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Economic Analysis and Forecasting Potential Flexibility in District Heating

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ABSTRACT:

Demand-side flexibility is a significant part of the global energy transformation and the rapid growth of renewable energy. The District Heating (DH) system, which represents a substantial amount of energy consumption in urban areas, due to its centralized infrastructure and thermal inertia, can offer potential flexibility. The accuracy in flexibility evaluation in a scalable way is still a challenge. This master's thesis assesses the DH demand flexibility potential by breaking it down into temperature-dependent and temperature-independent components. The key focus of this study, the temperature-independent component, which is the key indicator for flexibility potential, can be adjusted without affecting the consumer's comfort. Linear methods (Linear Regression, Ridge, Lasso) were used as a baseline, advanced machine learning algorithms (XGBoost, LightGBM), and recurrent neural networks (GRU, LSTM) were utilized to model the DH data to capture the breakdown.

The analysis was conducted based on real-life data of Helsinki's DH network, and operational data sets were trained to validate the models and to estimate the flexibility potential of DH demand. A range of modeling techniques has been utilised on the data sets, and among all these, specifically gradient boosting, is effective in evaluating the flexibility potential of district heating (DH) systems. The findings highlighted the flexibility of the DH system towards market stability enhancement and facilitating the demand response strategies. However, several limitations have been identified in the scope of available datasets and fundamental speculations of the models. To establish the result as accurate and reliable, and impactful in real life, more research is required on enlarging the types of datasets and adopting hybrid modeling approaches.

KEYWORDS: District heating; flexibility; machine learning; deep learning; forecasting.

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Abbreviations

DH	District Heating
RES	Renewable Energy Sources
DSM	Demand Side Management
LR	Linear Regression
RNN	Recurrent Neural Network
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
LightGBM	Light Gradient Boosting Machine
XGBoost	Extreme Gradient Boosting
RMSE	Root Mean Squared Error

1 Introduction

District Heating (DH) systems serve as a centralized system for heat distribution to residential and commercial buildings and have traditionally been a crucial component for urban energy planning. Rising global energy demand is now associated with the urge towards sustainability, and there is growing attention for integrating Renewable Energy Sources (RES) into DH systems. There is a revolutionary transformation in the energy systems, becoming more flexible, efficient, and cost-effective solutions (Guo et al., 2024a). To achieve carbon neutrality, Europe is addressing issues like energy scarcity and focusing on energy conservation and renewable energy targets (Wittenburg et al., 2023). Incorporating RES like biomass, solar power, geothermal heat, heat pumps (HPs), and waste heat into DH systems is required for mitigating carbon emissions (Kirppu et al., 2018).

1.1 Background

DH systems denote to a centralized network that is responsible for heat distribution as a form of hot water or steam from a centralized production to multiple buildings through an insulated pipe network. Integration with various energy sources like RES, waste heat management, and biomass significantly facilitates the DH system to be significant for providing reliable heating systems with cost-effective measures (Dang et al., 2024). Hence, DH is an essential element for urban development, mostly used in Asia, Europe, and parts of North America within their residential and commercial area.

In terms of ongoing energy transitions, the DH system is becoming widely recognised as a potential contributor to flexibility. Grid stability is facing challenges due to fluctuations of RES, and this has raised a significant demand for demand-side flexibility, which will facilitate the whole system to reach an equilibrium condition by shifting or altering energy according to heat demand (Fernqvist et al., 2023).

1.2 Research Questions

This thesis work aims to improve the forecasting demand process and flexibility estimation in DH systems by analysing predictive efficiency of different modeling approaches and their implications in the energy systems. This part is organised with three leading queries.

(1) How accurately can different modeling approaches predict DH demand?

The question comes with the methodological challenges in identifying the best forecasting technique. Generally, a linear model is simple and provides an easier and interpretable baseline. However, the combination of machine learning approaches (XGboost, LightGBM) and deep learning frameworks (LSTM, GRU) can demonstrate a more flexible and real-time modelling for complex forecasting circumstances. The purpose of this study is to seek the modelling approach and evaluate the advantages and disadvantages within DH systems, considering real-world limitations.

(2) What is the Estimated Flexibility in the DH System, which is Temperature Independent?

The outdoor temperature impacts the DH system significantly, although it’s not the only primary aspects that solely control the DH systems. The residuals analysis derives from the isolation of a temperature-independent component, which can be shifted or adjusted without affecting the end user’s thermal comfort and can be identified as the key component of the flexibility potential. The question focuses on the scope of potential flexibility and the application of different ML models to demonstrate the flexibility.

(3) How do Estimation Vary within Different Models?

In addition to forecasting accuracy, it requires evaluating the different modeling methods to determine the flexibility potential based on their consistent and diverse outcomes.

The evaluation approaches allow the system to integrate with RES that provides peak load mitigation and Demand Side Management (DSM) improvement strategies. To connect the methodological outcomes and the extensive strategic and operational applications of energy systems, the findings promote forecasting methodologies' implications and policy-making techniques.

1.3 Research Objectives

The primary goal of this research work is to find out the feasible optimization for the DH systems based on a few defined criteria. To achieve this, a few objectives as described below –

(1) Comparison of Different Models to Predict DH demand: An extensive number of models, including basic linear regression, sophisticated boosting methods, and recurrent neural networks, are demonstrated and compared to predict the appropriate DH demand. Standard error metrics such as Root Mean Squared Error (RMSE) and R^2 have been used to determine an extensive evaluation of prediction accuracy.

(2) Flexibility Estimation Using Temperature-Independent Component: The isolation of the temperature-dependent component from the DH system is required to identify the temperature-independent portion. This allows a predicted range of estimated flexibility, where the portion can be adjusted or shifted to improve the demand response.

(3) Practical Applications of the Models in the DH Systems: To improve the technical evaluation methodology, along with the purpose of extracting knowledge of their systematic implications, was the main goal of utilizing these models. Operational planning, along with the enhancement of forecasting accuracy to achieve the optimised performance of the systems, is considered a practical implication. The models facilitate the coordinated operation of unpredictable RES supply with heat demand, improving the flexibility of the system as well as promoting sustainability to integrate with RES.

1.4 Prospects and Limitations

The study was done based on the historical data of Kaisaniemi, a small neighborhood in Helsinki, Finland, from 2015 to 2023, to identify critical factors influencing DH consumption. Since 2023, energy prices have started to influence, as well as temperature divergence and fluctuation, which were identified as the key aspects of the analysis. The scope was limited to a certain place and limited historical data accessibility without exploring diverse geographical areas, inter-variability, and alternative climates. Besides, based on statistical residuals, flexibility was estimated, which may vary with real-time end users' behavioural or usage patterns.

1.5 Structure of the Thesis

The thesis is followed in a structured way.

- Chapter 1 provided the background of the study and the motivation for this research. This also includes the purpose of this study, the objectives, and the further work to be carried out.
- Chapter 2 covers the current trend in DH demand, modeling, and flexibility assessment. The review of literature outlines existing knowledge, identifies shortcomings, and provides the research foundation for the questions and objectives.
- Chapter 3 defines the research methodology, including a description of data sets, procedures of pre-processing and post-processing, and different modeling methods used for analysis. It also covers detailed procedures of how air temperature and DH demand data were prepared and structured for different methods. This chapter also covers the statistical analysis, machine learning, and deep learning algorithms, as well as the implications of evaluation metrics for performance evaluation and flexibility potential estimation.
- Chapter 4 presents the experimental findings of the study and evaluates the efficacy of different models, such as linear regression, combined machine

learning methods, and deep learning methods, in forecasting the flexibility of DH systems. This chapter explored the temperature-independent component of the DH system for each model, which leads to promoting the extent of flexibility in the DH system.

