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Robust Energy Forecasting: Harnessing Deep Learning and Grey-Box Building Models

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Abstract

Forecasting is a critical cornerstone in the efficient operation of smart grids. This thesis introduces an integrated approach that prioritizes advanced forecasting methods to optimize operational efficiency and minimize energy consumption and costs. The core objectives revolve around three vital aspects: wind power generation forecasting, energy demand prediction, and the evaluation of forecasting methodologies.

To tackle the complexities of wind power forecasting, a novel deep neural network-based model, Neural Expansion Analysis for Time Series Forecasting (N-BEATS), is proposed. N-BEATS leverages a tailored loss function to mitigate forecast bias and provides insightful outputs by decomposing components like trend and seasonality. Demonstrating its competitiveness, the model surpasses established counterparts in terms of accuracy and superiority across various scenarios, using real-world wind power data spanning 15 European countries.

In the realm of energy demand prediction for grid optimization, this study underscores the critical importance of considering both qualitative and quantitative indicators. Metrics such as mean absolute percentage error (MAPE) and root mean square error (RMSE) gauge forecast quality, while the tangible results for a given energy community, encompassing aspects like load coverage, supply capacity, on-site energy ratios, and electricity expenses, assess forecast value. This holistic framework accentuates the intrinsic link between precise predictions and the enhancement of energy community performance. It underscores the necessity of incorporating both quality and value indicators in the selection of an optimal forecasting approach.

Moreover, this study scrutinizes the efficacy of diverse forecasting techniques in streamlining energy community operations amid volatile energy prices. Diverse methods, ranging from machine learning algorithms to statistical models, are deployed to anticipate energy and domestic hot water (DHW) demand. The outcomes endorse advanced approaches such as XGBoost, Prophet, and Neural Basis Expansion Analysis for Time Series with Exogenous variables (NBEATSx) for their superiority over rudimentary methods, translating into substantial savings and substantial reductions in grid imports and exports compared to baseline models.

Collectively, this integrated study underscores the pivotal role of precise forecasts in optimizing energy community operations and achieving self-sufficiency. The introduction of a deep learning approach as a wind power forecasting model, alongside sophisticated machine learning algorithms for energy demand prediction, not only enhances accuracy but also provides interpretable outputs. The findings accentuate the necessity of integrating both quality and value indicators when selecting an appropriate forecasting approach, offering valuable insights for practitioners and policymakers navigating the intricacies of energy community management amidst a backdrop of volatile energy prices.

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Kurzfassung

Die Prognose ist ein entscheidender Eckpfeiler für den effizienten Betrieb intelligenter Stromnetze. Diese Dissertation stellt einen integrierten Ansatz vor, der fortschrittliche Prognosemethoden implementiert, um die betriebliche Effizienz zu optimieren und den Energieverbrauch sowie die Kosten zu minimieren. Die Kernziele drehen sich um drei wesentliche Aspekte: die Prognose der Windleistung, die Vorhersage des Energiebedarfs in einer Stromgemeinschaft und die Bewertung von Prognosemethoden.

Um die Komplexität der Windleistungsprognose zu bewältigen, wird ein neues Modell auf Basis von Deep Neural Networks, das Neural Expansion Analysis für die Zeitreihenprognose (N-BEATS), vorgestellt. N-BEATS nutzt eine maßgeschneiderte Verlustfunktion, um Prognosefehler zu minimieren, und liefert aufschlussreiche Ergebnisse durch die Zerlegung von Komponenten wie Trend und Saisonalität. In verschiedenen Szenarien übertrifft das Modell etablierte Methoden hinsichtlich Genauigkeit und zwar anhand von realen Windenergiedaten aus 15 europäischen Ländern.

Im Bereich der Vorhersage des Energiebedarfs zur Optimierung eines Mehrparteienhauses betont diese Studie die entscheidende Bedeutung sowohl qualitativer als auch quantitativer Indikatoren. Metriken wie der mittlere absolute Prozentsatzfehler (MAPE) und die Quadratwurzel des mittleren quadratischen Fehlers (RMSE) bewerten die Prognosequalität, während die konkreten Ergebnisse für eine gegebene Energiegemeinschaft Aspekte wie Lastabdeckung, Versorgungskapazität, Eigenenergieverbrauch und Stromkosten bewerten. Dieser ganzheitliche Ansatz betont die intrinsische Verbindung zwischen präzisen Vorhersagen und der Verbesserung der Effizienz von Energiegemeinschaften. Er unterstreicht die Notwendigkeit, sowohl qualitative als auch quantitative Indikatoren bei der Auswahl eines optimalen Prognoseansatzes zu berücksichtigen.

Darüber hinaus untersucht diese Studie die Wirksamkeit verschiedener Prognosetechniken bei der Optimierung des Betriebs von Energiegemeinschaften angesichts volatiler Energiepreise. Unterschiedliche Methoden, von maschinellem Lernen bis hin zu statistischen Modellen, werden eingesetzt, um den Energie- und Warmwasserbedarf vorherzusagen. Die Ergebnisse befürworten fortschrittliche Ansätze wie XGBoost, Prophet und NBEATSx aufgrund ihrer Überlegenheit gegenüber klassischen Methoden. Dies führt zu erheblichen Einsparungen und deutlichen Reduzierungen der Netzimporte und -exporte im Vergleich zu Basismodellen.

Insgesamt unterstreicht diese integrierte Studie die Schlüsselrolle präziser Prognosen bei der Optimierung des Betriebs von Energiegemeinschaften und der Erreichung von Autarkie. Die Ergebnisse betonen die Notwendigkeit der Integration sowohl qualitativer als auch quantitativer Indikatoren bei der Auswahl eines geeigneten Prognoseansatzes und bieten wertvolle Erkenntnisse für Fachleute und Entscheidungsträger.

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Abbreviations

ADAM	Adaptive Momentum
ANN	Artificial Neural Network
ARIMA	Auto-Regressive with Integrated Moving Average
BERT	Bidirectional Encoder Representations from Transformers
BESS	Battery energy storage system
BGA	Binary Genetic Algorithm
CFA	Conditioned Floor Area
COP	Coefficient of Performance
DHW	Domestic Hot Water
DNN	Deep Neural Network
ES	Exponential Smoothing
FCNN	Fully Connected Neural Network
GFA	Gross Floor Area
GPR	Gaussian Process Regression
HVAC	Heating, Ventilation, and Air Conditioning
kNN	k-Nearest Neighbour
KPI	Key Performance Indicator
LEC	Local Energy Community
LP	Linear Programming
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
ML	Machine Learning
MPC	Model Predictive Control
MSNet	Multiple Seasonal Patterns
N-BEATS	Neural Basis Expansion Analysis for Time Series Forecasting
N-BEATSx	N-BEATS with Exogenous Variables
NN	Neural Network
nRMSE	normalized Root Mean Square Error
nZEB	nearly Zero-Energy Building
OER	On-Site Energy Ratio
OLS	Ordinary Least Square

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PV	Photovoltaic
RF	Random Forest
ReLU	Rectified Linear Unit
RES	Renewable Energy Sources
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
sMAPE	symmetric Mean Absolute Percentage Error
SUT	System Under Test
SVR	Support Vector Regression
VAT	Value-Add Tax
VSTWPF	Very Short-Term Wind Power Forecasting
WT	Wavelet Transformation
XGBoost	eXtreme Gradient Boosting

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1. Introduction

1.1. Motivation

The increasing integration of renewable energy sources, energy storage technologies, and load management techniques in smart grids has led to the emergence of local energy communities (LECs) as key components of sustainable energy systems. LECs strive to optimize energy generation, consumption, and storage within their boundaries, aiming for self-sufficiency and reduced reliance on the central grid. To achieve these goals, accurate forecasting of both renewable energy generation and energy demand is crucial.

However, several challenges hinder the efficient operation of LECs. Firstly, wind power generation, which has immense potential as a renewable energy source, exhibits inherent uncertainty and stochastic behavior due to the random nature of wind speed. Accurate forecasting of wind power generation is essential for effective scheduling and integration into the grid. Existing forecasting models often struggle to capture the non-linear and stochastic characteristics of wind speed, limiting their accuracy and hindering optimal decision-making in LECs.

Secondly, energy demand within LECs is subject to fluctuations influenced by factors such as weather conditions, user behavior, and the availability of renewable energy sources. Accurate forecasting of energy demand is essential for load management, resource allocation, and optimal utilization of renewable energy generation and storage capacities. Traditional forecasting approaches often rely solely on statistical methods and fail to capture the complex dynamics and interdependencies within LECs, limiting their effectiveness in supporting decision-making processes.

Moreover, the selection of an appropriate forecasting approach for LECs is often based solely on quality metrics, such as mean absolute percentage error (MAPE) or root mean square error (RMSE), without considering the value of the forecast in terms of its impact on LEC performance measures and cost optimization. This approach neglects the specific characteristics and requirements of LECs, leading to suboptimal outcomes and potential

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financial losses.

To address these challenges, there is a need for an integrated approach that combines advanced forecasting techniques tailored to the unique characteristics of LECs. Such an approach should provide accurate and interpretable forecasts of wind power generation and energy demand, enabling optimal decision-making for LEC operation, load management, and cost optimization.

Therefore, this study aims to develop and evaluate an integrated forecasting framework for LECs, incorporating novel methodologies such as neural expansion analysis for time series forecasting (N-BEATS) for wind power generation forecasting and advanced machine learning algorithms for energy demand forecasting. By considering both quality and value indicators, the study seeks to provide a comprehensive assessment of the forecast performance in terms of accuracy, cost optimization, and LEC performance measures. The contributions are based on three first-author publications in scientific journals (Putz et al. (2021), Putz et al. (2023), Putz et al. (2024)). The findings of this research will contribute to the advancement of forecasting methodologies for LECs and provide valuable insights for practitioners and policymakers in enhancing the efficiency and sustainability of local energy communities.

1.2. Research questions

This thesis aims to answer three research questions related to integrated renewable energy forecasting in energy communities. This Section describes each of the research questions in detail and then provides an overview on the relation between the research questions. In accordance with rigorous professional peer-review processes, the studies presented in this thesis have undergone comprehensive evaluation and scrutiny, ensuring the robustness and credibility of the research findings.

The core objective of this study is to develop an integrated forecasting framework for local energy communities (LECs) that addresses the challenges of wind power generation and energy demand forecasting. The primary goal is to improve the accuracy and interpretability of forecasts, enabling optimal decision-making for LEC operation, load management, and cost optimization. The study aims to achieve this objective by combining advanced methodologies, such as neural expansion analysis for time series forecasting (N-BEATS) for wind power forecasting and advanced machine learning algorithms for energy demand forecasting. The evaluation of forecast performance will consider both quality metrics and value indicators, providing a comprehensive assessment of forecast

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effectiveness for LECs.

Research question 1: *How does the novel N-BEATS approach for wind power forecasting, considering the uncertainty and stochastic behavior of wind speed, compare to established models in terms of accuracy and forecast bias reduction?*

In the first contribution of this thesis (Putz et al. (2021)), a novel approach, called N-BEATS, for wind power forecasting in the presence of uncertainty and stochastic behavior of wind speed is presented. The results demonstrate that N-BEATS outperforms established models, providing comprehensive and accurate forecasts while addressing the issue of forecast bias through a tailored loss function.

The study expects that the N-BEATS approach will demonstrate competitive performance and even outperform established models in terms of accuracy for wind power forecasting. Additionally, it anticipates that the tailored loss function used in N-BEATS will effectively mitigate forecast bias, leading to improved forecast quality.

Building upon the advancements in wind power forecasting from the first study, the subsequent studies delve into the broader context of energy communities and their demand forecasting challenges. They explore the importance of accurate energy demand forecasts, considering the random nature of weather, and emphasize the value of forecasts in optimizing the operation of local energy communities and minimizing energy consumption and costs.

Research question 2: *How can the quality and value of energy demand forecasts be assessed and optimized to support the effective and continuous operation of energy communities, considering the random nature of weather and the interconnected dynamics of the energy system?*

The core objective of the second contribution is to develop a comprehensive framework for assessing the quality and value of energy demand forecasts in the context of energy communities (Putz et al. (2023)). By considering both quality metrics and value indicators, the study aims to evaluate the performance of different forecasting approaches and highlight the connection between accurate forecasts and improved energy community performance measures, providing insights for optimal decision-making and resource utilization.

Research question 3: *How effective are different forecasting methods in supporting the forecast-based optimal control of local energy communities under high and volatile energy prices, and what are the implications for selecting and utilizing forecasting methods in*

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the context of LECs?

The core objective of the third contribution (Putz et al. (2024)), which is currently under review, is to assess the true value of energy demand forecasts in the context of local energy communities (LECs) by considering different energy price scenarios. The study aims to evaluate the effectiveness of various forecasting methods in the forecast-based optimal control of LECs, with a focus on minimizing energy consumption and costs under uncertain energy price conditions, and provide guidance for practitioners and policymakers on the selection and utilization of forecasting methods in LECs.

The three studies collectively contribute to the field of energy forecasting and optimization in the context of renewable energy integration and local energy communities. While the first study focuses on wind power forecasting using the N-BEATS approach, the second and third studies extend the scope to energy demand forecasting in energy communities. The second study emphasizes the assessment of quality and value indicators for forecasting approaches, while the third study examines the effectiveness of forecasting methods specifically in relation to high and volatile energy prices. Together, these studies provide a comprehensive understanding of the challenges, methodologies, and implications of accurate forecasting for optimal decision-making and performance optimization in local energy communities.

1.3. Structure of the thesis

The structure of this thesis is outlined as follows: Chapter 2 provides a comprehensive literature review on forecasting and optimization in local energy communities. It begins with an introduction to the concept of energy communities, followed by an examination of state-of-the-art forecasting models and optimization techniques relevant to wind power generation and energy demand. The chapter also discusses the social and regulatory aspects of energy communities. Progress beyond the current state-of-the-art is summarized at the end of the chapter in Section 2.3.

Chapter 3 details the methods employed to address the research questions. This includes the presentation of the N-BEATS approach for wind power forecasting and advanced machine learning algorithms for energy demand forecasting. Each method is explained in a dedicated section, starting with an overview of the problem and followed by a detailed mathematical formulation and nomenclature. The chapter is based on Putz et al. (2021), Putz et al. (2023) and Putz et al. (2024).

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The presentation of results in Chapter 4 is divided into two parts: Section 4.1 showcases the outcomes related to the first research question regarding N-BEATS applied to wind power forecasting. Section 4.2 presents the findings pertaining to the second and third research questions. Case studies are conducted to evaluate the effectiveness of different forecasting methods under varying energy price scenarios in the context of local energy communities. The chapter is based on Putz et al. (2021), Putz et al. (2023) and Putz et al. (2024).

Chapter 5 consolidates the overall findings of the research questions and provides a synthesis of the results obtained from the wind power and energy demand forecasting studies. It offers insights into the implications and significance of the research outcomes for decision-making in local energy communities. The chapter is based on Putz et al. (2021), Putz et al. (2023) and Putz et al. (2024).

The final chapter, Chapter 6, concludes the thesis by summarizing the key findings, discussing their implications, and providing an outlook on potential future research directions in the field of forecasting and optimization for local energy communities.

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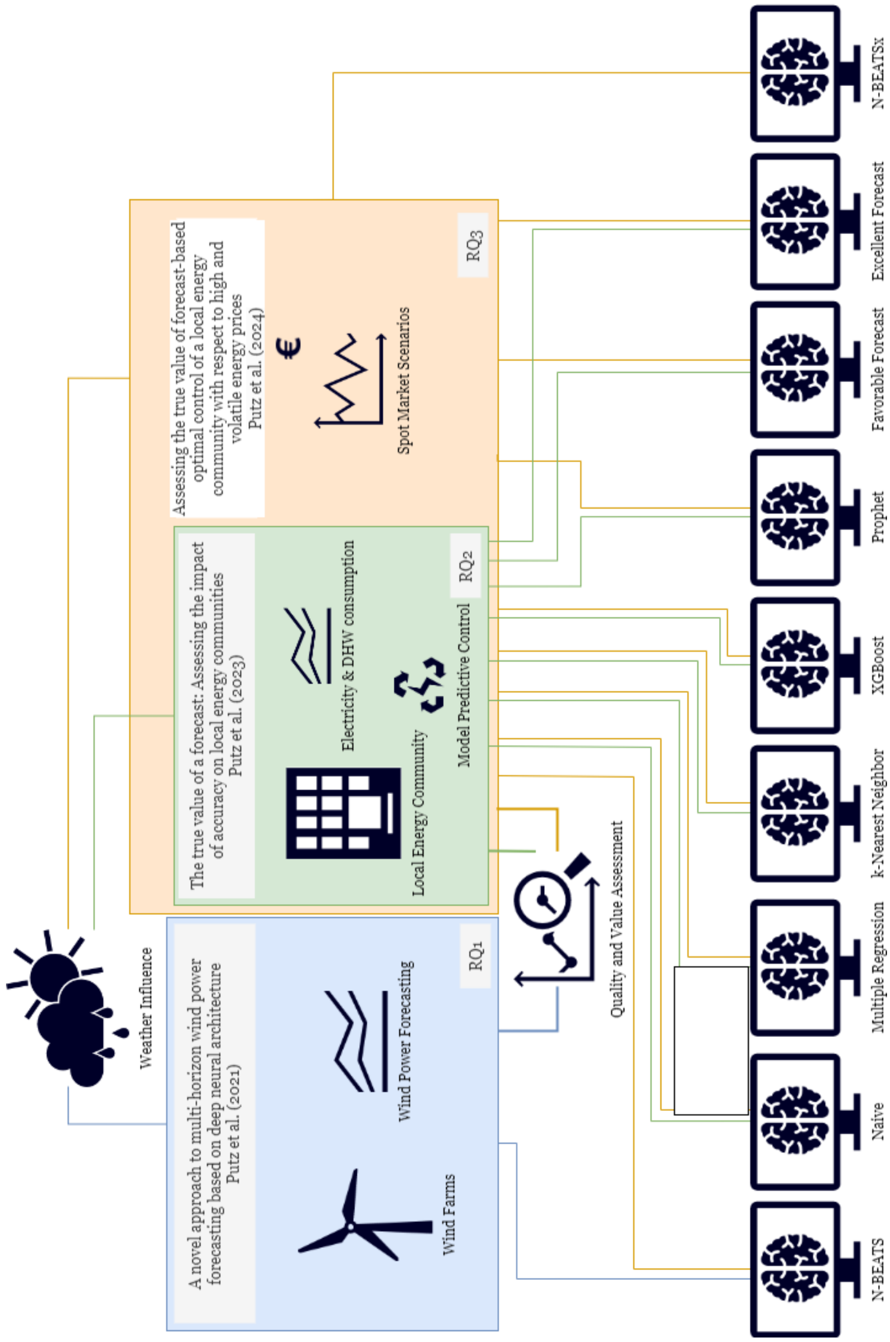

Figure 1.1.: Relation and implementation of the research questions based on three contributions (Putz et al. (2021), Putz et al. (2023), Putz et al. (2024))

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2. State-of-the-art and progress beyond

This chapter provides a comprehensive review of recent scientific literature pertaining to energy communities and their associated challenges, with a focus on forecasting and optimization. Section 2.1 introduces the importance of accurate energy forecasting for renewable integration, specifically highlighting the challenges and stochastic nature of wind power generation. Section 2.2 is divided into two parts: In Subsection 2.2.1, the focus shifts to energy demand forecasting for local energy communities, exploring state-of-the-art models and techniques that account for the dynamic interplay between renewable resources, energy storage, and load management. Subsection 2.2.2 examines the optimization of operation and participation in energy communities, considering social and policy aspects, such as participation models, contracts, and regulatory frameworks. Lastly, Section 2.3 highlights the thesis's contribution to progressing beyond the current state-of-the-art, presenting novel approaches and methodologies that extend the existing knowledge in the field.

2.1. Very short-term wind power forecasting

Zhao et al. (2012) finds that wind power forecasting methods can be divided into two major groups: physical and statistical approaches. Physical methods described by Khalid and Savkin (2012), Nielsen and Madsen (2000) and Sanchez (2006) use physical laws that govern the atmosphere behaviour and rely on extensive meteorological information to estimate the local wind speed and direction. Taslimi Renani et al. (2016) explains that statistical methods use extensive historical data and optimise model parameters in order to minimise the error between the predicted and the observed values. Prasad et al. (2009), Zhang et al. (2017) show that the statistical approaches have been proven to deliver more accurate results for very short-term prediction as long as overfitting issues are avoided which are described by Croonenbroeck and Ambach (2015).

According to Lydia et al. (2016), statistical approaches can be further categorised into classical models, machine learning (ML) models and hybrid models. Classical models are

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often limited in terms of adaptability. As a result, researchers have become increasingly interested in ML algorithms. The neural networks (NN), which are excellently researched in the field of forecasting, are a prime example thereof. They offer great advantages, such as modeling nonlinear relationships, learning from data and strong parallelisation. A large variety of reliable approaches based on neural networks are shown by Okumus and Dinler (2016), Celik and Kolhe (2013), Chitsaz et al. (2015) and Taslimi Renani et al. (2016). However, due to the considerable success of deep learning in other applications this architecture has also been applied to the forecasting of wind power.

deep learning includes modern NN architectures, which are composed of the combinations of fundamental structures such as multilayer perceptrons, recurrent NNs (RNNs) and convolutional NNs (CNNs). They use sophisticated mechanisms for learning and are therefore are far more complex than simple neural networks. Hochreiter and Schmidhuber (1997) proposes the long short-term memory (LSTM) address the problem of the vanishing or exploding gradient that occurs during the learning process of RNNs. An LSTM consists of a cell and several non-linear gates that control the information inside the cell and choose which data should be kept and propagated to the next time step. The success of LSTMs is evident, including in forecasting. Yan et al. (2018) shows that they deliver better results than ML models, such as ARIMA, support vector machine and classical NNs. One reason for the big success of LSTMs is that they can be combined impressively well with other methods resulting in so-called hybrid approaches.

Currently, hybrid models are considered as the most promising approaches, further substantiated by the fact that an ES+LSTM (exponential smoothing) approach, which is a hybrid model and proposed by Smyl (2020), won the M4 competition founded by Zheng et al. (2017). The M4 competition is the continuation of three previous ones intended to identify the most accurate forecasting method(s) for different types of predictions. Hybrid approaches for wind power prediction that deliver satisfactory results are based on LSTMs and signal decomposition described by Memarzadeh and Keynia (2020), Liu et al. (2018) and Wang et al. (2015). Independently, other architectures have been proposed, such as the WaveNet architecture by Oord et al. (2016) for speech synthesis, which uses so-called dilated causal convolutions to learn the long range dependencies.

Another architecture was introduced by Chorowski et al. (2015), based on the so-called attention mechanism developed for sequence to sequence learning proposed by Chorowski et al. (2014). This approach uses encoder-decoder architectures, where the encoder (RNN) learns a representation of the input while the decoder (RNN) is trained to predict the target sequence one step at a time using the representation learned by the encoder. Inspired by the success of attention models, a so-called Transformer model has been developed by Vaswani et al. (2017), that removes RNNs altogether and uses attention,

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in combination with feed-forward NNs to achieve state-of-the-art results. In addition, the proposal by Li et al. (2020) has already been improved for forecasting as well as for natural language processing, such as Bidirectional Encoder Representations from Transformers (BERT) described by Devlin et al. (2019).

2.1.1. Meta-learning

Meta-learning, described by Hu et al. (2018), Ma et al. (2020), Zang et al. (2020), also known as learning how to learn, has recently emerged as a potential learning paradigm that can absorb information from one task and generalise that information to unseen tasks proficiently. This structure is helpful in real-world applications for the following reasons:

- Sufficiently large datasets may be unavailable or contain gaps with missing information.
- ML paradigms can easily be broken when trying to handle uncommon situations that humans are able to handle comfortably, leading to undesired outcomes.
- It is possible to learn something new without training the model from the beginning due to a certain degree of similarity to the base dataset.

2.1.2. Most promising forecast approaches

So far, a wide variety of approaches has been applied to wind power forecasting that hybridise or build upon some of the most successful classical methods and have led to the discovery of completely new areas of ML. The state-of-the-art architectures are currently considered the most promising according to Benidis et al., 2022:

- The expansion of hybrid models and further research thereof with advanced LSTMs as their core component have great potential according to Benidis et al. (2022). For instance, using optimised Wavelet Transformation, feature selection, LSTM and crow search algorithm for forecasting delivers outstanding results shown by Memarzadeh and Keynia (2020), and so do similar approaches such as the study by Wang et al. (2015).

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- The principle of dilated causal convolutions is used by the WaveNet architecture founded by Oord et al. (2016) and Alexandrov et al. (2019). It offers very efficient training due to the use of high parallelism. This advantage increases the WaveNet's competitiveness against common RNN architectures.

- The attention mechanism described by Chorowski et al. (2014) and particularly the transformer proposed by Vaswani et al. (2017), where the mechanism is extended to intra- or self-attention to learn where to focus on in order to get good feature representations is described by Li et al. (2020).

- Pure deep learning approaches, such as N-BEATS. It is a deep neural architecture based on backward and forward residual links and a very deep stack of fully connected layers. The architecture has a number of desirable properties, being interpretable, applicable without modification to a wide array of target domains, and fast to train. One conclusion of the M4 was that hybrid statistical models are superior, while pure ML models may offer one or two pleasant surprises but only by a small margin as shown in Makridakis et al. (2018). This was further evidenced by six of the pure ML models submitted to the competition not even meeting the competition benchmark. Nevertheless, a recent study by Oreshkin et al. (2020) shows that N-BEATS is capable of achieving higher forecast accuracy than the winner of the M4 competition.

2.2. Forecasting in energy communities

This section presents the current state of research on the respective topics and is divided into two major parts. The first part explains as follow: Proven and state-of-the-art forecast models for load and DHW demand forecasting in the context of LECs. The emphasis is placed on machine learning (ML)-based approaches. Commonly used metrics that measure the quality of a forecast, as well as papers that address its value are mentioned. Lastly, the second part highlights the impact of high and volatile energy prices on integrated forecasting in an energy community.

2.2.1. Forecasting models in ECs

The two main types of demand forecasts related to LECs described below are load and DHW forecasts. There are numerous proven and successfully applied cases in the

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literature:

- In Eseye et al. (2019), a ML-based hybrid feature selection method is proposed to obtain the most relevant and non-redundant features for improved short-term forecasting of electricity demand in decentralised energy systems. The binary genetic algorithm (BGA[1]) is applied for the feature selection process, and Gaussian Process Regression (GPR[2]) is used for measuring the fitness score of the features. The primary focus of this contribution is to provide an effective and efficient hybrid ML-based feature selection approach for electricity demand forecasting models. This paper's findings verify that the combination of effective feature selection methods and forecasting models has robust forecasting power compared to forecasting with arbitrary features without predictor selection methods.

- In Nguyen et al. (2020), forecasting approaches are classified into four main categories: support vector regression (SVR[3]), recurrent neural networks like long short-term memory (LSTM[4]), random forest (RF[5]), and statistical methods like multiple linear regression (MLR[6]), autoregressive integrated moving average (ARIMA), or k-nearest neighbour (kNN).

- In Dimitropoulos et al. (2021), four ML algorithms are proposed (LSTM, SVR, MLR, and eXtreme gradient boosting (XGBoost[7]) to produce high-accuracy short-term forecasts up to 6 hours ahead. The best-performing algorithm for accuracy was found to be XGBoost, which performed reasonably well in different forecast horizons, thus making it possible to achieve short-term forecasts. The approach requires very few previous observations to make extremely accurate forecasts for the next hour, and particularly good forecasts for the next three and six hours, demon-

[1] Genetic Algorithms are a subclass of Evolutionary Computing and are population-based optimisation methods. It is inspired by Darwin's theory of evolution.

[2] Gaussian process regression is a nonparametric, Bayesian approach to regression. It has several benefits, working well on small datasets and having the ability to provide uncertainty measurements on the predictions.

[3] In machine learning (ML), support-vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis.

[4] Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning (DL).

[5] Random Forest is an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time.

[6] Linear regression is a linear approach to modelling the relationship between a scalar response and one or more explanatory variables. The case of one explanatory variable is called simple linear regression; for more than one, the process is called multiple linear regression.

[7] Gradient boosting is a ML technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

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strating its efficiency in an energy community environment, where the availability of data is often limited.

- In Pirbazari et al. (2021b), an ensemble approach with two levels is proposed to develop forecasting models for energy and DHW consumption of household communities at multi-steps ahead. In the first level, multiple forecasting algorithms as base learners predict both target outputs in one step forward. In the second level, the predictions for each target are used to train a meta learner aimed at generating multi-step predictions separately for each target. Three influential factors are considered input variables in the forecasting models: time variables, meteorological data, historical electricity consumption, and photovoltaic (PV) power output. Before model development, two feature selection techniques and two ML algorithms were used to select the optimal subset of input variables. The results show that applying an ensemble learning strategy enables the model to provide more robust and accurate results than individual predictive methods. Moreover, deep recurrent neural networks, as strong predictive algorithms for time series prediction tasks, provide the model with highly accurate base estimations. Additionally, because the ensemble model is not reliant on the structure of a particular deep network, it can adapt better to new datasets than individual neural networks that are heavily tuned for a given dataset. Finally, unlike the boosting approach, which involves sequential learning, the applied stacking strategy offers the ability to train base learners separately, thereby reducing training time in distributed computational environments.

