 7.3 TWh per year. Average electricity consumption for the same time period has been at approximately 6.2 TWh per year, which gives Helgeland an annual average energy surplus of 1.1 TWh.

1.3 Project

As mentioned in the project description in Section 1.1, Cegal aims to develop a tool that can provide flexibility to the energy system to accommodate the challenges the Norwegian energy system is facing. Currently they are working with a system which can communicate with Statnett's product, eBestill [40], in order to automate the bidding process between the energy production companies and Statnett in the balancing market. In addition, Cegal wants to develop a demand-response system which can provide flexibility automatically to a local flexibility market. Additionaly, Cegal wants to investigate the potential of creating a local flexibility market at Helgeland. As a contribution to this, the thesis will explore the energy balance in the area and look into one consumers' ability to participate in a local flexibility market in terms of their ability and financial aspects.

Developing a demand-response system is a complex task. For the system to effectively manage the consumers' trades against a LFM, it needs to have an estimate of the energy consumption. This thesis will contribute to this by investigating different forecasting methods which can be used to predict the consumption for two purposes. Both the total consumption in the area and one consumers consumption. A prediction of the total energy demand in the Helgeland region can provide valuable information to the demand-response system about when flexibility is needed, while a prediction of the consumers' consumption can provide a baseline which can be used to calculate the compansation that the consumer should get.

The project has three goals. First is to explore various forecasting methods that can be utilized in the demand-response system as described earlier where both short-term and long-term forecasting is of interest. The second objective is to analyze the future energy demand in the Helgeland region to assess the necessity of flexibility in the area. The third aim is to examine the potential of a local prosumer's participation in a LFM.

1.3.1 Research Questions

Based on the project description and goals, the following research questions can be formulated:

1. Is there a viable opportunity for establishing a local flexibility market in the Helgeland region?

2. Are the proposed forecasting methods capable of predicting the total energy consumption in the area as well as predicting the consumers energy consumption for short-term and long-term?

3. What are the potential benefits and ability for the prosumers to participate in a local flexibility market?

1.4 Technical Background

In this section, we will provide technical background information that the project is based on. We will start by going deeper into the NODES marketplace, which was introduced in Subsection 1.2.3. After, we will provide an overview of time series forecasting in general, as well as previous research on load forecasting.

1.4.1 NODES Marketplace

The NODES marketplace is an independent platform for trading flexibility among grid operators, producers, and consumers. As shown in Figure 1.4, the flexibility providers are located on the right side of the platform, while the buyers are on the left. The buyers include grid operators such as DSOs, TSOs, and BRPs. The flexible resources available for trading are owned by prosumers, who may have contracts with aggregators, acting as intermediaries and offering the flexibility to the market. The flexible resources can include DSF assets, such as electric vehicles or building heating systems, as well as energy production resources.

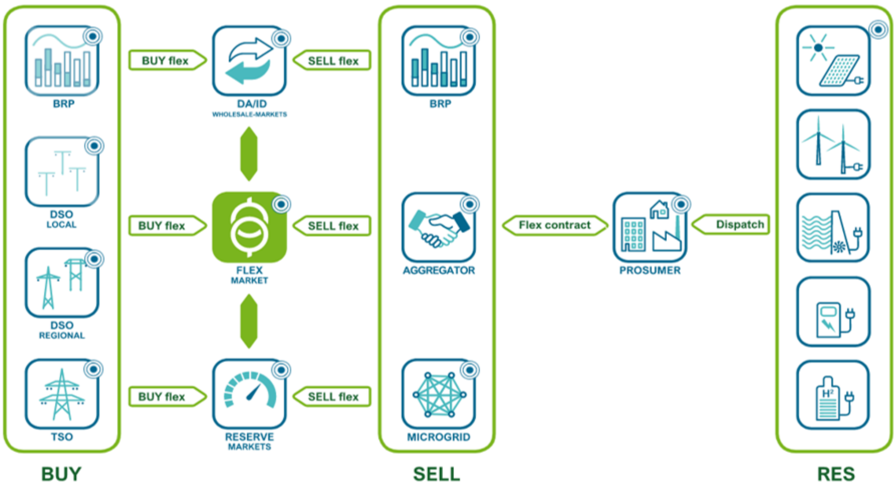


Figure 1.4: Illustration of NODES market design [41].

In the NorFlex project, the NODES marketplace was utilized to trade flexibility, as mentioned in Subsection 1.2.3. ShortFlex and LongFlex were the two products traded during the project. ShortFlex allowed flexibility to be traded between 7 days and two hours before the physical delivery, and orders had a duration of one hour. However, NODES supports products with durations of 30 and 15 minutes as well. Prices fluctuated during the project, but eventually settled between 8500-10 000 NOK/MWh. LongFlex, on the other hand, is a NODES product for flexibility reservation. Two LongFlex contracts were utilized in the NorFlex project with different durations, namely LongFlex season and LongFlex week. The weekly contract's prices ranged from 70 - 500 NOK/MWh, while seasonal contracts were priced between 75 - 250 NOK/MWh. Over 2400 assets were provided into the market by eight participating aggregators from January 2021 until March 2022. During this period, more than 12000 trades occurred with a total volume exceeding 600 MWh. NODES operates with a resolution of 0.001 MW, which implies that at least 1 KW of flexibility is required to make a valid trade [42] [11].

$$\text{Income} = MW * p * \% \tag{1.1}$$

For ShortFlex products the recived sum for each trade was calculated by Equation 1.1, where MW is the traded quantity, p the price and $\%$ represents the payment percentage, which is a factor determined by the delivery percentage regarding the actual delivered flexibility.

$$\text{Available income} = MW * p * h \tag{1.2}$$

Income for LongFlex contracts was calculated by Equation 1.2 where MW is the traded quantity, p the available price and h hours in the contract.

This section has provided an overview of the NODES marketplace, including the products traded in the NorFlex project, the number of participants and trades, and the minimum resolution for valid trades. It has also outlined how prosumers can offer their flexible resources to the market through aggregators, and how they are compensated for providing flexibility.

1.4.2 Forecasting

This section will discuss the general theory behind forecasting time series and related research on forecasting energy consumption, which forms the foundation of the selected forecasting methods utilized in this thesis.

Forecasting is a tool which is used for a number of applications. Examples of such applications are weather forecasts [43], forecasting stock prices [44] and forecasting electricity prices [45]. In general, having an accurate prediction of future values is a useful tool in planning and decision making.

In [46] different methods for forecasting electric load is presented. They are divided into conventional methods and computational intelligent methods. Whereas the conventional methods includes time series models and regression models. Time series methods models the electricity demand as a function of historical data, which assumes that the data follow a certain stationary pattern. Regression models on the other hand, uses a linear combination of variables in order to predict one variable. The authors also presented some computational intelligent methods which has been used for forecasting electricity load. Amoung these: Artifical Neural Networks and Expert Systems.

All electricity consumers today has smart electricity meters which hourly registers the energy consumption [47]. Hence, forming a time series. A time series is a set of data points that are indexed or ordered by time. Time series are commonly encountered in various fields such as finance and economics, where stock prices or interest rates can be modeled as time series. In physical sciences, temperature and other meteorological observations are often recorded as time series. Time series data can be discrete, meaning observations are taken at specific intervals of time, or continuous, where observations are recorded continuously. Typically, observations in a time series are dependent on previous values, meaning they can be deterministic or stochastic. Deterministic time series can be predicted exactly based on past observations, while stochastic time series have a degree of randomness or unpredictability, and future values can only be estimated with some level of uncertainty [48].

A time series containing electricity consumption can thus be described as a discrete time series, whereas a prediction of the next value can be refered to as a stochastic value.

1.4.3 One-step Forecasting

One-step forecasting involves predicting the next value in a time series. The forecasting process can rely on both dependent and independent variables, where the dependent variable is the one being predicted, and independent variables are those that may impact the dependent variable. The model uses these variables at each time step to forecast the next value. While single-step forecasting is useful in managing resources and maintaining balance in the grid, it may be limiting for long-term planning since it only predicts the next time step.

1.4.4 Multi-step Forecasting

Multi-step forecasting is used when the aim is to predict multiple future values in a time series. Similar to one-step-ahead forecasting, multi-step forecasting can utilize both dependent and independent variables to predict future observations. The main difference is that multi-step forecasting predicts several future values instead of just one. However, accurately predicting multiple steps into the future can be challenging as the accuracy tends to decrease with increasing forecasting horizon [49]. Accurate forecasting of electricity consumption for several hours can give grid operators more time to manage resources to keep the grid in balance.

1.4.5 Forecasting Energy Consumption

Predicting energy consumption is important for several reasons. Knowing the future electricity consumption can help the grid operators and utilities plan which resources is needed in order to meet demand. Accurate predictions can help ensure that available capacity has the ability to meet demand at all times, which in turn can help balancing the grid and preventing power outages. The predictions can also be used as a tool to identify opportunities for energy efficiency measures. Understanding when and where energy is used creates an opportunity for consumers and utilities to develop strategies in order to reduce or shift their energy usage. Prediction of electricity consumption can also create cost savings. By anticipating changes in demand, utilities can make decisions based on the expected demand when selling or buying energy. This in turn can reduce the costs of the electricity consumer. There is a lot of research on load forecasting. However, this section will give a brief presentation of some related research.

In [50] it was conducted a review of forecasting methods used in energy planning models where forecasting energy demand and load was the main objectives of the forecasting. The review investigated 483 energy planning models between 1985 and 2017. They found that among the 50 methods used in the models, statistical methods were 18% more used than computational intelligence (CI) methods and mathematical programming. However, it was found that CI methods had better accuracy than the statistical ones. CI methods uses a combination of fuzzy logic, neural networks, evolutionary computation, learning theory and probability methods.

In [51] they created models for predicting the consumption load for electric snowmobiles. They found out that using a XGBoost model to forecast the consumption load on short-term (1 hour horizon) gave quite good results and using LSTM for long-term (day-ahead) prediction gave satisfactory results.

In [52] several CI methods was tested for energy load forecasting. The different algorithms were used to predict one hour a head load and was compared by Mean Absolute Error (MAE), R-squared, Root Mean Squared Error (RMSE) and Coefficient Variation of Root Mean Squared Error (CVRMSE). The models compared in the study was two deep learning models, Multi-layer Perceptron (MLP) and Long short-term memory recurrent neural network (LSTM), and three machine learning algorithms, Decision tree, Random Forest and Extreme Gradient Boosting (XGBoost). Their results showed that XGBoost, MLP and LSTM were the models that had best results when evaluating their metrics.