- Chapter 5 covers the discussion of the analysis and findings in terms of pointed questions and current literature. This clarifies the models' specifications, combination of methods, acquired prediction accuracy, and more consistent flexibility estimation. This finding connects with the previous findings focusing on the similarities and differences.
- Chapter 6 concludes the thesis by reviewing the major contributions, including an evaluation of flexibility potential and a comparison of forecasting models in the DH system. The findings can be implemented for both academic research and practical applications. It addresses the significant limitations and proposes future study.

2 Literature Review

The DH systems have gone through significant advancements over the past few decades. At the beginning of the 20th century, urban heating systems depended on centralized steam-based systems. Later, it gradually evolved by adapting the combined heat and power (CHP) and RES integration (*Fifth Generation District Heating and Cooling: A Comprehensive Survey - ScienceDirect*, n.d.). Current research development on DH systems has increased significantly because of its necessity in cold climate regions. An increased emphasis on the ability to adapt to flexibility, especially in heating systems, has been promoted due to the shift towards sustainable energy systems (Lo Piano & Smith, 2022). The significance has led to an increasing demand for precision in forecasting and the flexibility potential in DH systems, as they are needed for waste reduction and energy consumption optimization (Wei et al., 2024). To mitigate dependencies on fossil fuels and achieve carbon neutrality, the ongoing development of the DH flexibility system's extended RES integration and resources like geothermal, solar, and biomass (*Trends of European Research and Development in District Heating Technologies - ScienceDirect*, n.d.).

The DH systems are much needed in extremely cold regions, where heating demand fluctuates significantly. To achieve system optimisation and efficient energy management, research has focused on demand-side flexibility management (Sneum et al., 2025). To portray the accurate energy consumption patterns and sync with the heat supply, DH systems require advanced forecasting strategies, since energy demand keeps getting unpredictable due to weather conditions (Ragupathi et al., 2024). To develop innovative and cutting-edge forecasting models, both internal dynamics of systems (structure of thermal inertia and networks) and external factors (weather patterns and consumer behaviour) have been taken into consideration by current research. To improve the DH system's potential to be adaptive to the unpredictable fluctuations, along with load prediction enhancement, these models have been proposed (*An Artificial Intelligence (AI)-Driven Method for Forecasting Cooling and Heating Loads in*

Office Buildings by Integrating Building Thermal Load Characteristics - ScienceDirect, n.d.).

The literature on DH systems highlights the growing collaboration of RES to sustain the forecasting accuracy and potential flexibility to continue to fulfil the shifting requirements in the cold regions. These strategies are expected to be crucial in promoting energy consumption reduction, reducing the environmental impacts, and enhancing the efficiency of heating systems.

2.1 Flexibility Concept in District Heating

The ability of the systems to respond to demand fluctuations, generation, and external factors such as weather conditions and energy price fluctuations is denoted as flexibility (*Power System Flexibility: A Review - ScienceDirect*, n.d.). Synchronisation of flexibility into DH systems enables the RES adaptation, fossil fuels reduction, as well as effective energy demand management (Bashir et al., 2021). To respond to the heat supply to real-time demand fluctuations to meet the heating loads, DH systems may store surplus heat in thermal energy storage (TES) along with the heat pump integration to absorb additional electricity generation by RES (Guo et al., 2024b).

Traditionally, temperature is the most influential factor that affects the DH consumption. The relationship is very crucial for DH systems' operation, as it determines how much heat is needed to make buildings convenient (Kök et al., 2025). The demand prediction of DH systems can be accurately forecasted by using historical temperature data and previous consumption trends. The temperature influence on DH systems is gradually being overcome by the increasing significance of economic factors like energy prices (Hua et al., 2024). Numerous sources emphasised that heat demand is temperature-driven, yet a component is recognised as not temperature-dependent, which is associated with hot water consumption, consistent operations throughout the year, and manufacturing operations, which have the potential to be the source of flexibility (Huckebrink & Bertsch, 2022).

2.2 Flexibility Estimation Approaches

Most of the flexibility estimation methods are based on two main methodological approaches –

i. Physics-based Modeling: The amount of potential shifting loads in a DH system needs to be analyzed by a few factors, such as thermal building models, heat transfer equations and the dynamics of the system. To determine the shift of heating demand, such as from the peak period to the off-peak period, cost optimisation as well as energy consumption optimisation can be evaluated through this method (Von Krannichfeldt et al., 2025).
ii. Data-driven Modeling: It combines statistical and machine learning algorithms to assess heating demand by making a breakdown of the temperature-dependent component and the residual component. Regression methods, a combination of boosting methods and deep learning methods, are effective tools to identify nonlinearities in heating demand in the DH system. Factors that influence heating demands, such as temperature, energy consumption, energy prices, and performance of the system, can be identified by utilising these approaches (Von Krannichfeldt et al., 2025).

By simulating the physical mechanisms that regulate heat distribution, energy circulation, and the dynamics of systems, physics-based modeling has been utilised for flexibility estimation and efficiency of the DH systems. To analyse the system's parameters (heat exchangers, boilers, pumps, pipelines and storage systems) and external factors (temperature, consumption demand and energy fluctuations), physical-based models have been utilised (Kuntuarova et al., 2024). Data-driven methods consist of mathematical optimisation, models for simulation and data-driven approaches to analyse the DH system's potential in responding to energy demand fluctuations, availability and external factors (Bergsteinsson et al., 2022). Figure 1 shows the hybrid approaches, a combination of data-driven and physics-based modelling. A common breakdown of a data-driven model is provided below.

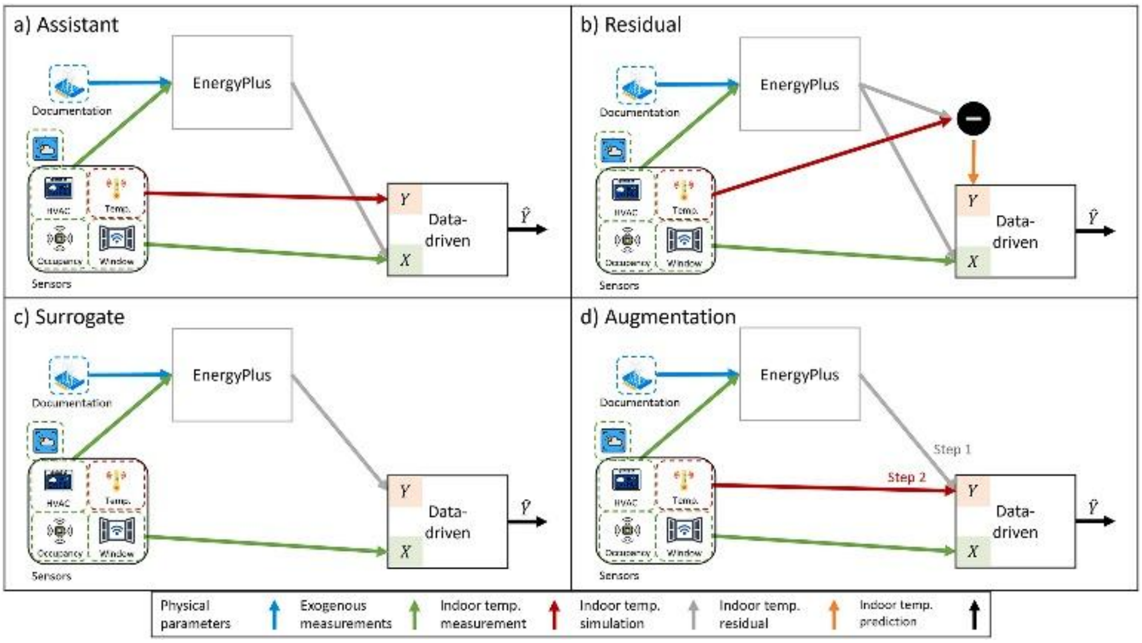

Figure 1. Overview of hybrid modelling approaches with physics-based and data-driven (Von Krannichfeldt et al., 2025).