- In Muzumdar et al. (2021), state-of-the-art methods for short-term load forecasting on varying loads of each customer were tested and analysed. It was observed that the integration of LSTM, SVR, and RF as base predictors can help in reducing the errors significantly, as these methods can handle uncertain load patterns to achieve robustness and improve accuracy. In addition, the parameters were further tweaked after rigorous testing on different loads of consumers. The output of each predictor is ensembled using the proposed efficacy-based dynamic weighted averaging method for final decision making. It helps to significantly reduce forecasting errors. In the model, LSTM helps to address the problem of higher inconsistency in load, as it works well for temporal correlation learning. random forest offers higher stability and robustness against outliers, while SVR works well for the aggregated load. Nevertheless, no other influencing variables, such as weather, were considered, although LECs were highly dependent on them.

- In Tits et al. (2020), a methodology and case study are proposed to evaluate the impact of the size of an LEC and the availability of historical data on its

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predictability. Through random sampling of various numbers of residents, several virtual ECs were generated. The 24-h-ahead hourly load forecast is based on ridge auto-regression and a baseline model (3-week MA) on previous month observations and on various exogenous calendar features. Results show that, according to the constraints of the community, a compromise can be achieved around a community of 10-30 participants and a history of about 2-12 months. Furthermore, the ML-based model may be more efficient for both small and large communities as soon as sufficient historical data are available.

- In Györi et al. (2019), the potentials of six prediction methods were investigated to forecast loads. The predictions are used to balance loads and align energy production and consumption. Commonly used forecast approaches were applied: baseline naïve persistence, autoregressive integrated moving average (ARIMA), ordinary least square (OLS) regression, dual-stage attention-based recurrent neural network, gradient tree boosting, and multi-layer artificial neural network (ANN). The given prediction quality indicates that the expected nonlinear relationship between the weather data is complex as the exogeneous data did not provide a significant improvement in prediction quality. In comparison, shallow models provided a lower (better) MAPE score. Analysing the parameters during grid search indicated that increasing the model size by adding layers to the ANN and changing the activation function from linear to a rectified linear unit (ReLU) decreased performance, which may indicate overfitting on the problem parameters.

Additional results from the literature described above showed that the aggregate load of communities with larger consumers was more accurately predicted by ML-based models. This would appear to imply that the ML-based model can take advantage of the more repetitive patterns of these large consumers. This can be explained by the fact that more demanding households tend to include large appliances with regular schedules, such as heat pumps, water heaters, and heated pools. It is worth noting that this effect could be offset by flexible load-scheduling strategies for collective self-consumption.

2.2.1.1. Assessments of forecasts

In the literature, forecasts are always judged based on their quality. On this topic, quality can be equated with accuracy according to Duan et al. (2019). There are many widely used and well-established KPIs that are conditionally well suited for this purpose. A guide to understanding how a “good" forecast is quantified or can be defined depends on particular factors according toMurphy (1993). In the context of forecasting for LECs,

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certain factors shown in Table 2.1 are selected.

Aspect	Definition	considered
Bias	Correspondence between mean forecast and mean observation	yes
Assocation	Overall strength of linear relationship between individual pairs of forecasts and observations	yes
Accuracy	Average correspondence between individual pairs of forecasts and observations	yes
Skill	Accuracy of forecasts of interest relative to accuracy of forecasts produced by standard of reference	yes
Reliability	Correspondence between conditional mean observation and conditioning forecast, averaged over all forecasts	yes
Resolution	Difference between conditional mean observation and unconditional mean observation, averaged over all forecasts	no
Sharpness	Variability of forecasts as described by distribution of forecasts	no
Discrimination 1	Correspondence between conditional mean forecast and conditioning observation, averaged over all observations	no
Discrimination 2	Difference between conditional mean forecast and unconditional mean forecast, averaged over all observations	no
Uncertainty	Variability of observations as described by distribution of observations	no

Table 2.1.: Definitions of certain factors for forecast quality described by Murphy (1993).

To quantify the described factors, several KPIs are widely applied in demand forecasting. Table 2.2 explains the most frequently used KPIs and their strengths and weaknesses summarised by Hyndman et al. (2006).

With this toolset of metrics, the quality of a forecast can be assessed. However, these metrics do not provide information about the true value of a forecast. In fact, forecasts have no intrinsic value in themselves. Instead, the value is in assisting users or organisations that use these forecasts in their decision making. To generate economic value, forecasts need to be appropriate to the business context. Based on Murphy (1993), the value of a forecast can be quantified in several ways. For example, it can be in terms of monetary benefits or expenses, or in terms of non-monetary gains or losses. Four attributes were identified as requirements to quantify the value of a forecast, and how they align in the context of LECs is shown in Table 2.3.

These requirements can be fulfilled with a suitable choice or with a real example of an LEC. Thus, a further set of KPIs is obtained that relate to the LEC and thus represent a value metric for the forecast of load and DHW demand. These can be related to the known forecast metrics in the subsequent step. Several research groups have contributed extensive work on the topic of energy forecasting for LECs. Similarly, there is much

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Type of error	KPI	Strength / Weakness
Scale-dependent	MAE Mean Absolute Error	(S) simple to apply and easy to understand (W) not meaningful for assessing a method's accuracy across multiple series
Percentage	MAPE Mean Absolute Percentage Error sMAPE symmetric MAPE	(S) comparable between different data series (W) being infinite or undefined if there are zero values (W) can have extremely skewed distribution when values are close to zero (S) sMAPE penalizes positive and negative errors in the same way
Scale-free	MASE Mean Absolute Scaled Error	(S) scale independent (W) infinite or undefined when all observations are equal

Table 2.2.: Definitions of commonly used forecast KPIs. Strengths (S) and weaknesses (W) are highlighted for each error class.

Impact on value	Translated in the context of LECs
Courses of action available to the decision maker	Existence of PV or other generation assets to have a generation surplus at least during a certain period
The payoff structure (e.g., benefits or expenses)	Existence of battery storage or other controllable assets to shift the generation surplus to a certain period where energy scarcity reigns
Quality of the information used as a basis for decision making in the absence of the forecasts	Existence of a fallback method (e.g., baseline forecasts that use measurements from one week or one day before)
Quality of the forecasts	Commonly used forecast KPIs like MAPE or RMSE

Table 2.3.: The four determinants that are required in the context forecast value to allow an evaluation.

research that deals with the optimal operation of LECs. Nevertheless, only a few have combined the two topics and investigated them from a forecasting perspective. At this point, Coignard et al. (2021) is worth mentioning, which attempts to determine the quality and value of forecasts based on the self-sufficiency of LECs. However, this work only deals with load forecasting. Furthermore, only self-consumption is considered, which provides a solid basis for decision making, but further KPIs are still necessary.

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2.2.1.2. Integrated forecasting with model predictive control

Previous research on energy forecasting in communities such as Nia et al., 2021 has focused on a range of issues related to the accuracy, reliability, and usefulness of forecasting methods for predicting energy demand and supply in diverse types of communities and settings. Tziolis et al., 2023, Inteha et al., 2022, Mokarram et al., 2023 and Pirbazari et al., 2021a have reviewed a variety of statistical and machine learning techniques, such as time series analysis, artificial neural networks, and support vector machines, to model energy consumption and production patterns and to improve the accuracy of forecasts. Each of these methods has its strengths and limitations, and the choice of method depends on the specific characteristics of the problem being addressed. These findings have important implications for energy forecasting in LECs, where accurate and reliable forecasting is crucial for energy planning and management.

Other researchers have examined the potential benefits of integrating forecast-based control systems, such as MPC, into energy management systems in communities. MPC is a control strategy that is increasingly being used in LECs to optimise energy management and improve system efficiency described by Joe et al., 2023 and Orozco et al., 2022. MPC works by using a predictive model of the energy system to anticipate future energy demand and production, and then uses this information to make real-time control decisions that optimise energy consumption and production explained by Kumar et al., 2023. Maltais and Gosselin, 2022, Bourdeau et al., 2019a and Nakabi and Toivanen, 2021 show that this approach allows for more efficient and dynamic energy management and can help to reduce energy costs and improve system reliability. A few researchers, i.e. Khan et al., 2023, have focused on integrating energy forecasting models in an MPC to to further improve energy management and controlling of LECs.

Muzumdar et al., 2021 showed that energy forecasting in LECs faces several challenges, including the availability and accuracy of data, the complexity of the energy system, and the need for appropriate forecasting models. However, these challenges also present opportunities for innovation and development of new forecasting techniques, such as the use of big data, advanced analytical, and hybrid models that combine different forecasting methods. Meeting these challenges and leveraging these opportunities will be crucial for enabling LECs to effectively plan and manage their energy resources stated by Coignard et al., 2021.

The evaluation of energy forecasts in the literature is typically based on their quality, which is often equated with accuracy. Several commonly used KPIs are suitable for evaluating the accuracy of forecasts. The criteria for defining a “good" forecast examined

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by Murphy, 1993, however, may vary depending on the specific context and factors being considered. Using simple accuracy metrics, one can evaluate the quality of a forecast. However, it is important to note that the value of a forecast itself is not intrinsic. Rather, its value lies in its ability to assist users or organisations in making informed decisions. To generate economic value, forecasts must be relevant to the specific business context. As outlined by Murphy, 1993, the value of a forecast can be measured in several ways, such as in terms of monetary benefits or expenses, or in terms of non-monetary gains or losses. To quantify the value of a forecast in an LEC framework one comprehensible value metric for instance is the total cost.

2.2.2. The impact of high and volatile energy prices on communities

Liu et al., 2023 shows that electricity prices in Europe have been rising in recent years due to a variety of factors, including increasing demand for electricity, the transition to renewable energy sources and the phasing out of fossil fuel subsidies. Additionally, there has been increasing volatility in electricity prices due to factors such as weather events, the closure of power plants, and the emergence of innovative technologies. According to Bojnec, 2023, there has also been increasing volatility in electricity prices due to the increasing reliance on variable renewable energy sources, such as wind and solar energy, which are affected by weather conditions. This has led to the need for more flexible electricity generation and storage capacity to manage the intermittent nature of these sources. Overall, according to the study by Leal et al., 2023, the trend in Europe is towards higher and more volatile electricity prices, which will have implications for electricity consumers and the energy sector as a whole, including the following:

- High and volatile energy prices can have a range of economic impacts on communities, including increased energy bills for households and businesses, which can reduce disposable income and impact spending and investment decisions described by Shi and Sun, 2017 and Liu et al., 2022. Increased operating costs for energy-intensive industries can affect their competitiveness and profitability. Reduced affordability of energy for low-income households can lead to energy poverty and social exclusion.

- High and volatile energy prices can have environmental impacts on communities demonstrated by Li et al., 2019 and Al-Ghandoor et al., 2009, including increased energy consumption and greenhouse gas emissions, as high energy prices may discourage the adoption of energy-efficient technologies and practices. Reduced incentives for the adoption of renewable energy sources, may cause fossil fuels prices

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to be more competitive.

- High and volatile energy prices can have social impacts on communities according to Akkemik, 2011, including increased stress and uncertainty for households and businesses, as they may struggle to budget for and manage energy costs. Increased inequality, as low-income households may be disproportionately affected by high energy prices. Quality of life may be lowered, as high energy prices may limit access to essential services and amenities, such as heating and transportation.

Therefore, understanding the impact of high and volatile energy prices on communities is an important research topic, as it can inform policies and strategies to mitigate these impacts and support the transition to more sustainable and resilient energy systems.

2.3. Contribution to the progress beyond state-of-the-art

In relation to the research questions defined in Section 1.2 and the literature presented in this Chapter, this thesis' contribution to the progress beyond state-of-the-art is presented in the following.

In respect to research question one, a deep neural network model was developed that predicts very short-term wind power generation. The approach developed in this thesis includes the following novelties:

- The N-BEATS architecture is applied on VSTWPF for the first time since the N-BEATS algorithm gained attention due to its remarkable results.

- It is one of the first attempts to model an interpretable time series forecast using deep learning methods in the field of wind power forecasting. The approach is parameterised in such a way that the individual parts of the result like trend and seasonality are interpretable while not having any noticeable impact on the forecast accuracy. Current deep learning approaches often have difficulties in providing interpretability of results. Either this possibility does not exist at all, or it is associated with an increased computational effort or a decrease in accuracy.

- A customized loss function is proposed that is well suited for the use in wind power forecasting. With the implementation of a loss function that is optimally designed for the application, a decisive advantage of deep learning can be exploited. The first-time usage of a so-called pinball sMAPE error metric in a deep learning

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architecture provides reliable and exceptionally accurate very short-term forecasts results in the short term.

In order to address the second research question a novel multi-step short-term forecasting framework is presented that predicts load and DHW demand values in a flexible manner, ideally integrated in a model predictive control (MPC). Additionally, this framework proposes a novel method for describing a building's thermal behaviour using a second-order RC chain to evaluate building performance in combination with forecast inputs. The progress of this work, which goes beyond the current state of the research, is outlined in the following items:

- Comparison and evaluation of widely used forecasting methods for load and DHW demand in a cost-and comfort-optimised LEC using selected KPIs.

- Grey box model of a dynamic thermal building model based on a linear programming-based optimisation framework with differential algebraic equations that is fully integrated with the forecast module.

- A selection of LEC KPIs was used to evaluate the forecasts' value. Findings related to cost and comfort level are derived, and a statement about the impact of improved forecasts on LEC KPIs is highlighted.

In order to address the third research question the multi-step short-term forecasting framework is further extended with respect to high and volatile energy prices and outlines how this work advances the current state of the art in this research topic:

- This study assessed the value of modern forecast approaches in the context of an LEC with respect to high and volatile energy prices, an important but understudied topic. In particular, NBEATSx, a further development of NBEATS that can take advantage of future weather covariates, is, for the first time, applied to forecast energy demand and DHW.

- The study compared the accuracy of several different forecasting methods (perfect foresight, naïve approach, multiple regression, k-nearest neighbour, XGBoost, Prophet, and NBEATSx, as well as two hypothetical methods) and utilised their results as input for an LEC operated by an MPC; this provided valuable insights for practitioners and policy makers seeking to optimise the operation of these buildings.

- The study used advanced forecasting methods such as XGBoost, Prophet, and

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NBEATSx, which are not commonly used in the context of LECs as forecast-based optimal control input. The results of this study provide evidence for the effectiveness of these methods in optimising the operation of LECs and highlight the importance of accurate forecasts.

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3. Methods

This chapter describes in detail the methods that are developed to answer the research questions defined in Section 1.2. Therefore, this chapter is divided into two major parts, each focusing on one of the methods where the second part is further separated into two parts. In Section 3.1, a deep neural architecture to answer the first research question is presented. Next, Section 3.2.1 presents a grey-box building model with integrated forecasting as posed by the second research question, and in Section 3.2.2, the grey-box model from the previous question and the forecast algorithm from the first research question are further developed to answer the third research question. Each section is organized as follows. We start with an overview on the methodology including flow charts, then we continue with a description of the problem including mathematical formulation, and finally we present nomenclature. This chapter is based on Putz et al. (2021), Putz et al. (2023) and Putz et al. (2024).

3.1. Deep neural architecture for very short term wind power forecasting

3.1.1. N-BEATS

The N-BEATS architecture itself does not rely on time-series-specific feature engineering or input scaling. Instead, it uses a small set of key principles. For instance, it does not treat forecasting as a sequence-to-sequence problem, but rather as a non-linear multivariate regression problem. This leads to the basic building block which has a fork architecture and is shown in Figure 3.1.

The basic block has an input $\mathbf{x}_l$ and two output vectors $\hat{\mathbf{x}}_l$, $\hat{\mathbf{y}}_l$ where the length of the input is a multiple of the forecast horizon. The output vectors describes the block's forward forecast $\hat{\mathbf{y}}$ and the block's best estimate which is the so-called backcast $\hat{\mathbf{x}}$ as proposed by Oreshkin et al. (2020). The backcast represents the contribution to the

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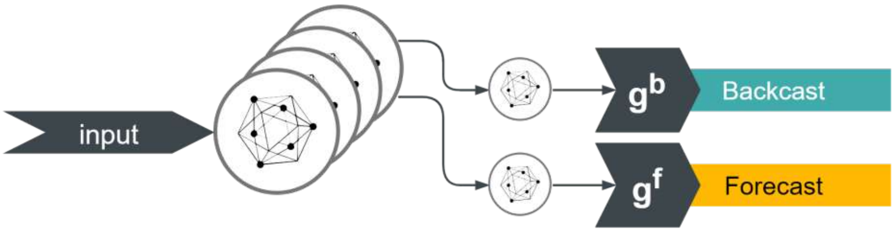

Figure 3.1.: The architecture has two residual branches, one running over backcast prediction of each layer and the other one is running over the forecast branch of each layer. Basically the backcast branch can be understood as sequential analysis of the input time series. The basic block uses a lookback sample as input for the stacked dense layers network with ReLu activation. This network delivers two coefficients as output Θ^b, Θ^f, which are fed into the basis layers following mapping of $g^{f,b}$ to retrieve the forecast and backcast.

decomposition of the input. Thus, it learns the parameters of the context. The input of the l-th block $\mathbf{x}_l$ are residual outputs of the previous blocks. In particular, this network consists of fully-connected (dense) layers with a rectified linear unit (ReLu)proposed by Nair and Hinton (2010) regressor shown in Equation 3.1 with weights $\mathbf{W}_{r,l}$ and bias $\mathbf{b}_{r,l}$, referring to $\mathbf{x}$ as the input of the architecture, using residual blocks and layer superscripts (r and l respectively) and denoting the fully connected layer with weights $\mathbf{W}_{r,l}$ and bias $\mathbf{b}_{r,l}$.

$$\mathbf{h}_{r,l-1} = \mathrm{ReLu}(\mathbf{W}_{r,l}\mathbf{x}_{r,l-1} + \mathbf{b}_{r,l}) \tag{3.1}$$

The output is forked and fed into the basis layer network to retrieve the forecast and the backcast predictors of expansion coefficients Θ_l^f and Θ_l^b, shown in Equation 3.2.

$$\Theta_{r,l}^{f,b} = \mathbf{W}_{r,l}(\mathbf{h}_{r,l-1}) \tag{3.2}$$

They are projected on $g^{b,f}$ consisting of the set of basis functions $\mathbf{v}_i^{b,f}$ and summed up to obtain the results $\hat{\mathbf{x}}_l$ and $\hat{\mathbf{y}}_l$ shown in Equation 3.3 and Equation 3.4.

$$\hat{\mathbf{x}}_l = \sum_{i=1}^{dim(\Theta_l^b)} \Theta_{l,i}^b \mathbf{v}_i^b \tag{3.3}$$

$$\hat{\mathbf{y}}_l = \sum_{i=1}^{dim(\Theta_l^f)} \Theta_{l,i}^f \mathbf{v}_i^f \tag{3.4}$$

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The residual principle is used to stack many layers together. Basically, the classical residual architecture adds the input of the stack of layers to its output before passing the result to the next stack which adds the input of the stack of layers to its output as described by He et al. (2015). This architecture has already been extended by Huang et al. (2018) by introducing extra connections from the output of each stack to the input of every other stack that follows it. On the one hand this extension improved the trainability of deep neural network architectures. On the other hand they result in network structures that are difficult to interpret. The proposed architecture was enhanced to provide interpretability, shown in Figure 3.2 proposed by Oreshkin et al. (2020). In general the skip connections facilitate to determine whether the intermediate layer is useful or not. In this architecture the skip connections are modelled in a different way, to make subsequent blocks have an easier job forecasting by removing the backcast outputs from the next block's inputs. It is actually similar to an unrolled LSTM, where the skip connections act like forget gates in an LSTM in order to remove information that is not needed. It passes the processed inputs to the next block, facilitating the preparation of more accurate forecasts. At the same time, each block has a forecast output that is added up with subsequent forecasts in the block to provide a combined forecast. It is possible to stack hundreds of layers and residual blocks effectively using this principle.

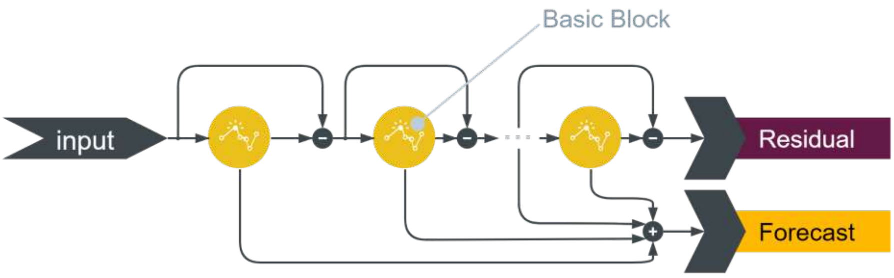

Figure 3.2.: The basic blocks are multi-layer fully connected networks with ReLu activation function. They provide the expansion coefficients $\Theta^{b,f}$ and are connected according doubly residual stacking architecture.

In contrast to classical approaches deep learning approaches for time series forecasting often suffer from lack if interpretability. This is one of the most challenging obstacles when it comes to applying those approaches in practice as stated by Ismail et al. (2020). N-BEATS can be made interpretable by setting the functions $g^{b,f}$, that can be either learned or instead engineered to account for different effects such as trend and seasonality. By changing the mapping functions $g^{b,f}$ for $\Theta^{b,f}$ to a trend and seasonality form makes the stack outputs interpretable, shown in Figure 3.3. A typical characteristic of trend is that most of the time it is a monotonic function, or at least a slowly varying function. In order to obtain this behaviour $g^{b,f}$ is set to be a polynomial of small degree, a function

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slowly varying across the forecast horizon. To model seasonality a cyclical, recurring fluctuation is required. An intuitive choice for a cyclical function is the Fourier series.

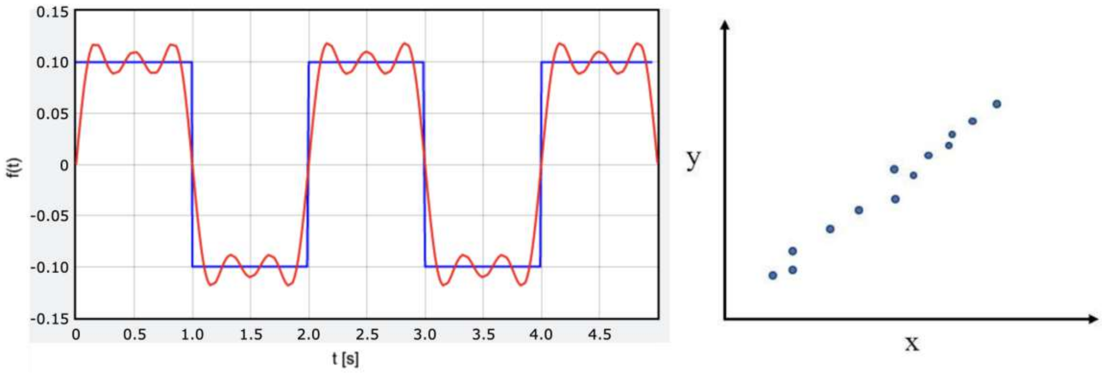

Figure 3.3.: Schematic example for a cyclical or monotonic functions $y(x)$ for $g^{b,f}$.

The output components of the model can be separated and analysed. By knowing the nature of each basis layer, the user can estimate the contribution of each component, since the total global output is a simple sum of the partial outputs of each block. Thus providing interpretability. It was observed that the impact of this change on the error is negligible. It is similar to how the hidden state of an RNN is shared across all time steps. In addition to interpretability and accuracy benefits, as measured on several well-known datasets, the model is very fast to train and easy to apply.

Consequently, N-BEATS uses a dense layer as a multivariate regression block with a ReLu for non-linearity, which gets repeated many times. This architecture is actually very similar to an unrolled LSTM, where skip connections act like forget gates in LSTM to remove unneeded information and pass the processed input to the next block, facilitating the production of better forecasts.

3.1.2. Loss Function

The most used error metrics for forecasting are the mean absolute percentage error (MAPE) shown in Equation 4.2 and the symmetric mean absolute percentage error (sMAPE) shown in Equation 3.6. These were also used in the M4 competition Makridakis et al. (2018).

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{|y_t|} \tag{3.5}$$

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$$\text{sMAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{|y_t + \hat{y}_t|/2} \tag{3.6}$$

Both are similar in that they normalise the absolute difference between prediction and observed values. The approach may produce more accurate results, because training, validation and performance error metric goals are identical and ideally aligned by using MAPE during training as well as for performance evaluation. Nevertheless, there occur two main issues:

- Firstly, the denominator $(y_t + \hat{y}_t)$ can become negative or even 0. In the case of wind power forecasting, 0 can occur and has to be treated separately. In brief, both nominator and denominator become 0, a case that is basically undefined.

- Secondly, the sMAPE treats over- and underprediction unequally. As an example for underprediction, if the observed value is 100 and the predicted value 90, then the sMAPE delivers 5.26%. By contrast, a target value of 100 and predicted value of 110 constitutes an overprediction and delivers a sMAPE of 4.76%. There are modifications of the sMAPE that allow to measuring the direction of the bias, which provides additional information about the quality of the result.

In this work it, is found that during backtests the models tend to have a positive bias. A solution for this is for example the pinball function, shown in Equation 3.7 and described by Smyl (2020). It is an asymmetric function, that penalises actual values that are above and below a certain quantile τ in different ways in order to counteract the bias.

$$L_t = \begin{cases} (y_t - \hat{y}_t)\,\tau & \text{if } y_t \geq \hat{y}_t \\ (\hat{y}_t - y_t)\,(1-\tau) & \text{if } \hat{y}_t > y_t \end{cases} \tag{3.7}$$

The τ parameter can be adjusted, and it is advised to keep it low to avoid overforecasting. The basic pinball loss is an important loss function on its own; minimizing it produces quantile regression as explained by Smyl (2020). Setting $\tau \in (0{,}0.5)$ tends to compensate overestimation bias, and setting $\tau \in (0.5{,}1)$ tends to compensate under-estimation bias. In this work, an adaptation of the pinball function (pinball-sMAPE) from 3.8 is shown in Equation as a loss function within the N-BEATS is introduced. This is a novel solution for N-BEATS to alleviate the well-known bias problem. A convenient feature of NN-based systems is used: the simplicity of creating a loss function aligned with any business/scientific targets.

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$$P_t = \frac{100\%}{n} \sum_{t=1}^{n} \begin{cases} \frac{(y_t - \hat{y}_t)}{(y_t + \hat{y}_t)} \tau & \text{if } y_t \geq \hat{y}_t \\ \frac{(\hat{y}_t - y_t)}{(y_t + \hat{y}_t)} (1 - \tau) & \text{if } \hat{y}_t > y_t \end{cases} \tag{3.8}$$

In the case of the pinball-sMape the denominator becoming 0 could only occur if the actual and predicted values are both 0 at the same timestep, since only non-negative values are allowed. All $y_t = 0$ rows are dropped in order to prevent division-by-zero errors. This approach does not have a noticeable effect on the model because there exist hardly any of such cases in the used datasets. This can be explained by the fact that the datasets show aggregated numbers from several wind farms across a country and an occurence with no generation at all is rare. The majority of zero generation values can be traced back to missing or invalid measurement values.

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3.2. Forecast models for model predictive control of a local energy community

In this section, the key components and methodologies that underpin the research questions 2 and 3 are elucidated, providing a detailed insight into how these studies were conducted and their contributions to the field of sustainable energy management.

3.2.1. Integrated assessment with constant energy tariff

The structure of the methodical framework is formed by two core components, as Figure 3.4 shows. On the one hand, there is a functional block that contains the forecast methods that are used to predict electrical household load and DHW demand. These forecasting methods are the systems under test (SUT) and are further described in Section 3.2.1.1. On the other hand, there is the building MPC block, which acts purely as the test environment for forecasting methods. It enables the possibility to calculate cost-and energy-related performance indicators in the context of communal housing but is not under intrinsic review within this research. Section 3.2.1.2 provides a detailed description of this system and its underlying assumptions. The motivation to simulate the interplay of time series load forecasting with an energy community, including the optimal utilisation of electrical storage capacity and even the active usage of thermal building masses, is to get an isolated view of how forecast accuracy can deplete the quality of an otherwise optimally designed and controlled energy system.