In [53] two machine learning model was compared for multi-step forecasting of electric load on three different datasets. ARIMA and LSTM was compared where the evaluation of the models is based on their respective RMSE. Different prediction horizons were tested from 2 steps ahead to 10 steps ahead. From their results it was concluded that LSTM outperformed the ARIMA model.

2

Methods and Data

During this project, various methodologies were employed. This chapter will begin by outlining the general approach taken and then provide more detailed descriptions of the specific methodologies used.

2.1 Approach

The primary goal of this thesis has been to answer the research questions stated in Subsection 1.3.1. In order to accomplish this, the following objectives were established:

1. Investigate the future energy situation in the Helgeland region to determine the need for flexibility.

2. Explore and evaluate forecasting methods for predicting energy consumption.

3. Evaluate the accuracy of the selected methods for both short-term and long-term predictions.

4. Investigate the potential cost and earnings for one potential consumer participating as a flexibility provider in a LFM.

To achieve these objectives, different research methodologies were employed. A review of the existing literature on future energy estimations in the Helgeland region was conducted. During the experimental phase of the project, a suitable forecasting model was sought after by reviewing previous research on forecasting techniques. Additionally, an interview was conducted with a potential consumer to obtain insights into the possible flexibility the consumer could provide.

2.2 Literature Review

To address the first objective of the thesis, which relates to the first research question on the potential for establishing a local flexibility market in Helgeland, a literature study was conducted. In Subsection 1.2.6, we presented an overview of the current and historical energy consumption and production in the region. To obtain future estimates, we searched for literature on the need for grid investments in the area.

2.3 Available Data

The experimental part of this project was to develop a forecasting method for predicting the energy demand to be able to know when the need for flexibility is, as well as predicting the energy consumption to the flexibility provider, which can be used as a baseline. To this end, two datasets containing historic energy consumption has been worked on throughout this project. The different data used during the experimental phase is represented in this section.

2.3.1 Consumption Data

As mentioned in Section 2.5, the original plan was to study the DSF potential of multiple consumers at Helgeland. To this end, consumption data was collected from 17 different consumers operating in various business areas, which are listed in Table 2.1. To maintain anonymity, the consumers have been grouped based on their main business area. However, this study has primarily focused on the consumer with business code N (Consumer N), which has been interviewed and studied in detail.

Code	Description	Datasets
B	Mining and extraction	3
R	Cultural, entertainment and leisure activities	4
L	Sales and operation of real estate	4
O	Public administration and defence, and social security schemes subject to public administration	3
I	Accommodation and catering business	1
C	Industry	1
N	Commercial service provision	1

Table 2.1: The number of datasets provided for this thesis with their main business area and code

Furthermore, the total energy consumption in the Helgeland area was obtained by aggregating data from 66 exchange points. This data was combined into a single dataset and will be referred to as the Helgeland dataset.

This section presented data collected from Elhub [54], which includes hourly measurements of energy load in KWh. However, for ease of readability, the Helgeland dataset was converted to MWh. It is worth noting that Elhub only stores historical data for up to three years [55], so each dataset used in this study contains a maximum of three years of data.

2.3.2 Weather data

Hourly weather statistics were obtained from the Norwegian Centre for Climate Services [56]. The data includes information on temperature, precipitation, and medium wind from the Mosjøen Lufthavn weather station. However, there was a data gap between 1 October and 22 October 2021, so statistics from a nearby weather station were utilized during that period.

2.4 Forecasting Methods

In relations to Objective 2 and 3 from Section 2.1, two forecasting methods has been investigated, namely the XGBoost and LSTM models. The selection of these methods is based on the related research presented in Subsection 1.4.5, as well as our own knowledge and experience with the methods. The focus has been on predicting the total energy consumption at Helgeland, which can be utilized in the demand-response system to assess the requirement for flexibility. Furthermore, the energy consumption of Consumer N (referenced in Table 2.1) is predicted which can provide a baseline for flexibility provision.

Two models were created for each of the forecasting methods. One for single-step prediction (1 hour ahead) and one for multi-step prediction (4 hours ahead). The decision to make a four-hour prediction was based on several factors. Firstly, the ShortFlex product trade at NODES had a deadline of two hours before the physical delivery, as presented in Subsection 1.4.1. Secondly, it was deemed unlikely that the consumer investigated in this thesis could provide flexibility for more than four hours. Therefore, there was no need for a baseline calculation exceeding four hours to determine the financial compensation.

In order to evaluate and compare the performance of the models, error rates were calculated using unseen data. Python was used to implement both models, along with NumPy [57] and Pandas [58] to format and analyze the data.

The next two subsections will provide an overview of the two forecasting methods used in this study, along with their implementation details.

2.4.1 Long Short Term Memory

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) which is designed to avoid the vanishing gradient problem. The method was proposed in 1997 [59]. RNN is a type of neural network that can remember the past, allowing information to persist.

Neural networks contain several layers. Layers holds the neurons, where each neuron is a mathematical operation that multiplies the weight of the neuron with the input. The sum of the operation is then passed through the activation functions to the other neurons. The input to a neural network is multi-dimensional. The input layer will then have an equal number of neurons as the number of variables passed into the network. The weight associated with a neuron represents how much the output depends on the input passed through the neuron. During training the weights changes. An activation function is used to compute the weighted sum of the inputs. There are several different functions that can be used as the activation function. There are two processes in neural networks, feedforward, and backpropagation. The feedforward is the process of getting the initial output, in other words, sending the input through all the layers and getting an output. Backpropagation is updating the weights at each neuron based on the error of the output. The goal of the backpropagation is to try to minimize the error for the output. The input layer receives the input, the output layer predicts the final output, hidden layers are in between the input and output layer and do most of the computations in the network.

However, RNN struggles with the vanishing gradient problem. Gradients are found using backpropagation where the derivative of each layer is multiplied by each other, from the final layer to the initial layer. When the derivatives are getting close to zero, the gradient in the early layers of the network "vanishes". Gradients are used to update the weights of the neuron. Thus, a small gradient will lead to initial layers not updating their weights which is called the vanishing gradient problem.

As stated, LSTM is designed to avoid this problem. In LSTM, the regular neurons used in RNNs are replaced with memory cells, where each memory cell contains an internal state. An illustration of a memory cell can be observed in Figure 2.1, where the top horizontal line represents the internal state. It can also be observed that there exists different processes in the cell, called gates. The first gate is called the forget gate, in figure denoted at f_t. It uses the Sigmoid function and determines what information should be remembered and forgotten in the cells state. The Sigmoid function takes any input and turns it into a number between 0 and 1. The second gate is called the input gate, denoted at i_t in the figure. The input gate decides how much of the new information should be stored in the current internal state. This process uses both Sigmoid and Tanh, where the former is used to determine which values to update and the latter to assign weights to the values. The last process is called the output gate, denoted as o_t. It uses Sigmoid and Tanh to decide which part of the current cell state to be selected as output.

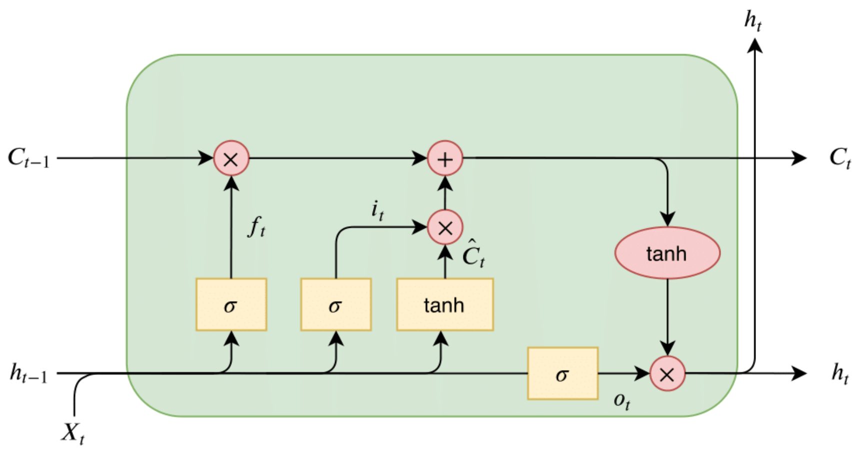


Figure 2.1: Illustration of a single LSTM cell [60] where the different gates are represented as f_t, i_t and o_t.

The LSTM model implementation is performed using Keras in Tensorflow [61]. To obtain a satisfactory LSTM model, the number of LSTM layers and hyperparameters were experimented with. Typically, adding more LSTM layers can capture complex patterns in the data, but it can also cause overfitting, especially when dealing with limited training data. The Adam optimizer with a clip value of 0.3 was used to prevent gradient explosion during training, and the learning rate was set to 0.001.

The short-term LSTM model built in this study consists of five LSTM layers, with each layer having 120 units, followed by a dropout layer with a rate of 0.2. The dropout layer randomly drops out 20% of the inputs to the layer during training, helping to reduce overfitting. Finally, the model has a dense layer that generates the prediction.

Early stopping was applied to save time and prevent overfitting during training. MSE was monitored during training, and if no changes to the MSE occurred for three epochs, training was stopped, and the model was restored to the weights with the lowest MSE.

The multi-step LSTM model was constructed using the same hyperparameters, but with each of the five LSTM layers having 110 units.

2.4.2 Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is a tree boosting system introduced in 2016 that is known for its scalability and high performance [62]. It is an ensemble learning method based on decision trees and gradient boosting. Ensemble methods combine multiple models to improve prediction accuracy over that of a single model. Each model is trained on the same data, but they may differ in terms of architecture, parameters, or random initialization. XGBoost builds decision trees sequentially, with each subsequent tree correcting the errors of the previous tree. The final prediction is obtained by aggregating the predictions of all the models, where the weights are higher for more accurate models. XGBoost uses gradient descent optimization to minimize the loss function of the decision trees to gradually reduce prediction errors. In gradient boosting, decision trees are scaled with a learning rate.

To implement the XGBoost model, the XGBoost library [63] was utilized with hyperparameters adjusted to obtain optimal models. For the short-term model, 2000 estimators (corresponding to the number of decision trees) were used with a maximum tree depth of 5 and a learning rate of 0.01. The long-term model, on the other hand, utilized 4000 decision trees with a maximum depth of 7 and a learning rate of 0.01. Similar to the LSTM model, early stopping was employed to prevent overfitting in both short-term and long-term models.