2.3 Breakdown of Data-Driven Models

To evaluate the demand and potential flexibility estimation in DH, the ongoing trend is to adopt numerous data-driven approaches.

2.3.1 Traditional Statistical Model

In earlier periods, most of the research related to DH demand forecasting used a linear regression model considering a direct correlation between external temperature and heating demand. According to studies, air temperature is considered the primary predicting variable that accounts for almost 80% variance in heat load (Ding et al., 2022). Regardless of the fact that these models have been recognised for their key factors like interpretability and simplified computational requirements, they are still insufficient to detect nonlinear patterns, abrupt changes, and extreme meteorological variations. Lasso and Ridge fail to provide accuracy and precision in complex conditions, as they were utilized to identify the convergence and regularization implications.

2.3.2 Machine Learning Models

Emerging trend of machine learning application for advanced DH forecasting techniques, particularly tree-based models like Random Forests, XGBoost, and LighGBM, has surpassed the linear models, enabling the identification of the nonlinearities and complex correlation between variables (Pokharel & Ghimire, 2023). Analysing and optimising enormous datasets requires dealing with vital issues such as threshold effects, missing data, and noise, which becomes a crucial aspect. Boosting methods have outperformed dealing with these issues and have proven efficient for operational use (*(11) (PDF) Overview of Data-Driven Methods for District Heating Systems Diagnosis*, n.d.).

2.3.3 Deep Learning Models

DH systems have extensively executed deep learning approaches in recent years. Deep learning methods, such as Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM), have been especially developed to detect temporal dependencies within the sequential data. Additionally, when paired with high-resolution, multidimensional inputs, including factors, solar radiation, temperature, and historical demand, a Recurrent Neural Network (RNN) can withstand traditional models (Suryanarayana et al., 2018). Deep learning models deal with the complicated temporal dependencies, allowing more accurate prediction and optimization in the DH systems. However, deep learning is least appropriate when the data sets are limited in features (Kim et al., 2025).

2.4 Forecasting in DH Systems

Flexible operation of DH systems is based on precision in forecasting. Predicting accurate heating demand, the DH systems allow operators to achieve energy consumption optimisation. (*Explainable District Heating Load Forecasting by Means of a Reservoir Computing Deep Learning Architecture - ScienceDirect*, n.d.). Conventional forecasting methods mostly depend on statistical methods. For resilient data, ML algorithms have been used to enhance accurate predictions. To achieve a dynamic and flexible approach, numerous ML algorithms like XGBoost, LightGBM, and Lasso regression are utilized for efficiency enhancement and accuracy of demand prediction. The temperature-independent components acknowledgement is crucial, and it allows ML approaches to forecast accurate energy consumption patterns within the DH system (Chen et al., 2025).

2.5 Research Gaps

Despite the growing interest, numerous gaps remain in the literature.

1. Most of the studies are based on a single year and on a specific region's dataset, and this leads to limiting generalizability.
2. Flexibility is mostly estimated indirectly through residuals; this may not be purely temperature-independent and end-user load-related.
3. Experimental validation of flexibility estimation in terms of real-world measures is limited, such as load shifting.
4. The accuracy of the models and interpretability have been studied, and environmental operation and impact have been rarely explored.
5. High resolution and multidimensional factors were not taken into consideration.
6. Numerous ML approaches (like GRU and LSTM) are often referred to as black boxes.
7. Data interpolation and noise filtering could be developed and taken into consideration.
8. Future research should focus on the variability of climate and its impact.
9. Further research can demonstrate how market-based pricing mechanisms and economic factors could be optimized by utilizing ML algorithms.
10. Centralized DH systems were used, but multi-agent systems (MAS) related to the distributed control method for the decentralized heating network have received no attention.

3 Methodology

This methodology process forecasts potential flexibility of DH power consumption and economic analysis in parallel. The five-stage work procedure contains both theoretical and computational tasks, for instance, data pre-processing and cleaning, data analysis and feature engineering, developing and retraining forecasting models (including model tuning), and data visualization. Figure 2 shows the methodology flow diagram of this thesis work.

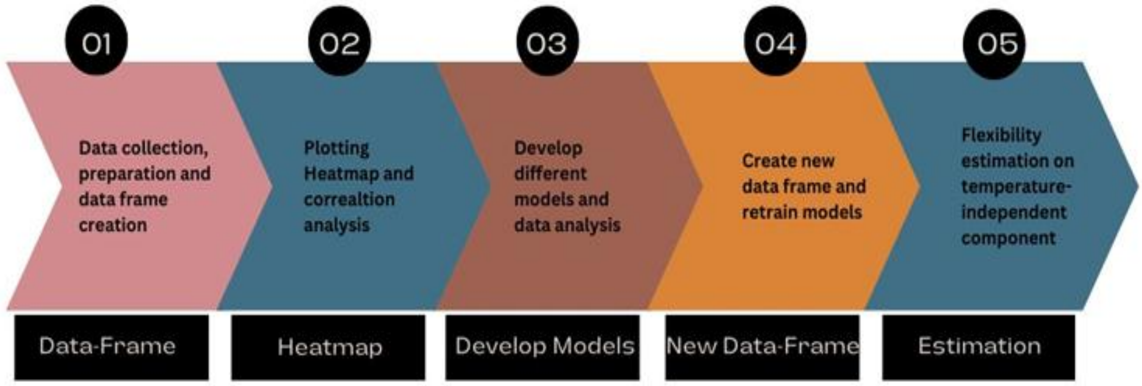

Figure 2. Methodology flow diagram

The escalating penetration of renewable energy sources (RES), integrating with solar and wind power, has attained reliability and stability with a steady power supply. Regardless of offering numerous advantages, there is still a growing demand for the assessment of both economic viability and operational flexibility in district heating systems to maximize the global energy landscape (Hassan et al., 2023). Ongoing advancement leads to the complex modeling and simulation of DH systems, and these complexities extend to design, planning, and operational management of DH systems. Despite this complex scenario, there is an ongoing need to choose the most dynamic modelling with a defined methodology (Kuntuarova et al., 2024). The methodology connects several approaches, including economic analysis, data-driven and flexible forecasting techniques, and future assessment.

i. Data-driven and flexible forecasting approaches: Adaptation with the fluctuations of energy networks that include RES input fluctuation and energy prices based on market scenarios refers to the flexibility in DH systems. Data-driven and adaptive forecasting techniques are important to improve accuracy and optimization, and sustain grid stability.
ii. Future assessment: Future assessment of DH systems enables opportunities to be adaptive with cutting-edge technology, more challenges, and the global energy trend landscape. The current evolution of DH reflects how it can be influential in the global energy market in the future. With technological advancement, decarbonization, economic feasibility, and adaptability to the global energy transition, DH systems can provide a robust, sustainable, and affordable solution to the global heat demand.