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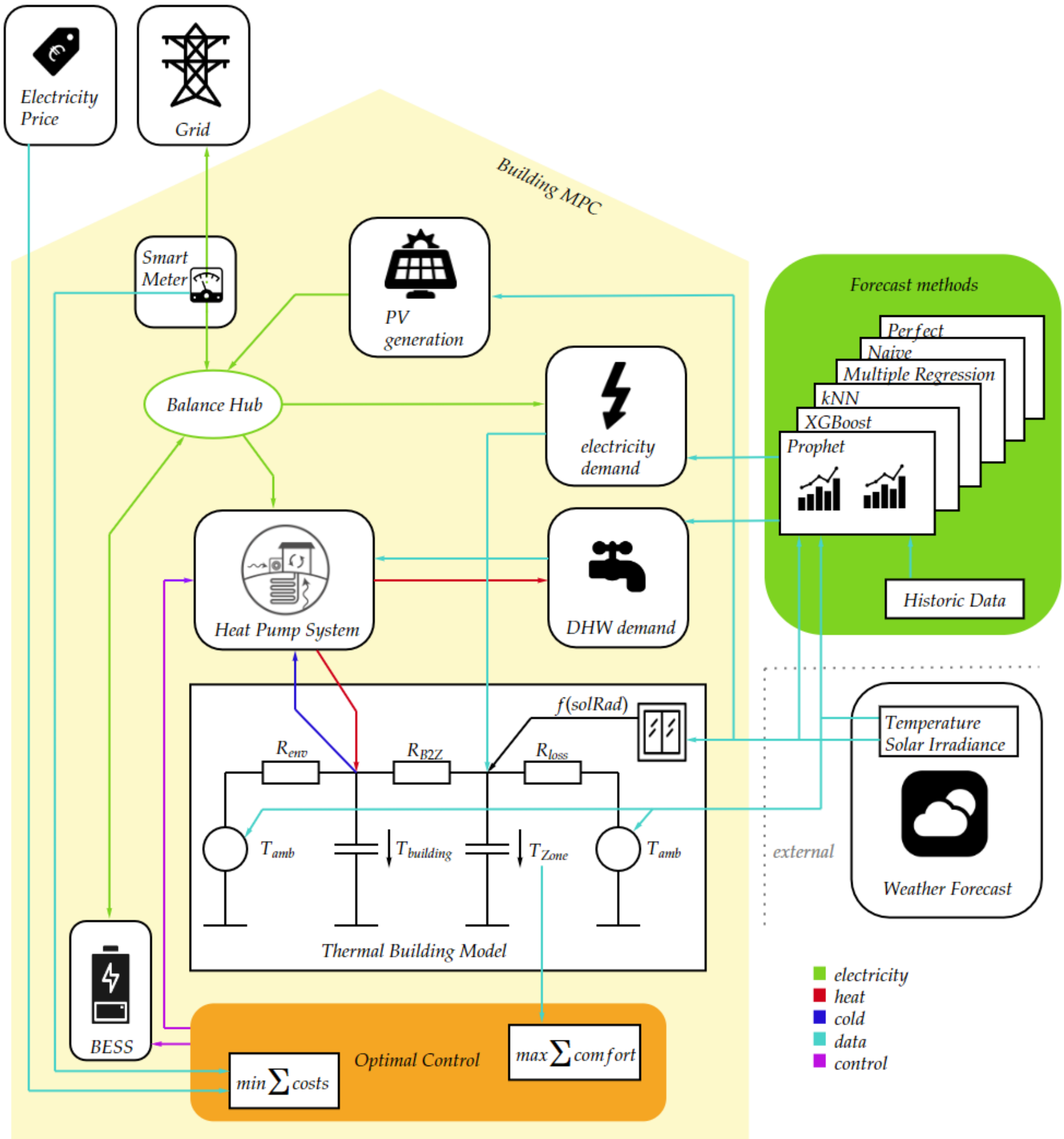

Figure 3.4.: Schematical structure of the implemented methodology.

Both functional blocks operate in a closed loop, as shown in Figure 3.5. In general, forecasts for load and DHW demand are triggered once a day (e.g., 00:00) to optimally schedule battery operation and heating/cooling in the energy community. The forecast horizon is 48 hours, with a time resolution of 15 minutes. Thus, forecast values are available for the following optimisations, which have a planning horizon of 24 hours.

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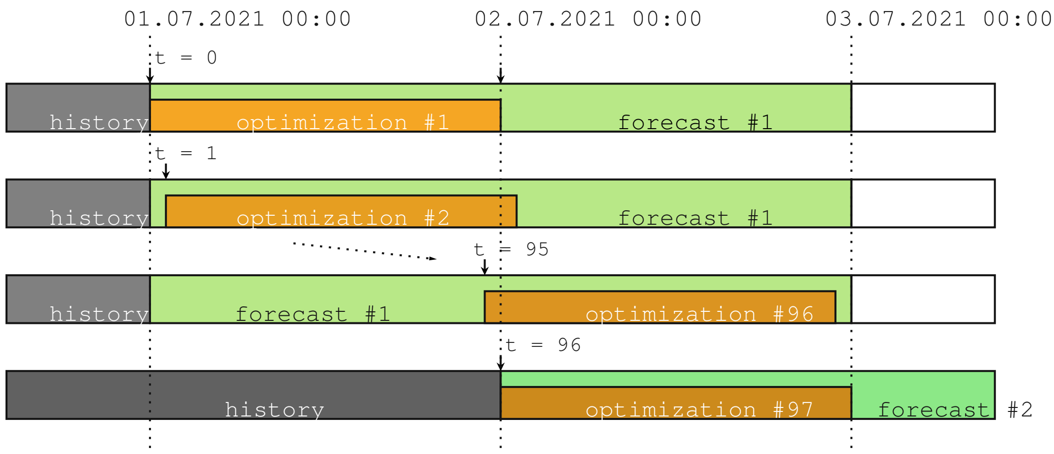

Figure 3.5.: Cyclic operation of forecast and control systems.

3.2.1.1. Forecasting methods

Several state-of-the-art forecasting approaches have been implemented, and their results are benchmarked in the context of quality and value. The quality metrics used for the forecasting algorithms are listed in Section 3.2.1.1, and the datasets used are outlined in Section 3.2.1.1. The forecasts are based on historical data; derived time features and additional features, such as external weather forecasts, are summarised in Table 3.1.

Feature	Unit/Scale	Category
minute of the hour	0/15/30/45	seasonality/calendar
hour of the day	0-23	
day of the week	0-6	
week of the year	0-52	
ambient air temperature	°C	weather
global solar irradiance	$\mathrm{W\,m^{-2}}$	
24h lagged demand	W	demand
168h lagged demand	W	

Table 3.1.: The complete feature set for demand consists of lagged demand, seasonal (or calendar) parameters, and weather parameters. The features used for each forecasting algorithm may vary due to various restrictions. For instance, the prediction method Prophet does not support multivariate forecasting. Thus, only seasonality/calendar features were considered.

The implemented forecasting approaches used in this study are listed below and implemented in Python 3.10:

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- Perfect: This method represents real measurements as a forecast (perfect forecast) to get results from the MPC, which can be compared with realistic methods afterwards. These results provide information about how much the MPC results with theoretically perfect input parameters (i.e., if forecasts and real conditions completely match and no errors were made) differ from the actual results.

- Naïve: The naïve forecast is based purely on historical data and takes the respective daily pattern as a forecast that has the same or similar seasonality. Holidays are not considered in this approach. As a result, the naïve forecast can be very inaccurate under certain circumstances, since the stochastic behaviour of weather naturally means that the sun can be shining clearly one day, and the sky is heavily overcast the next. However, the naïve forecast has another aspect that should not be neglected in terms of a backup mechanism. In the introduction, the reliability of a forecast is briefly described, and the data used in case an advanced forecast technique fails. In this scenario, the naïve forecast can act as a best guess and a fallback method. The naïve approach serves as another main benchmark, in addition to the perfect forecast, as it is assumed to be always available. In the literature, this approach is often referred to as the baseline, which must be outperformed by other more advanced forecast approaches in terms of accuracy.

- Multiple regression: A widely used method in the field of time series analysis, which has proven to be especially useful in load forecasting shown by Amral et al. (2007). Regression analysis has the advantage of being easy to implement, interpret, and has fast execution time as explained by Hinman and Hickey (2009). Multiple regression fits a linear model with coefficients $w = (w_1, ..., w_p)$ according to ordinary least squares approach. The residual sum of squares between the measured values X and the predicted values y by the approximation is minimized according to Equation 3.9.
$$\min_w \|Xw - y\| \tag{3.9}$$
This approach was implemented in Python with the Scikit-learn package founded by Pedregosa et al. (2011) with *fit_intercept* set to True and *n_jobs* set to None due to the relative small problem.

- K-Nearest neighbours: The principle behind the nearest neighbour method is to find a predefined number of training samples closest in distance to the new point and predict the label from these according to Fan et al. (2019). Despite its simplicity, nearest neighbours has been successfully applied in many classification and regression problems. In this study, uniform weights were used so that each point in the local neighbourhood contributed uniformly to the classification of a query point. The number of *n_neighbors* is set to 3 and *weights=distance* to assign

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weights proportional to the inverse of the distance from the query point. This approach was implemented with the Scikit-learn package by Pedregosa et al. (2011).

- XGBoost: This is a tree boosting system for supervised learning problems that is used widely by data scientists to achieve state-of-the-art results on many ML challenges as described by Chen and Guestrin (2016b). XGBoost is built upon decision trees, ensemble learning and gradient boosting. Decision trees create a model that predicts the value by evaluating a tree of if-then-else true/false feature questions, and estimating the minimum number of questions needed to assess the probability of making a correct decision. The term gradient boosting comes from the idea of boosting or improving a single weak model by combining it with a number of other weak models in order to generate a collectively strong model. With XGBoost, trees are built in parallel, instead of sequentially like GBDT. It follows a level-wise strategy, scanning across gradient values and using these partial sums to evaluate the quality of splits at every possible split in the training set. In the context of load or DHW demand forecasting, the model can be represented as a linear combination of weighted input features, which are the same as for the multiple regression approach. It was developed with deep consideration for system optimisation and the principles of ML. The number of *n_estimators* was set to 50 and other parameters were set to default according to the *XGBRegressor* interface. This approach was implemented based on Chen and Guestrin (2016a).

- Prophet: This is a modular regression model with interpretable parameters that can be intuitively adjusted. The concept is based on an additive model in which nonlinear trends $g(t)$ fit with yearly, weekly, and daily seasonality $s(t)$ with holiday effects $h(t)$ and an error term $\varepsilon(t)$ to represent changes which are not accommodated by the model as described by Taylor and Letham (2018) and shown in Equation 3.10.
$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t) \tag{3.10}$$
This approach is parameterised to address the high volatility of the demand of a small energy community, and has been successfully applied to short-term load forecasting for example by Beydoun et al. (2021) and Rocha et al. (2020). The prediction method is parameterised with a *changepoint_prior_scale* set to 0.01 and *frequency* set to 15min and only supports univariate time series forecasting. Apart from that, the parameters are set to default according to the Prophet forecaster interface. This approach was implemented based on Taylor and Letham (2018).

- Fictive methods: Besides comparing existing forecasting approaches, the purpose of this paper is to provide information on other likely future developments and to assess their impact. For this purpose, two fictive forecast approaches that are

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more accurate than the best real ones are implemented. Random values based on a uniform function are used as a basis, which are multiplied by the perfect forecast. The random values were scaled depending on the average error of all implemented prediction methods for each time step. Thus, the fictive methods will perform more accurately than the other methods, but they will still have higher errors during the day instead of uncommonly high errors during the night.

KPIs for forecasting methods

To assess forecast results in terms of quality or accuracy, several commonly used error metrics are applied, which address the aspects described in Table 2.1. One of the most frequently used KPI for forecast results, MAPE , is used as the basis for the accuracy aspects shown in Equation 3.11 with y_t as the measured value and $\hat{y}_t$ as the forecasted value at timestep t and described by Deb et al. (2017) and Martínez-Álvarez et al. (2015).

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{|y_t - \hat{y}_t|}{|y_t|}\cdot 100\right) \tag{3.11}$$

Additionally the symmetric MAPE shown in Equation 3.12 is used to tackle the issue of MAPE by putting heavier penalty on positive errors than on negative errors as explained by Makridakis and Hibon (2000). However, if y_t is zero, the forecast $\hat{y}_t$ is likely close to zero. Thus, a division by a number close to zero is involved and has to be excluded in the calculation.

$$sMAPE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{|y_t - \hat{y}_t|}{(y_t + \hat{y}_t)}\cdot 200\right) \tag{3.12}$$

The normalized RMSE (nRMSE) facilitates comparisons between models with different scales. It relates the RMSE to the observed range of the variable. Thus, the nRMSE can be interpreted as a fraction of the overall range shown in Equation 3.13.

$$nRMSE = \frac{1}{max(y_t) - min(y_t)}\sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{3.13}$$

To overcome the issues of skewed distributions, such as MAPE and sMAPE , when values are close to zero, division by zero, and supporting scale independency at the same time, the mean absolute scaled error (MASE) proposed by Hyndman et al. (2006) is used and shown in Equation 3.14. It gives an indication of the effectiveness of the forecasting algorithm with respect to a naïve forecast. A value greater than one 1 indicates that the algorithm is performing poorly compared to the naïve forecast. Another advantage is that MASE is independent of the forecast scale since it is defined using the ratio of mean absolute errors in the forecast.

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$$MASE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - \hat{y}_t}{\frac{1}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|}\right| \tag{3.14}$$

The reliability aspect is inherent in the implemented model, as it is considered over a period of one year. This means that factors such as seasonality, days of the week, and weather are included in the model. This specifically facilitates evaluating forecast algorithms in varying situations and ranking them according to their accuracy in certain situations. For example, it is worth mentioning how (in)accuracy at certain time periods (e.g., at noon or at night rest) affects the overall result.

Data

To solve the optimisation problem, it is necessary to forecast load and DHW consumption several steps in advance. Thus, a forecasting class is implemented, including widely used prediction methods based on traditional statistical and state-of-the-art ML approaches reviewed by Bourdeau et al. (2019b). In contrast to the research of Coignard et al. (2021), which uses a similar approach but is only based on historical data, exogenous influencing factors such as weather variables are included in this paper. In addition, not only load but also DHW demand is a matter of forecasting. This module's complete integration into the optimisation framework is a significant contribution of this research. The data used for forecasting were retrieved from Schlemminger et al. (2021), an open-source dataset from southern Germany. In real-world applications, data are unfortunately often not sufficiently available. Above all, there is a lack of adequate history. To take this circumstance into account, only the year 2021 was used as a dataset. In this case, the dataset was divided into two halves of the year, with a split date of 01.07.2021 00:00:00. This means that at the beginning of the experiment, only six months of information is available. However, the available history grows as the forecast models are retrained on Mondays at 00:00:00 with the maximum available history to prevent excessively high errors due to outdated model fitting. To forecast load demand, DHW demand is excluded and vice versa to have only weather effects and calendar data as exogenous variables. Figure 3.6 shows the correlation between the features.

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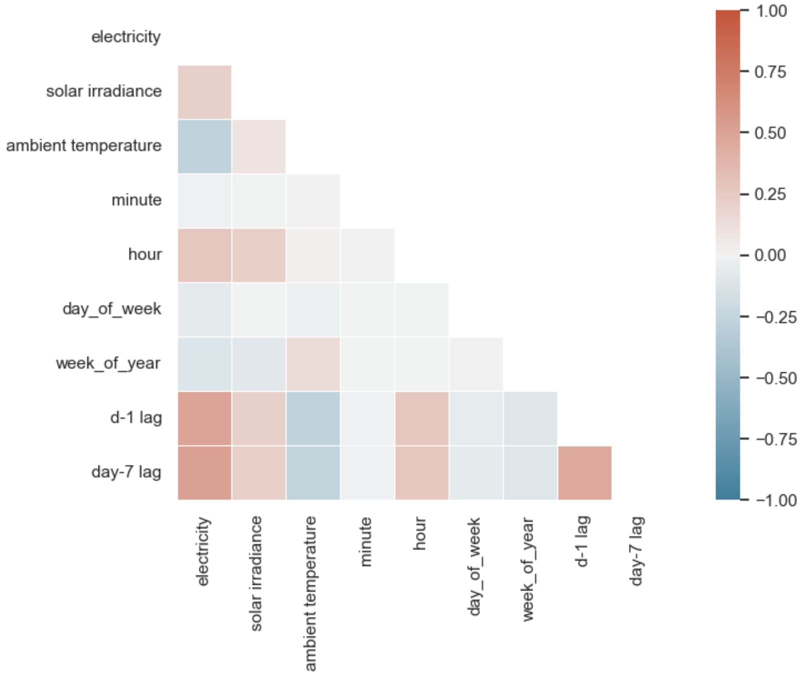

Figure 3.6.: The colour encoded heat map shows the relationship between all features and the dependent variables. For instance, load demand has a strong relationship with the same load one day and one week ago. Moreover, an inverse relationship between load demand and total temperature can be observed, which can be interpreted that load demand is generally higher the lower the total temperature is due to heating effects.

The exogenous weather data is not subject to any errors to conserve the selectivity for the errors made by the tested forecast algorithms. This is especially important as the proposed method uses the exogenous data not only for the forecasts itself but also for the operation of the MPC, which relies on weather data. If this data forecast was inaccurate it would cause effects on the resulting operation through both ways. This would make the segregation of impacts in this dynamic system tremendously more complex and would be a research question for its own. For completeness, it must be mentioned that the naive forecast has a disadvantage compared to the other forecasting methods in such a setting because it can not profit from the perfect knowledge of the future weather.
For training and prediction, the forecasting module was adjusted to achieve the required accuracy and computational speed due to the large number of runs. Prior to the pilot period, various hyperparameters and characteristics were systematically tested for the different algorithms. Practically, walk-forward cross-validation was applied, which signifies a sliding window on the training dataset and a rolling extension of the training

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dataset for each fold. The optimum configuration was chosen by repeating this procedure with several algorithms and hyperparameters. For training, the CPU *Intel(R) Core(TM) i7-11850H @ 2.50GHz* was used. The distributions of load as well as the DHW demand throughout three sample months representing the seasons of summer, autumn, and winter are shown in Figure 3.7. Generally, DHW demand is less volatile than load demand. However, the peak values are similar to those of the load.

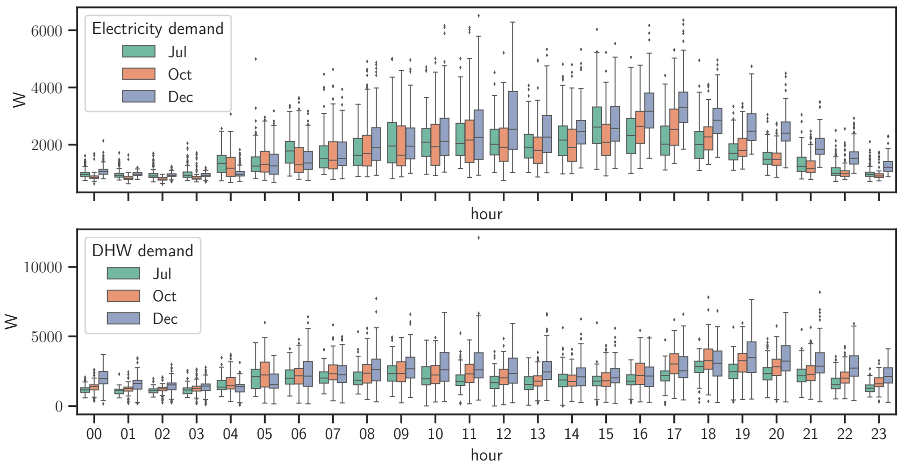

Figure 3.7.: Distribution of load demand (top) and DHW demand (bottom) according to different seasons (summer, autumn, and winter). In winter, the load demand is considerably higher compared to summer due to the more required illumination. The DHW demand is generally higher in winter, since more baths are taken usually. Furthermore, during summer and autumn, the load demand is decreased at noon because less illumination is required.

3.2.1.2. Building MPC

The proposed forecasting methods are used as input parameters in a building energy control and simulation system to perceive cost-optimal operation for a fictional LEC in a multi-apartment residential building. The setup is based on the characteristics of a typical LEC, with the goal of distributing and using the renewable energy produced at the local level in an optimal manner across all energy sectors, both thermal and electrical, and close to real time. Thus, the main goal is to use the flexibilities already present within the LEC as optimally as possible in accordance with the provided objective functions. An MPC framework was used for control and simulation. By solving an optimisation problem for the entire prediction horizon of 24 hours, the MPC design calculates the control set points for each time step and then applies the initial values of the computed controls to the system. The following subchapters describe the details of the assumed

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communal building and LEC, how it is abstracted and simulated in this study, and which performance indicators can be drafted from the results.

Building and energy system components

A core part of the hypothetical energy community introduced here is the building model. It is based on the general case of a three-storey multi-apartment building with a gross floor area (GFA) of $842.4\,\mathrm{m}^2$ and a conditioned floor area (CFA) of $735.8\,\mathrm{m}^2$ distributed over nine dwellings. The underlying building with all the included boundary conditions was defined as a reference case for zero-energy residential buildings in Austria within the nationally funded research project Sol4City[1]. The buildings' disposition towards efficiency, including the highly insulated building hull, the heating, ventilation, and air conditioning (HVAC) systems, and the overall architectural design make it a likely candidate for hosting the participants of a LEC.

Figure 3.8.: Rendered 3-D illustration of the defined sample building, including the roof-mounted PV generator.

Detailed heat transmittance figures for the building hull can be found in Table 3.2. Heating and cooling are achieved via fluid-based thermal concrete core activation of the ceilings. The allowed room comfort temperature range was set between 21.5 °C and 25 °C, with the possibility that the MPC controller could use the thermal inertia of the building for load-shifting purposes. DHW demand totals were set to 30 L/d at 45 °C (cold water 10 °C) per person, based on typical values from SIA 2024 (2015). A ground source borehole heat exchanger together with a $10\,\mathrm{kW_{el}}$ brine to water heat pump supply the room heating and cooling load and the DHW demand. In combination with the roof-mounted $21\,\mathrm{kW_p}$ PV generator, this example building is expected to meet the

[1]Sol4City Project: https://nachhaltigwirtschaften.at/de/sdz/projekte/sol4city.php

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net zero-energy standard for the reference climate of Graz, Austria.

Parameter	North	East	South	West
External wall Area (in m^2)	88	83	75	60
External wall U-value construction (in $W\,m^{-2}\,K^{-1}$)	0.116	0.116	0.116	0.116
Windows Area (in m^2)	35.1	40.4	48.7	65.4
Windows U-value tot (in $W\,m^{-2}\,K^{-1}$)	0.75	0.75	0.75	0.75
Windows g-value	0.49	0.49	0.49	0.49
Top floor ceiling Area (in m^2)	280	280	280	280
Top floor ceiling U-value construction (in $W\,m^{-2}\,K^{-1}$)	0.114	0.114	0.114	0.114

Table 3.2.: Physical parameters of the building hull. U-values (sometimes referred to as heat transfer coefficients or thermal transmittances) are used to measure how effective elements of a building's fabric are as insulators. That is, how effective they are at preventing heat from transmitting between the inside and the outside of a building. The g-value is a measure of how much solar heat (infrared radiation) is allowed through a particular part of a building. A low g-value indicates that a window lets through a low percentage of solar heat.

Model formulation and operation

The implemented energy system and the derived control-oriented model are structured according to Figure 3.10 and are built around an electricity balance hub that enables energy exchange between the electricity grid, the roof-mounted PV generator of 20 kWp, electric household loads, a collective battery energy storage system (BESS) of 20 kWh capacity, and a heat pump system. A distinct feature in this setup is the use of a dynamic thermal building model, which incorporates thermal building inertia and does therefore introduce an additional measure of flexibility to the optimisation. The optimisation problem is formulated as a linear programming problem with differential algebraic equations. This was realised with a Python-based framework and the GEKKO package, as it offers a powerful toolset for MPC applications proposed by Beal et al. (2018) of this type. A variable time base is used to implement 15-minute steps for the first two hours of the horizon and hourly steps for the remaining 24 hours. This ensures high accuracy for the immediate future but reduces computing effort significantly.

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Symbol	Type	Description
t		Time
i		Iterator for the time step within the optimization horizon
$Cost_{el}$	v	Total cost for electricity from grid
$P_{Grid,in}$	v	Electrical power from the grid into the EC balance hub
$P_{Grid,out}$	v	Electrical power from the EC balance hub out to the grid
P_{HP}	v	Electrical power demand of the heat pump
P_{El}	p	Electrical household power demand
$P_{Bat,charge}$	v	Battery charging power
$P_{Bat,discharge}$	v	Battery discharging power
P_{PV}	p	Electrical power generation of the PV system
$c_{Grid,in}$	p	Electricity cost for consumption
$c_{Grid,out}$	p	Electricity cost for grid feed-in
$\dot{Q}_{SH}$	v	Heat flow from heat pump to the building for space heating
$\dot{Q}_{SC}$	v	Heat flow from heat pump to the building for space cooling
$\dot{Q}_{DHW}$	p	Heat flow from heat pump to supply the DHW demand
COP_{SH}	p	Heat pump coefficient of performance (COP) for space heating loads
COP_{SC}	p	Heat pump COP for space cooling loads
COP_{DHW}	p	Heat pump COP for DHW loads
E_{Bat}	v	Electrical energy stored in the battery
η_{charge}	p	Battery system charging efficiency
$\eta_{discharge}$	p	Battery system discharging efficiency
Φ	v	Zone comfort objective function
e_{hi}	v	Zone comfort higher boundary violation
e_{lo}	v	Zone comfort lower boundary violation
f_{weight}	p	Weighting factor comfort objective
T_{Zone}	v	Mean temperature in the building thermal zone
$T_{Building}$	v	Mean temperature of the building structure
T_{Amb}	p	Ambient temperature
$\dot{Q}_{Building}$	v	Heat flow into the building structure
$\dot{Q}_{Zone}$	v	Heat flow into the building thermal zone
$\dot{Q}_{solar}$	p	Heat flow into the building through the windows
$\dot{Q}_{env}$	v	Heat flow from the building structure through the building envelope
$\dot{Q}_{B2Z}$	v	Heat flow from the building structure to the thermal zone
$\dot{Q}_{loss}$	v	Heat flow from the thermal zone to the outside via the envelope
C_{Zone}	p	Thermal capacity of the thermal zone
$C_{Building}$	p	Thermal capacity of the building structure
R_{env}	p	Thermal resistance of the building envelope part 1
R_{loss}	p	Thermal resistance of the building envelope part 2 and other leaks
R_{B2Z}	p	Thermal resistance from the building structure to the thermal zone

Table 3.3.: Collection and description of the symbols used for the mathematical model description (Types v:variable, p:fixed parameter).

The mathematical model can be divided into two interconnected thematic sections that focus on two objectives. In Equation 3.15, the first objective is minimising electrical energy cost. The variable time steps are used here to calculate the energy imports and

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exports in every step. In addition, the stored energy in the battery at the last time step is considered.

$$min\,Cost_{el} = \sum_{i=0}^{n} \left[P_{Grid,in_i} \cdot c_{Grid,in} - P_{Grid,out_i} \cdot c_{Grid,out} \cdot (t_{i+1} - t_i)\right] - E_{Bat_n} \cdot c_{Grid,out} \qquad (3.15)$$

$$subject\ to$$

The energy balance hub is formed by Equations 3.16 and 3.17, with energy consumers on the left and energy suppliers on the right side of the equation.

$$P_{HP} + P_{El} + P_{Bat,charge} + P_{Grid,out} = P_{PV} + P_{Grid,in} + P_{Bat,discharge} \qquad (3.16)$$

$$0 \leq P_{El}, P_{Grid,out}, P_{Grid,in}, P_{PV} \qquad (3.17)$$

Equations 3.18 to 3.23 describe the geothermal heat pump system in a simplified manner using constant time constant COPs. This simplification is justified as the focus is not on heat pump performance and the COPs in the proposed geothermal heat pump system are less effected by seasonal effects than for example in air source heat pumps. Detailed building system simulations for the demonstration case conducted with IDA ICE[2] show that the temperature range on the brine side is typically within 5 K which does not significantly affect the COP during the course of the year. Adding onto that, an annual temperature degradation of the geothermal borehole is prevented by using it as a heat sink for the cooling demand in summer and therefore regenerating it during the course of the year. The higher COP for space heating is caused by a lower flow temperature level and the low COP for space cooling is considering the reverse operation of the heat pump in this case.

$$P_{HP} = \frac{\dot{Q}_{SH}}{COP_{SH}} + \frac{\dot{Q}_{SC}}{COP_{SC}} + \frac{\dot{Q}_{DHW}}{COP_{DHW}} \qquad (3.18)$$

$$0 \leq \; P_{HP} \leq 10\,\mathrm{kW} \qquad (3.19)$$

$$0 \leq \dot{Q}_{DHW} \leq 15\,\mathrm{kW} \qquad (3.20)$$

$$0 \leq \dot{Q}_{SH} \leq 17.5\,\mathrm{kW} \qquad (3.21)$$

$$0 \leq \dot{Q}_{SC} \leq 9\,\mathrm{kW} \qquad (3.22)$$

$$COP_{SH} = 4, \quad COP_{SC} = 2, \quad COP_{DHW} = 3 \qquad (3.23)$$

In Hoppmann et al. (2014) it is shown that the economically perfect sizing of PV generators and BESS for domestic use follow roughly the ratio of 1 kWh storage capacity per 1 kWp for the PV system which was used to dimension this BESS. The parameters defined in Equations 3.24 to 3.28 are provided by industry partners in the research project Sol4City.