2.4.3 Feature Selection

To accurately forecast a consumer's load, it is crucial to understand the factors that influence their behavior. In [64] there were identified several factors that affect a consumer's load profile, which can be categorized into four groups: time, weather, economy, and random disturbances. The authors highlighted that the time factor has the greatest impact on a consumer's load, with periodicity occurring on a daily, weekly, monthly, and yearly basis. Weather was identified as the most important independent variable, with temperature, humidity, precipitation, wind speed, and cloud cover having an impact. The economy was also found to affect load, with higher electricity prices leading to lower consumption. Random disturbances were attributed to high peaks caused by industrial load starting up or shutting down, as well as special events such as religious or cultural celebrations.

Various analyses were performed on the two datasets used in this project to identify the factors that influence load behavior. The first step was to determine whether temperature had a significant impact on the load behavior by examining the correlation coefficient between the two variables and plotting them on a scatter plot. Another important aspect was to identify any time-dependent patterns in the datasets, such as seasonality or trend. This was done by analyzing the daily average load profile as well as the load output for the entire dataset. The autocorrelation plot was also examined to identify the relationship between past and future observations. Additionally, various timestamp-related features, such as hour of the day, day of the week, month, year, day of the year, day of the month, week of the year, and quarter, were extracted. However, the use of these timestamp features was determined by analyzing the model's performance with different input combinations.

2.4.4 Data Splitting

The datasets were divided into three subsets for each model: training, validation, and test sets. 80% of the data was used for training, with the remaining 20% split evenly between validation and testing. In Figure 2.2 the two datasets splitted into the three subsets can be observed. On the top is the commercial building (Consumer N) and at the bottom the Helgeland dataset.

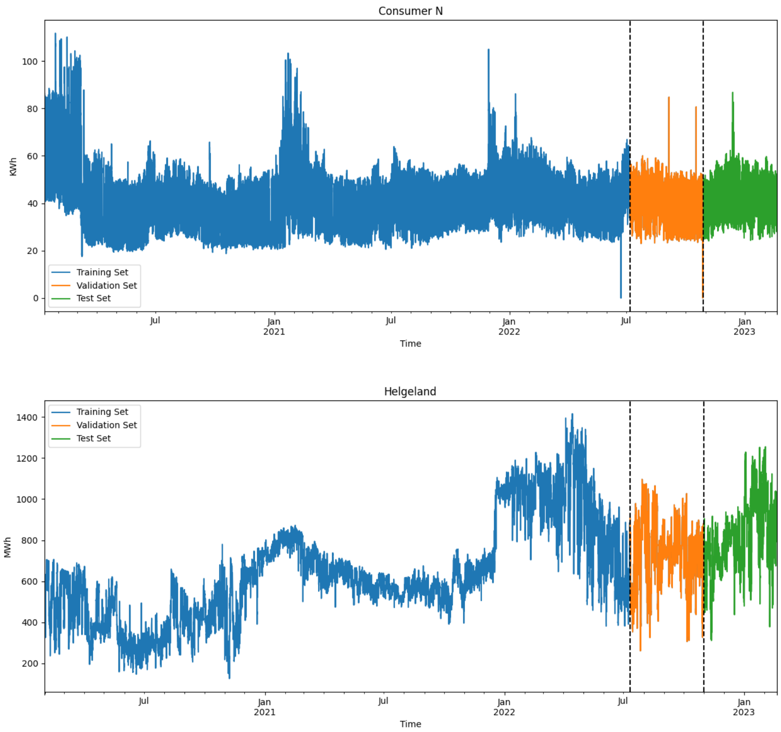


Figure 2.2: The two dataset split into the subsets: training, validation and test set.

2.4.5 Performance Metrics

Assessing the performance of the forecasting models is done by utilizing commonly used error metrics for regression problems. The Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are employed in our evaluation in order to accommodate objective 3 Section 2.1.

The MAE calculates the average absolute error in a prediction set where all individual differences are of equal weight. MSE measures the average of the squared differences between the actual and predicted values. RMSE is derived from MSE by taking its square root, and it yields an error measure in the same unit as the actual values. It is important to note that MAE, MSE, and RMSE are scale-dependent error metrics, meaning that they should not be utilized to compare models across different datasets. However, MAPE is scale-independent and can provide a better understanding of the error in relative terms. One disadvantage of MAPE is its sensitivity to cases where the actual value is 0, which can result in an undefined or infinite error [65]. The various error metrics can be defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(p_i - r_i)^2 \tag{2.1}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - r_i)^2} \tag{2.2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|p_i - r_i| \tag{2.3}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|p_i - r_i|}{r_i} \tag{2.4}$$

The performance metrics are obtained by testing the models using a set of unseen test data. This ensures an unbiased and independent assessment of the models. In these metrics, N represents the total number of predictions made, p represents the predicted value, and r represents the actual or target value.

2.5 Potential Flexibility Providers

It was initialy meant to investigate several consumers ability to provide DSF, however, due to the time limitations of the project only one consumers ability and possible benefits of providing DSF was investigated. The consumer that has been investigated is Consumer N from Table 2.1. This section describes the methodologies used in order to accommodate objective 4 from Section 2.1.

2.5.1 Identifying demand-side-flexibility

This study investigated one consumers ability to offer DSF. More specifically, this consumer is a commercial building located at Helgeland. To identify the resources that could potentially be flexible, an interview was conducted with the consumer. During the interview, the consumer was asked about the equipment that could be disconnected. However, certain requirements had to be met in order for the resources to be considered. Since the delivery resolution in both the mFFR market and the NorFlex project, as well as the time resolution in the dataset, is one hour, it was necessary for the resources to be able to be disconnected for at least one hour. Additionally, disconnecting the resources for at least one hour should not cause any discomfort in the day-to-day management.

2.5.2 Financial Aspects

In this project, it was not only important to determine the flexible assets that commercial buildings could offer, but also to estimate the potential earnings for the consumer and the associated costs. To enable the disconnection of loads, specific equipment must be installed, and its cost was determined by consulting a former electrician employed at Cegal. However, only the cost of the physical equipment and installation was considered, and the cost of the software required to automatically offer the flexibility to the market was excluded.

In order to find an approximately income for the consumer we have used the income calculations presented in Subsection 1.4.1. Although, we are assuming that the consumer delivers all the flexibility that the commercial building can provide in one trade. Additionally, it was stated in Subsection 1.4.1, that the price per MWh for the ShortFlex product settled between 8500-10 000 NOK in the NorFlex project. To have a fixed price which can be used in Equation 2.5 we have set the price to be 9000 NOK/MWh. Thus, using the load of the resources (KW) multiplied by the duration (h) of the disconnection further multiplied by the price of flexibility gives the potential earnings of one trade:

$$I_t = KW \times h \times 9NOK/KWh \tag{2.5}$$

3

Results

The results obtained from the various methods described in Chapter 2 are presented below. Firstly, we will show the future energy balance estimation at Helgeland. Then, we will present the findings from the experimental part of the project, including the analysis described in Subsection 2.4.3 for determining the input to the models, and the results from the two forecasting models. Finally, we will present the results obtained from investigating Consumer Ns potential to participate in a LFM.

3.1 Future energy situation at Helgeland

During the search for anticipated future energy scenarios at Helgeland, two reports were found: one from Linea (DSO) at Helgeland, which studied two scenarios related to the future energy balance and load balance in the region [39], and another report on future energy demand at Helgeland, conducted by Kunnskapsparken Bodø in 2020 [66].

The Linea report presents two scenarios that estimated the possible future developments in energy consumption and production in the Helgeland area. The first scenario, named "basis," is deemed the more probable one. The second scenario, "high," is based on high levels of electrification and new demand, resulting in higher estimated production than in the "basis" scenario. Both scenarios provide estimates for production, consumption, and balance, presented for the total energy balance, and the maximum and minimum load balance in a year. Figure 3.1 displays the balances for both scenarios. The load balance is represented as minimum and maximum which are based on seasons. Minimum load balance is when the production is expected to be at its lowest and the consumption at its highest. In turn, the maximum load balance is when production is at its highest and consumption low.

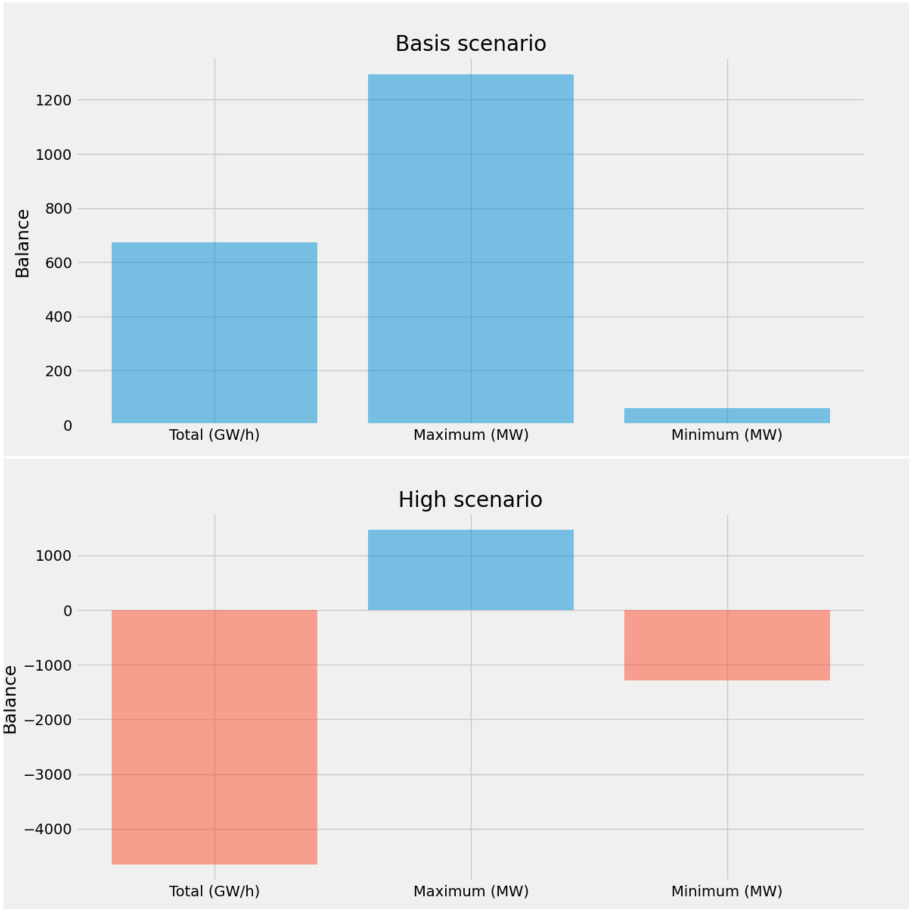


Figure 3.1: Energy and load balance for the two scenarios at Helgeland in 2032. Numbers from Linea's report [39].