3.1 Data Frame Phase

The base of the dataset is divided into four columns. Data is included from 2015 to 2023 (*Open Data | Helen*, 2019), including Date, Hourly District Heating Consumptions (in MWh), Hourly Temperature of a specific region, Kaisaniemi in Helsinki (in °C), and day-ahead Hourly Spot Price in Finland (in €/MWh). Multiple datasets are needed from various sources, for instance, district heating data is sourced from energy company Helen Oy, and weather data is collected from the Finnish Meteorological Institute (https://en.ilmatieteenlaitos.fi, n.d.), and the ahead-of-hourly price is collected from the European Network of Transmission System Operators for Electricity (*Data View*, n.d.).

3.2 Heatmap Plotting

Heatmap plotting for both Pearson and Spearman correlation coefficients has been developed to identify the underlying correlation between DH energy consumption, energy price and temperature. The Pearson correlation coefficient was utilized to determine the linearity among the datasets, and to identify the potential non-linear relationship, the Spearman Correlation was used. To simplify the temporal connections over the years, the data sets were separated into individual years, and to observe the correlations over the period. To develop the patterns and annual energy consumption variations and fluctuations identification, the heatmap visualization provides meaningful insight. This heatmap visualization also offers an extensive knowledge of DH energy demand affecting factors like environmental and economic.

3.3 Model Development

Various models have been developed for forecasting and observing the dynamic shift in DH power consumption dependency for the period 2015 to 2023. The splitting had to consider variations in the structural correlations between DH power consumption and influencing factors, including energy pricing and temperature, as indicated by previous correlation analysis. Due to the moderate linear correlations, a simple linear regression model was utilised as the initial baseline.

(1) Linear Regression: Both testing and training data sets give consistent performance, and errors are relatively close, which indicates that the model is neither overfitting nor underfitting. The data set fits well, but more sophisticated models can perform better, as shown by lower RMSE values.

(2) Lasso: To recognize the underlying data patterns, Lasso demonstrates poor performance as seen in both testing and training RMSE values, which are high and closely related. For this task, Lasso might not be the perfect model.

(3) Ridge: Ridge regression fits well for both testing and training data sets, and this model performs similarly on training and testing data as the model generalizes well. Ridge provides a generalization factor by preventing overfitting.

(4) ElasticNet: For both testing and training data sets, RMSE values are high, along with similar training and testing errors. It indicates that the model is not well fitted to capture the underlying patterns like Lasso. Higher RMSE values indicate the model’s poor performance for predicting accuracy.

(5) Random Forest Regression: Lower RMSE on training datasets makes the model a good fit compared to other models. Although Random Forest Regression has a

minor error increase, the model can generalize effectively and performs better than other models. Since the model balances both accuracy and generalization, it can be considered a good predictive model.

(6) Gradient Boosting Regression: Gradient Boosting Regression shows good performance by generalizing to new data and having a lower RMSE value for both training and testing data sets. This can be a good alternative to Random Forest Regression because of its slightly greater RMSE value. It balances well between testing and training performance, for which Gradian Boosting Regression can be considered a reliable prediction model.

(7) Extra Trees Regressor: Extra Trees Regressor has an exceptional performance for training data sets, which shows that the model is fitting training data well, but higher testing RMSE values decline the model's performance as it encounters unseen data. The variance between testing and training data indicates possible overfitting, and overfitting makes the model unlikely to be suitable for real-world prediction.

(8) XGB Regressor: The model has an effective balance between fitting the training data and generalizing unseen data, with a very negligible difference between training and testing RMSE values. Compared to other models, it can be considered the most suitable option for regression and can be a good fit for predictive modeling.

(9) LGBM Regressor: LGBM Regressor shows a consistent performance with a slight difference between training and testing RMSE values, and that can be effective in generalizing new data. LGBM can be a good alternative for regression due to its highly efficient speed and memory utilization.

(10) KNeighbors Regressor: KNeighbors Regressor showed proper prediction accuracy; however, models like XGB Regressor and Random Forest exceeded it by showing lower RMSE. KNeighbors Regressor may encounter more complex datasets and make this model less suitable where higher accuracy is required.

(11) Poly Linear Regression: Poly Linear Regression comparatively performs well with low overfitting, as there is minimal difference between testing and training

RMSE values. Still, Poly Linear is lagging other sophisticated models as it has performance limitations with complex patterns. This model is suitable for simpler data sets rather than the more complicated ones used here.

(12) RNN: Recurrent Neural Network models (RNN) perform the best compared to the other developed models with lower testing and training RMSE values, indicating the model's generalization capabilities is a crucial component for prediction accuracy. RNN is an appropriate option for sequential and time-series data, although it may require a larger amount of data and computational resources.

(13) GRU: Gated Recurrent Unit (GRU) performs well with a lower RMSE value on testing data compared to training data. The model's generalization capabilities on unseen data can prove that it can be efficient for understanding sequential patterns. In case of sequential dependencies on data, the outperformance ability on testing data makes the GRU an exceptional option for regression tasks.

(14) LSTM: Long-Short Term Memory (LSTM) has a strong performance ability with similar RMSE values for both testing and training datasets. It is almost identical to GRU with a bit better RMSE value. LSTM can perform well with sequential data, along with generalizing to new data, and it can be a solid option for time-series and sequential data.

3.4 New Data-Frame Development for 2023

A remarkable transition was observed at the start of 2023 in DH consumption patterns and a shift towards price. From the analysis of 2015 to 2023 historical data, consumption patterns were mostly determined by climate conditions, especially temperature. Energy prices started to become vital beginning in 2023, and by classifying the data frame solely in 2023, a feature selection method has been utilised. This allows for improving the model's accuracy and refinement process. Variables within the DH power consumption that carried out the correlation coefficients greater than 0.2 were classified as the most significant predictors. Poorly correlated variables come with the noise; the reduction of this noise leads to a refinement method that can enhance the interpretability and accuracy of the model. The outcomes require the consideration of consumption patterns shifting, which needs to include meteorological and economic variables in prediction models and policy planning for DH systems.

3.5 Model Training, Evaluation, and Estimation

To make a comparison between real-time district heating demand and predicted values using test data sets, air temperature and energy price were considered as the independent variables, and DH demand was considered as the target variable. Potential forecasting energy demand has been pointed out through the graphical representation of the prediction method. Through this process, effective planning methods, operational efficiency, and optimisation of cost management in DH systems can be achieved.

To evaluate the DH system's flexibility, an analysis of the temperature-independent component of DH energy consumption was carried out. The Python framework was assigned to extract the temperature-independent consumption that is not directly influenced by temperature variation. The temperature-independent component was used to estimate the flexibility using linear regression, executed as a baseline method. To further develop the analysis method, additional ML approaches such as XGBoost, LightGBM, Lasso and Ridge Regression were implemented in comparison to the Linear Regression method. The evaluation from the comparison across different models demonstrated the variations in the accuracy of prediction and resilience. The models' comparison allows the system to facilitate and employ the most suitable and viable ML option for flexibility estimation. To regulate DSM and possible forecasting implications, this holistic model evaluation approaches promote the flexibility dynamics comprehensively and insightfully.

4 Forecasting Analysis

To estimate the DH energy consumption considering explanatory variables like energy price and temperature, the forecasting analysis involves the development of a prediction. Followed by the data pre-processing, data processing, and feature selection, several ML methods were trained and validated. An organized framework has been developed, which facilitates proper operational planning, flexibility estimation and strategic development in DH systems.