[2]https://www.equa.se/de/ida-ice

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$$\frac{E_{Bat}}{dt} = \frac{P_{Bat,charge}}{\eta_{charge}} - P_{Bat,discharge} \cdot \eta_{discharge} \tag{3.24}$$

$$0 \leq \ E_{Bat} \leq 20\,\mathrm{kWh} \tag{3.25}$$

$$0 \leq P_{Bat,charge} \leq 20\,\mathrm{kW} \tag{3.26}$$

$$0 \leq P_{Bat,discharge} \leq 20\,\mathrm{kW} \tag{3.27}$$

$$\eta_{charge} = \eta_{discharge} = 0.94 \tag{3.28}$$

Energy costs are defined in Equations 3.29 and 3.30.

$$c_{Grid,in} = 0.20\,€/\mathrm{kWh} \tag{3.29}$$

$$c_{Grid,out} = 0.04\,€/\mathrm{kWh} \tag{3.30}$$

The second thematic section of the equation system is based on a 3R2C lumped-parameter grey box building model, also shown in Figure 3.10. The average temperature of the thermal zones in the building must suffice with the comfort boundaries set in Equations 3.32 and 3.33. To ensure this, a second objective function is introduced in Equation 3.31, which represents an l1-norm error function with a dead-band. A weight factor for the comfort objective is added to enable balancing with the economic objective.

$$\min_{T_{Zone}} \Phi = (e_{hi} + e_{lo}) \cdot f_{weight} \tag{3.31}$$

$$\textit{subject to}$$

$$e_{hi} \geq \ T_{Zone} - 25\,^{\circ}\mathrm{C} \tag{3.32}$$

$$e_{lo} \geq \ 21.5\,^{\circ}\mathrm{C} - T_{Zone} \tag{3.33}$$

$$e_{hi} \geq 0 \tag{3.34}$$

$$e_{lo} \geq 0 \tag{3.35}$$

Equations 3.36 to 3.40 form the core of the thermal building model, with the differential heat balance equations for the building structure and the thermal zone.

$$\dot{Q}_{SH} - \dot{Q}_{SC} = \dot{Q}_{Building} + \dot{Q}_{B2Z} + \dot{Q}_{env} \tag{3.36}$$

$$\dot{Q}_{Zone} = \dot{Q}_{B2Z} - \dot{Q}_{loss} + \dot{Q}_{solar} + P_{El} \tag{3.37}$$

$$\dot{Q}_{Building} = C_{Building} \cdot \frac{dT_{Building}}{dt} \tag{3.38}$$

$$\dot{Q}_{Zone} = C_{Zone} \cdot \frac{dT_{Zone}}{dt} \tag{3.39}$$

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$$0 \leq \dot{Q}_{solar} \tag{3.40}$$

The heat transfer from the building structure to the thermal zone is described in Equation 3.41.

$$\dot{Q}_{B2Z} = \frac{T_{Building} - T_{Zone}}{R_{B2Z}} \tag{3.41}$$

Equations 3.42 and 3.43 define heat losses through the building envelope and leaks.

$$\dot{Q}_{env} = \frac{T_{Building} - T_{Amb}}{R_{env}} \tag{3.42}$$

$$\dot{Q}_{loss} = \frac{T_{Zone} - T_{Amb}}{R_{loss}} \tag{3.43}$$

The building model parameters are listed in Table 3.4 and were extracted with a dynamic parameter estimation process based on time series simulation data. These data were generated with a highly detailed virtual model of the sample building generated with the software IDA ICE according to Hedengren et al. (2014).

Symbol	Value	Dimension
$C_{Building}$	245.6	$\mathrm{kWh\,K^{-1}}$
C_{Zone}	3.2526	$\mathrm{kWh\,K^{-1}}$
R_{B2Z}	0.00015862	$\mathrm{K\,W^{-1}}$
R_{env}	0.099999996	$\mathrm{K\,W^{-1}}$
R_{loss}	0.003409852	$\mathrm{K\,W^{-1}}$

Table 3.4.: Building model parameters retrieved from parameter estimation based on time series simulation data.

The described model is used within a two-stage process for every control time step, as shown in Figure 3.9. In the first step, the initial state derived from the previous cycle and the fixed input parameters household load and DHW demand are fed with predicted values from the forecast method component. Based on these input data, an optimisation for the operation in the next 24 hours is performed. The optimised control variables for the zone-heating/cooling power and the batteries' charging or discharging are then used for the second stage and locked in place for the first 15-minute time step. Again, using the initial condition from the last control iteration, the forecast data for electricity and DHW demand are now based on historic measurement data. This results in the second stage being different from the first and, therefore, enables the evaluation of the impacts of forecasting inaccuracies. The system state after the second solve run is then used as the initial condition for the next control iteration. This setup reflects an offset-free MPC control loop with controller and plant where the forecast deviation represents the disturbance and the plant's state space can be fully observed and fed back to the controllers' state. Using the same model and initial state conditions for the

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optimiser and the plant mitigates model mismatches and offsets. This ensures that the control error is purely affected by forecast quality.

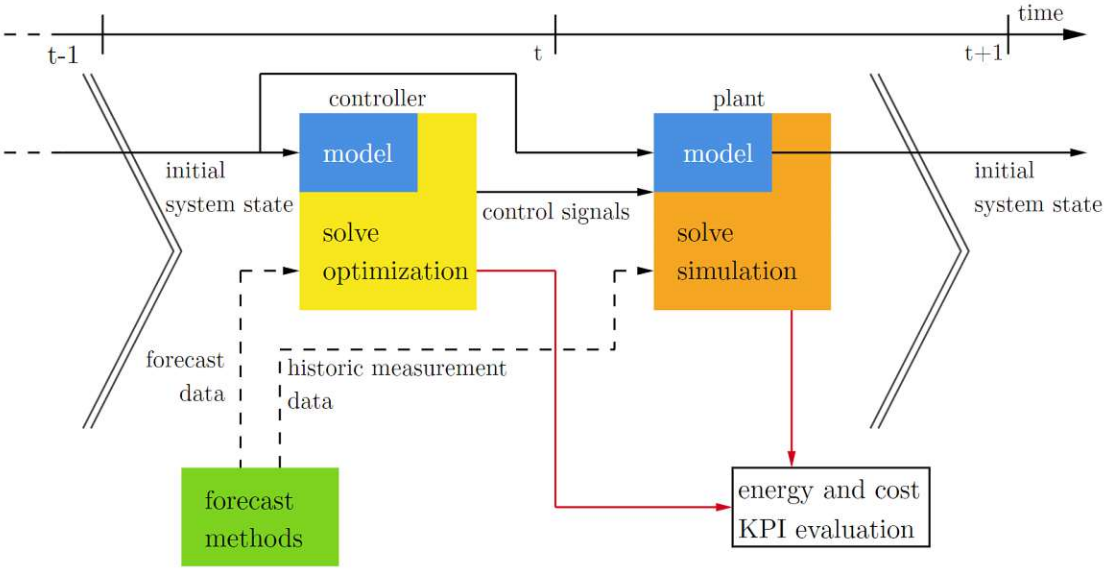

Figure 3.9.: MPC internal optimization and simulation process showing how different forecast and historic measured data is used and how control signals and the initial system states are handled.

Energy and cost-related KPIs

KPIs are indispensable for quantifying a building's energy flexibility and estimating how different features influence the sharing of renewable energies and the reduction of peak energy loads. Indicators are useful for effectively showing the concept of energy flexibility, providing a common language between energy players as described by Airò Farulla et al. (2021). Moreover, the use of energy KPIs can contribute to determining the proper technologies for systems that are able to store energy and to improve buildings' load-shifting potential proposed by Jensen et al. (2017). In the selected literature according to Junker et al. (2018), Salom et al. (2014) and Lopes et al. (2016), KPIs are used to investigate aspects of LECs. For this work, the classification for LEC KPIs proposed in Airò Farulla et al. (2021) is used: load-matching indicators.

Load-matching indicators are a helpful tool for a preliminary performance assessment due to the clarity of their mathematical descriptions. When derived from high-time-resolution data, load-matching KPIs fully illustrate the relationship between local energy demand and supply. They also illustrate hourly, daily, and seasonal effects; the relationship between load and generation; the production patterns of various renewable energy technologies; and the effects of implemented control strategies. However, it is impossible to determine which KPI values are best for the examined energy systems

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without fully understanding all their characteristics.
The percentage of the electrical demand that is met by on-site power generation is known as the load cover factor and is indicated in Equation 3.44. The load cover factor value is 0 at times when there is no on-site generation, while the maximum values occur when self-generation and the profile shape of the energy load meet explained by Salom et al. (2011), with g_t as on-site electricity generation, S_t as stored energy, ζ_t as power losses, and l_t as electric power load.

$$\gamma_{load} = \frac{\sum_{t=1}^{T} min\left[g_t - S_t - \zeta_t, l_t\right]}{\sum_{t=1}^{T} l_t} \tag{3.44}$$

The amount of on-site generation that is utilised by the building, in contrast, is known as the supply cover factor shown in Equation 3.45. In Salom et al. (2011), these two KPIs are often used to research various energy systems at both neighbourhood and single-building levels. However, they do not directly provide data on net energy, consumption, or supply, as well as data on power exchange peaks and connection capacity utilisation.

$$\gamma_{supply} = \frac{\sum_{t=1}^{T} min\left[g_t - S_t - \zeta_t, l_t\right]}{\sum_{t=1}^{T} g_t} \tag{3.45}$$

The ratio of energy demand to energy availability from nearby renewable sources is known as the on-site energy ratio (OER), as shown in Equation 3.46. If the OER is 1, it signifies that the renewable energy sources (RES) supply meets the demand for energy when viewing a net yearly balance. A number greater than 1 indicates that the yearly energy supply from domestic renewable energy sources is greater than the annual energy demand. The various kinds of energy are not considered independently in the OER. Without considering the energy mismatch for each energy type, it describes the situation in which demand is met by on-site production.

$$OER = \frac{\sum_{t=1}^{T} g(t)dt}{\sum_{t=1}^{T} l(t)dt} \tag{3.46}$$

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3.2.2. Forecast models for model predictive control considering energy price uncertainty

In the context of this study, the LEC used was a multi-unit residential building that is designed to optimise the use of renewable energy produced at the local level in an optimal manner across all energy sectors, both thermal and electrical and in close to real-time as proposed by Putz et al., 2023. The LEC was optimised, with the goal of distributing and using the renewable energy produced at the local level in an optimal manner as well as considering comfort boundaries in terms of indoor room temperature.

To achieve this goal, the LEC is equipped with a range of technologies and systems, such as photovoltaic panels, heat pumps, and battery energy storage systems. These technologies and systems are integrated and controlled by a building energy control and simulation system. The control and simulation system uses forecasted energy demand, DHW demand and weather data as input parameters to optimise the operation of the LEC in accordance with the provided objective functions. MPC is a control technique that involves predicting the future behaviour of a system based on a set of input variables, and then optimising the control actions based on this prediction. In the context of LECs, MPC can be used to optimise the operation of the energy system by minimising energy consumption and costs while maximising the use of renewable energy sources. This is achieved by solving an optimisation problem for the entire prediction horizon of 48 hours, which calculates the control set points for each time step based on the forecasted energy demand. The control set points are then applied to the system, and the process is repeated at regular intervals, such as 15 minutes, to continuously optimise the operation of the LEC. The use of MPC in LECs requires accurate forecasts of energy demand and production, which can be obtained using various forecasting methods and tools. The MPC framework used in this study is based on Putz et al., 2023.

The structure of the methodical framework was formed by two core components, as shown in Figure 3.10. On the one hand, there is a functional block containing the forecast methods used to predict energy and DHW demand. These forecasting methods were the systems under test (SUT) and are further described in Section 3.2.2.1. On the other hand, there is the building MPC block, which acted purely as the test environment for forecasting methods. It enabled the calculation of cost- and energy-related performance indicators in the context of communal housing, which is further described in Section 3.2.2.3.

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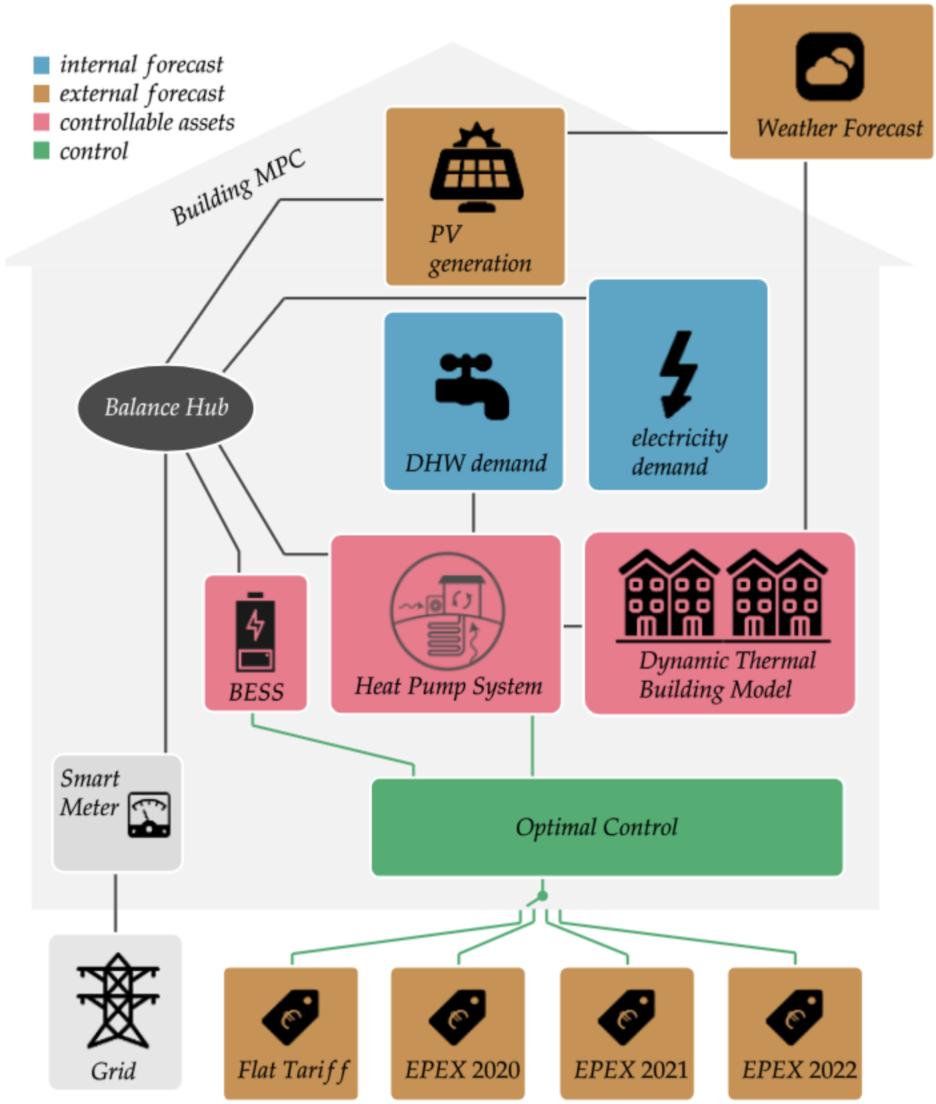

Figure 3.10.: Schematic structure of the implemented methodology. External forecasts are provided for PV production and weather variables, which are used for the dynamic thermal building model as well as price scenarios. In this study, energy and DHW demand were the subjects to forecast. The MPC framework provided optimal control of the battery energy storage system and the heat pump system. Different energy price scenarios were used to assess their impact on LEC KPIs.

The forecast component delivers forecasts for energy and DHW demand every day at the same time (i.e. midnight) for the upcoming 48 hours at a 15-minute time grid. The forecasts are based on real-time measurements and exogenous weather data from a local weather service provider. Subsequently, the predictions are used as input parameters for

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the optimisation problem, which outputs a collection of set-points for the upcoming 24 hours for flexible assets such as battery energy storage systems. Lastly, the first value of the calculated set-point sequence is sent to the virtual twin. This is referred to as an open-loop environment. The MPC framework runs an optimisation every 15 minutes and retrieves updated forecast time series daily. The open-loop environment delivers the first set-point at $t = 0$ of a flexible asset and is used as the initial set-point of the same asset in the following time step $t = 1$. This leads to optimisation runs that are coupled across time, where at each successive optimisation step, the horizon is shifted and more information becomes available.

3.2.2.1. Forecasting methods

The forecasting methods used in the study include perfect foresight, naïve approach, multiple regression, k-nearest neighbour, XGBoost, Prophet and two hypothetical forecast methods called favourable and excellent. These forecast approaches are described in detail in Putz et al., 2023 and used in the same configuration. To extend the existing forecasting module another well-performing forecast approach called NBEATSx proposed by Olivares et al. (2021), a further developed approach of NBEATS described by Oreshkin et al. (2019) was implemented during this study.

3.2.2.2. Neural Basis Expansion Analysis with Exogenous variables

NBEATS is a deep-learning forecasting method that uses attention mechanisms to enable the model to learn complex patterns in the data and make accurate predictions. It is well-suited for handling time series data. The attention mechanism is implemented using a multi-headed attention layer that allows the model to weigh the importance of different input features at each time step based on their relevance to the prediction task. The NBEATS model consists of two main components: a basis expansion component and a forecast component. The basis expansion component is responsible for learning the underlying patterns in the data, while the forecast component is responsible for making predictions. The two components are connected by an attention layer, which enables the model to focus on the most relevant features when making a prediction. The NBEATS model is only capable of considering past covariates as regressors for the backcast period of the target value $\mathbf{y}^{back}$. Continuing the development of this architecture led to NBEATSx, which incorporates covariates in its analysis denoted as $\mathbf{X}$, as shown in Figure 3.11. To assist with related work, the same annotation is used as proposed in Olivares et al., 2021.

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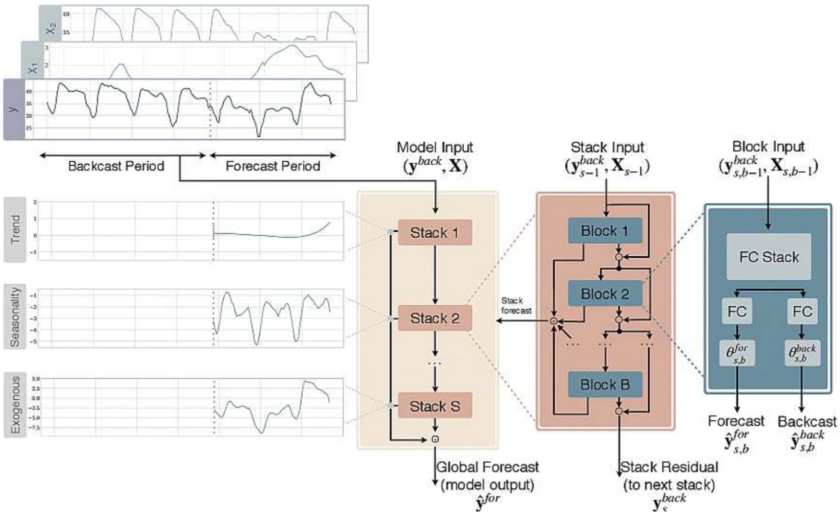

Figure 3.11.: The NBEATSx is made up of blocks, which are organised as a series of fully connected networks with ReLU-based nonlinearities as described and depicted by Olivares et al., 2021. These blocks overlap using the doubly residual stacking principle to generate both backcast $\hat{\mathbf{y}}_{s,b}^{back}$ and forecast $\hat{\mathbf{y}}_{s,b}^{for}$ outputs for the b-th block within the s-th stack. Finally, the predictions $\hat{\mathbf{y}}^{for}$ are obtained by combining the outputs from all the stacks. The architecture consists of S stacks, with each consisting of B blocks. $\mathbf{y}^{back}$ represents the input of the first block, which consists of L lags of the time series $\mathbf{y}$ to be predicted and the exogenous matrix $\mathbf{X}$. The residual connections with the backcast output of the previous block are included in the inputs of each of the subsequent blocks.

The principle of the basic block is to deliver forecast and backcast parts which are fed to the next block. A fully connected neural network (FCNN) is applied on $\mathbf{y}_{s,b-1}^{back}$ and $\mathbf{X}_{s,b-1}$ to learn hidden units $\mathbf{h}_{s,b}$, as shown in Equation 3.47.

$$\mathbf{h}_{s,b} = \mathbf{FCNN}_{s,b}\left(\mathbf{y}_{s,b-1}^{back}, \mathbf{X}_{s,b-1}^{back}\right) \tag{3.47}$$

The hidden units are linearly adapted into the forecast $\theta_{s,b}^{for}$ shown in Equation 3.48 and the backcast $\theta_{s,b}^{back}$ described by Equation 3.49 which are called expansion coefficients proposed by Putz et al. (2021).

$$\theta_{s,b}^{back} = \mathbf{LINEAR}^{back}\left(\mathbf{h}_{s,b}\right) \tag{3.48}$$

$$\theta_{s,b}^{for} = \mathbf{LINEAR}^{for}\left(\mathbf{h}_{s,b}\right) \tag{3.49}$$

The operation that gives NBEATS its name called basis expansion is applied between the learnt coefficients and the block's basis vectors $\mathbf{V}_{s,b}^{back}$ and $\mathbf{V}_{s,b}^{for}$ leading to the backcast $\mathbf{y}_{s,b}^{back}$ and forecast $\mathbf{y}_{s,b}^{for}$ shown in Equation 3.50 and Equation 3.51.

$$\mathbf{y}_{s,b}^{back} = \mathbf{V}_{s,b}^{back}\theta_{s,b}^{back} \tag{3.50}$$

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$$\mathbf{y}^{for}_{s,b} = \mathbf{V}^{for}_{s,b}\,\theta^{for}_{s,b} \tag{3.51}$$

The first part of the doubly residual stacking principle, which is shown in Equation 3.52, can be understood as the composition of the modelled signal and prepares the inputs of the subsequent layer. The second part, described by Equation 3.53, aggregates the partial forecast blocks into stacks.

$$\mathbf{y}^{back}_{s,b+1} = \mathbf{y}^{back}_{s,b} - \hat{\mathbf{y}}^{back}_{s,b} \tag{3.52}$$

$$\hat{\mathbf{y}}^{for}_{s} = \sum_{b=1}^{B} \hat{\mathbf{y}}^{for}_{s,b} \tag{3.53}$$

The final result is obtained by aggregating all stack predictions shown in Equation 3.54.

$$\hat{\mathbf{y}}^{for} = \sum_{s=1}^{S} \hat{\mathbf{y}}^{for}_{s} \tag{3.54}$$

Two possible configurations are proposed in Olivares et al. (2021), that can be distinguished by choosing different basis vectors $\mathbf{V}^{back}_{s,b}$ and $\mathbf{V}^{for}_{s,b}$. The basis vectors design how the time series is decomposed and support the understanding of its underlying structure and patterns since they perform a projection. For instance, decomposing into a trend pattern can be done by selecting a polynomial function as a basis function. In the proposed NBEATS approach without exogenous variables two different basis functions are applied. The first one, which is responsible for extracting the trend part, is a polynomial function shown in Equation 3.55, with time vector $\mathbf{t} = [0, 1, 2, ..., H-2, H-1]\,/H$ and N_{pol} as the maximum polynomial degree.

$$\hat{\mathbf{y}}^{trend}_{s,b} = \sum_{i=0}^{N_{pol}} \mathbf{t}^{i}\theta^{trend}_{s,b,i} \equiv \mathbf{T}\,\theta^{trend}_{s,b} \tag{3.55}$$

The second basis function which extracts seasonal patterns, is a harmonic function described by Equation 3.56 and can be interpreted as Fourier transform coefficients. The hyperparameter N_{hr} controls harmonic oscillations.

$$\hat{\mathbf{y}}^{seasonal}_{s,b} = \sum_{i=0}^{\lfloor H/2-1 \rfloor} \cos\left(2\pi i \frac{\mathbf{t}}{N_{hr}}\right)\theta^{seasonal}_{s,b,i} + \sin\left(2\pi i \frac{\mathbf{t}}{N_{hr}}\right)\theta^{seasonal}_{s,b,i+\lfloor H/2 \rfloor} \equiv \mathbf{S}\,\theta^{seasonal}_{s,b} \tag{3.56}$$

The original NBEATS architecture by Oreshkin et al. (2019) consists of a trend stack followed by a seasonality stack, each containing three blocks. To extend this architecture to NBEATSx another stack must be defined that focuses on the exogenous part and performs a basis expansion on it, as described by Equation 3.57.

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$$\hat{\mathbf{y}}_{s,b}^{exog} = \sum_{i=0}^{N_x} \mathbf{X}_i \theta_{s,b,i}^{exog} \equiv \mathbf{X}\, \theta_{s,b}^{exog} \tag{3.57}$$

In this study, temperature and solar irradiance were used as exogenous weather variables. Both are time-dependent and can be treated as seasonal covariates. Thus, the same basic functions as shown in Equations 3.55 and 3.56 can be applied for decomposing the exogenous influence.

Overall, NBEATSx is a powerful forecasting method that can to handle complex and multivariate time series data and make accurate predictions. It has the advantage of being able to capture complex patterns in the data and adapt to changing patterns over time, but it can be computationally intensive and may require a large amount of training data to achieve good performance. The computational aspect is not within the scope of this study.

3.2.2.3. Model predictive control framework for building energy control and simulation

The setup of this study was designed to align with the characteristics of a typical LEC, with the primary objective of efficiently distributing and utilising locally generated renewable energy across both thermal and electrical energy sectors in near-real-time. To achieve this goal, the existing flexibilities within the LEC are optimally utilised based on the provided objective functions.

The MPC framework operates in two stages for each control time step. In the first stage, using forecasted data, it computes optimal control variables for zone heating/cooling and battery energy storage for the next 24 hours. These optimized control variables are then applied for the initial 15-minute time step. In the second stage, using actual measurements and historic data, the optimization process is rerun for the next 24 hours, allowing us to assess the impact of forecasting inaccuracies on LEC performance. The comprehensive energy system model described in Putz et al., 2023 within the MPC framework considers a range of factors, including the building's thermal characteristics, HVAC systems, DHW demand, renewable energy generation (e.g., photovoltaic), and energy storage (battery) dynamics. It is implemented as a linear programming problem with differential algebraic equations using Python-based tools and the GEKKO package, ensuring high accuracy for immediate forecasting while minimizing computational effort. These functions minimise the overall operational energy costs while maintaining the comfort level in terms of indoor room temperature. It optimises the charging of batteries and thermal building masses during surplus energy generation and strategically discharges them during high-demand periods or when renewable energy supply is insufficient. Load shifting and state-of-charge management are integral aspects, all guided by forecasting techniques to align energy storage actions with predicted generation and

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consumption patterns. The objective is to enhance energy efficiency, reduce costs, and maximize the utilization of renewable energy resources within the LEC. To adapt the MPC method described in Putz et al., 2023 for use with time variable electricity prices the additional Equations 3.58 and 3.59 are implemented to prohibit the charging of the battery energy storage system with energy from the grid. This is because the electric battery in the underlying energy community is intended to raise the self-consumption rate of on-site electricity generation and not to do price-driven energy trading with the grid.

$$P_{Bat,charge} \leq P_{PV} \tag{3.58}$$

$$P_{Bat,discharge} \leq P_{HP} + P_{El} \tag{3.59}$$

3.2.2.4. Price scenarios

Currently, most electricity tariffs are based on a flat tariff structure, which serves as the baseline for this study. A constant rate of 0.20 € per kWh for purchasing and 0.04 € per kWh for feed-in over the whole contractual period was chosen, as these values were typical for Austrian household electricity prices before the energy price surge of 2022 and ensure comparability with the research results in Putz et al. (2023). Other major electricity tariff structures exist, such as time-of-use, demand charge and real-time-pricing described by Houben et al. (2023). Time-of-use is a variable rate for the price depending on the time of the day or type of day. The demand charge tariff includes an additional power rate in € per kW as a penalty, which is multiplied with the highest peak demand. This tariff structure is especially prevalent in the US. The real-time-pricing tariff passes spot market prices down to the consumer as for example common in Norway. Real-time pricing tariffs are already available for household customers in Austria[3] together with day-ahead price forecasts and offer cost benefits for time flexible electric load. To assess the impact of different price scenarios a real-time pricing tariff for three different years was used as input for the MPC framework. The time series day-ahead price data for the years 2020, 2021 and 2022 were used as input for the proposed framework as those years show a gradual transition from low and stable electricity prices in 2020 to high volatile prices by the end of 2022. The data for day-ahead electricity prices were retrieved from the transmission system operator in Austria APG[4]. Figure 3.12 shows the hourly distribution for each year and outlines the increasing price as well as rising volatility for 2022 compared to 2020. Because the effective energy price for LECs also includes taxes and fees imposed by the energy supplier and the grid operator, Equations 3.60 and 3.61

[3] https://www.awattar.at/
[4] https://markttransparenz.apg.at/

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were implemented to calculate the final consumption and feed-in tariffs. It was assumed that energy suppliers must add the regular Austrian value-add tax (VAT) f_{tax} of 20 % to the electricity market price for imported electricity. The LEC also taxes its earnings for exporting electricity, as they are normally not seen as nonprofit organisations in Austrian tax law. The grid fee c_{grid} of 0.09 €/kWh only applies to the imported electricity, as it is typically paid by the recipient of energy. Additionally the assumed contract with the energy supplier includes specific handling fees with $f_{handling\,fee\,import}$ of 3 % and $f_{handling\,fee\,export}$ of 9 % on top of the day-ahead market price.

$$c_{Grid,import} = (c_{day\,ahead} + |c_{day\,ahead}| \cdot f_{handling\,fee\,import}) \cdot (1 + f_{tax}) \tag{3.60}$$

$$c_{Grid,export} = (c_{day\,ahead} - |c_{day\,ahead}| \cdot f_{handling\,fee\,export}) \cdot (1 - f_{tax}) \tag{3.61}$$

To compare the LEC KPIs with respect to different price scenarios, the other input data, such as energy and DHW demand are the same for each of the four scenarios, only the electrical price data vary. Table 3.5 shows the statistical indicators in terms of mean, standard deviation, minimum, maximum and percentile values for the day-ahead price of electricity.

scenario	mean	std	min	$P_{25\%}$	$P_{50\%}$	$P_{75\%}$	max
flat tariff	0.2	0	0.2	0.2	0.2	0.2	0.2
2020	0.132	0.019	0.048	0.121	0.131	0.143	0.272
2021	0.279	0.111	-0.032	0.196	0.25	0.343	0.887
2022	0.478	0.2	-0.79	0.323	0.46	0.625	1.257

Table 3.5.: Statistical values in terms of mean, standard deviation, minimum, maximum and percentile values for day-ahead electricity prices per year in € per kWh. In 2021 and 2022, negative prices appeared and the volatility as well as the average value grew substantially.