The report conducted by Kunnskapsparken Bodø investigated the estimated energy demand based on planned future development in the area. This was further analysed against the estimated production in the area as was done in Lineas report to find the future energy balance. Their estimations of the future production and demand is based on planned development of the two. They also considered the likelyhood of the planned development of new energy production and industries. The analysis is based on three different time horizons: short-term (0-5 years), medium-term (5-10 years) and long-term (10-15 years). In Table 3.1 the estimated energy balance from their analysis can be observed.

	short-term (0-5 years)	**medium-term** (5-10 years)	**long-term** (10-15 years)
GWh	-448	-3201	-1301

Table 3.1: Estimated energy balance for different time horizons. Numbers from [66].

Based on the report by Kunnskapsparken, it was found that the industrial sector in Helgeland is the main consumer of energy in the region. The report suggests that if new industries are established or the existing ones are expanded, the energy demand in the area is expected to double.

Numbers from both reports showes that the energy balance is going to decrease in all scenarios compared to the energy balance today. When production is at its lowest and the consumption at its highest, typically in the winter, Figure 3.1 showes that the basis scenerio has a small positive load balance compared to the total energy balance and to times when the production is high and consumption low, which is typically during the spring.

3.1.1 Summary

The important findings regarding the future energy situation at the Helgeland region can be summarized as follows:

- Helgeland is likely to experience a decrease in energy balance, with an increase in demand outpacing the estimated new production.
- The load balance is expected to be tight or even negative during periods of high demand.

3.2 Data Analysis

In Subsection 2.4.3, we discussed the techniques used for selecting the appropriate features to use as input for the forecasting models. Here, we will present the results of the data analysis conducted on two datasets: the total energy consumption at Helgeland and the energy consumption of Consumer N.

3.2.1 Load Profiles

The daily energy consumption pattern for Consumer N is illustrated in Figure 3.2, which shows the average consumption per hour throughout a day. The figure shows a clear trend of higher consumption during the daytime and lower consumption during nighttime. Which is not surprising since this is a building where most of the activities occur during opening hours, which in this case are from 7 AM to 11 PM.

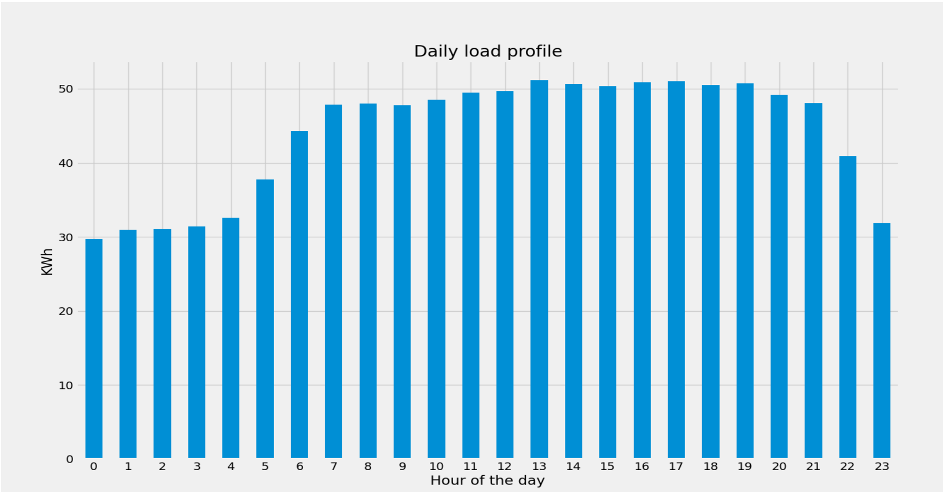


Figure 3.2: Average daily load profile for Consumer N.

The load profile for the entire dataset is displayed in Figure 3.3. The graph highlights that electricity consumption is elevated during winter periods, with smaller peaks during the summer, suggesting a seasonal pattern that repeats yearly.

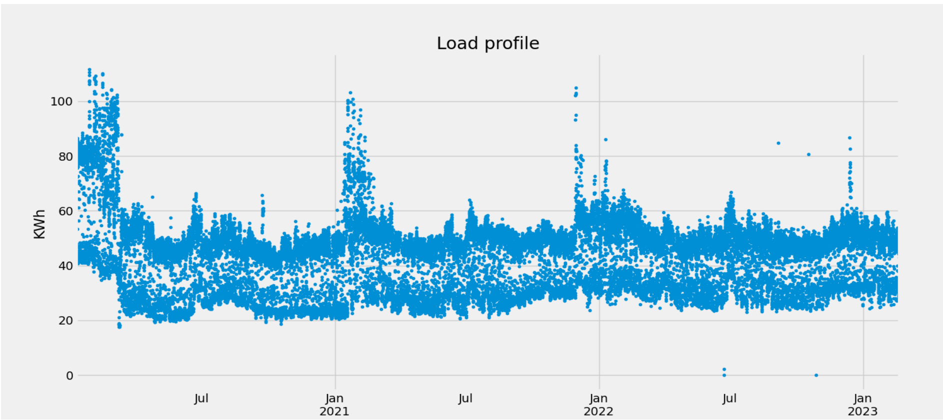


Figure 3.3: The load output for Consumer N.

The average daily load profile of the total energy consumption at Helgeland is presented in Figure 3.4. It is evident from the figure that the highest consumption occurs in the morning and late afternoon on average.

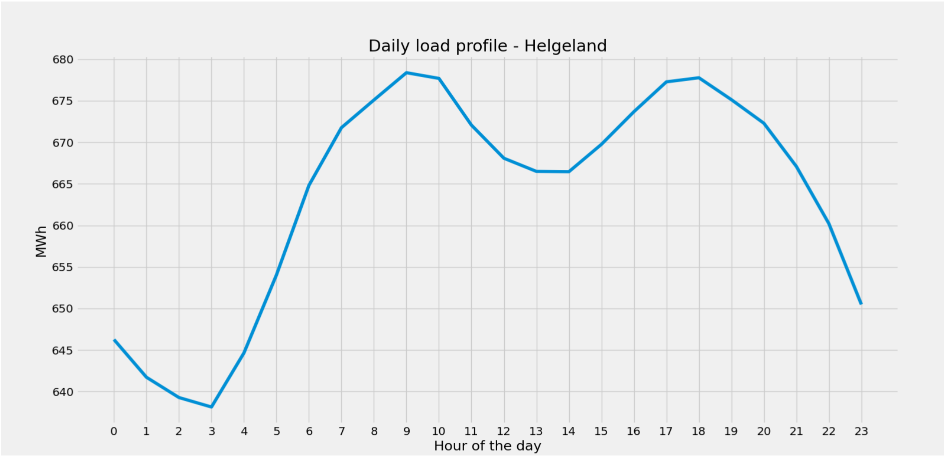


Figure 3.4: The load output for Helgeland.

The load profile for the whole Helgeland dataset is illustrated in Figure 3.5. The figure shows that there is a noticeable trend of increasing energy consumption from 2020 to 2023, as well as some yearly seasonality with higher consumption during winter months and smaller peaks during summer. The dataset consists of consumption data aggregated from 66 exchange points, as stated in Subsection 2.3.1, but there are missing values for at least three exchange points every hour throughout the three years of data. However, it is worth noting that Linea's report, mentioned in Subsection 1.2.6, states an average annual consumption of 6.2 TWh over the past decade, while the total consumption from Elhub data from 31 January 2020 until 1 March 2023 is 18.1 TWh, resulting in an approximate annual consumption of 6.0 TWh. This suggests that the missing consumption data is not significant.

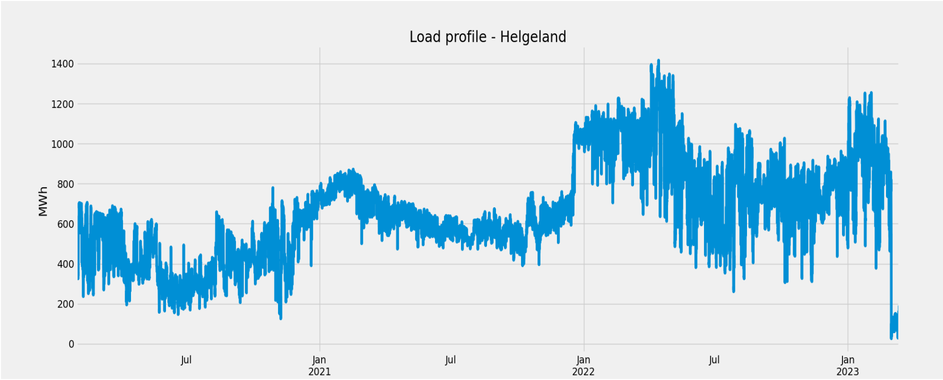


Figure 3.5: Electricity load profile at Helgeland.

3.2.2 Linear Relationship

In Figure 3.6, the linear relationship between the energy consumption of Consumer N and temperature is displayed. The correlation coefficient, which was calculated to be -0.114, indicates a weak negative linear relationship between the two variables. The scatter plot does not seem to reveal a clear linear relationship between them, the plot reveals a cluster of points in between 60 KWh and 20 KWh which suggest that an hourly consumption between those values is not affected by the temperature. However, when the temperature rises to 20 degrees the consumption is slightly increasing, and when the temperature is below 5 degrees we can observe some incresing tendencies in the consumption. This suggests a curvilinear relationship where the energy consumption increases when the temperature is below 5 degrees and slightly increases when the temperature is above 15 degrees.

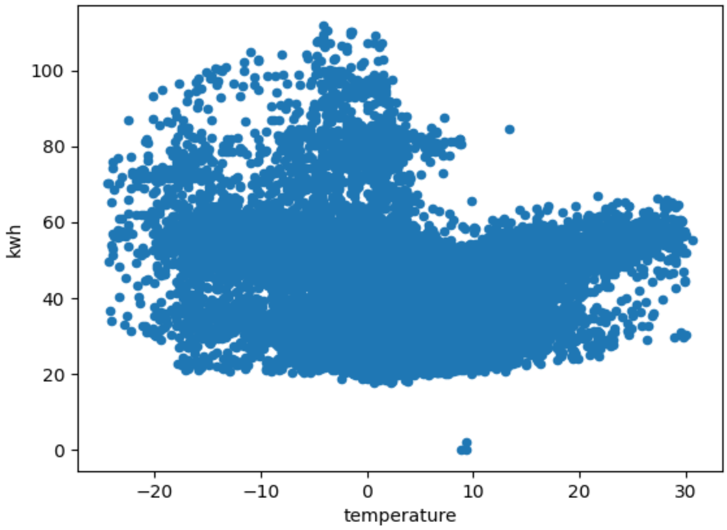


Figure 3.6: Relationship between energy consumption and temperature.