4.1 Data Compilation and Pre-processing

The data is formatted into Excel and CSV formats. This process ensures a more flexible data handling, accurate, and consistent for modeling and time-based operations. To enable an efficient time-based conversion, splitting, and aggregation, numerous Python libraries have been utilised. Pandas was used for data manipulation and conversion, where for statistical calculation and numerical operations, NumPy has been used, and Matplotlib and Seaborn have been utilized for the insightful graphical data representation. The final pre-processed data set is stored in a CSV and Excel format for easy access, and the final pre-processed step ensures that the data is error-free, well-structured, and ready for further analysis.

4.2 Heatmap Plotting and Correlation Analysis

To observe the correlation between DH power consumption, energy prices, and temperature, and to get proper visualization of both Pearson and Spearman correlation coefficients, Heatmap plots were generated. The Spearman correlation coefficient evaluates linear correlations; hence, it is appropriate for non-linear correlations, where the Pearson correlation coefficient evaluates the linear relationship among variables. The data set was split into years to enable a comparison of the correlation between years. There are two important observations made under the Pearson and Spearman correlation. Figure 3 represents the Pearson correlation matrix observation, and Figure 4 shows the Spearman correlation matrix observation from 2015 to 2023.

Figure 3. Pearson correlation matrix 2015-2023

4.2.1 Pearson Correlation Matrix Observation

- From the Pearson Correlation matrix, it shows that both energy price and temperature influenced DH consumption, but temperature seems to have a greater impact.
- Both price and temperature are correlated, as higher temperature reduces heating demand and higher prices are likely to increase DH consumption, which leads to system optimization.

4.2.2 Spearman Correlation Matrix Observation

- Based on the Spearman Correlation, it shows that DH is strongly affected by air temperature because heating demand is strongly affected by shifts in the temperature.

- Energy price has less significant correlation with DH consumption, although it has dependency on air temperature, and it reflects that energy price has a fluctuation based on the temperature-driven heating demand.

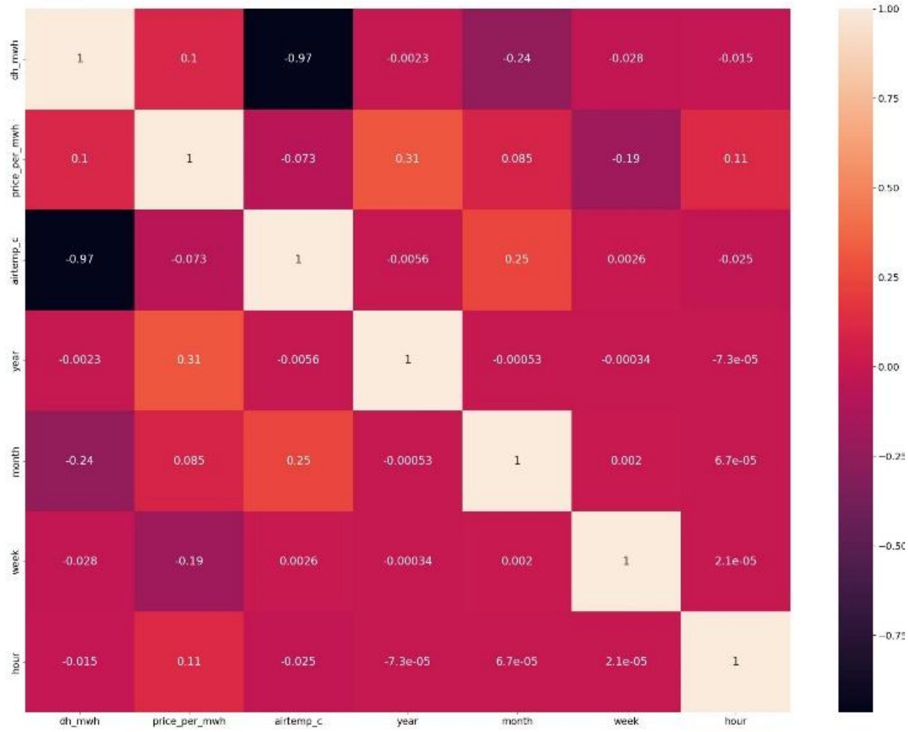

Figure 4. Spearman correlation matrix 2015-2023

4.2.3 Data Analysis of 2015 to 2023

Pre-2023 analysis indicates two significant factors from Pearson and Spearman correlation coefficients –

- Temperature seems to be one of the most dominant factors influencing DH power consumption during this time. The correlation coefficients show a significantly consistent connection between DH power consumption and temperature.
- Energy prices have no significant impact on DH power consumption. From heatmap plotting, both Pearson and Spearman correlation coefficients seem close to zero, which indicates that energy prices have little impact on the energy consumption pattern during this period.

4.3 Model Comparison Plotting 2015-2023

From the comparative result discussion, the model's features with advantages and shortcomings can be addressed, and comparisons facilitate the dynamics of DH power consumption. It is the methodological comparison that can classify the most consistent and precise modeling method. For providing consistent and accurate forecasts, the following models were implemented and evaluated. Figure 5 compares the various models from 2015 to 2023.

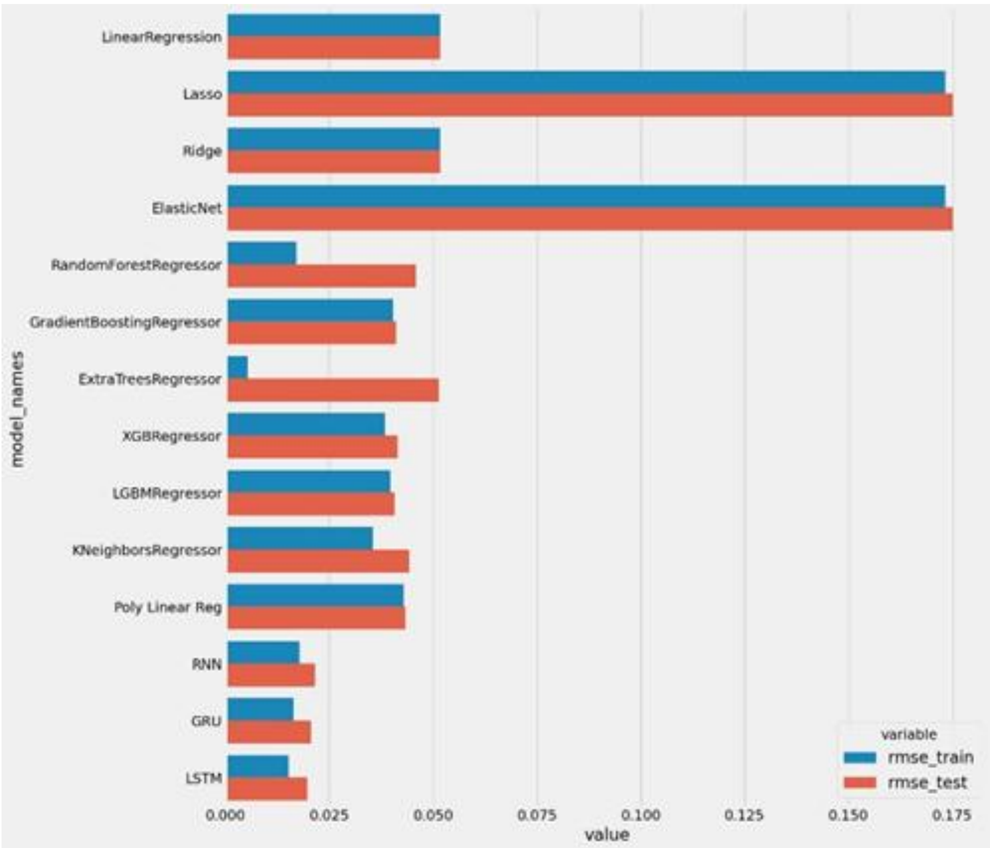

Figure 5. Model comparison for 2015-2023

4.4 New Data Frame Analysis for 2023

The connection in the Pearson in Figure 6, and the Spearman correlation matrix in Figure 7, can be further illustrated through graphical visualization, which provides clearer connections among the variables. The results demonstrate a shift in the variables that influence the DH power consumption over time.