3.2.3. Data

In this study, data for an LEC were collected. The data included energy, DHW demand, photovoltaic (PV) production, solar irradiance, and ambient temperature for a period of one year. The energy consumption data included the total electricity demand of the LEC, as well as the demand for different end-uses, such as lighting, appliances, heating, ventilation and air conditioning (HVAC). The energy production data included the total electricity production of the LEC and the production from PV panels.

The dataset used for forecasting was obtained from Schlemminger et al., 2021, an open-source repository in southern Germany. Unfortunately, in real-world scenarios, data are frequently inadequate, particularly with respect to historical information. To mitigate

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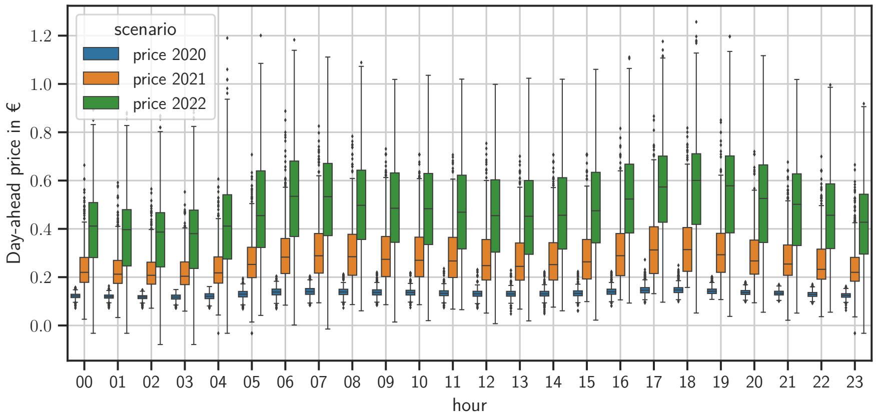

Figure 3.12.: Hourly distribution of day-ahead prices in Austria for the years 2020, 2021 and 2022. The increase of price level as well as volatility is apparent.

this issue, only the year 2021 was used for the dataset, and it was divided into two halves: the first half and the second half, with a split date of midnight on July 1, 2021. At the start of the experiment, only six months of data were available. However, the available historical data increases as the forecast models are retrained every Monday at midnight using the most recent data to avoid excessive errors caused by outdated model fitting. The exogenous weather data were not altered to maintain the specificity of the errors introduced by the tested forecast algorithms. This was critical since the proposed method employs exogenous data not just for the forecasts themselves but also for the operation of the MPC, which relies on weather data. Inaccurate weather forecasting would have an impact on the resulting operation through both pathways, making the segregation of impacts in this dynamic system more complicated and a research question of its own. To meet the accuracy and computational speed requirements of the large number of runs, the forecasting module was adjusted during training and prediction. Prior to the pilot period, various hyperparameters and characteristics were systematically tested for different algorithms. To achieve this, walk-forward cross-validation was used, which involved a sliding window on the training dataset and a rolling extension of the training dataset for each fold, as described in Putz et al., 2023. In particular for NBEATSx to train the neural network, the MAE was minimised using ADAM (stochastic gradient descent with momentum proposed by Kingma and Ba (2017)) which is common in the literature according to Smyl, 2020. For hyperparameter optimisation, the approach proposed by Lago et al. (2018) was used to guide the search for well-performing configurations. Table 3.6 summarises the chosen hyperparameters for NBEATSx.

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Hyperparameter	Considered Value
Input size of feature window (one week)	$L \in \{672\}$
Output size for 48 hours ahead forecasting	$H \in \{192\}$
Activation function	ReLU
FCNN layers within each block	2
FCNN hidden neurons on each layer of a block	$N_h \in \{50, ..., 500\}$
Degree of trend polynomials	$N_{pol} \in \{2, 3, 4\}$
Number of Fourier basis (seasonality smoothness)	$N_{pol} \in \{1, 2\}$
objective loss function	MAE

Table 3.6.: Hyperparameters of the NBEATSx network. The configuration that performed best on the validation set was selected automatically.

The NBEATSx approach was implemented in PyTorch[5] founded by Paszke et al. (2019). The optimal configuration was chosen by repeating this procedure with multiple algorithms and hyperparameters. The training was conducted on a CPU Intel(R) Core(TM) i7-11850H @ 2.50 GHz.

[5]https://pytorch.org/

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4. Results

This chapter showcases the results obtained from the three studies conducted to address the research questions. The chapter begins with Section 4.1, which provides results of the wind power forecasting using the N-BEATS approach based on Putz et al. (2021). Subsequently, Section 4.2 consists of Subsection 4.2.1 highlighting the forecast-based optimal control results based on Putz et al. (2023), showcasing the outcomes for a full year as well as specific time slots within the year. Furthermore, Subsection 4.2.2 expands on the case study based on Putz et al. (2024) by incorporating energy price and uncertainty, revealing the findings of this integrated analysis.

4.1. NBEATS performance on short term wind power forecasting

In this section, the proposed N-BEATS model for VSTWPF is applied to the real-world datasets described in Section 4.1.1. Additional models based on classical statistical methods and machine learning methods are implemented to compare them with N-BEATS in terms of accuracy. These models are briefly described in Section 4.1.2. The results regarding accuracy are shown in Section 4.1.3.

4.1.1. Dataset and Training

Real-world open-source[1] wind power datasets from 15 different European countries by *Open power system data platform* (2020) are used and can be found attached in Appendix A. Each data set represents the aggregated wind power of a country that is used and processed by control area operators. Currently, time series are mainly processed hourly. However, the trend is moving to finer time intervals. Therefore, data sets with a 30-minute and 15-minute resolution have also been examined:

- 15min (01/01/2020 - 30/09/2020): AT, DE, NL
- 30min (01/01/2020 - 30/09/2020): CY (with gaps), GB, IE
- 60min (01/01/2019 - 30/09/2020): DK, ES, FI, FR, GR, IT, NO, PL, RO

[1] https://open-power-system-data.org/

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The dataset of CY has some gaps in the history, and it is of interest to see how well the models can handle such cases.
The proposed method uses only windpower time series as input since it is a univariate time series forecasting architecture. The input is a time series of consecutive measured wind power values. N-BEATS does not process exogenous factors and influencing quantities such as wind speed. As a result, depending on the configuration, the predicted wind power for the next time step or a whole time series for the next time steps is obtained. In addition to this, further result components such as trend and seasonality are delivered.
Datasets are split into train, validation and test subsets. Table 4.1 shows the dates where these splits are located within the datasets for 15min, 30min and 60min time sets. In the first step the time series gets filtered to replace missing or NaN entries with 0. After splitting the datasets for each country a model is fitted with training and validated with validation data which leads to 15 different trained models. For performance evaluation the test sets are processed into multi-step time windows consisting of analysis and subsequent forecast time series (measured values). In general, the analysis window has multiple times the length of the forecast time series. The proposed approach delivers the forecast time series dependent on analysis time series. The predicted time series is followingly compared to the actual one to assess accuracy.

time resolution	countries	set	begin
		train	01/01/2020
15 minute	AT, DE, NL	validation	30/06/2020
		test	15/08/2020
		train	01/01/2020
30 minute	CY (with gaps), GB, IE	validation	30/06/2020
		test	15/08/2020
		train	01/01/2019
60 minute	DK, ES, FI, FR, GR, IT, NO, PL, RO	validation	28/02/2020
		test	15/06/2020

Table 4.1.: Split of datasets into training for fitting the model, validation for hyperparameter tuning and test to assess performance.

N-BEATS is implemented in Python[2] with *tensorflow* according to Abadi et al. (2016) as well as in *PyTorchForecasting* by Beitner (2020). The learning progress and results are visualised via *TensorBoard* described by Abadi et al. (2016). Table 4.2 lists the configuration of the model.

[2]https://www.python.org/about/

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parameter	value
optimizer	Adam
tensorflow	v2.6
PyTorchForecasting	v0.7
learning rate	optimised by PyTorch Lightning
max epochs	50
batch size	128
early stopping	true
reduce on plateau patience	1000
share stacks	true
stack types	trend + seasonality
weight decay	0.01
max. lookback horizon	variable - 24 time steps (6h-48h)
forecast horizon	variable - 4 time steps (15minute-12h)
shuffling of samples	true
hidden dense layers	512
layers in residual block	4
loss function	pinball sMAPE

Table 4.2.: Overview of the parameters for the N-BEATS approach.

4.1.2. Models

The models that are used for comparision are outlined below.

- ARIMA - Autoregressive Integrated Moving Average $ARIMA(p,d,q)(P,D,Q)_m$ model implemented via *statsmodels.tsa.arima.model.ARIMA* from *statsmodel* in Python. A seasonal ARIMA model is used where m refers to the number of periods in each season and P,D,Q refer to the autoregressive, differencing, and moving average terms for the seasonal part of the ARIMA model.

- MLP - multilayer perceptron, which is a feed forward NN with a single hidden layer. In general, this is the most commonly used NN with an activation function. MLP utilises a supervised learning technique called backpropagation for training. For activation, the commonly used sigmoidal function is employed. The implementation is chosen through *tensorflow* in Python according to Pełka and Dudek (2019).

- LSTM - a long-short-term memory, which can be classified as an RNN in the DL sector, implemented via *tensorflow* in Python. In contrast to standard MLP architecture, the LSTM has feedback connections for enhancement and avoids the vanishing of the gradient. The cell has the ability to forget part of its previously stored memory and replace it with part of the new information. In general, an

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LSTM consists of a cell, input gate, output gate and forget gate. The cell remembers information and all the other gates control the flow of information into and out of the cell. LSTM became very popular for time series forecasting due to its robust results. It is widely used and researched for VSTWPF.

- WT-LSTM - wavelet transformation with LSTM as hybrid model implemented via *pywt* and *tensorflow* in Python. This hybrid approach delivers significantly more accurate results compared to conventional models. In addition, the M4 competition stated that hybrid approaches will be more frequently used in the future due to their great potential. A prime example thereof is the WT-LSTM, where the Wavelet transformation is used to examine the stochastic nature of wind power. This leads to a decomposition where breakpoints and discontinuities are provided by the WT. Additional techniques, such as feature selection are used to further improve the accuracy according to Memarzadeh and Keynia (2020).
- LSTM-MSNet - LSTM with classical decomposition and multiple seasonal patterns (MSNet) implemented via *tensorflow* in Python according to Bandara et al. (2020). Its superiority lies in the fact that it is a globally trained LSTM, which means that a single prediction model is built across all the available time series to retrieve the so-called cross series knowledge of related time series. This can be further improved by including multi-seasonal decomposition.
- ES-RNN - exponential smoothing with an RNN, which is a multivariate hybrid DL algorithm is implemented via *tensorflow* in Python according to Smyl (2020). The ES decomposes the time series into level, trend and seasonality components. The RNN is trained with all series, has shared parameters and is used to learn common local trends among the series while the ES parameters are specific to each time series. The models are combined by including the output of the RNN as the local trend component in the ES model.

4.1.3. Results

Samples of forecasts with different forecast horizons are shown in Figure 4.1. Table 4.3 provides an overview of the forecasting metrics for Germany. The mean absolute percentage error (MAPE), symmetric mean absolute percentage error (sMAPE), mean percentage error (MPE), R2 score and mean average absolute error (MAE) are used as metrics.

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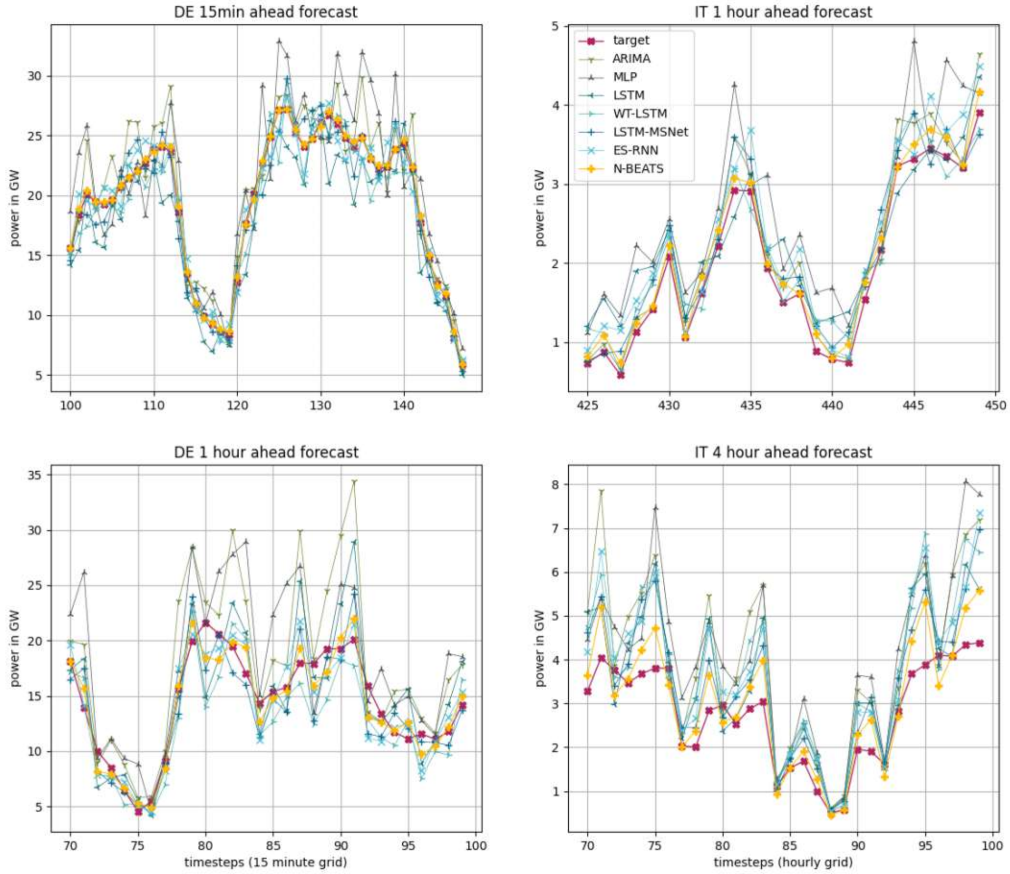

Figure 4.1.: Top left figure shows a sample of a 15 minutes ahead forecast (Dataset with 15 minutes time resolution). Bottom left figure shows a sample of a 1 hour ahead forecast (Dataset with 15 minutes time resolution). Top right figure shows a sample of a 1 hour ahead forecast (Dataset with 1 hour time resolution). Bottom right figure shows a sample of a 4 hour ahead forecast (Dataset with 1 hour time resolution).

The MPE is a metric to evaluate over- and underprediction while the MAPE is a metric for overall accuracy. A positive bias means underprediction and vice versa. The most remarkable result to emerge from the data is that N-BEATS outperforms all other used models in terms of accuracy with a MAPE of 3.98%. Generally, a MAPE below 4% is considered as major improvement. The hybrid model approaches deliver similar accuracy with ES-RNN as the second most accurate model with a MAPE of 4.04%. N-BEATS also delivers the lowest bias with an MPE of -0.56. In Section 4.1.4.1 other loss functions

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model	MAPE in %	sMAPE in %	MPE in %	R2 score
ARIMA	7.83	5.25	-2.22	0.965
MLP	15.32	9.37	-2.87	0.934
LSTM	12.11	7.21	-3.66	0.957
WT-LSTM	4.71	4.12	-1.26	0.982
LSTM-MSNet	4.22	3.89	-1.09	0.986
ES-RNN	4.04	3.67	-0.99	0.991
N-BEATS	**3.98**	**3.34**	**-0.56**	**0.998**

Table 4.3.: Overview of the forecasting metrics for German dataset with a forecast horizon of 15 minutes. The N-BEATS results are highlighted.

for N-BEATS are examined and it is shown that the pinball sMAPE as the selected loss function overall improves the approach. It has been observed that a τ of 0.375 delivers the most accurate results accross all datasets.
Figure 4.2 displays the MAPE for each country. The table shows that N-BEATS delivers stable and accurate results for most countries and that it is most accurate approach for 10 out of 15 countries. Despite CY having some gaps in its history, there is no significant impact on the forecast accuracy since the error metrics are in the same range as for the other countries.

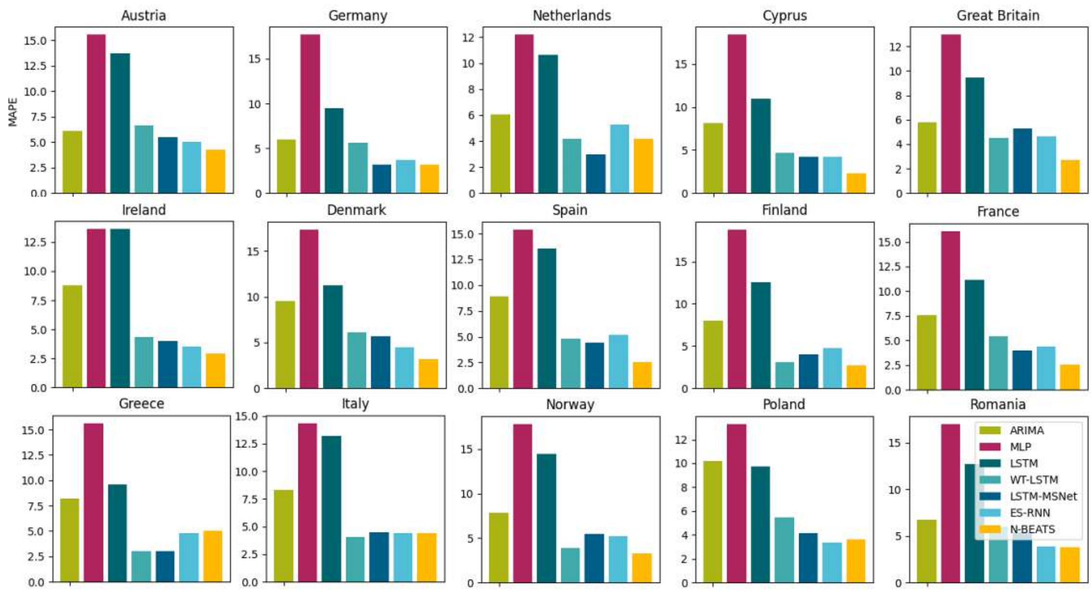

Figure 4.2.: MAPE for each country.

The forecast error varies throughout the year and hour of day as shown in Figure 4.3. During spring and autumn the forecast inaccuracy peaks. This is because the wind often

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fluctuates the most during these periods. The fact that the wind is most discontinuous during these seasons obviously makes forecasting more difficult. This behavior is highly dependent on location. Similar behavior is observed by examining the dependence of the forecast error on time of day. Generally, stronger winds do not occur until the afternoon, after the sun has warmed the ground and warmer air masses rise. This results in more turbulence, which increases the difficulty of forecasting. Overall the approach delivers robust results with minor variation since the error fluctuations are within the range of approximately 1% MAPE.

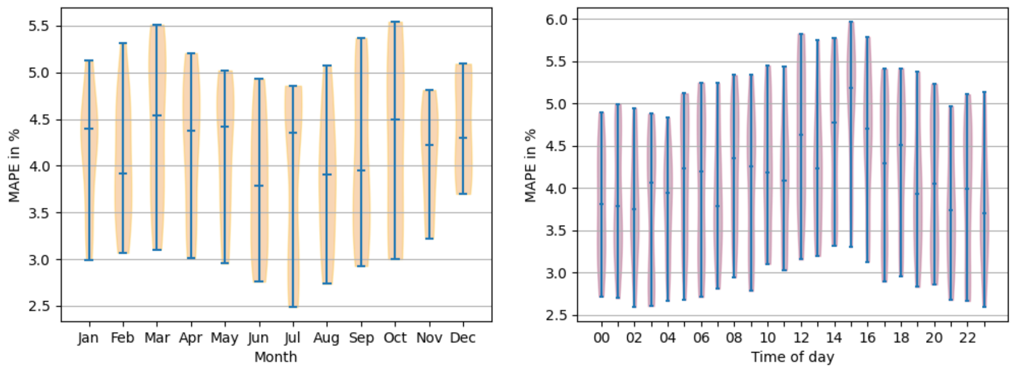

Figure 4.3.: Forecasting error in relation to time of the year (month) and time of day (hour).

4.1.4. Sensitivity analysis

This section examines the impact of varying some model parameters, such as different loss functions and time resolutions of datasets on the result in terms of accuracy.

4.1.4.1. Different Loss Functions

Different loss functions also provide different results in terms of accuracy. Table 4.4 shows the MAPE for the N-BEATS model for different loss functions. The result shows that the pinball sMAPE function significantly improves the accuracy.

4.1.4.2. Time Resolution

In general, historical time series occur in different resolutions. Often, an intermediate step exists to interpolate the time series to the desired resolution. The most commonly used time resolutions are 15 minutes, 30 minutes and 60 minutes. Table 4.5 summarises the errors at different time resolutions and forecast horizons.
Figure 4.4 reports the coefficient of determination for Germany for each approach. It was noted that some approaches (ARIMA, MLP) tend to overpredict more than others

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loss function	MAPE
MAE	7.72
MAPE	9.18
RMSE	12.25
sMAPE	8.78
pinball sMAPE, $\tau = 0.25$	9.62
pinball sMAPE, $\tau = 0.375$	**3.98**
pinball sMAPE, $\tau = 0.5$	8.78

Table 4.4.: Sensitivity analysis of the loss function for N-BEATS. The analysis is carried out with the Germany dataset and a forecast horizon of 15 minutes.

resolution	15min	30min	1h	2h	4h	6h	8h	10h	12h
15 min	3.78	5.99	7.98	13.89	17.23	22.51	27.47	32.88	36.33
30 min	-	4.04	6.48	11.72	14.37	19.94	26.92	31.11	34.11
60 min	-	-	4.12	9.27	12.76	18.34	24.83	30.72	33.88

Table 4.5.: Sensitivity analysis of the time resolution for N-BEATS. The forecast horizon varies from 15 minutes to 12 hours. For the time resolutions of 15 and 30 minutes, only the corresponding data sets were examined. For the others, all data sets were examined and the result values are calculated by averaging them. Results are displayed in MAPE percentages.

(LSTM, WT-LSTM, LSTM-MSNet). The developed architecture, however, is in most cases only accompanied by a relatively small overprediction, which depends on the data set. For the selected example forecast in Figure 4.1, it can be seen that N-BEATS also tends to overpredict for Italy dataset. In contrast, it was observed that for some other data sets this issue is negligible. Overprediction can be dealt with to a large extent by a suitable selection of τ. However, this parameter has to be tuned for each model and cannot be determined in general.

Figure 4.5 shows the forecast error distributions of all results by varying the forecast horizon from 15 minutes up to 12 hours ahead. The analysis horizon is set as a multiple of the forecast horizon. Several tests have shown that an analysis period of 4 to 6 times the forecast horizon delivers the best results. After comparing the results with similar publications in this field, such as Okumus and Dinler, 2016, it can be concluded that the accuracy of the results of the proposed architecture is exceptionally good for very short-term results, in the range of 4 hours or shorter. Moreover, it was observed that the error varies greatly for longer forecast horizons and is highly dependent on the dataset.

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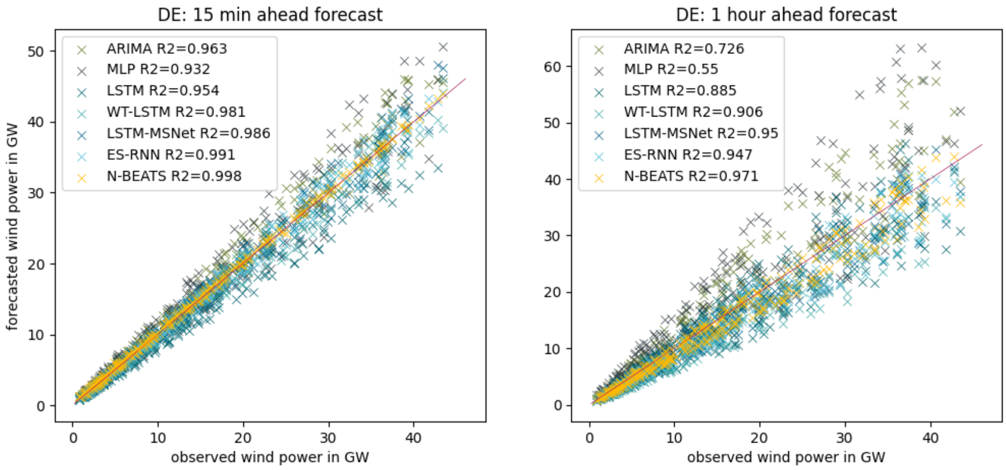

Figure 4.4.: Scatter plot of forecasted vs observed wind power for all implemented models. Left figure displays the coefficient of determination for forecast horizon of 15 minutes for Germany. Right figure displays the coefficient of determination for forecast horizon of 1 hours for Germany.

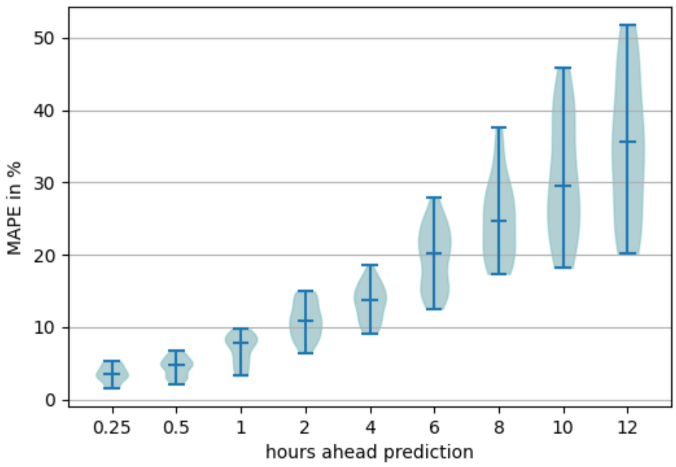

Figure 4.5.: The MAPEs for all countries are depicted as distribution for the corresponding forecasting horizon to be predicted as well as the median and extremas for the 15-minutes, 30-minutes and hourly sample rates.

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4.2. Forecast-based optimal control of a local energy community

In the following Subsection 4.2.1 and 4.2.2, the outcomes and implications from research question 2 and 3 are explored. These two interconnected papers collectively contribute to a comprehensive understanding of forecasting models performance and their impact on LECs. Through rigorous analysis and evaluation, valuable insights into the accuracy and forecast value of advanced forecasting methods, their suitability for optimizing LEC operation, and the influence of different energy price scenarios are unveiled.

4.2.1. Performance Evaluation of Forecasting Models in the context of LECs

This section is divided into two parts to distinguish between forecast-related KPIs and LEC-related KPIs. All simulations were conducted with a horizon from 01.07.2021 00:00 to 31.12.2021 23:45.