The plot in Figure 3.7 illustrates the linear relationship between the temperature and the total energy consumption at Helgeland. The calculated correlation coefficient of -0.405 suggests a negative correlation between the two variables, which is confirmed by the scatter plot. Lower temperatures correspond to higher energy consumption, whereas higher temperatures correspond to lower energy consumption.

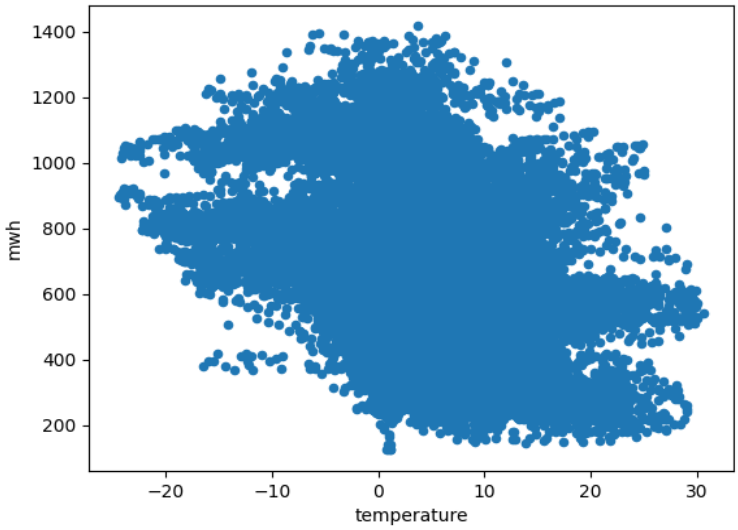


Figure 3.7: Relationship between energy consumption and temperature, at Helgeland.

3.2.3 Autocorrelation

The autocorrelation plot of the consumption variable is displayed in Figure 3.8. The plot indicates a correlation between past and future values in the dataset, suggesting that the time series is not completely random. Additionally, the plot shows a clear pattern of daily seasonality, with significant peaks at lag intervals corresponding to 24-hour intervals.

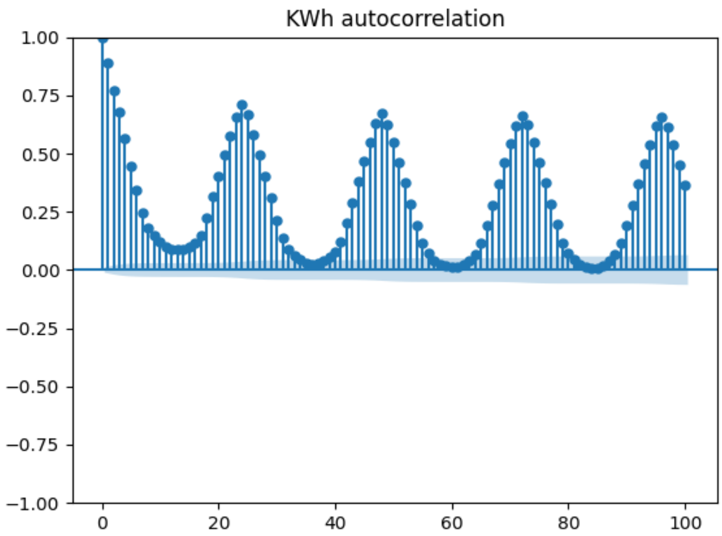


Figure 3.8: Autocorrelation for the energy use for the Consumer N.

From Figure 3.9 it can be seen that the past an future values of the energy consumption in the Helgeland dataset is highly correlated. This suggests that there is a strong persistence in the dataset, where each observation is dependent on the previous.

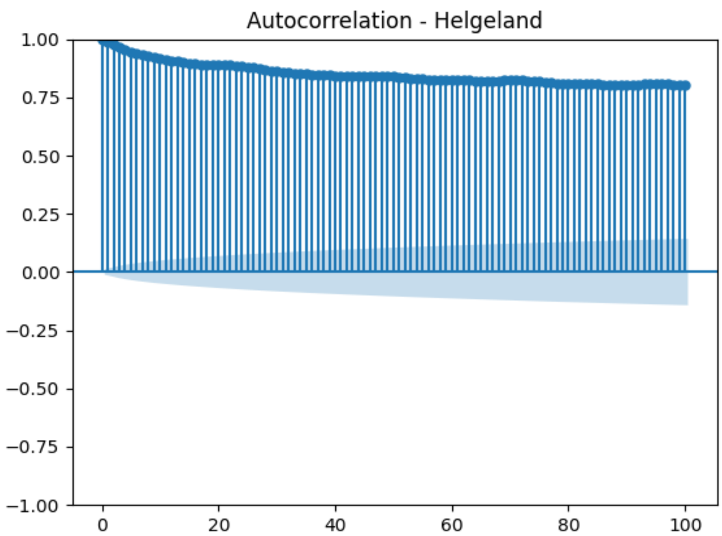


Figure 3.9: Autocorrelation for the energy use for the Helgeland dataset.

3.2.4 Summary

The analysis of the data yielded several findings:

- Daily seasonality was observed in both datasets.
- The Helgeland dataset showed a negative linear correlation with temperature, for Consumer N, a curvilinear relationship between consumption and temperature was observed.
- Autocorrelation analysis indicated a strong daily seasonal pattern in Consumer N and persistence in the Helgeland dataset.

Considering the patterns observed in the data analysis, it was concluded that using temperature and 24-hour lags as input variables would be appropriate for the models.

3.3 Forecast

This section presents the experimental outcomes obtained from the forecasting models utilized in this project. It is divided into two subsections, namely the single-step prediction results and the multi-step prediction results. The outcomes are displayed as error metrics calculated when testing the models with unseen data, along with illustrations of the predicted values compared to the target values.

3.3.1 One-step Prediction

The results from Consumer N shows that the best performing model for one hour ahead prediction is the XGBoost model Table 3.2. The overall error metrics are lower using the XGBoost model compared to the LSTM model. The best results was obtained by having a feature vector containing the hour of the day, month, the day of the week, temperature as well as the last 24 observations of the energy consumption for Consumer N.

The results presented in Table 3.2 show that the average difference between the predicted and actual values was 2.364 MAE for XGBoost, with some variability observed between the RMSE and MAE values. Nevertheless, the RMSE was not significantly greater than the MAE, indicating that there were no extreme errors.

	MSE (KWh)	RMSE (KWh)	MAE (KWh)	MAPE %
LSTM	15.54	3.94	2.681	6.370
XGBoost	13.71	3.703	2.364	5.670

Table 3.2: Error metrics calculated for Consumer N using unseen test data when attempting to predict one hour ahead.

In Figure 3.10 the actual values (blue line) and the predicted values (orange line) are illustrated where XGBoost performance is on the top of the figure and LSTM on the bottom.

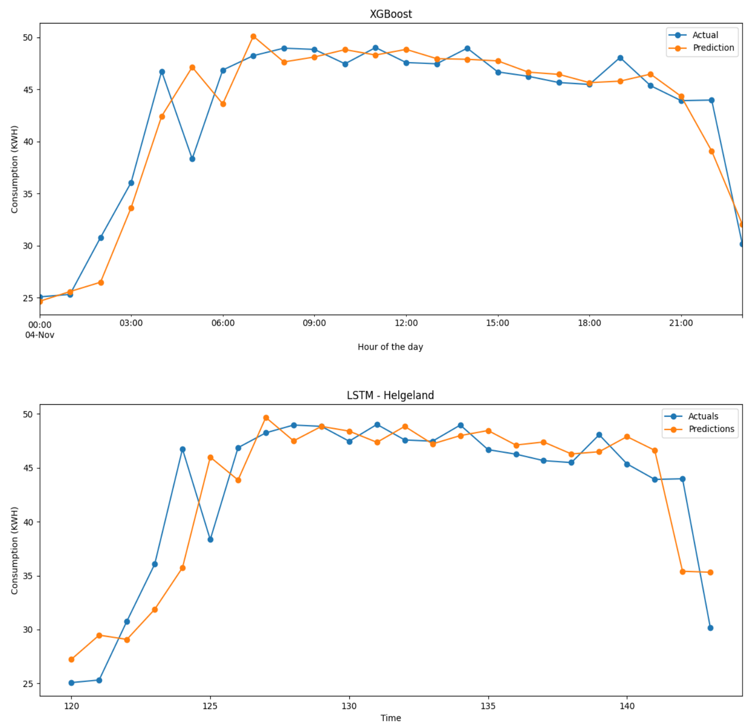


Figure 3.10: On top is the XGBoost performance during testing on the Consumer N dataset. On the bottom is the LSTM model performance.

In Figure 3.11, the relationship between the predicted and actual values for both models is visualized through scatter plots. The red line indicates perfect prediction, while the y-axis shows the actual observations and the x-axis shows the predicted values. It can be observed that the error variance is not uniform for all the observations. The plots reveal that there is larger variance in the error in the range of 35 to 50 KWh as well as consumption exceeding 60 KWh, where most of the values are underestimated.

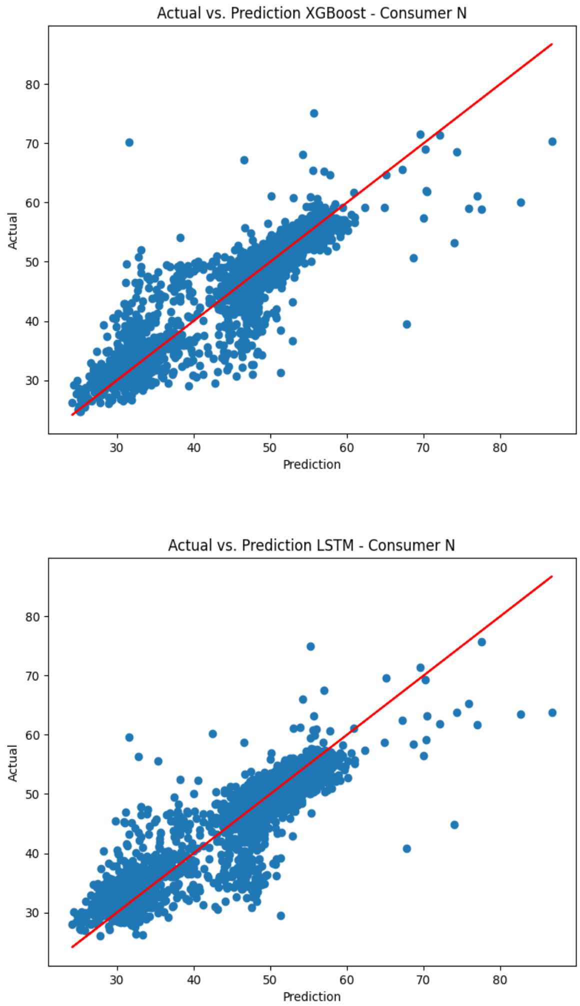


Figure 3.11: Illustration of the relationship between actual observations and predictions on the testset for Consumer N.