4.4.1 Pearson Correlation Matrix 2023

From 2023, the correlation observation indicates a remarkable ascending graph, where, before 2023, the correlation between the electricity price and the DH consumption graph of Pearson and Spearman was negligible. In 2023, energy prices began to have a strong impact on the DH power consumption. The Pearson correlation coefficient between DH power consumption and energy price was 0.36, which indicates a moderate linear relationship between hourly energy price fluctuations and DH energy consumption.

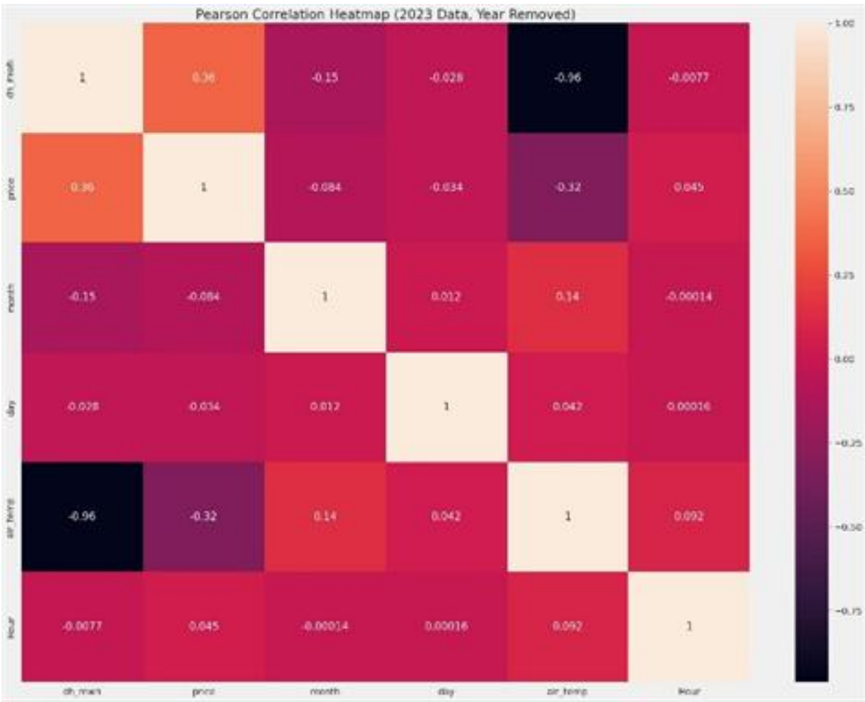

Figure 6. Pearson correlation matrix 2023

4.4.2 Spearman Correlation Matrix 2023

The transformation towards shifting to price indicates that DH consumption and DH operators are not only weather-dependent but also sensitive to increasing energy price fluctuations. Spearman correlation coefficient increased to 0.43, indicating a strong linear relation, where consumers are responding to the fluctuating pricing. These facts suggest that there is a significant relationship, which makes energy prices a considerable factor. This shift highlights a trend in the factors influencing DH power consumption, with energy prices becoming more of a concern, and this shift suggests a few aspects potentially driven by:

- A shift towards a system of demand-side flexibility.
- Promotes cost-saving approaches among the end-users and operators.
- To maintain and enhance the forecasting techniques and to integrate with the price fluctuations in demand prediction, DH operators should consider refined forecasting models.
- The end-users, especially commercial and industrial users, would benefit from the autonomous demand response systems, which will maximise the use of heating according to real-time pricing.

Figure 7. Spearman correlation matrix 2023

From 2023, the patterns of DH consumption indicate a dual model, shifting from a climate-driven factor, where economic indicators like spot pricing have an influential role.

The observation pattern highlights increasing integration among technical implementation, the dynamics of the market, and energy consumption patterns.

4.5 Flexibility Estimation Process

The flexibility estimation process has been further developed by applying several ML strategies to identify the temperature-independent component underlying the DH energy consumption. Along with the baseline LR method, sophisticated ML algorithms were employed to integrate a regularization feature that improved stability as well as overfitting reduction. The ML algorithms provide a deep understanding of the DH system's adaptability, followed by accuracy and precision.

4.5.1 Prediction vs Real Values using RNN

The model RNN was utilised to observe the DH energy demand prediction. From Figure 8, the findings of the model prediction through RNN are analyzed.

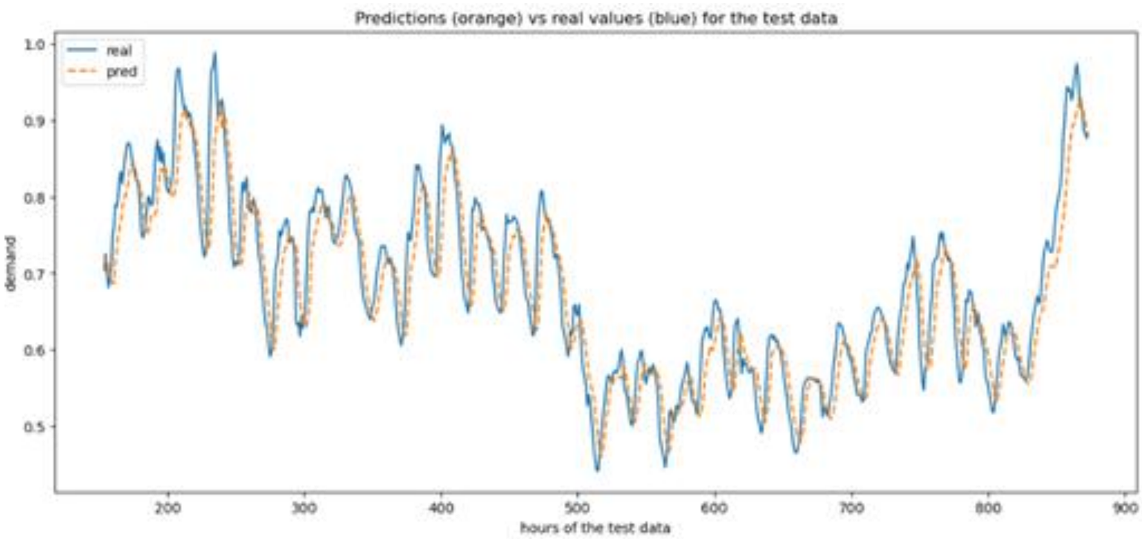

Figure 8. RNN model prediction for actual vs predicted test data

- From the graph, both lines, blue (real value) and orange (prediction values), are very close, which indicates the model can generalise well.

- An indication of air temperature and price both play a vital role in DH energy demand.
- Repetitive oscillations over the graph represent the seasonality or variability within the data.
- At some points, like at ~200 and ~870hours, the predicted lines significantly lag the actual lines.
- In the heavily populated and speedily changing areas, like at ~250-400hours and ~700-850hours, the model has a consistent alignment with the actual data without showing considerable fluctuation.

From the observation, the selected model can be utilised for forecasting techniques, and RNN can retain and utilize the historical data over noisy patterns. It can also handle the variability and periodic trends without showing significant deviation.

4.5.2 Prediction vs Real Values using GRU

The main predictive variables are air temperature and the price of energy, and the objective of the model is to explain the DH energy consumption variation.