4.2.1.1. Forecast quality

The calculation of the errors is based on 24-hour time windows and compared with the actual value, since forecasts are updated once a day. Figure 4.6 shows the sample results of each prediction method, excluding the fictive ones, for the load as well as DHW demand for 2 days in July. The naïve forecast performed the worst and was very volatile in contrast to the other methods. A certain structure can be identified in which statistical methods (multiple regression, kNN) have more volatility than the ML approaches (XGBoost, Prophet) at certain periods of time.
Table 4.6 summarises all error metrics regarding load and DHW demand. The results show that for load forecasting, Prophet was the most accurate, slightly better performing than XGBoost in every aspect. Additionally, these highly advanced forecasting approaches have about a 14 % lower MAPE than the naïve method. Moreover, predicting DHW demand is more difficult compared to the load indicated by the higher error metrics. Another interesting result is that one prediction method is not always the best performer in all metrics. For instance, Prophet and XGBoost deliver different results in terms of MAPE and sMAPE. This is because MAPE and sMAPE work differently for values close to zero. Based on the DHW dataset, it appears that the distribution is extremely skewed due to the values close to zero as well as different penalisations of positive and negative errors for MAPE . Another interesting aspect that should not be neglected is the time required for training and prediction. In general, advanced ML methods require much more time for training. However, when it comes to executing the predictions, XGBoost shines with a comparable short execution time in contrast to

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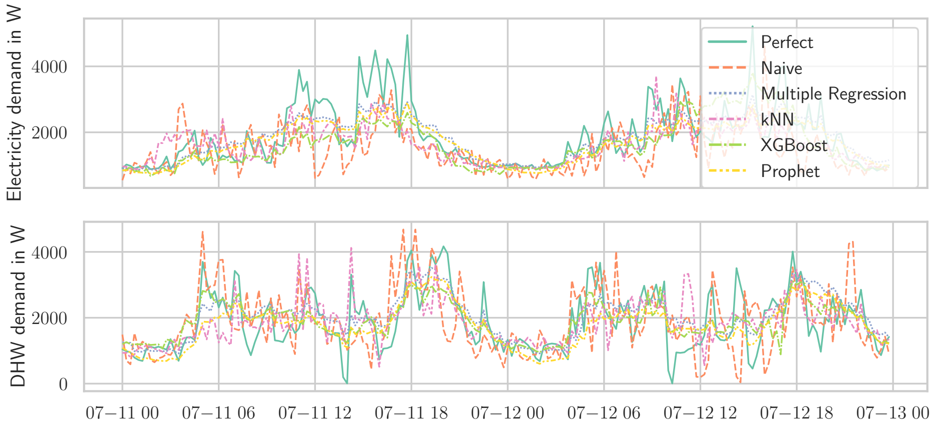

Figure 4.6.: Forecasted result samples for load demand (top) and DHW demand (bottom) for two days in July.

Prophet.

	forecast approach	Accuracy				Time in s	
		MAPE	sMAPE	nRMSE	MASE	Train	Pred.
electricity	Naïve	37.31	36.26	0.1478	1.000	0.1	0.1
	Multiple Regression	27.85	24.15	0.0876	0.836	3.4	0.5
	k-Nearest Neighbor	27.60	24.77	0.1061	0.916	6.6	0.9
	XGBoost	23.89	21.79	0.0885	0.877	14.2	1.2
	Prophet	**23.53**	**21.54**	**0.0857**	**0.826**	13.8	1.1
	Favorable Forecast	19.99	20.38	0.0699	0.509	0.1	0.1
	Excellent Forecast	14.95	15.15	0.0521	0.403	0.1	0.1
domestic hot water	Naïve	77.39	46.83	0.1004	1.000	0.1	0.1
	Multiple Regression	65.78	28.82	0.0616	0.836	3.2	0.4
	k-Nearest Neighbor	62.86	31.77	0.0711	0.913	4.5	0.8
	XGBoost	58.17	**27.43**	**0.0594**	0.841	12.3	1.1
	Prophet	**55.82**	28.63	0.0601	**0.837**	12.8	1.0
	Favorable Forecast	45.15	23.66	0.0523	0.740	0.1	0.1
	Excellent Forecast	35.59	18.08	0.0498	0.666	0.1	0.1

Table 4.6.: Comparison of forecasting approaches with respect to errors for load and DHW demand. The metrics used are MAPE, sMAPE, nRMSE, and MASE, which are widely used in the literature. Favorable and excellent forecasts are hypothetical forecasting methods designed to achieve a certain accuracy. The best performers are highlighted with bold letters, excluding fictive forecasts.

Figure 4.7 shows the absolute error distribution for load and DHW demand for each

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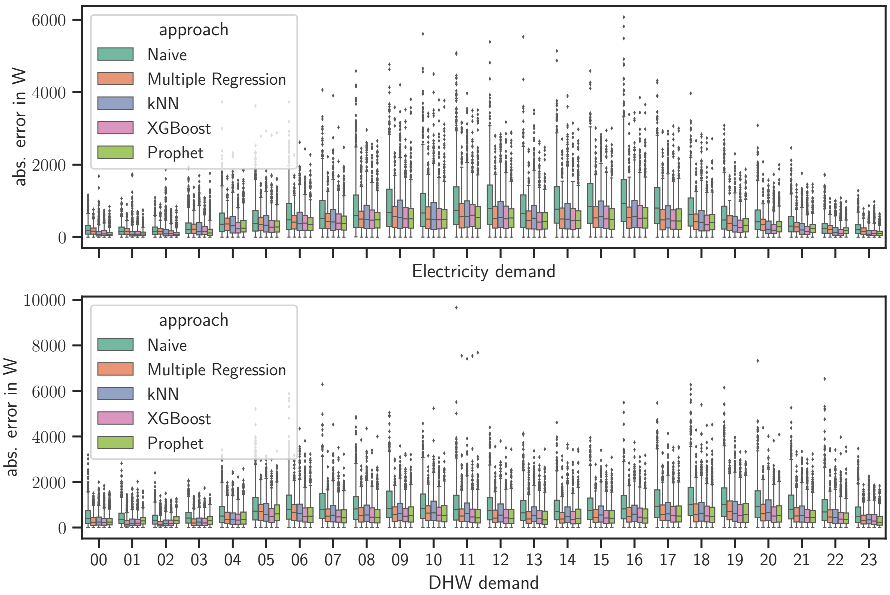

Figure 4.7.: Absolute error distribution for each prediction method on an hourly basis for load demand (top) and DHW demand (bottom).

hour. During the day, higher errors occur, and overnight errors are much lower for both predicted variables. Error peaks for load demand occur in the morning and late afternoon to evening routine, depending on user behaviour. In this case, it can be assumed that the largest proportion of residents spend their time outside the community (e.g., at work) over the day, particularly over midday. As expected, the naïve method has the lowest accuracy every hour. Another surprising outcome is that Prophet performs more accurately during the day and XGBoost is slightly more accurate overnight.

4.2.1.2. Energy community balance

The optimisation problem and the described management approach were simulated in the setup application proposed in Section 3.2.1.2, considering $E_{Bat,init} = 0.2\,\text{kWh}$, a total domestic hot water demand of 9180.65 kWh and total PV production of 13 026.50 kWh. The results are shown in Table 4.7 and plotted in Figure 4.8.

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	Naïve	Mult. Regr.	kNN	XGBoost	Prophet	Favorable	Excellent	Perfect
Grid_in	4 845.12	4 776.61	4 747.08	4 716.18	4 734.96	4 683.96	4 650.83	4 496.80
Grid_out	4 307.43	4 276.97	4 236.63	4 214.75	4 238.05	4 158.02	4 119.64	3 971.91
DHW	9 180.65	9 180.65	9 180.65	9 180.65	9 180.65	9 180.65	9 180.65	9 180.65
HP_el	5 665.98	5 640.61	5 644.82	5 640.14	5 637.89	5 661.30	5 662.96	5 662.17
BESS_ch.	3 238.43	3 132.41	3 181.86	3 166.25	3 164.79	3 205.69	3 191.66	3 171.47
BESS_disch.	2 901.13	2 808.43	2 850.04	2 839.72	2 839.64	2 874.52	2 858.45	2 843.34
Load	7 561.08	7 561.08	7 561.08	7 561.08	7 561.08	7 561.08	7 561.08	7 561.08
PV_el	13 026.50	13 026.50	13 026.50	13 026.50	13 026.50	13 026.50	13 026.50	13 026.50
BESS_start	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
BESS_end	9.83	10.56	10.86	10.40	10.74	11.15	11.20	8.41
BESS_gain	9.63	10.36	10.66	10.20	10.54	10.95	11.00	8.21
BESS_loss	327.67	313.61	321.16	316.33	314.61	320.22	322.21	319.92

Table 4.7.: The energy community results in kWh including all energy demands and generations for total scheduled horizon. The best performing results are marked in bold (excluding fictive and perfect forecast methods).

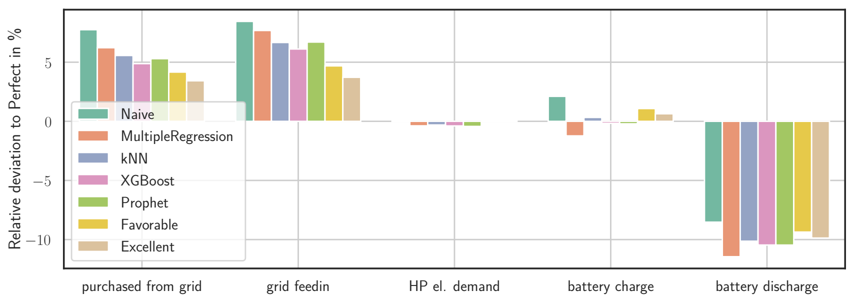

Figure 4.8.: The results for assets relative to the perfect forecast.

Unsurprisingly, the more accurate the forecasts, the less energy is needed from the grid. At the same time, the cumulative results also show that the lower the forecast error, the less energy is fed into the grid. It can therefore be assumed that there is a clear correlation between forecast accuracy and the degree of self-consumption in terms of load cover and supply cover factors. In other words, the more accurate the forecasts are, the more local renewable energy is used by the energy community itself. The heat pump operates consistently over all forecast variants. This is because the comfort level (i.e., room temperature) must be maintained within certain ranges; any deviations in the objective are penalised. Another result can be seen for charging and discharging the battery. In general, these two values are little to hardly dependent on forecast accuracy. However, the naïve forecast means that more use is made of the battery. This also resulted in the largest value for storage losses.

Table 5.3 shows the evaluation of the LEC according to the KPIs for each forecasting method. In the results shown previously, Prophet provided the most accurate forecasts. An examination of the load cover factor and supply cover factor shows that XGBoost performs better, or in other words, achieves a higher level of self-consumption. From

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this, it can be deduced that the most accurate forecasting method, as measured by certain defined forecast quality metrics, does not necessarily lead to the best LEC result in terms of self-consumption.

	Perfect	Naïve	Mult. Regr.	kNN	XGBoost	Prophet	Favorable	Excellent
Load Cover Factor	0.660	0.634	0.638	0.640	0.643	0.641	0.646	0.648
		−4.16 %	−3.42 %	−3.05 %	**−2.69 %**	−2.92 %	−2.20 %	−1.80 %
Supply Cover Factor	0.687	0.660	0.663	0.666	0.668	0.666	0.673	0.675
		−4.05 %	−3.63 %	−3.15 %	**−2.87 %**	−3.14 %	−2.18 %	−1.75 %
On-Site Energy Ratio	0.960	0.959	0.962	0.961	0.962	0.962	0.960	0.960
		−0.11 %	0.20 %	0.10 %	0.18 %	0.21 %	−0.02 %	−0.05 %

Table 4.8.: Benchmarking of all prediction methods with MPC management of energy community. The examined KPIs are load cover factor, supply cover factor and on site energy ratio.

The on-site energy ratio is subject to only minor fluctuations; forecast accuracy is not considered to have a significant impact on this KPI. Since the building has an on-site energy ratio of almost 1, it can be considered a nearly zero-energy building (nZEB).

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4.2.2. Forecast-based Optimal Control Strategies in LECs under price uncertainty

All simulations were conducted with a horizon from 01.07.2021 00:00 to 31.12.2021 23:45 and extrapolated to a full year to increase comparability with other studies. All input data for the MPC were identical for each scenario; only the price changed in each scenario to set the price as the unique sensitivity. The major findings of this study are presented at the end of this section, as well as any limitations of the study that could not be accommodated. Furthermore, opportunities for future research are provided, which emerged over the course of the study.

4.2.2.1. Comparison of the accuracy of forecasting methods

To draw conclusions about the forecast quality, several suitable metrics were applied. In general, one single metric was not sufficient; several applicable metrics were used to obtain a full understanding of which forecast algorithm delivered the most accurate results. Thus, three different and widely used metrics in the scientific field were used to assess quality. The first metric is the MAE, which is shown in Equation 4.1, is one of the most common error metrics in the field of forecasting. It provides information about the average magnitude of forecast errors, is robust to outliers and simple to understand. However, it assigns equal weight to all errors, which may not be appropriate in situations where large errors are more significant.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}(|y_t - \hat{y}_t|) \tag{4.1}$$

The second used metric was the MAPE, as shown in Equation 4.2. Because it is a relative metric, it was used to compare the accuracy of forecasts across different datasets. MAPE can be misleading if the actual values are zero or close to zero.

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{|y_t - \hat{y}_t|}{|y_t|} \cdot 100\right) \tag{4.2}$$

To account for the scale and the variance of forecast errors, the nRMSE, shown in Equation 4.3, was the third metric used. It provides a standardised measure but could be difficult to interpret.

$$nRMSE = \frac{1}{max(y_t) - min(y_t)}\sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{4.3}$$

Additionally, the Mean Squared Error (MSE) was utilised, as depicted in Equation 4.4. MSE calculates the average of the squares of the errors, which penalizes larger errors

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more significantly than MAE. This can be advantageous in situations where large errors are particularly undesirable.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{T}(y_t - \hat{y}_t)^2 \tag{4.4}$$

Furthermore, the Mean Absolute Scaled Error (MASE) was employed to assess forecast accuracy. MASE, presented in Equation 4.5, compares the MAE of the forecast to the MAE of a naive or benchmark forecast, providing insight into the relative accuracy of the forecast. This metric is valuable for evaluating forecast performance in comparison to a baseline, especially when assessing the effectiveness of forecasting models across different time series or datasets.

$$\mathrm{MASE} = \frac{\mathrm{MAE}}{\frac{1}{T-1}\sum_{i=2}^{T}|y_t - y_{t-1}|} \tag{4.5}$$

In this study, MAE, MAPE, MSE, and nRMSE are opted as primary error metrics for the following reasons:

1. Interpretability: MAE, MAPE, MSE, and nRMSE are intuitively interpretable metrics that provide a clear sense of the magnitude of forecast errors. This interpretability is valuable, especially in the context of energy forecasting for multi-apartment buildings and energy communities, as it allows stakeholders to readily understand the practical implications of forecast accuracy.

2. Robustness to Outliers: MAE, MAPE, and MSE are robust to the presence of outliers in the data. Given the dynamic and occasionally unpredictable nature of energy consumption and generation in these settings, robustness to extreme values is a desirable characteristic in error metrics.

3. Meaningful Percentage Error: MAPE, in particular, provides a percentage-based error measure that is meaningful for stakeholders, as it quantifies the relative forecast error. This is valuable for understanding the significance of errors in the context of energy cost and planning.

4. Normalised Metric (nRMSE): nRMSE is included to account for the scale of the data and to facilitate comparisons across different forecasting horizons or datasets. Normalisation ensures that the metric remains meaningful even when dealing with variables of varying magnitudes.

5. Penalising large errors: MSE calculates the average of the squares of the errors, which penalises larger errors more significantly than MAE. This can be advantageous in situations where large errors are particularly undesirable.

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6. Direct comparison to a baseline: MASE compares the MAE of the forecast to the MAE of a naive or benchmark forecast, providing insight into the relative accuracy of the forecast. This metric is valuable for evaluating forecast performance in comparison to a baseline, especially when assessing the effectiveness of forecasting models across different time series or datasets.

Together, these metrics offer a comprehensive evaluation of forecast accuracy, capturing different aspects such as average error magnitude, squared error, relative accuracy compared to a benchmark forecast, and robustness to outliers.
As presented in Section 3.2.2, forecast methods were applied to energy and DHW demand. Table 4.9 summarises the error metrics for each prediction method. The results of the comparison showed that the accuracy of the forecasting methods varied depending on the metrics being used. In general, the approaches for predicting energy demand included NBEATSx, Prophet and XGBoost, the best performers. The k-nearest neighbour and multiple regression were intermediate solutions and the naïve approach was a simple but weak performer. The metrics for predicting DHW demand appear contradictory at first but can be explained because MAE and nRMSE are absolute measures. Thus, they do not consider the scale or magnitude of the actual values and treat all errors equally. Consequently, NBEATSx forecast errors were generally smaller in magnitude than Prophet. On the other hand, Prophet delivered a remarkable MAPE that considers the magnitude of the actual values. In conclusion, which forecast method performed better depended on the specific context and requirements of the problem. Because total cost was an important research question in this study, the absolute error metric was weighted as more significant because it could be associated with cost increases or reductions. Hence, NBEATSx was, overall, selected as the best-performing forecast approach for energy and DHW demand in this study. The two hypothetical approaches, favourable and excellent, are later used in the analysis of the LEC KPIs to provide a possible outlook for more accurate forecast methods that could be developed in the future.

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	energy					
	MAE in W	MAPE in %	nRMSE	MSE in W^2	MASE	training in sec
Naïve	662.45	37.31	0.1478	911 469	1.0	0.1
Multiple Regression	528.79	27.85	0.1101	491 428	0.953	3.4
k-Nearest Neighbor	581.98	27.60	0.1329	718 440	0.989	6.6
NBEATSx	**411.15**	**22.96**	**0.0956**	371 773	0.741	22.4
XGBoost	496.78	23.89	0.1109	500 207	0.895	14.2
Prophet	487.34	23.53	0.1074	469 455	0.878	13.8
Favourable Forecast	214.79	19.99	0.0438	76 614	0.385	0.1
Excellent Forecast	171.84	14.95	0.0349	49 798	0.309	0.1
	domestic hot water					
Naïve	897.45	77.39	0.1004	1 477 951	1.0	0.1
Multiple Regression	702.57	65.78	0.0776	878 426	0.738	3.2
k-Nearest Neighbor	790.86	62.86	0.0892	1 164 396	0.831	6.6
NBEATSx	**654.29**	68.20	**0.0737**	729 665	0.656	19.7
XGBoost	660.18	58.17	0.0746	813 319	0.694	12.3
Prophet	675.49	**55.82**	0.0757	836 793	0.71	12.8
Favourable Forecast	627.74	45.15	0.0721	680 339	0.593	0.1
Excellent Forecast	607.71	35.59	0.0707	620 785	0.542	0.1

Table 4.9.: Comparison of forecasting approaches with respect to errors in energy and DHW demand. The metrics used are MAE, MAPE, MSE, nRMSE and MASE, which are widely applied in the topic of forecasting. Favourable and excellent forecasts are hypothetical forecasting methods designed to achieve a certain level of accuracy. The best performers are highlighted with bold letters, excluding hypothetical forecasts. Additionally, average time for training each forecast model is listed.

To assess the costs of forecast errors appropriately, the errors must be distinguished by time step, because an error at a certain hour does not necessarily inflict the same cost if the same error occurs at a different hour. In other words, small forecast errors may inflict higher costs compared to higher forecast errors at various times of the day. To address this circumstance, Figure 4.9 shows the absolute forecast error for three selected approaches (naïve, Prophet and NBEATSx) for each hour of the day. In general, at the beginning of the day and in the late afternoon, forecast errors are greater than overnight due to the swarm behaviour of consumers. This result, combined with Table 4.9, shows when forecast errors lead to excessive costs or reduce the possible revenue due to fewer grid exports. This fact has been discussed in detail in previous work Putz et al., 2023. The total costs consist of the grid energy exchange, the PV, which receives remuneration for feed-in, and the battery storage, which can only be charged by PV generation.

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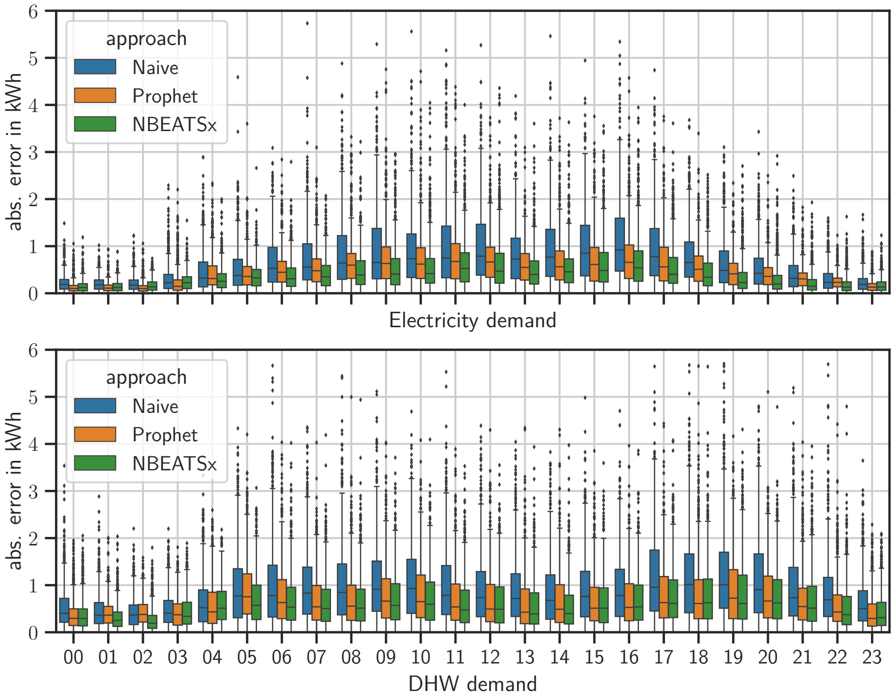

Figure 4.9.: Hourly distribution of absolute forecasting error for load demand (top) and DHW demand (bottom) for naïve, Prophet and NBEATSx approaches. To make the results comprehensible, the absolute error was aggregated to an hourly value instead of displaying the error for every 15 minutes.

To assess the real value of each forecast, Table 4.10 summarises the total grid imports, exports and sum of annual energy transferred to the battery in kWh for every scenario and each forecast method.

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	Grid in			
	FT	2020	2021	2022
Naïve	9609.2	9883.8	10332.0	10420.4
LR	9526.6	9838.0	10224.5	10247.0
kNN	9533.2	9768.4	10128.2	10230.8
NBEATSx	9358.5	9675.2	10046.0	10028.3
XGBoost	9452.9	9748.4	10158.0	10161.1
Prophet	9482.1	9729.6	10088.6	10095.0
Favourable	9200.3	9539.8	9809.3	9985.0
Excellent	9173.9	9495.1	9826.9	9907.6
Perfect	8972.3	9309.3	9571.6	9612.8
	Grid out			
	FT	2020	2021	2022
Naïve	8526.2	8693.3	8919.3	9003.8
LR	8529.6	8747.5	8885.6	8898.8
kNN	8516.1	8662.9	8839.1	8923.8
NBEATSx	8313.5	8519.7	8678.8	8678.0
XGBoost	8461.0	8662.2	8836.9	8834.6
Prophet	8468.9	8643.3	8794.6	8800.2
Favourable	8157.7	8391.8	8459.7	8525.2
Excellent	8120.6	8336.1	8447.4	8471.1
Perfect	7928.0	8140.4	8190.7	8190.3
	Battery charge			
	FT	2020	2021	2022
Naïve	6405.3	6782.9	7163.7	7652.7
LR	6244.1	6617.4	7031.5	7556.7
kNN	6350.6	6714.9	7108.1	7609.8
NBEATSx	6345.1	6735.9	7100.2	7606.0
XGBoost	6316.9	6668.9	7071.7	7616.2
Prophet	6319.6	6655.4	7078.0	7594.1
Favourable	6363.8	6779.6	7165.5	7697.8
Excellent	6370.5	6763.2	7172.2	7716.4
Perfect	6355.9	6757.8	7157.3	7719.9

Table 4.10.: The total energy figures for the LEC results in kWh, including energy exchange with the grid and battery charge for every forecast method and each scenario with flat tariff (FT).

In general, grid import, export and battery usage increased in scenarios with higher and more volatile energy prices. The grid import in 2022 has already increased by 3.2 % compared to 2020 for the perfect forecast and by 7.1 % compared to the flat tariff scenario. In a realistic environment that uses the naïve approach, grid import increased by 8.4 % when comparing flat tariff and 2022 price data. The study showed that a highly sophisticated method such as NBEATSx also delivers an increase of 7.2 %, which

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is already close to perfect foresight. Similarly, grid export increased at a smaller rate. Contrary to this, battery usage increased remarkably. In numbers, the total energy charged/discharged by the battery increased by almost 14 % for all forecast methods compared to the variable tariff in 2020, 2021 and 2022. Additionally, battery usage increased by approximately 20 % compared to the flat tariff and 2022 scenarios. There are three major conclusions:

1. By investigating the grid usage of an LEC, which is controlled by an MPC with minimising total energy costs and maximising comfort level as objective, higher and volatile energy prices lead to significant higher grid import and export.
2. The impact of forecast accuracy on total energy costs is even more substantial in the case of higher and volatile energy prices. This effect is exceeded by the previous one and leads to a greater impact of forecast accuracy on LEC results during higher and volatile energy prices.
3. Battery use is increased significantly, which leads to reduced battery life due to the increased number of load cycles.

Figure 4.10 presents the total energy and costs compared to the perfect approach for naïve, NBEATSx and Prophet methods for each scenario. This result shows how far the forecast approaches are from the optimum. In summary, grid imports are rising, and at the same time battery usage is decreasing. Nevertheless, a more accurate forecast approach, such as NBEATSx or Prophet, has a lower total cost increase compared to the naïve approach.

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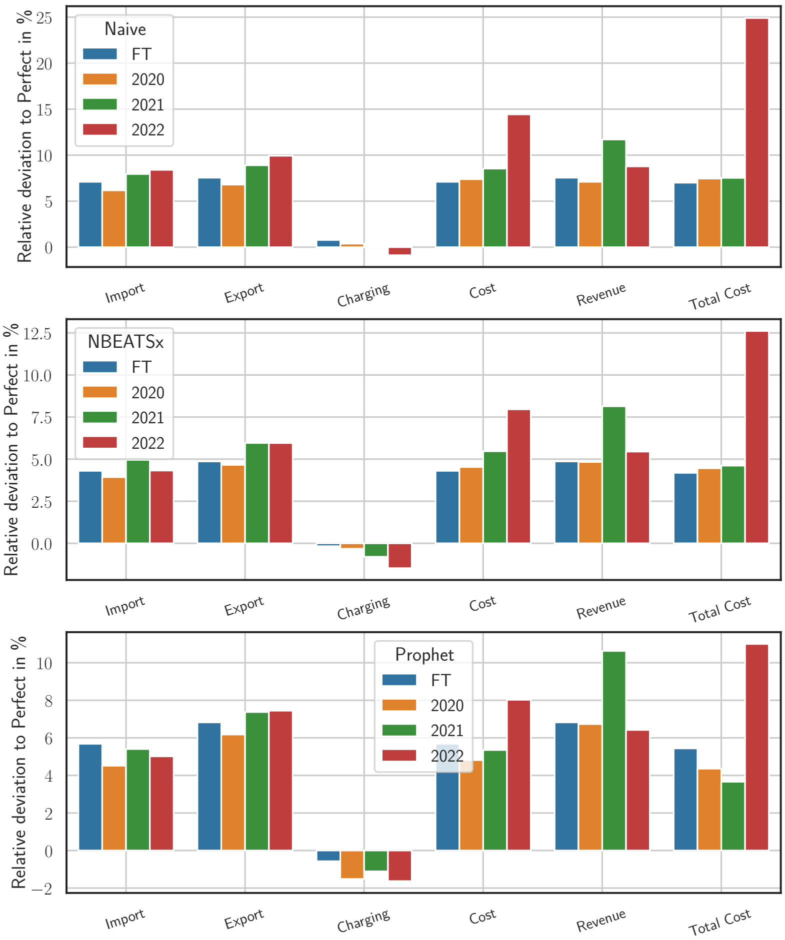

Figure 4.10.: Energy and cost results for naïve (left), NBEATSx (centre) and Prophet (right) approaches in relative deviation to the perfect forecast results. Grid exchange increased and battery usage decreased with higher and more volatile energy prices. At the same time, costs increased substantially in 2022 due to extreme price conditions. NBEATSx and Prophet could deliver more accurate forecasts and weaken the cost increase in comparison to the naïve approach.

In a typical real-world environment, the naïve approach is used as a reference; thus, more sophisticated forecast methods must be benchmarked with this baseline. Figure 4.11 shows the relative deviation of NBEATSx and Prophet, as well as excellent forecast

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results compared to the naïve approach results. By simply using an approach such as NBEATSx or Prophet, the total costs can be reduced significantly, in particular for high-price scenarios. Moreover, if the trend of more accurate forecast approaches continues, the possible cost reduction is even greater, as presented by the excellent forecast approach.