The performance of the LSTM and XGBoost models on the test data from the Helgeland dataset is presented in Table 3.3. The input vector for this dataset included the hour, temperature, and energy consumption from the previous 24 hours. The results show that the XGBoost model has a lower MAE and MAPE than the LSTM, indicating that the XGBoost model has a lower bias than the LSTM. However, the LSTM produced a slightly lower RMSE and MSE, suggesting that the LSTM has a lower variance than the XGBoost.

	MSE (MWh)	**RMSE** (MWh)	**MAE** (MWh)	**MAPE** %
LSTM	2433.49	49.33	31.05	3.908
XGBoost	2442.02	49.41	30.27	3.861

Table 3.3: Error metrics calculated for Helgeland using unseen test data when attempting to predict one hour ahead.

The performance of the XGBoost and LSTM models for one hour prediction of the total consumption at Helgeland is presented in Figure 3.12. It can be observed that both models have a delay of one hour in their predicted values when compared to the actual values.

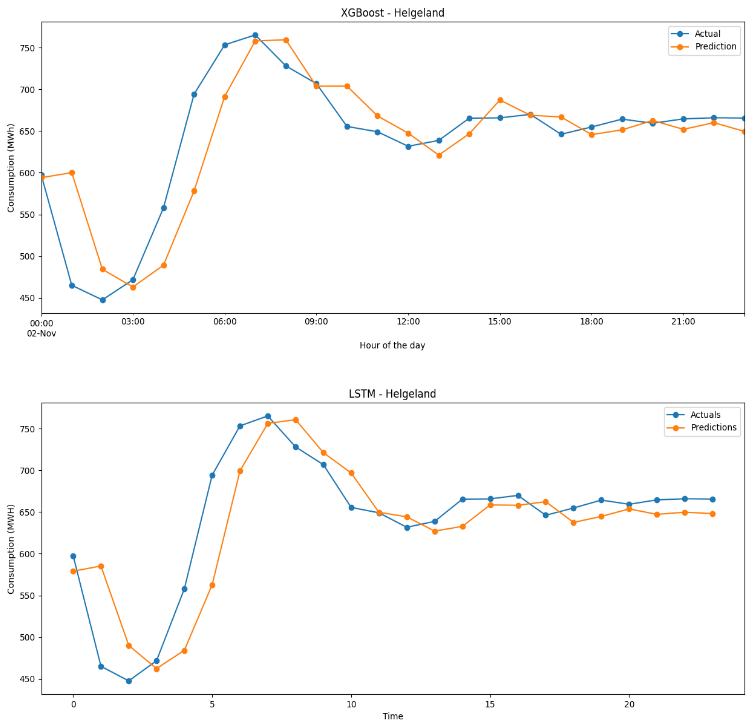


Figure 3.12: On top is the XGBoost performance during testing on the Helgeland dataset. On the bottom is the LSTM model performance.

The relationship between the actual observations and the predicted values in MWh is presented in Figure 3.13, where the red line represents a perfect relationship. The XGBoost model's performance is shown at the top of the figure, while the LSTM model's performance is shown at the bottom. Both models exhibit a clear linear relationship between the actual values and predictions. However, some observations are still clearly over or underestimated.

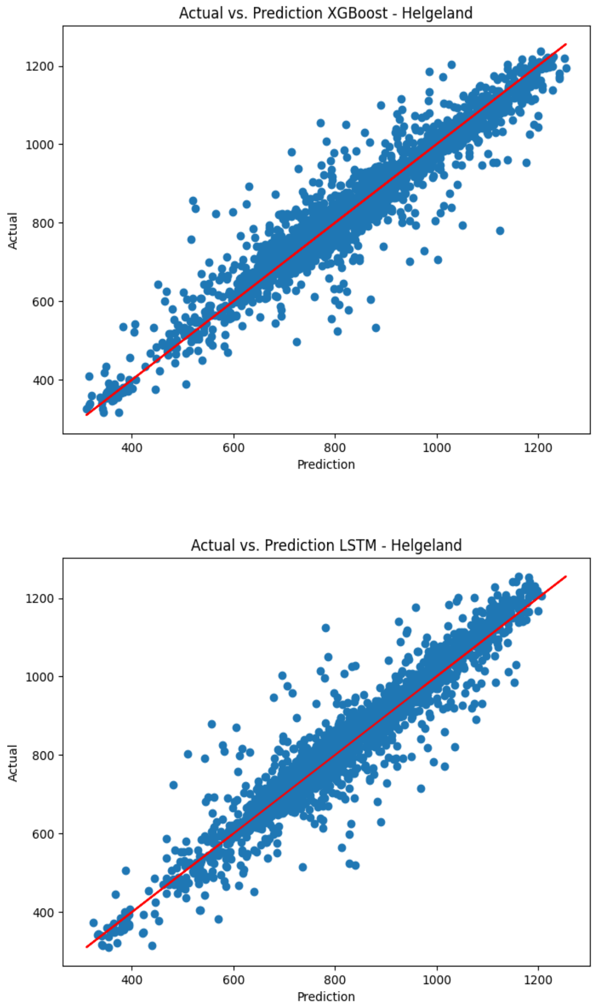


Figure 3.13: Illustration of the relationship between actual observations and predictions on the testset for Helgeland.

3.3.2 Multi-step Prediction

In Table 3.4 the MSE, RMSE, MAE and MAPE when testing Consumer N on the XGBoost and LSTM model for 4 hour ahead prediction can be observed. It can be observed that for this dataset the XGBoost had the best performance. Thus, the XGBoost came on top for this dataset both for one hour and four hour ahead prediction. When comparing the XGBoost performance for four hour ahead with the single step it can be seen that the errors has increased. More specifically the MAE increased with 0.293 KWh, RMSE increased by 0.404

KWh and the MSE increased by 3.16 KWh. Calculating the increases in percent gives us the relative measure of the deterioration where the MSE increased by 23.05%, RMSE 10.91% and MAE 12.39%.

	MSE (KWh)	**RMSE** (KWh)	**MAE** (KWh)	**MAPE** %
LSTM	21.29	4.614	3.195	8.006
XGBoost	16.87	4.107	2.657	6.379

Table 3.4: Error metrics calculated for Consumer N using unseen test data when attempting to predict four hour ahead.

The performance of the XGBoost and LSTM models on four-hour ahead prediction can be observed in Figure 3.14. The green line represents the actual values for the next four hours, the orange line represents the predicted values, and the blue line represents the past four observations.

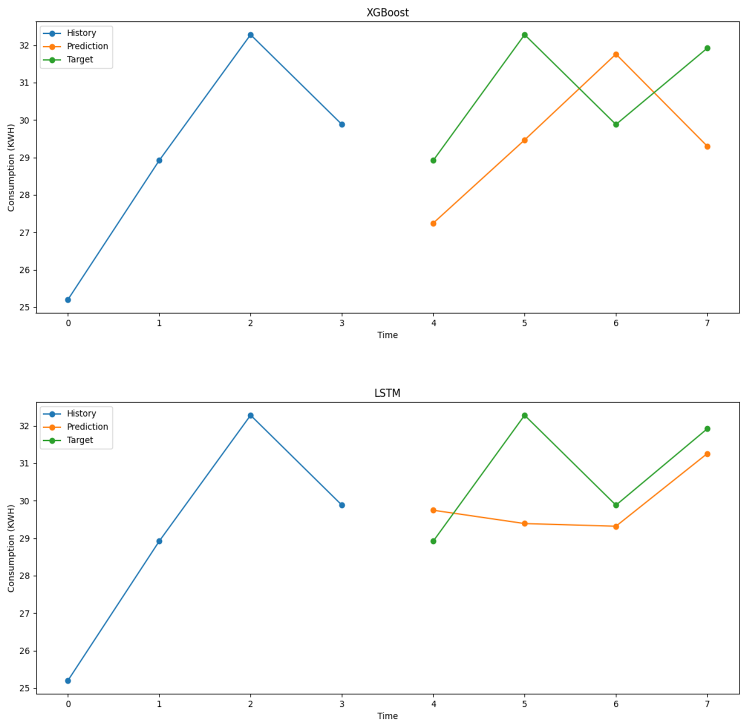


Figure 3.14: On the top is the XGBoost model performance during testing on the Consumer N dataset for four hour prediction. The bottom plot is the LSTM model performance.

In Figure 3.15, we can observe the relationship between the actual observations and the predicted values for both the XGBoost (top) and LSTM (bottom) models on the Consumer N dataset. The figure shows variability in the error, and similar to the one-hour-ahead prediction, the largest variance can be observed in the range of 35-50 KWh and above 60 KWh. However, while the one-hour-ahead prediction underestimated most of the values over 60 KWh, the four-hour-ahead prediction tends to overestimate them.

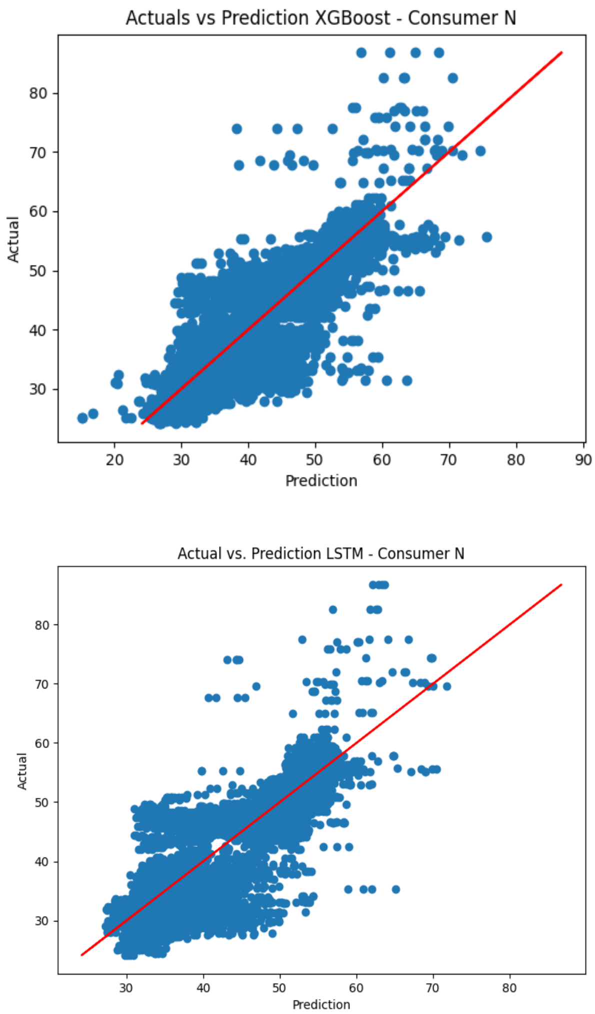


Figure 3.15: Illustration of the relationship between actual observations and predictions on the testset for Consumer N when predicting four hour ahead.