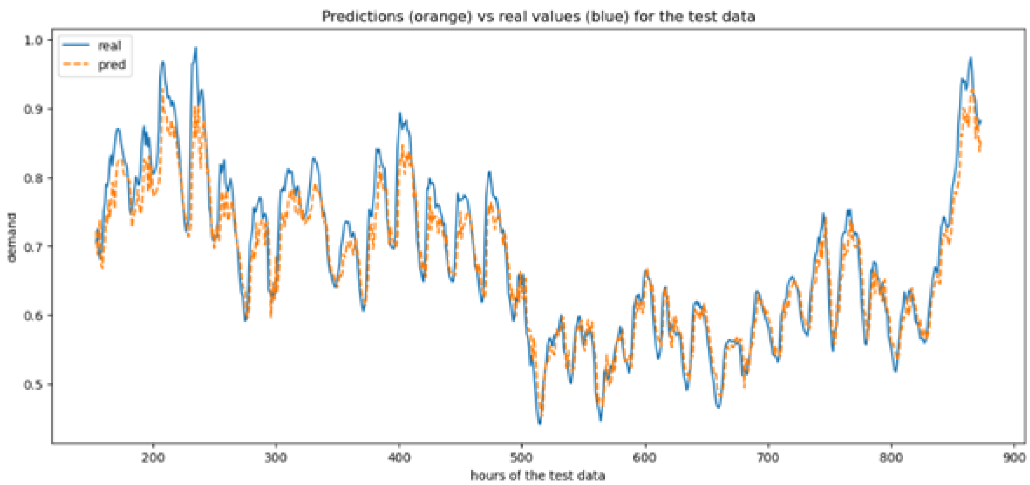

Figure 9. GRU model prediction for actual vs predicted test data.

The visualisation of Figure 9 acts as an essential part of assessing a model's prediction efficacy in predicting DH energy demand.

- GRU has strong predictive power since the line of prediction (orange) is similar to the demand in reality.
- GRU gives an accurate and stable prediction, which attests to its expertise in dealing with time series.
- GRU can effectively detect the short-term and mid-range dependencies within the data.
- GRU is capable of capturing the periodic pattern that is composed of amplitude and frequency oscillations.
- At hours ~270, 370hours, and 500-520hours, predicted values are lower than actual values.

From the graphical plotting, it is observed that GRU was properly trained for the time series and had sufficient training data to generalise the new and unexpected cycles. It can be a suitable option for a forecasting method since economic and energy markets are influenced by consumption patterns, as GRU has the dynamic adaptation of a memory mechanism.

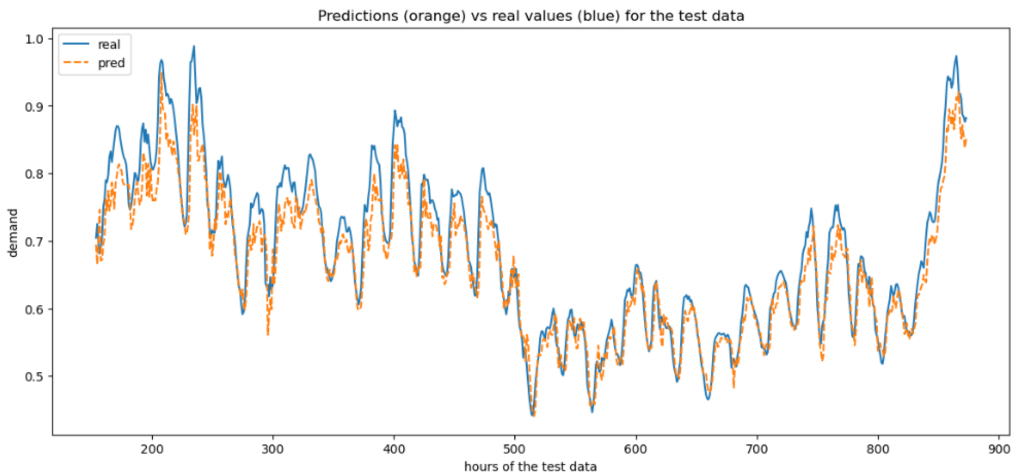

Figure 10. LSTM model prediction for actual vs predicted test data

4.5.3 Prediction vs Real Values using LSTM

The visualisation of Figure 10 shows how effectively the LSTM model can capture temperature dependencies and fluctuations in heating demand.

- The LSTM provides accurate forecasting values of DH energy demand, where predicted values closely align with actual values.
- LSTM is capable of capturing both long and short-term periodic changes and demonstrates the capability to gain sequential dependencies.
- LSTM stores previous data inputs of extended hours, which is important for time series analysis like energy demand, where historical usage patterns influence future patterns.
- LSTM can effectively capture the repetitive pattern, like, at ~150-450hours and ~700-850hours, the predicted lines closely align with the actual lines.
- LSTM has no overfitting, where the basic pattern is learned instead of training noise being memorised.

LSTM can adapt to the unpredictable patterns as the predictive curves shift with the actual demand pattern. It has appropriate regularisation as well as a precise number of hidden units and layers. LSTM has strong generalisation ability and error reduction since it can be the optimised fit for complex time-series forecasting tasks.

4.6 Model Performance Analysis 2023

Followed by the various trained machine learning and deep learning models for the 2023 DH data sets, their effectiveness was evaluated through Root Mean Square Error (RMSE) for both training and testing data sets. The importance of RMSE is that it shows the level of average magnitude of errors, smaller values of which imply higher accuracy of predictions. Comparing RMSE values allows the models to evaluate prediction effectiveness, as well as checking whether the model is overfitting or underfitting. As illustrated in Figure 11, the level of performance is compared between various models in 2023.