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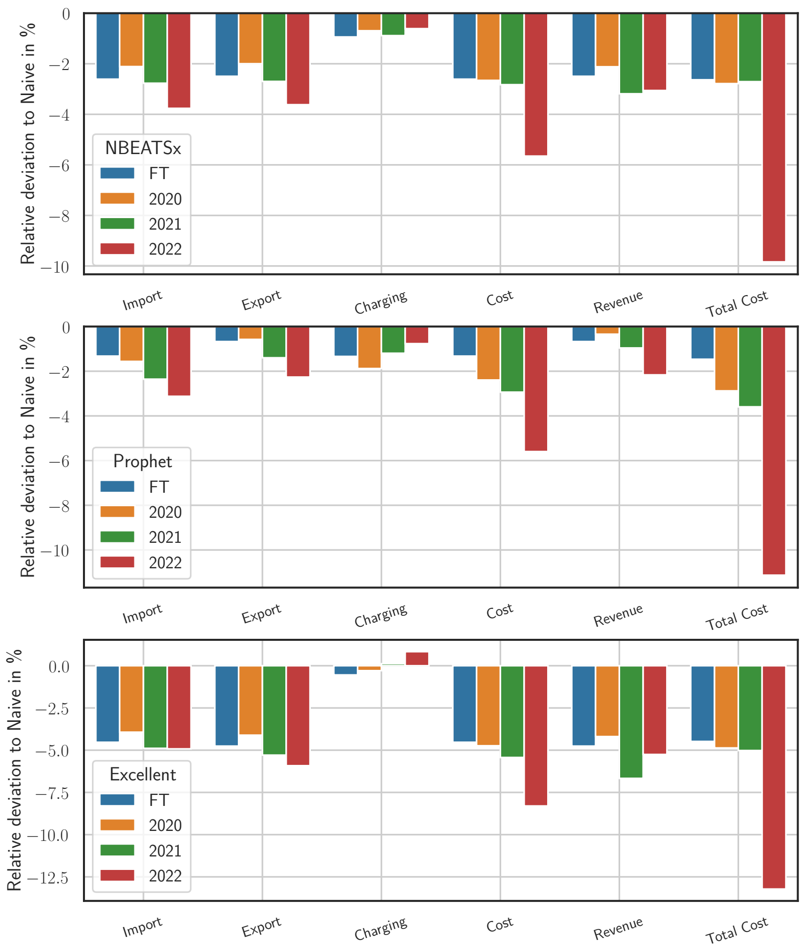

Figure 4.11.: Energy and cost results for NBEATSx (left), Prophet (centre) and excellent (right) approaches in relative deviation to the naïve forecast results. Grid exchange and battery usage decreased with higher and more volatile energy prices, except for the case of excellent forecast in 2022. Total costs could decrease significantly in 2022 due to smaller forecast errors. The excellent forecast results show that significant cost reductions are further possible if forecast errors decrease in the future.

Table 4.11 summarises the total costs for each forecast method and price scenario. Additionally, the relative difference between the perfect and naïve approach is shown. Best performers, except for the favourable and excellent approaches, are emphasised and

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marked in bold. A significant result was that a year of high and volatile prices did not directly imply high total costs. On the contrary, it offers opportunities to optimise consumption and flexibility to benefit from price volatility, as it is the case for the price scenario in 2022.

	Total costs in €			
	FT	2020	2021	2022
Naïve	1580.80	1071.74	2468.28	1541.11
LR	1564.13	1049.40	2395.63	1377.36
kNN	1565.99	1051.94	2396.54	1443.28
NBEATSx	**1539.17**	1041.90	2401.46	1389.51
XGBoost	1552.14	1043.09	2396.94	1396.86
Prophet	1557.66	**1040.88**	**2379.57**	**1369.61**
Favourable	1513.74	1024.59	2336.84	1357.80
Excellent	1509.96	1019.58	2344.40	1337.37
Perfect	1477.34	997.42	2295.55	1233.89
	Difference to Perfect in %			
	FT	2020	2021	2022
Naïve	7.0	7.45	7.52	24.9
LR	5.87	5.21	4.36	11.63
kNN	6.0	5.47	4.4	16.97
NBEATSx	**4.19**	4.46	4.61	12.61
XGBoost	5.06	4.58	4.42	13.21
Prophet	5.44	**4.36**	**3.66**	**11.0**
Favourable	2.46	2.72	1.8	10.04
Excellent	2.21	2.22	2.13	8.39
	Difference to Naïve in %			
	FT	2020	2021	2022
LR	-1.05	-2.08	-2.94	-10.62
kNN	-0.94	-1.85	-2.91	-6.35
NBEATSx	**-2.63**	-2.78	-2.71	-9.84
XGBoost	-1.81	-2.67	-2.89	-9.36
Prophet	-1.46	**-2.88**	**-3.59**	**-11.13**
Favourable	-4.24	-4.4	-5.33	-11.89
Excellent	-4.48	-4.87	-5.02	-13.22
Perfect	-6.54	-6.93	-7.0	-19.93

Table 4.11.: Total costs based on actual flat tariff prices for energy purchase and feed-in and price scenarios 2020, 2021 and 2022. In addition, the relative difference between the perfect and naïve approach is shown; the best results except fictive approaches are marked in bold.

An additional major finding is that NBEATSx, which was selected as the most accurate forecast approach in Section 4.2.2.1, on average, emerged as the most accurate forecasting

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approach, consistently outperforming other methods in terms of traditional error metrics such as MAE, MAPE, nRMSE, MSE and MASE. However, a compelling aspect of this finding is that despite its superior accuracy, NBEATSx does not consistently translate into the best LEC performance in terms of total costs. This observation might initially appear counter intuitive, given the volatile and non-constant nature of energy prices. To elucidate this apparent paradox, it is crucial to consider the concept of forecast value, which extends beyond mere accuracy. In dynamic and fluctuating energy markets, forecast errors can have significant financial implications. In such scenarios, even a small deviation from the actual values can result in substantial cost differentials. Prophet, although ranking slightly lower in terms of accuracy when compared to NBEATSx, excels in delivering more valuable forecasts under conditions where forecast errors can lead to excessive costs. This is a critical consideration, especially in the context of LECs, where cost optimization is a primary objective. Furthermore, it is noteworthy that a simpler forecasting approach, multiple regression, yields similar total cost results for the year 2022. This highlights the importance of evaluating forecasting methods not only in terms of accuracy but also with a keen eye on their practical implications and cost-effectiveness within the specific operational context. In summary, this study underscores the multifaceted nature of forecasting methods' performance in LECs, where accuracy and forecast value are intertwined. While NBEATSx excels in accuracy, it may not always lead to the most cost-effective LEC operation as Table 5.1 shows. Prophet's ability to deliver valuable forecasts in volatile price scenarios and the competitive performance of a simpler approach like multiple regression further emphasise the need for a holistic evaluation approach that considers both accuracy and forecast value.

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5. Discussion and synthesis of results

This chapter serves as a platform for the discussion and synthesis of the findings obtained from the three studies, aiming to address the initial research questions. Section 5.1 and 5.2 focus on the individual results outlined in Section 4, providing a comprehensive analysis and interpretation of the results. Through these discussions, key insights and implications of the findings are explored, shedding light on their significance and contributing to the broader understanding of the research area. Finally, the Section 5.3 synthesizes the collective results, providing comprehensive answers to the initial research questions and offering valuable insights for future research and practical applications. This chapter is based on Putz et al. (2021), Putz et al. (2023) and Putz et al. (2024).

5.1. Deep neural architecture for short term wind power forecasting

The evidence in this work demonstrates that N-BEATS is a new, valuable and pure DL approach for VSTWPF. It can compete and outperform statistical and classical ML as well as hybrid models. This work tailors the N-BEATS approach by customising a pinball loss function which is a cutting-edge solution to the forecast bias.

Considerable progress has been made with regard to interpretability. One of the most common criticisms of deep learning methods for time series is that they are a black box and the inner processes are not intuitively interpretable. Thus, it is not possible to understand how the result is obtained, in contrast to classical models such as ARIMA, the N-BEATS forecast is discomposed into distinct, human-interpretable outputs. These outputs can be used by utilities or system operators to facilitate their decision making, as highlighted in Figure 5.1. Therefore, any developed model that is interpretable, or at least being interpretable, is beneficial.

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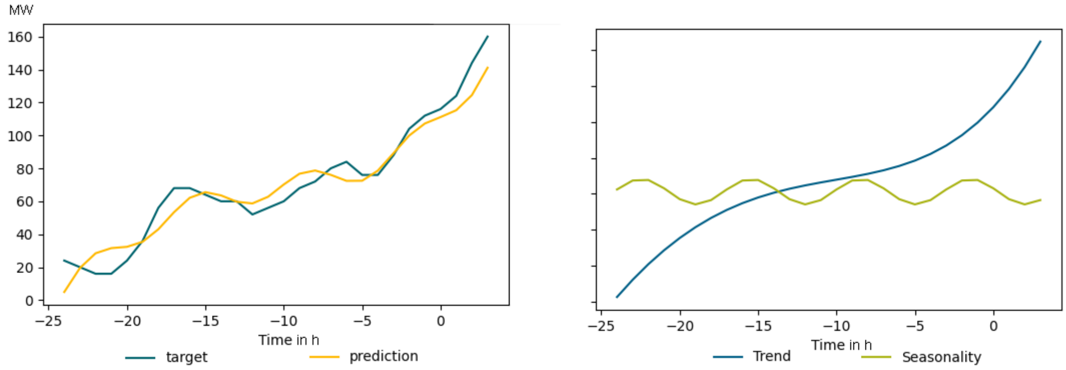

Figure 5.1.: Constraining N-BEATS by adapting $g(\theta)$ to a monotonic and cyclical graph produces an interpretable output. The resulting components, i.e., trend and seasonality, are extracted and may be considered in further processes. A sample output for Austria and a forecast window of 24 time steps which is equivalent to 6 hours is shown.

Regarding meta-learning, the learning process can be decomposed into an inner and outer training loop according to Antoniou et al., 2019. The inner training loop focuses on task-specific knowledge while the outer loop focuses on across-task knowledge. This can be analogised to N-BEATS, where Θ is learnt inside the blocks and makes use of the parameters that are learnt from the outer loop, where gradient descent trains the weight matrices that Θ depends on. As the input passes through the blocks, Θ is slowly updated, and as the backcast is residually stacked with the input, it conditions the learning of Θ as the data feeds through the blocks.

Taken together, these findings confirm that a pure DNN model can deliver competitive forecast results, in contrast to the conclusion of the M4 competition. Moreover, during the implementation of the other models it was found that N-BEATS needs less time to be implemented. It does not require any decomposition and hardly any data pre-processing which is an essential and time-consuming part of the modeling process. Many ML or statistical approaches require additional preliminary steps, such as deseasonalisation or differencing, since they do not deal with non-stationary or non-linear relationships between input and output. In fact, working with raw historic data and using built-in mechanisms, such as residual links, backcast, and the aggregation of partial forecasts, leads to accurate and reliable forecasts.

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5.2. Strengths and Limitations of forecast-based optimal control approach

In this Section, the insights gathered from the investigations conducted by research question 2 and 3 are combined. These studies collectively explore the intricate dynamics of local energy communities and their optimization strategies. Section 5.2.1 delves into the realm of advanced forecasting methodologies, shedding light on their potential to enhance the performance of local energy communities. Meanwhile, Section 5.2.2 navigates the intricate landscape of optimal control strategies within these communities, emphasizing the crucial role of real-time decision-making under volatile energy prices.

5.2.1. Discussion of integration of advanced forecasting in LECs

In this section, the previously shown results are examined in more detail, and various conclusions are drawn from them. There is a correlation between forecast KPIs and some LEC KPIs. Building on this, it is also possible to provide evidence of cost reduction using more accurate forecasting methods. For this purpose, the prices for energy purchase, 0.20 €/kWh and feed-in 0.04 €/kWh are multiplied at current flat tariff conditions and extrapolated up to one year for easier comparison. Table 5.1 summarises the derived costs for each prediction method and compares them with the perfect and naïve forecasts.

Forecast approach	Total costs in €	Difference to Perfect in €	Difference to Naïve in €	Difference to Perfect in %	Difference to Naïve in %
Naïve	1 592.68	112.37	-	7.59	-
Multiple Regression	1 567.66	87.35	25.03	5.90	1.57
kNN	1 559.05	78.74	33.63	5.32	2.11
XGBoost	1 548.48	68.17	44.21	**4.60**	**2.78**
Prophet	1 554.10	73.79	38.59	4.98	2.42
Favorable	1 540.07	59.76	52.62	4.04	3.30
Excellent	1 529.88	49.57	62.80	3.35	3.94
Perfect	1 480.31	-	112.37	-	7.06

Table 5.1.: Derived costs based on actual flat tariff prices for energy purchase and feed-in. Accumulated energy is extrapolated to one year for easier comparison.

Based on these results, a feasible cost reduction of up to 3 % can be assumed by using more sophisticated forecast algorithms instead of naïve prediction. In this case, XGBoost is used in contrast to the naïve approach. It demonstrates that predictions of significantly greater quality do result in a marginally higher value in terms of KPIs for the energy community. The results show that XGBoost provides better results in terms of costs compared to Prophet, although it is less accurate. This outcome is of particular

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importance and can be explained by the fact that it is not only the average error that matters, but at what time and to what extent the error occurs. Figure 5.2 shows the comparison of XGBoost and Prophet approaches in regard of the average load cover factor which is directly related to the costs involved.

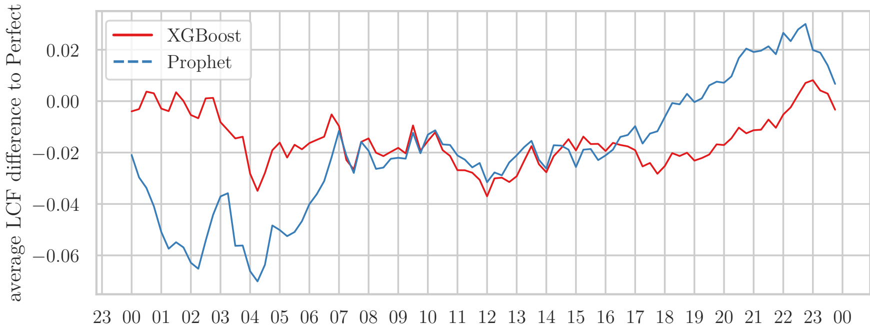

Figure 5.2.: Detailed comparison between XGBoost and Prophet showing average load cover factor difference to perfect forecast for each hour of the day. XGBoost provides very similar results to the perfect forecast during the early morning hours, and Prophet provides a significantly lower LCF, causing more grid purchases. During the hours when there is a substantial amount of PV generation, both perform almost identically. In the evening hours, though, Prophet outperforms XGBoost and delivers higher LCFs than the perfect forecast due to an increased usage of the battery.

The complex interaction of all assets and their constraints can lead to results, which are not intuitive at first sight, but deliver the finding that evaluating forecasts based only on accuracy might be misleading. An in-depth investigation has shown that there is no apparent and time-coherent relationship between forecast errors and the costs caused by them. The explanation for this is that, due to the dynamics of the building, there are always different primary system conditions, such as various interior temperatures or stored energy in the battery, or in the building mass. On the basis of this, it can be deduced that a forecast error does not always have the same impact on costs across the board. This means that the day with the largest deviation is not necessarily the day with the worst cost balance deviation. To quantify this fact, Figure 5.3 shows the average resulting electricity price per hour which directly indicates when the individual forecasts cause the highest cost deviations from the Perfect scenario. Comparing this with the absolute errors shown in Figure 4.7 indicates when a forecast error has a major cost impact.

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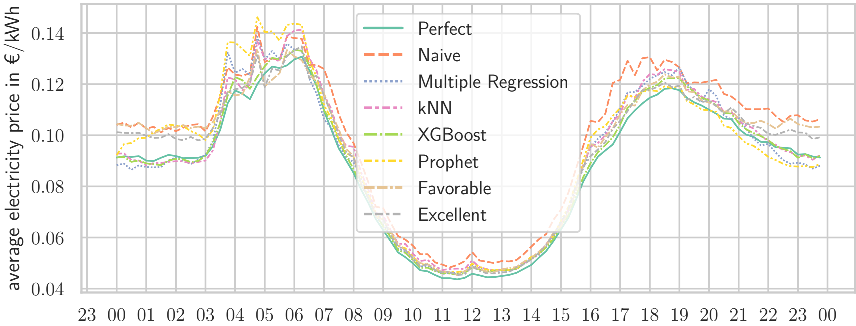

Figure 5.3.: The average electricity prices are calculated on the basis of the demand and the costs incurred for each time step. The demand is composed of the electrical demand of the heat pump, the household electricity demand and the energy for charging the battery. The total costs consist of the costs caused by the grid, the PV, which receives remuneration for feedin, and the battery, which can only be charged by PV generation. The figure shows for each forecast method how severe the deviation of the average electricity price is in comparison to the perfect scenario at a certain hour of the day, which is caused by the forecast error.

Due to increasingly accurate forecasts in the future, it can be assumed that there is also potential for the degree of self-consumption. Based on these results, it can be assumed that just around a 1 % improvement potential if one assumes that a highly sophisticated algorithm such as XGBoost or Prophet is already being used. In most cases, however, it should be assumed that the naïve method is implemented and thus expects a self-consumption improvement of theoretically 3 %. Additionally, the results of the favorable and excellent forecast show an ongoing trend to further increase the value of such an forecast-based optimised control. Nevertheless, the improvement from a current state-of-the art method to a hypothetical better method, demonstrated by the excellent forecast, is less than that from a naive approach to XGBoost. Figure 5.3 represents the connection between quality in terms of accuracy of a forecast method and value in terms of cost reduction of the energy community.

From another point of view, the whole energy community, all members added together, has annual costs of electricity and heating of 1592.68 €. On average, this would mean a household bill of 176.96 € per year, or 2.16 € per m^2. The results show that the use of more accurate forecast algorithms results in a price reduction of almost 3 % compared to a naïve forecast. This means that the total bill would decrease by 48 € per year. The cost difference using a modern forecasting algorithm is about 0.05 € per m^2 per year. At first glance, this reduction appears negligible. Nevertheless, it must be noted at this point that the simulated multi-party house already complies with all the latest norms and building standards, and thus unfortunately does not reflect most households

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in the building stock. This is verified by the total on-site energy ratio, which is close to 1 and means that it is almost a zero-energy building. Thus, it can be assumed that the calculated value represents a lower limit, and that the savings are significantly higher in, for example, poorly insulated buildings or even old stock as long as there is a degree of freedom in energy pricing. This price gradient could be provided by an on-site PV generator like in the demonstrated building as well as any other electricity source taking part in the energy community or even time or power dependent grid tariffs. The investigation of such a building already provides a topic that would be interesting and necessary to investigate. However, the data situation for such buildings is a significant challenge, since they are typically not equipped with sensors for recording measured values.

	heating in kWh	cooling in kWh	heating in $\mathrm{kWh\,m^{-2}\,a^{-1}}$	cooling in $\mathrm{kWh\,m^{-2}\,a^{-1}}$
Perfect	6 970.30	1 718.76	18.95	4.67
Naïve	7 015.22	1 705.00	19.07	4.63
Mult. Reg.	6 947.32	1 685.68	18.88	4.58
kNN	6 976.15	1 681.46	18.96	4.57
XGBoost	6 956.15	1 682.04	18.91	4.57
Prophet	6 939.69	1 684.53	18.86	4.58
Favorable	6 976.79	1 714.48	18.96	4.66
Excellent	6 974.85	1 718.06	18.96	4.67

Table 5.2.: Heating demand and cooling demand summed up for the period from 01.07.2021 to 31.12.2021. From this, the specific heating and cooling demand in $\mathrm{kWh\,m^{-2}\,a^{-1}}$ was extrapolated to a whole year for a living space of $735.8\,\mathrm{m^2}$.

Another interesting finding from Table 5.2 is that some of the forecasts results in lower heating and cooling energy compared to the perfect scenario. This is surprising at first sight, considering that, in Figure 5.3, this exact scenario uses the least amount of energy from the grid. An explanation for this, can be found in the dynamic building model section. The forecasts affect the operation of the heat pump system and the expected heat gains in the building in a way that leads to a violation of the zone's temperature boundaries for some points in time. In these cases, the optimal control is not always able to correct for forecast inaccuracies simply due to the dynamic weight of the building. For some forecast algorithms, this causes a slightly lower mean zone temperature during the heating season and a higher mean zone temperature during the cooling season. In terms of this, energy demand is reduced slightly over the course of a year. Because this violation of temperature constraints is also a reduction in user comfort, it must be considered as a pivotal indicator. Comparing XGBoost and Prophet as the two most promising approaches, Prophet causes more comfort violations.

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In addition to the previously outlined results, several other aspects pose challenges related to forecasting in the context of energy communities. The major concerns identified during the compilation of this paper are briefly outlined below.

- When building ML models, the quantity and quality of historical data are crucial. Initially, there are many settings to understand and optimise. In addition, there are several hyperparameters that must be adjusted by the modeller based on the chosen model. Due to the difficulty in obtaining high-quality labelled datasets, this problem remains unresolved. The main cause of this is that service providers and utility corporations keep real-time and historical data private, owing to different security and privacy issues as described by Zhou et al., 2016.

- Current research, such as Van der Meer et al., 2018, shows that many forecasting studies for PV energy generation offer only solutions for single solar farms. They nevertheless form a network in a distribution system and are geographically dispersed. In comparison to single-location methodologies, spatiotemporal prediction algorithms are thought to be more accurate and practical for future smart microgrids. Because the volatile PV generation in combination with the described framework is outside the scope of this work, it is worth further investigation.

- Another challenge that motivates the research community to use ML in a way that is helpful and intelligible for both expert and novice users is heterogeneous users and their varied skill levels. For instance, a few of the mentioned papers solely pay attention to residential or business clients. Additionally, ML models must be able to accommodate both huge and small heterogeneous data while maintaining their efficiency.

- Data acquired for distributed energy generation or load forecasting are frequently obtained in private locations, making them vulnerable to privacy problems. Additionally, excessive data transfer necessitates the purchase of costly communication equipment. It is therefore impracticable to provide all the data to a single place for deep learning model training. It is crucial to develop new models that can be trained locally on remote devices using the collected data to solve the aforementioned issues. This process is known as federated learning, and it involves cooperatively establishing a shared regional learning platform.

- The importance of probabilistic forecasting of load demand and renewable energy source generation cannot be overstated according to Hong and Fan, 2016. Uncertainty quantification is necessary for accurate and trustworthy forecasting as shown by Abdar et al., 2021. The main goal of uncertainty quantification is to reveal trustworthy confidence scores for predicting outcomes produced by ML techniques and for information that the ML method has not correctly learned. In the

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past few years, it has gained noticeable interest from the research community. Current studies, such as Raz et al., 2020 and Wang et al., 2019, show its applications and advantages. Therefore, there is still a need for more research in this field to improve the accuracy and dependability of ML models.

5.2.2. Discussion on forecast-based optimal control in local energy communities with energy price uncertainty

In the context of the literature review, the results of this study provide insight into the effectiveness of different forecasting methods for predicting energy and DHW demand in an LEC. The results showed that the accuracy of the forecasts had a significant impact on the total energy costs for the LEC, also shown in Putz et al., 2024. In general, more accurate forecast methods directly imply lower total costs. However, the most accurate forecast method, NBEATSx, did not result in the lowest total costs. The results of this study were consistent with previous research on energy forecasting in communities; they demonstrated, that accurate forecasts are critical for optimising the operation of energy systems and minimising energy consumption and costs. The results also highlight the importance of using appropriate forecasting methods and tools that are well-suited for the specific characteristics of the energy system and the data being used.

Introducing additional KPIs, such as Load Cover Factor, Supply Cover Factor, On-site Energy Ratio, and Grid Interaction Index, provides a more comprehensive assessment of forecasting methods' value proposition within LECs. By integrating these KPIs alongside traditional error metrics, stakeholders can gain deeper insights into the practical implications and cost-effectiveness of forecasting approaches, facilitating informed decision-making and optimisation of LEC operations.

- The Load Cover Factor (LCF) described in Equation 5.1 measures the proportion of energy demand covered by on-site energy generation within the local energy community. A higher LCF indicates greater self-sufficiency in meeting energy demand locally.

$$LCF = \frac{\text{On-site Energy Generation}}{\text{Total Energy Demand}} \cdot 100\% \tag{5.1}$$

- The Supply Cover Factor (SCF) described in Equation5.2 measures the proportion of energy demand covered by on-site energy generation and storage capacity within the local energy community. It provides a holistic view of the community's ability to meet its energy demand.

$$SCF = \frac{(\text{On-site Energy Generation} + \text{Energy Storage Capacity})}{\text{Total Energy Demand}} \cdot 100\% \tag{5.2}$$

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- The On-site Energy Ratio (OER) described in Equation5.3 measures the ratio of on-site energy generation to total energy consumption within the local energy community. It reflects the extent to which the community relies on on-site energy generation.

$$OER = \frac{\text{On-site Energy Generation}}{\text{Total Energy Consumption}} \cdot 100\% \tag{5.3}$$

- The Grid Interaction Index (GII) described in Equation 5.4quantifies the level of interaction between the local energy community and the external energy grid. A higher GII indicates greater reliance on the external grid, while a lower GII suggests a higher degree of self-consumption and local energy generation.

$$GII = \frac{(\text{Grid Imports} + \text{Grid Exports})}{\text{Total Energy Consumption}} \tag{5.4}$$

The results shown in Table 5.3 indicate that while LCF values for each year (2020, 2021, 2022) varied slightly, Prophet method consistently achieved the highest values, indicating a greater degree of coverage of energy demand by on-site generation. Additionally, SCF values remained relatively consistent across methods and years, with Prophet also achieving the highest values, indicating a high level of coverage of energy demand by on-site generation and storage. Similarly, OER values were consistent across methods and years, with Prophet consistently achieving the highest ratio of on-site energy generation to total energy consumption. Furthermore, GII values showed minimal variation across methods and years, with kNN method achieving slightly higher values compared to others.

In conclusion, the comprehensive assessment of forecasting methods conducted in this study reveals a nuanced understanding of their performance within LECs. While NBEATSx initially demonstrates superior accuracy compared to Prophet, the evaluation of LEC KPIs demonstrates that Prophet delivers higher value in terms of self-sufficiency, energy generation, and interaction with the external grid. As a result, despite its lower accuracy metric, Prophet ultimately leads to lower total costs within LEC operations. This highlights the importance of considering not only accuracy but also the broader implications of forecast value when selecting forecasting methods for optimising LEC operation and minimising costs.

There are some limitations to this study that should be considered when interpreting the results:

1. The study was conducted using data from a single LEC, which may not be representative of other LECs. Therefore, the results should be treated carefully before directly transferring them to other communities.

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	Load Cover Factor			Supply Cover Factor		
	2020	2021	2022	2020	2021	2022
Naïve	0.573	0.819	0.837	0.127	0.574	0.819
LR	0.568	0.82	0.838	0.13	0.574	0.82
kNN	0.576	0.822	0.842	0.129	0.58	0.821
NBEATSx	0.575	0.823	0.842	0.13	0.581	0.823
XGBoost	0.573	0.822	0.839	0.13	0.577	0.822
Prophet	0.577	0.825	0.837	0.131	0.58	0.825
Favourable	0.58	0.828	0.837	0.131	0.589	0.83
Excellent	0.582	0.83	0.837	0.131	0.589	0.831
Perfect	0.586	0.836	0.834	0.134	0.596	0.839
	On-site Energy Ratio			**Grid Interaction Index**		
	2020	2021	2022	2020	2021	2022
Naïve	0.856	0.124	0.57	0.815	0.852	0.131
LR	0.859	0.126	0.573	0.818	0.856	0.131
kNN	0.862	0.125	0.576	0.817	0.859	0.132
NBEATSx	0.861	0.125	0.58	0.821	0.859	0.132
XGBoost	0.858	0.127	0.577	0.82	0.855	0.131
Prophet	0.855	0.126	0.579	0.824	0.851	0.131
Favourable	0.858	0.127	0.584	0.828	0.854	0.136
Excellent	0.858	0.128	0.586	0.83	0.854	0.135
Perfect	0.856	0.131	0.595	0.838	0.853	0.137

Table 5.3.: Comparison of KPIs across implemented Forecasting Methods for the LEC. The table presents the values of Load Cover Factor, Supply Cover Factor, On-site Energy Ratio, and Grid Interaction Index for the years 2020, 2021, and 2022, evaluated across forecasting methods including Naïve, LR (Linear Regression), kNN (k-Nearest Neighbors), NBEATSx, XGBoost, Prophet, Favourable, Excellent, and Perfect. The values provide insights into the effectiveness of each method in optimizing LEC operation and minimizing total costs.

2. The study considered a limited set of forecasting methods and KPIs; there may be other methods and KPIs that could provide additional insights. For example, the study did not consider the impact of weather conditions and weather forecast errors, since historical weather predictions were not available or external factors affecting forecast accuracy.

3. The study did not consider the economic impacts of the different forecasting methods, such as the costs associated with implementing and using different methods nor computational effort. This is a key factor to consider when evaluating the value of forecasts but may get neglectable due to economies of scale.

Given these limitations, there are several directions for future research that could build

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on the results of this study. For example, further research in the field of LECs could explore additional dimensions of sensitivity analyses to enhance our understanding of forecasting models' robustness and performance. Investigating the sensitivity of hyperparameters, such as neural network architectures and training settings, could shed light on the optimal configurations for different LEC scenarios. Additionally, assessing the impact of varying data sources, including the integration of real-time data and alternative renewable energy generation inputs, would contribute to the refinement of forecasting models tailored to specific LEC contexts.