The resulting error metrics for predicting four hours ahead with the XGBoost and LSTM models on the Helgeland dataset are presented in Table 3.5. It can be observed that the XGBoost model produced slightly lower MAE and MAPE values while the LSTM scored better on the RMSE and MSE. This is consistent with the findings for the one-step-ahead prediction.

Upon investigating the increase in error metrics for the XGBoost model from one-step to four-step prediction, we found that the MAE increased by 20.86 MWh, RMSE increased by 29.58 MWh, and MSE increased by 3797.11 MWh. In relative terms, the MSE increased by 155.49%, MAE by 60.91%, and RMSE by 59.87%. The relative increase in error metrics for the Helgeland dataset is quite high compared to the increases found for the Consumer N dataset.

	MSE (MWh)	**RMSE** (MWh)	**MAE** (MWh)	**MAPE** %
LSTM	6172.64	78.56	52.72	6.678
XGBoost	6239.13	78.99	51.13	6.630

Table 3.5: Error metrics calculated for Helgeland using unseen test data when attempting to predict four hour ahead.

The XGBoost and LSTM models' performance on the test data is displayed in Figure 3.16. The blue line represents the historical observations, the green line represents the actual values, and the orange line represents the predicted values. Both models have overestimated their predictions, but XGBoost (top figure) appears to slightly follow the pattern to the actual values.

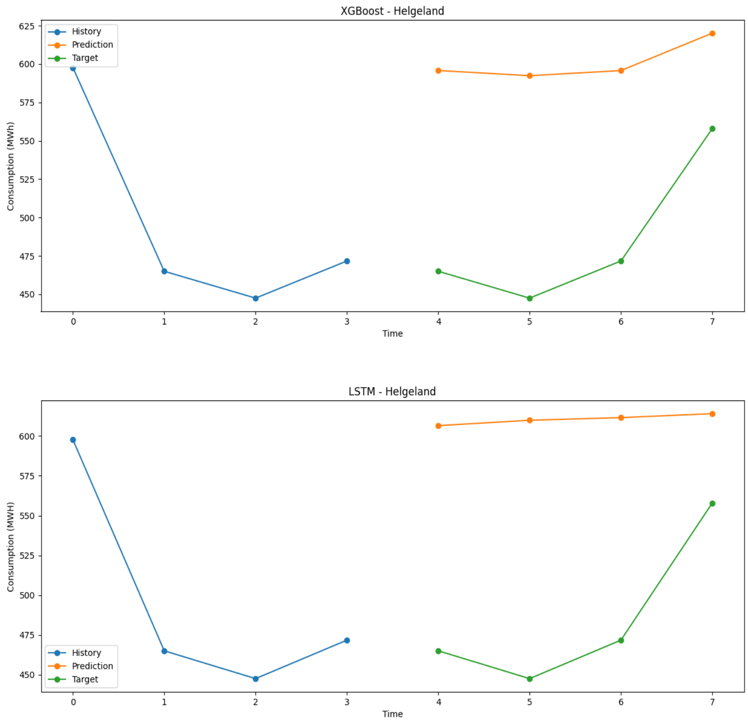
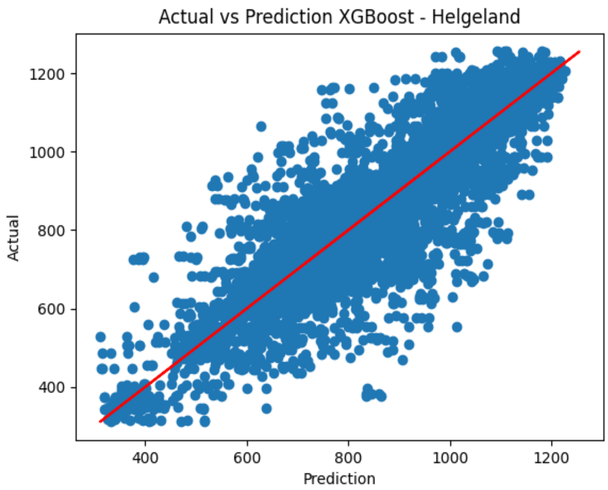


Figure 3.16: On the top is the XGBoost model performance during testing on the Helgeland dataset for four hour prediction. The bottom plot is the LSTM model performance.

In Figure 3.17, the scatter plots depict the relationship between the predicted values (x-axis) and the actual observations (y-axis) on the test set for both the XGBoost and LSTM models. The red line represents the perfect prediction, and the plots show that both models have large errors across all values, with significant deviations from the perfect prediction line. This suggests that the models have not captured the underlying pattern in the data.



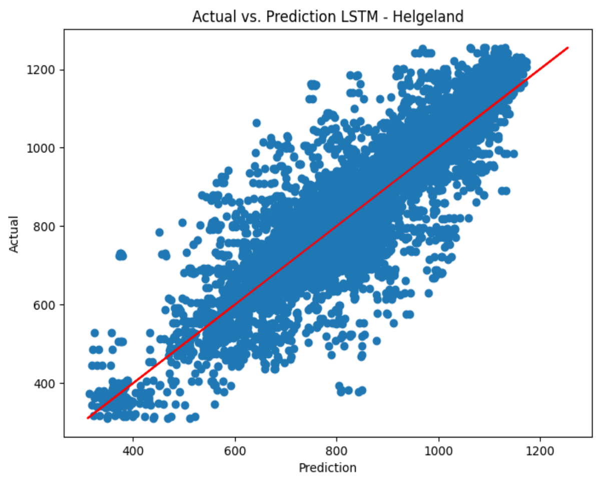


Figure 3.17: Illustration of the relationship between actual observations and predictions on the testset for Helgeland when predicting four hour ahead.

3.3.3 Summary

In summary, the results of the single-step and multi-step forecasting experiments are as follows:

- The XGBoost model performed better than the LSTM model in terms of all error metrics for the single-step prediction of the Consumer N dataset. The models had the largest variance in errors when the actual values were between 35-60 KWh and above 60 KWh.

- For multi-step predictions on the Consumer N dataset, the XGBoost model produced better results than the LSTM model. However, we observed a larger increase in error variance. When predicting four hours ahead, the XGBoost model had a 12.39% increase in MAE, a 10.91% increase in RMSE, and a 23.05% increase in MSE compared to one-hour predictions.

- In one-step predictions on the Helgeland dataset, both models exhibited a one-hour delay in their predictions. While the XGBoost model outperformed the LSTM model in terms of MAE and MAPE, the LSTM model achieved lower RMSE and MSE scores.

- For four-hour predictions on the Helgeland dataset, the XGBoost model achieved lower MAE and MAPE scores compared to the LSTM model. However, the LSTM model had lower RMSE and MSE scores, as observed in one-step predictions. Both models showed high bias in their predictions. When comparing the one-step to four-step predictions, the relative increase in error metrics was 60.91% for MAE, 59.87% for RMSE, and 155.49% for MSE.

3.4 Flexibility Provider

We will now present the findings from our investigation into the potential of Consumer N to provide DSF, as well as the financial aspects of offering flexibility.

3.4.1 Flexibility Resources

The consumer with code N in Table 2.1 provided information about the resources which could potentially be flexible. These resources is listed in Table 3.6. There was few constraints regarding when these resources could be disconnected, however there was a time constraint of the duration which was 2 hours.

Equipment	**KW**
Freezer boxes	15.7
Refrigerator	7.2
Cold room	0.75
Freezer room	0.24
Total	23.86

Table 3.6: The resources available to be flexible for Consumer N.

3.4.2 Financial Aspects

When calculating the potential earning by using Equation 2.5 we assume that all the resources presented in Table 3.6 is disconnected at the same time for one hour. From Equation 3.1 we can observe that the potential earning from one trade gives the consumer a earning of 214.74 NOK.

$$I_t = 23.86 \text{ KW} * 1 \text{ h} * 9 \text{ NOK/KWh} = 214.74 \text{ NOK} \tag{3.1}$$

From conversation with a Cegal employee we found that an estimated cost of the equipment needed and the installation would be approximately 25 000 NOK. It has to be noted that this is a rough estimate and that the price can vary dependent on the load that is supposed to be controlled as well as how much electrical work that is needed. From the initial cost and the earning found in Equation 3.1 we can calculate the number of trades (with a duration of one hour) the assets needs to be disconnected in order for Consumer N to break even:

$$T = \frac{25000 \text{ NOK}}{214.74 \text{ NOK}} = 116.42 \tag{3.2}$$

3.4.3 Summary

Findings regarding the commercial buildings cost and benefits can be summarized as follows:

- The amount of flexibility Consumer N could provide was a total of 23.86 KW
- One trade with a duration of one hour would result in a income of 214.74 NOK
- Given the cost and income of one trade it would take 117 trades for Consumer N to break even

4

Discussion

This chapter comments and discusses the results represented in the previous chapter. It will go through the results in the same order as they are represented in Chapter 3. Lastly, we will discuss our results up against the research questions raised in Subsection 1.3.1.

4.1 Future energy situation at Helgeland

In Section 3.1 findings about the estimated energy balance at Helgeland was respresented. The numbers represented was from two seperate reports where both reports presented different scenarios of the energy balance and load balance based on the development in energy production and consumption in the area. Although the energy balance represented in Table 3.1 and at the top of Figure 3.1 is considered the likely scenarios, it has to be noted that the reports are from 2020 and 2022, meaning that the future plans for developing new energy production and/or planned power-intensive industry in the area might have changed and should be further investigated in order to find the likelyhood of the scenarios today. In addition, interviewing both Statnett and Linea about their experience of the grid capacity in the Helgeland region today would have been a different approach in order to collect information about the need for flexibility in the area. However, this was not prioritized during this project.

4.2 Data Analysis and Forecasting

The initial aim of the experimental part of this project was to investigate forecasting models that could be used to predict the total energy demand in the area and predict the energy consumption to a potential asset provider which can be used as a baseline. The two datasets was analysed and further used in a LSTM and XGBoost model respectivly. We will further comment on our results regarding the analyses conducted on the datasets as well as the resulting predictions.

4.2.1 Data Analysis

The results from the analysis of the two datasets were presented in Section 3.2. The average daily load profile for Consumer N exhibited daily seasonality, while the total load output suggested yearly seasonality with a slight increase during winter and summer. The average daily load profile for the Helgeland region showed a daily pattern with two peaks, one in the morning and another in the late afternoon, which is consistent with the peak consumption periods for households and secondary/tertiary industries around 9 AM and 10 AM [67]. The load output for the entire region suggested a possible increasing trend in consumption. However, missing data in the dataset (as noted in Subsection 2.3.1) makes it difficult to determine the accuracy of this trend in reflecting the actual pattern in the region. It should also be noted that both datasets only contain three years of hourly measured observations, which may not be sufficient to draw conclusions on yearly seasonality or trends in the data.

In section 3.2.2, we explored the linear relationship between consumption and temperature. While none of the scatter plots indicated a clear linear relationship, using temperature as an input produced better results than not including it. However, we found that for Consumer N, there appeared to be a curvilinear relationship between consumption and temperature. Specifically, consumption was affected when the temperature exceeded 20 degrees or was below 5 degrees. To investigate whether this relationship has changed over the last three years, we could have examined the relationship for each year separately, as we suspect that the installation of a new ventilation system in the building may have impacted the relationship. Furthermore, other independent variables, such as those mentioned in section 2.4.3, could have been explored. During this project, we have only considered temperature as an independent variable.

4.2.2 One-step and Multi-step Forecast

In the results presented in Subsection 3.3.1 for single step predictions, the actual and predicted values plotted in Figure 3.10 and Figure 3.12 suggest a delay in the predictions. This is most likely due to the input vector containing the previous 24 observations, and the models relying too heavily on the last seen observation. To address this issue, incorporating more historical data in the input vector, such as the consumption data from the last 48 or 72 hours, could be explored to better capture the underlying patterns in the data and reduce this bias.

In Subsection 3.3.2, the results of the multistep predictions were presented, and as expected, the error rates increased compared to the single step predictions. This is due to the fact that predicting further into the future is generally harder. However, there was a significant difference in the increase of error rates between the two datasets. It is believed that this difference can be attributed to the input vectors used. The input sequence was not changed when going from single step to multistep predictions, and therefore, the absence of features such as the month and day of the week for the Helgeland dataset may have resulted in a weaker model. Hence, it is recommended to conduct additional research on suitable independent and dependent variables to be included in the input vector.

During testing of the LSTM model, we observed different error metrics without making any changes to the hyperparameters or data. For example, in Table 3.2, the Consumer N dataset had a MSE of 15.54 KWh, RMSE of 3.94 KWh, MAE of 2.681 KWh, and MAPE of 6.37%. However, when we trained the model again with the same settings, we obtained a MSE of 18.22 KWh, RMSE of 4.269 KWh, MAE of 2.996 KWh, and MAPE of 7.122%. Similar variations were also observed when training the LSTM with the Helgeland dataset. The reason for this variation is likely the addition of the dropout layer after each LSTM layer, as explained in Subsection 2.4.1. During training, the dropout layer randomly selects neurons to ignore. As a result, each training run produces a slightly different model, which can result in slightly different prediction results. Thus, obtaining reproducible results with the LSTM model can be challenging.

The XGBoost model came on top for the Consumer N dataset, for one hour ahead prediction as well as four hour ahead prediction. For the Helgeland dataset the MAE and MAPE had better scores on the XGBoost model, while the RMSE and MSE proved better on the LSTM model. This suggest that the XGBoost model was better at predicting the direction of the observation, while the LSTM model was better at predicting the magnitude of the observation.

This project has investigated XGBoost and LSTM to forecast the consumption, one hour ahead and four hours ahead, for the two datasets, Consumer N and Helgeland. Due to reciving the Helgeland data later than the Consumer N data there has been spent more time on hyperparameter tuning the models based on the Consumer N dataset as well as experimenting with the input vector. Additionally, due to the computational resources needed when training an LSTM model and the time constraint for this project the LSTM model can probably be better optimized by experimenting more with the hyperparameters.

4.3 Flexibility Provider

The flexible resources available for disconnection were identified in Section 3.4, along with the estimated investment required to install equipment for disconnection. Additionally, the potential earnings from disconnecting all resources for one hour were calculated based on rough estimates of cost provided by a Cegal employee, as described in Subsection 2.5.2. It should be noted that the installation cost is highly dependent on the load of the resources, and the income from one trade is based on prices used in the NorFlex project, but may not accurately reflect actual earnings. Thus, the calculated income should be taken as an indication, rather than an accurate representation of potential earnings.

The analysis showed that the commercial building could provide a limited amount of flexibility, namely 23.86 KW, which is considerably smaller than the peaks observed in the total consumption, as shown in Figure 3.4. Nonetheless, the required amount of flexibility in a specific area depends on the grid capacity, and it may be worth investigating further and consulting with the local DSO to determine the relevance of the identified flexibility volume. However, it is clear that this amount of flexibility is not sufficient to be of significant value in the mFFR-market used by the TSO to manage the grid. Although, the amount required in the NODES marketplace was only 1 KW, as stated in Subsection 1.4.1, making the amount of flexibility provided by the commercial building sufficient.

Additionally, the load of the flexible resources listed in Table 3.6 was found by reading of the lable of the equipment. Hence, some loads may refer to the equipment running on maximum load, which probably is not the case all the time. Thus, there is some uncertainty regarding how much volume the commercial building can provide.

The analysis showed that Consumer N would need to provide all of their flexible assets for about 117 hours to break even. Given the load balance estimated in Section 3.1 and the average daily load profile in Figure 3.4, it is reasonable to assume that flexibility may be required for at least two hours every day. Therefore, the 117-hour threshold for Consumer N to break even does not appear to be overly demanding.

Although there are some uncertainty with the findings regarding the cost, income of a trade and the amount of flexibility that can be provided from the investigated consumer we would say, based on our findings, that the consumer could benefit from participating in a LFM. However, given that the area the commercial building is located in needs flexibility.

4.4 Addressing the Research Questions

In Subsection 1.3.1, three research questions were presented that this thesis aims to answer. In the following paragraphs, we will provide our findings in response to these questions.

4.4.1 Question 1

Research question 1 aimed to investigate the feasibility of establishing a LFM in the Helgeland region. Our analysis of the future energy situation in the area suggests that there is a viable opportunity in terms of energy and load balance. However, the success of an LFM depends on the participation of multiple prosumers who can offer flexibility. Since this thesis only investigated one consumer, further research is necessary to identify other potential asset providers and evaluate the overall viability of an LFM in the region. The different consumers listed in Table 2.1 can be a starting point for identifying and analyzing additional potential asset providers.

4.4.2 Question 2

The second research question was whether the proposed forecasting methods could accurately predict the total energy consumption in the area, as well as short-term (one hour) and long-term (four hours) energy consumption for individual consumers. From our results, both models showed promising performance in terms of prediction accuracy. However, XGBoost was found to be the most accurate model for the consumer dataset, while the two models' accuracy was quite similar for the total consumption dataset. Based on this, we recommend using XGBoost for forecasting energy consumption. However, further research should be conducted to explore the impact of variables in the input vector on the models' performance.

4.4.3 Question 3

Research question 3 aimed to explore the benefits and ability of prosumers to participate in a LFM. However, only one consumer's potential benefits and ability to participate were investigated. In general, the main benefit of offering demand side flexibility to a LFM is the potential financial compensation. The investigated commercial building had potential flexible assets, indicating the ability to participate. However, the earnings from participation depend on the needs of the DSO and TSO, and are therefore difficult to estimate. However, the benefits of a LFM can be viewed from a wider perspective. If a LFM in the Helgeland region could impact grid management such that grid upgrades are no longer necessary due to capacity issues, the benefits would extend beyond those offering flexibility to all customers of the DSO. This is because all customers must pay the grid tariff, which covers the DSO's costs.

5 Conclusion

In this thesis, we have explored the energy situation of the Helgeland region to assess the need for flexibility in the area. We have also examined the capability of one consumer to provide demand-side flexibility. Additionally, a significant scientific contribution of this thesis has been the investigation of forecasting methods for predicting future energy demand in the region, as well as the energy consumption of a single consumer. Specifically, we have explored two methods, LSTM and XGBoost, for both single-step and multi-step predictions.

According to the findings, it appears that the energy balance in Helgeland is anticipated to decrease, which implies that the demand will exceed the estimated new production. Furthermore, during peak demand periods, the load balance is predicted to come under strain. However, based on this information alone, it is difficult to draw a conclusion regarding the feasibility of a LFM. Nevertheless, it does suggest that there may be an opportunity for one.

It was found that the consumer investigated in this thesis is capable of providing up to 23.87 KW of flexibility. Based on the financial analysis conducted, it can be concluded that the consumer would benefit from participating in a LFM. However, the degree of benefit is highly dependent on the TSOs and DSOs demand for flexibility.

The experimental part of this project is a contribution to the development of a demand-response system at Cegal. The study investigated two forecasting methods that can estimate the need for flexibility and predict consumer energy consumption, providing a baseline for financial compensation. The results show promising performance for both XGBoost and LSTM models. However, further investigation is required to identify and incorporate relevant independent and dependent variables in the input vector.

5.1 Future Work

Based on our experience, we recommend using XGBoost for this problem as it is easier to understand, requires less hyperparameter tuning, and is less computationally expensive than LSTM. However, if the forecasting horizon were to increase, it may be worth revisiting the LSTM model.

In terms of future work on the short-term and long-term models, we suggest exploring the potential of using additional independent and dependent variables as input to see if the models can capture the underlying pattern in the dataset more accurately. Independent variables, such as electricity prices and weather data, including humidity and precipitation, could be of interest.

To obtain a clearer understanding of the feasibility of establishing a LFM at Helgeland, we suggest engaging in discussions with the local DSO and TSO to determine their level of interest. Moreover, it would be beneficial to investigate additional prosumers who may be interested in participating in such a market.

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