Furthermore, future studies might consider sensitivity analyses that encompass a broader spectrum of operational variables within LECs. This could involve examining the sensitivity of energy storage system sizing, demand-side management strategies, or the integration of emerging technologies like electric vehicles. By conducting comprehensive sensitivity analyses across these dimensions, researchers can provide LEC stakeholders with more actionable insights for informed decision-making in dynamic energy environments.

The research framework employed in this study demonstrates significant methodological adaptability, making it applicable to diverse compositions within LECs. As elucidated in previous work, the comprehensive grey-box building model at the core of this methodology offers flexibility that extends to various LEC contexts, encompassing residential, commercial, and industrial components. The framework can be customized for different building types and sizes by estimating specific building parameters, ensuring its suitability for a wide range of scenarios.

Moreover, this methodology exhibits geographic variability, accounting for variations in climate typical of different regions. This adaptability is achieved through two key factors: the ability to adjust the grey-box building model to accommodate varying local climate conditions and the capacity to incorporate different weather data sources. This enables precise modeling and forecasting in diverse geographic settings, enhancing the framework's applicability across a spectrum of climates.

In terms of market structures, while the study predominantly addressed flat tariff and spot market pricing inputs, it acknowledges the importance of considering additional market configurations. Future research endeavors could explore the integration of various pricing mechanisms, such as time-of-use pricing, demand response programs, or real-time market dynamics. This broader perspective would offer insights into how the framework functions under a variety of market conditions.

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To emphasize the versatility of this approach, a case study was presented based on a three-storey multi-apartment building. This model was chosen as a reference case for zero-energy residential buildings in Austria, showcasing the framework's real-world applicability. While the focus was on this specific case, the methodology remains readily adaptable to diverse building profiles and LEC scenarios. Encouraging further investigations to explore its adaptability and robustness in different settings, this research lays the foundation for broader applications.

Additionally, as energy systems become more complex and the demand for sustainable energy grows, the need for accurate and reliable energy forecasting in LECs is more important than ever. Future research in this field should focus on developing new models and techniques that can address emerging challenges and opportunities, such as the need for more accurate data, the integration of innovative technologies and energy sources, and the increasing importance of environmental factors in energy planning and management. Addressing these challenges and exploring new research directions, it can pave the way for more sustainable and efficient energy systems in LECs.

5.3. Findings with respect to the research questions

The detailed key findings referring to each research question are outlined in this Section. We will state the research questions once again and answer them with the findings and insights gained in this work. We start with research question one.

Research question 1: *How does the novel N-BEATS approach for wind power forecasting, considering the uncertainty and stochastic behavior of wind speed, compare to established models in terms of accuracy and forecast bias reduction?*

The results show that it is possible to build a pure deep-learning model for time series predictions that takes long-term trends and seasonality into consideration and surpasses the accuracy of existing models that combine ML and statistical approaches when applied to the same datasets. N-BEATS emerged as the top-performing model in terms of accuracy, achieving a MAPE of 3.98%. This result represents a significant improvement, as a MAPE below 4% is considered substantial. The hybrid model approaches, particularly ES-RNN, also demonstrated competitive accuracy, with a MAPE of 4.04%. However, N-BEATS exhibited the lowest bias, with an MPE of -0.56. This indicates that N-BEATS consistently provided accurate forecasts without significant over- or underprediction.

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The evaluation of different loss functions for N-BEATS revealed that the pinball sMAPE loss function improved the overall approach. Notably, a τ value of 0.375 yielded the most accurate results across all datasets.

Analysing the forecast accuracy for each country, N-BEATS consistently delivered stable and accurate results for the majority of countries. It outperformed other models in 10 out of 15 countries. Even for a country with data gaps in its history, the forecast accuracy remained within the same range as other countries, indicating the robustness of the approach.

The study also investigated the variation in forecast errors throughout the year and during different times of the day. Inaccuracies were observed to peak during spring and autumn, attributed to the fluctuating nature of wind patterns during these seasons. The dependence of forecast error on the time of day showed that stronger winds typically occur in the afternoon, resulting in increased turbulence and forecasting challenges. Despite these variations, the overall approach consistently delivered robust results, with error fluctuations within approximately 1% MAPE.

To assess the sensitivity to forecast horizons, the study examined forecast error distributions by varying the forecast horizon from 15 minutes up to 12 hours ahead. Results indicated that an analysis period of 4 to 6 times the forecast horizon produced the best results. Comparisons with similar publications in the field confirmed that the proposed architecture achieved exceptionally accurate short-term forecasts, particularly within a range of 4 hours or shorter. However, it was observed that forecast errors varied significantly for longer horizons and were highly dependent on the dataset being considered.

Although it seems tempting to apply the approach to other areas, the findings might not be transferable since energy related problems often require domain knowledge, which ML has no ability to tackle. Nevertheless, this approach, which is particularly suitable for STWPF specifically, can be a powerful addition to the repertoire of every forecaster. Results so far have been very promising, and the approach could eventually be implemented in real-world forecasting applications in order to assist decision makers.

Overall, the study demonstrated the vital importance of accurate demand and generation forecasting, with N-BEATS emerging as the top-performing model. The results showcased the model's accuracy, stability, and robustness across different countries and highlighted its effectiveness for very short-term forecasts. These findings have significant implications for transmission system operators, distribution system operators, and market participants in the energy market, as accurate forecasting is crucial for grid

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management, resource planning, market optimization, and overall operational efficiency.

Research question 2: *How can the quality and value of energy demand forecasts be assessed and optimized to support the effective and continuous operation of energy communities, considering the random nature of weather and the interconnected dynamics of the energy system?*

The second study compared different forecasting methods for load and DHW demand. The results showed that Prophet was the most accurate for load forecasting, slightly outperforming XGBoost in every aspect. Both advanced methods had a lower MAPE compared to the naive method. However, predicting DHW demand was more challenging, resulting in higher error metrics. It was found that different prediction methods performed better in different metrics, indicating the influence of the data distribution and error calculations. Training time was longer for advanced ML methods, but XGBoost had a shorter execution time for predictions compared to Prophet.

The absolute error distribution for load and DHW demand showed higher errors during the day, with lower errors overnight. The naive method consistently had the lowest accuracy throughout the day. Surprisingly, Prophet performed more accurately during the day, while XGBoost was slightly more accurate overnight.

There was a correlation between forecast accuracy and the degree of self-consumption, indicating that more accurate forecasts led to higher self-consumption of local renewable energy. The results also showed that the most accurate forecasting method did not necessarily result in the highest value in terms of self-consumption. The evaluation of LEC metrics revealed that XGBoost achieved a higher level of self-consumption compared to Prophet, despite being less accurate in terms of forecasting.

Cost analysis demonstrated that using more sophisticated forecast algorithms instead of the naive approach could lead to a feasible cost reduction of up to 3%. XGBoost provided better cost results compared to Prophet, although it was less accurate. The average load cover factor, directly related to costs, also favored XGBoost over Prophet.

The results highlighted the complex interaction of various assets and their constraints, showing that evaluating forecasts based solely on accuracy could be misleading. Forecast errors did not always have the same impact on costs due to the dynamic nature of the building and its systems. There were instances where lower heating and cooling energy were observed compared to the perfect scenario, but this resulted in comfort violations.

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XGBoost caused fewer comfort violations compared to Prophet.

The study also identified several challenges related to forecasting in the context of energy communities. These challenges included the availability and quality of historical data, spatio-temporal prediction algorithms for distributed energy generation, accommodating heterogeneous users and data sizes, privacy concerns, and the importance of probabilistic forecasting and uncertainty quantification.

In conclusion, the study demonstrated the trade-offs between forecast accuracy, self-consumption, and costs in energy communities. It emphasized the need for considering multiple metrics and understanding the specific requirements and constraints of the system when selecting forecasting methods. It also highlighted the importance of addressing challenges related to data availability, privacy, and uncertainty quantification in future research.

Research question 3: *How effective are different forecasting methods in supporting the forecast-based optimal control of local energy communities under high and volatile energy prices, and what are the implications for selecting and utilizing forecasting methods in the context of LECs?*

Different forecasting methods have varying levels of effectiveness in supporting the forecast-based optimal control of LECs under high and volatile energy prices. The implications for selecting and utilizing forecasting methods in the context of LECs are multifaceted and depend on several factors, including the specific characteristics of the LEC, the accuracy of the forecasting methods, and the operational objectives. NBEATSx is identified as one of the most accurate forecasting methods in the study. It consistently delivers low MAE, MAPE and nRMSE values. However, the study highlights that NBEATSx's superior accuracy doesn't always translate directly into the lowest total energy costs. Prophet, while ranking slightly lower in terms of accuracy compared to NBEATSx, excels in delivering more valuable forecasts in scenarios where forecast errors can lead to excessive costs. This is critical in the context of LECs where cost optimization is a primary objective. Prophet's ability to capture the value of forecasts in volatile price scenarios makes it a valuable choice.

The study emphasizes that the total cost of LEC operation is not only dependent on forecast accuracy but also on the cost implications of forecast errors. In high and volatile energy price scenarios, even small forecast errors can lead to significant cost differentials. Simple forecasting approaches like multiple regression also yield

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competitive performance in terms of total cost. This suggests that forecasting methods should be evaluated not only on their accuracy but also on their practical implications and cost-effectiveness within the specific operational context of the LEC. The concept of forecast value is crucial in the context of LECs. It extends beyond accuracy and considers the financial implications of forecast errors. LECs need forecasts that are not just accurate but also valuable in terms of cost savings or revenue generation. More accurate forecasts do not always guarantee the most cost-effective LEC operation. Forecast methods should be selected based on their ability to deliver valuable forecasts that align with the financial objectives of the community.

The study highlights that the impact of forecast accuracy on total energy costs is even more substantial in scenarios with higher and more volatile energy prices. In such scenarios, selecting the right forecasting method becomes critical. LECs should consider the specific energy price scenarios they are likely to encounter and select forecasting methods that perform well under those conditions.

The research underscores the need for a holistic evaluation approach that considers both accuracy and forecast value. LEC stakeholders should assess forecasting methods based on their ability to optimize costs, rather than relying solely on accuracy metrics. The choice of forecasting method should align with the LEC's operational goals, risk tolerance, and the specific market conditions it operates in.

The study identifies several directions for future research, including exploring the sensitivity of forecasting methods to hyperparameters, assessing the impact of weather conditions, and considering the economic costs associated with different methods. Future studies should also investigate the integration of various pricing mechanisms and market configurations, such as time-of-use pricing and demand response programs.

In summary, the effectiveness of forecasting methods in supporting forecast-based optimal control of LECs under high and volatile energy prices is contingent on their ability to provide valuable forecasts that align with the financial goals of the community. While accuracy is important, it is not the sole determinant of effectiveness. LECs should carefully evaluate forecasting methods based on their ability to optimize costs and consider the specific operational context and market conditions in which they operate.

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5.4. Comparison with respect to the research questions

Table 5.4 provides an overview of the key findings for each research question, highlighting the simplified questions addressed and the key insights derived from the analyses. Table 5.5 presents a comparison of research findings across various aspects, including forecasting methodology, accuracy metrics, operational implications, cost considerations, forecast value, sensitivity analyses, and future research directions. This comparative analysis offers insights into the diverse methodologies employed, the metrics used to evaluate forecasting performance, and the implications for operational decision-making in energy communities.

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RQ1	How does N-BEATS compare to existing models for wind power forecasting?
Key Findings	N-BEATS is the most accurate model. Forecast Bias can be mitigated by choosing proper loss function. Interpretabilty can be achieved using DL models. The importance of considering long-term trends and seasonality in wind power forecasting. Insights into the effectiveness of different loss functions in improving forecast accuracy. Robustness of N-BEATS across different countries and data scenarios.
RQ2	How to assess and optimize demand/DHW forecasts for LECs?
Key Findings	Cost reduction of up to 3% by using more sophisticated forecast algorithms. Prophet delivers superior accuracy but using XGBoost leads to lower total costs. There is no apparent and time-coherent relationship between forecast errors and costs caused by them. Building characteristics have high impact on overall performance. The impact of forecast accuracy on self-consumption and overall system efficiency. Identification of challenges related to data availability and privacy concerns in forecasting for LECs. The significance of probabilistic forecasting and uncertainty quantification in demand forecasting.
RQ3	How effective are forecasting methods for LECs under high and volatile energy prices?
Key Findings	NBEATSx is more accurate than Prophet but doesn't always lead to lowest costs. Prophet achieved the highest value indicating a greater degree of coverage of energy demand by on-site generation. Consideration of market conditions and pricing mechanisms in selecting forecasting methods for LECs. Importance of forecast value beyond accuracy in optimizing LEC operations. Implications of forecasting errors on operational costs and decision-making in LECs.

Table 5.4.: Key findings for each research question (RQ) in the study.

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Aspect	Research Question 1	Research Question 2	Research Question 3
Forecasting Methodology	ARIMA MLP LSTM WT-LSTM LSTM-MSNet ES-RNN N-BEATS	Naive Multiple Regression kNN XGBoost Prophet	Naive Multiple Regression kNN XGBoost Prophet N-BEATSx
Accuracy Metrics	MAPE sMAPE MPE R2	MAPE sMAPE nRMSE MASE	MAE MAPE nRMSE MSE MASE
Operational Implications	Transmission & Distribution Operators	Local Energy Communities	Local Energy Communities
Cost Considerations	Economic Viability Computational Efficiency	Cost Reduction Self-Consumption	Cost Reduction Self-Consumption
Forecast Value	Forecast Accuracy vs. Value Trade-offs	Accuracy vs. Cost-effectiveness	Accuracy vs. Cost-effectiveness
Sensitivity Analyses	Forecast Horizon Seasonal Variations	Forecast Errors Operational Constraints	Forecast Errors Market Conditions
Future Research Directions	Hyperparameter Sensitivity Weather Impact	Data Availability Privacy Concerns	Integration of Pricing Mechanisms Market Configurations

Table 5.5.: Comparison of Research Findings: A comprehensive overview of the methodologies, metrics, implications, and future research directions across the three research questions explored.

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6. Conclusions and outlook

The research questions posed in this dissertation were worth analyzing, as they addressed significant gaps in the current understanding of true value of forecasting methods in the context of energy systems, particularly in LECs and wind power forecasting. By examining the accuracy and true value of various forecasting techniques, this research aimed to provide valuable insights for improving energy management and decision-making processes within LECs and optimizing the utilization of wind power resources.

The chosen methods were deemed appropriate for addressing the research questions at hand across all three papers. Each method was carefully selected based on its suitability for the specific objectives of the research questions. For instance, the use of advanced machine learning techniques like N-BEATS, N-BEATSx, XGBoost and Prophet allowed for the exploration of cutting-edge forecasting approaches, while traditional methods such as Multiple Regression provided valuable comparative insights. Overall, the combination of these methods enabled a comprehensive analysis of forecasting methodologies in diverse energy contexts.

The synthesis of results and the general findings from this work reveal several important insights into forecasting methods for energy systems, spanning from wind power forecasting to demand forecasting in LECs. Key findings include the identification of highly accurate models like N-BEATS, N-BEATSx, XGBoost and Prophet, the importance of considering cost implications in forecasting decisions, and the impact of building characteristics on forecast performance. These results contribute to a deeper understanding of how forecasting methods can be optimized and adequately utilized for efficient energy management and resource allocation.

The promises from this contribution beyond the state-of-the-art and novelties have been confirmed through the validation of forecasting approaches and the generation of actionable insights for real-world energy applications across wind power forecasting and LEC investigations. By demonstrating the effectiveness of advanced techniques like N-BEATS, N-BEATSx, XGBoost and Prophet in forecasting energy demand and generation, this research has advanced the state-of-the-art in energy forecasting methodologies and paved the way for more accurate and reliable energy management

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strategies in LECs and wind power utilization.

While this work has made significant contributions to the field of energy forecasting, it is not without its limitations. One limitation is the reliance on historical data from a single reference LEC and wind power sites in Europe, which may not fully capture the variability and complexity of energy systems in different contexts or countries. To overcome this limitation, future work could involve the collection and analysis of data from multiple LECs and wind power sites to ensure the generalizability and robustness of the findings. Additionally, addressing the computational challenges associated with complex forecasting models could enhance the scalability and applicability of these methods in practical settings.

Looking ahead, there are several directions for future research that build on the work presented. These include investigating the application of forecasting methods in emerging energy technologies such as smart grids and renewable energy integration, exploring the potential of machine learning algorithms for predictive control in energy systems, and conducting comparative studies to evaluate the performance of forecasting methods across different energy markets and regulatory regimes or even focus on a universal forecasting service.

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Appendices

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Appendix A.

Deep neural architecture for very short term wind power forecasting

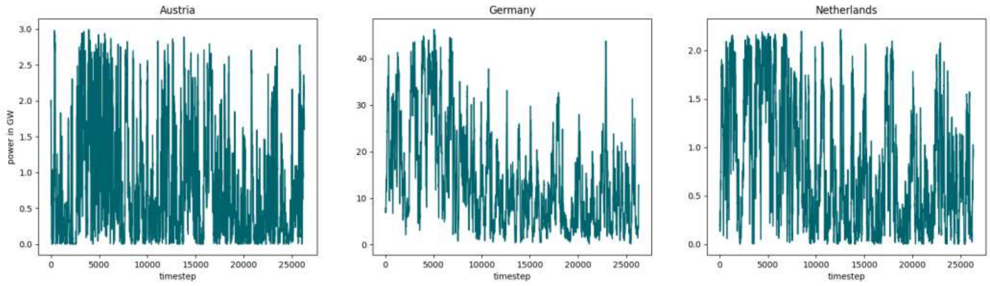

Figure A.1.: Aggregated wind power production in GW for AT, DE, NL in 15-minute time resolution between 01/01/2020 and 30/09/2020.

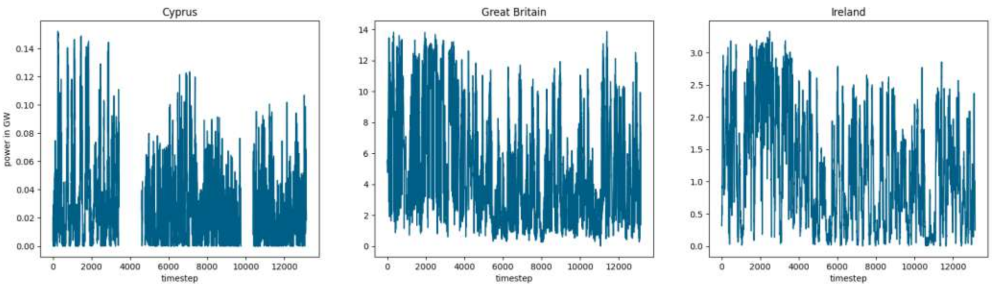

Figure A.2.: Aggregated wind power production in GW for CY, GB, IE in 30-minute time resolution between 01/01/2020 and 30/09/2020. Cyprus has some gaps in its history.

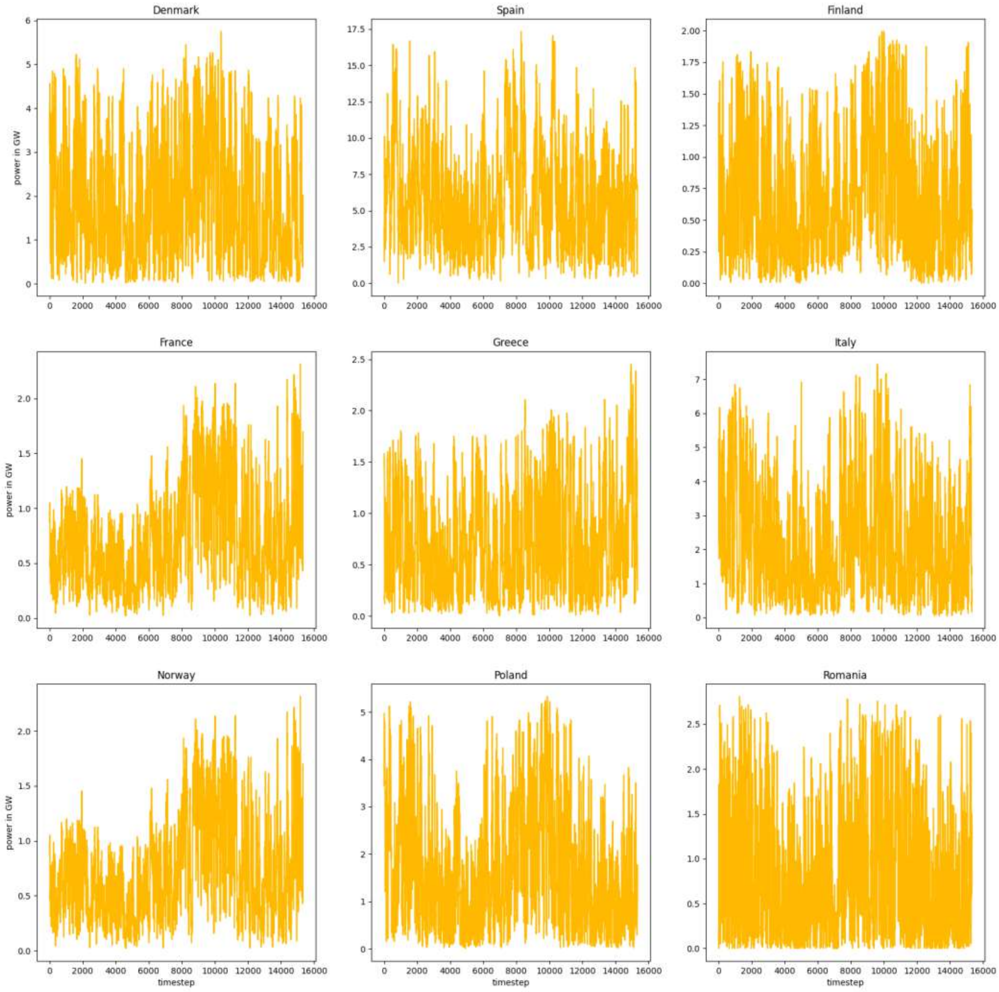

Figure A.3.: Aggregated wind power production in GW for DK, ES, FI, FR, GR, IT, NO, PL, RO in hourly time resolution between 01/01/2019 and 30/09/2020.

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Appendix B.

Forecast models for model predictive control of a local energy community

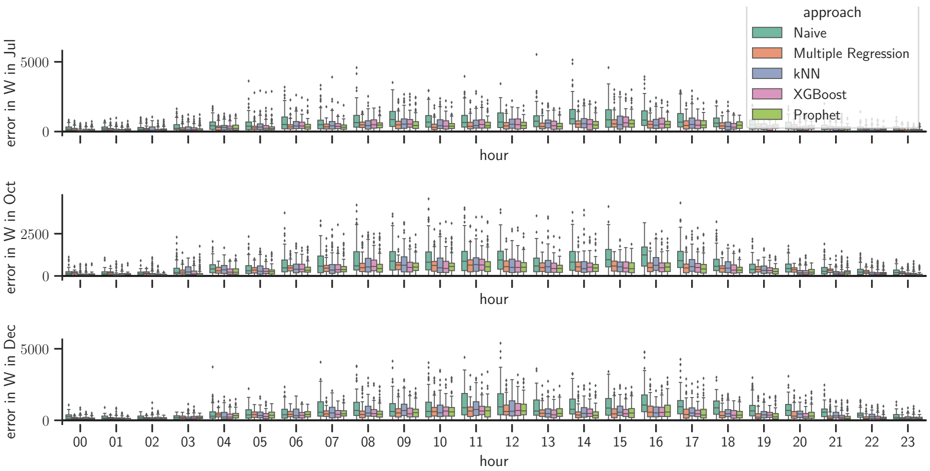

Figure B.1.: Absolute error distribution for each prediction method on an hourly basis for load demand. Three different months were examined (July, October, and December) to show the behaviour of error in different seasons according to switching weather conditions.

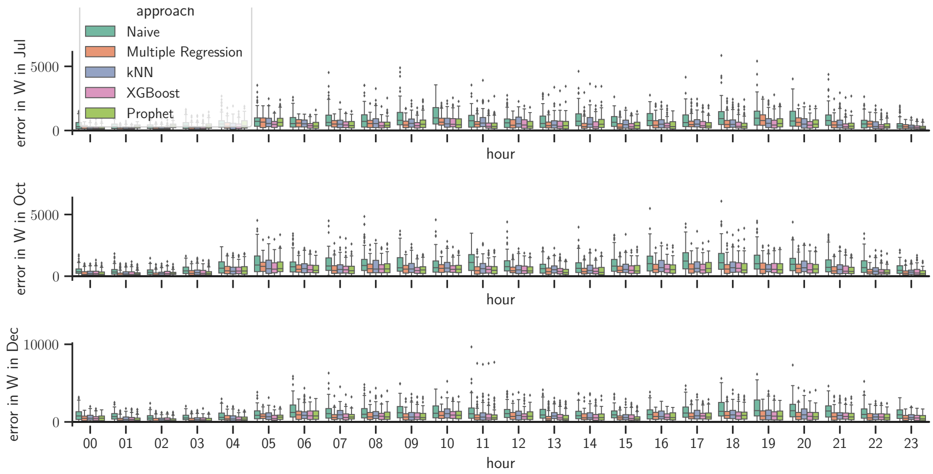

Figure B.2.: Absolute error distribution for each prediction method on an hourly basis for DHW demand. Three different months were examined (July, October, and December) to show the behaviour of error in different seasons according to changing weather conditions.

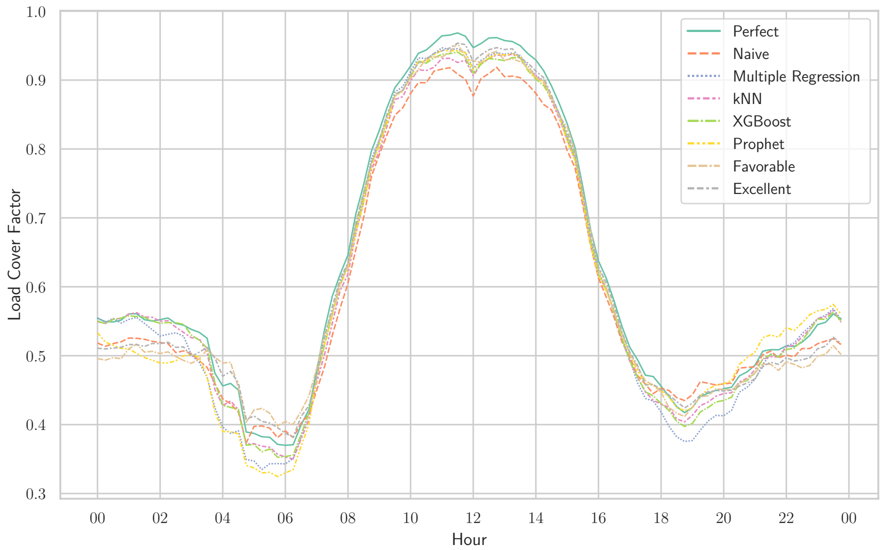

Figure B.3.: Average load cover factor for each timestep and forecasting method. During the dawn hours, the LCF drops to a minimum, as there is no PV generation available yet and the battery storage is most certainly empty. During the sun hours, however, the LCF is close to 1, which means that the demand can be almost completely covered by self-generation on average. In the evening hours, the advantage of a battery becomes apparent, which increases the LCF.

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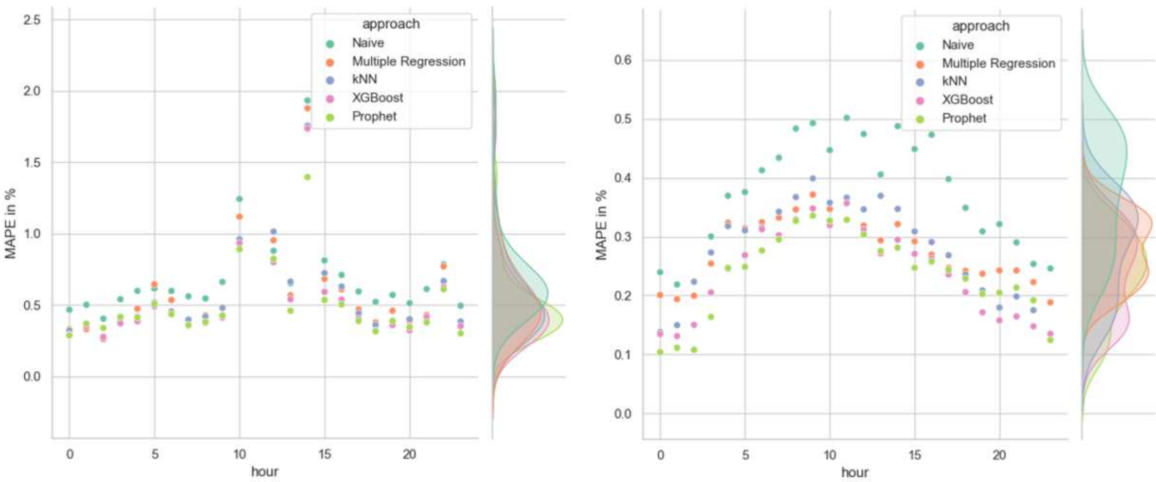

Figure B.4.: MAPE distribution for each prediction method on an hourly basis for load demand (left) and DHW demand (right).