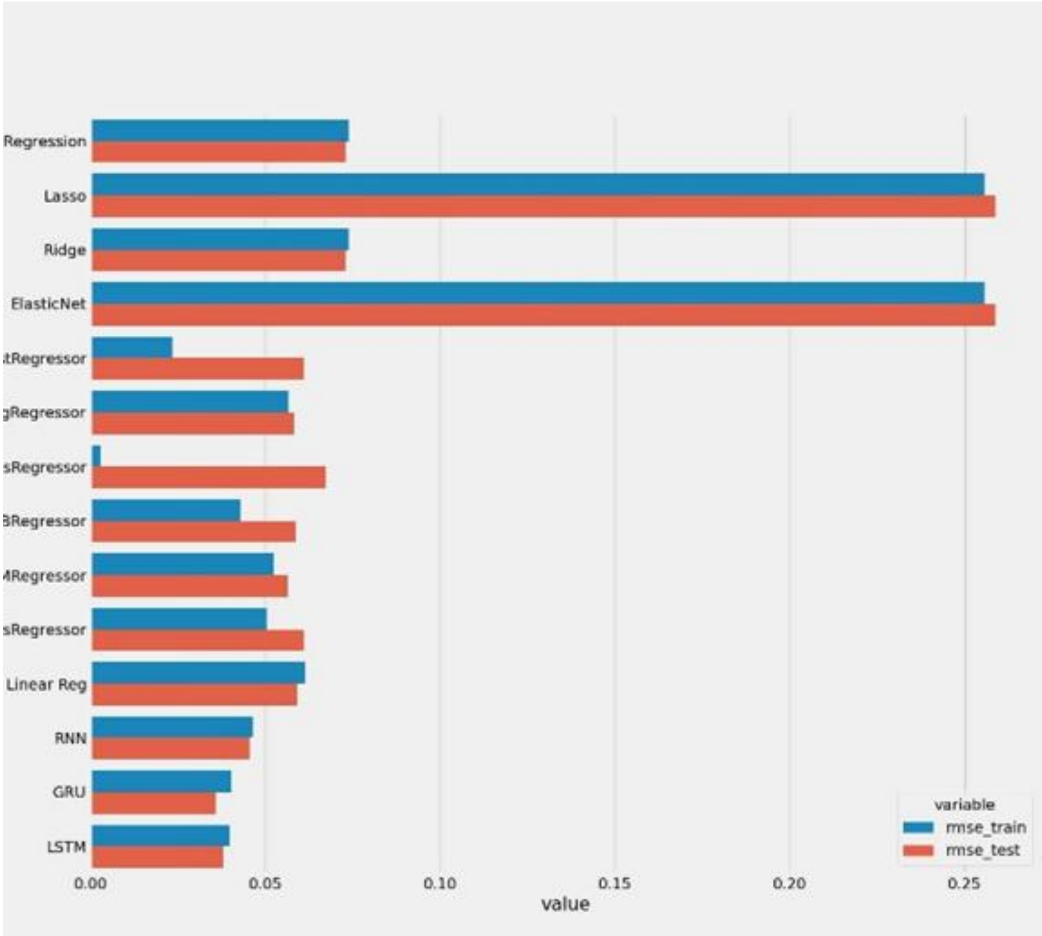

Figure 11. Comparison between different models for 2023

4.6.1 Linear Models (Linear Regression, Ridge, Lasso, ElasticNet)

Liner and Ridge have consistently performed with RMSE, suggesting a steady performance, while Lasso and ElasticNet showed greater RMSE, indicating poor forecasting ability.

4.6.2 Tree-Based Models

Random forest and Extra Trees come up with overfitting problems, and due to having a good balance with test RMSE, Gradient Boosting, XGBoost, and LightGBM proved a good generalization.

4.6.3 K-Nearest Neighbors & Polynomial Regression

They both have moderate performance which is not competitive comparing to the boosting models and recurrent models.

4.6.4 Neural Network Models (RNN, GRU, LSTM)

Neural network models performed well compared to others, where RNN exceeded most traditional models. Other RNN models like GRU and LSTM had the overall best performance. This performance suggests that recurrent networks are the optimised fit for capturing temperature-dependencies in the DH energy system.

4.7 Flexibility Estimation Analysis

Flexibility estimation of DH power is a very important stage and analysis of the degree to which the DH system can shift the extent of energy it needs without being disrupted by other influences, particularly weather. Being able to modify these parameters can be beneficial for making the DH system operate more effectively, especially in regions where prices for energy and weather fluctuations occur very often. The main objective of this phase is to measure the component of DH power usage that is not affected by temperature. It helps to determine what proportion of the consumption is affected by variables other than temperature, like the price of energy. Numerous machine learning models could be used to predict the temperature-independent component of DH systems; however, this study aims to further extend the understanding of flexibility in DH systems through the evaluation of several machine learning models to predict the most accurate forecasting estimation. The purpose is to model the connection between DH power consumption and temperature, then remove the impact of temperature by creating a component that is not affected by temperature. To achieve this, the following methods have been used –

(1) Machine Learning Models: Lasso, Ridge, XGBoost, GRU, LSTM, and LightGBM are the six different models used to achieve the desired comparative analysis. There are advantages to considering this procedure, as the models can help capture the excessive variation in temperature-dependent DH consumption.

(2) Residual Calculation: The difference between the actual and predicted values of DH consumption is known as the residuals, and it represents the component of DH consumption that is temperature independent. The basic concept is that the models consider temperature and attribute any remaining modifications to other factors like energy pricing, consumer behaviour patterns, or operational situations.

(3) Plotting: To make a visual comparative analysis, the residuals of each model are plotted in a time series graphic representation. The following graphical representation gives an assessment of the DH consumption dynamics with or without consideration of the status of temperature, providing an estimate of the extent and trends of variability independent of temperature among the different models.

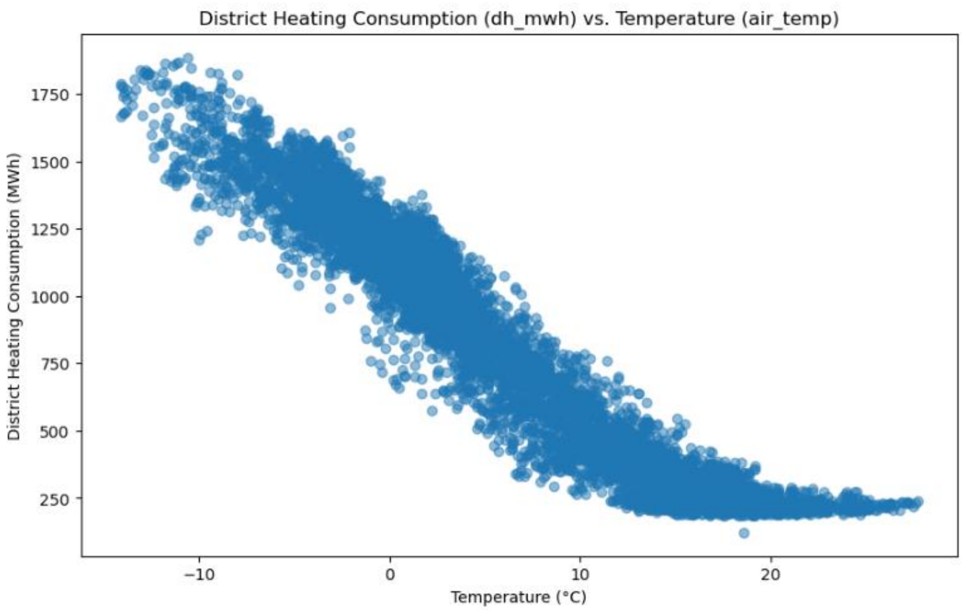

Figure 12. DH consumption (MWh) vs temperature (°C)

4.7.1 Temperature Independent Component Identification

From the illustrated plot of Figure 12, it is evident that district heating energy consumption is influenced by outdoor air temperature, and the demand for district heating in winter is remarkably high when the consumption in summer is relatively low. These variations of this energy demand and consumption indicate that a major portion of district heating energy consumption is directly temperature-based. This temperature-driven part is non-flexible and can not be altered due to consumers' behaviour and demand. Figure 12 illustrates the plotting of DH consumption in (MWh) vs Temperature in (°C).

Not all the components in DH systems are temperature dependent. For different applications like hot water supply, manufacturing operations, and other persistent activities throughout the year, a temperature-independent baseline is needed. Identification of a temperature-independent baseline is important, as it can be the actual measure of potential demand-side flexibility. Dh operators can estimate an overall power allocation and optimization without affecting consumers' comfort by isolating temperature-independent components.

4.7.2 Temperature-Independent and Dependent Identification

Evaluation of district heating use by splitting the difference between the DH mWh, between temperature-independent and temperature-dependent portions, makes the process simpler. A regression model can be applied by using district heating consumption as the dependent variable and outdoor temperature as the explanatory variable. The amount of energy required for indoor heating is explained by the temperature-dependent components. Inversely, the other portion of energy consumption, which remains unknown by the temperature, is captured by the model residuals and represents temperature-independent components.

4.7.3 Calculation of Temperature-Independent Component

Statistical parameters such as standard deviation and variance may be employed in order to test the flexibility of the temperature-independent component. Mean value calculation can determine the range of flexibility, and it can be extended by one standard deviation in both directions. Following this method, the actual estimation of district heating demand can be adjusted or shifted without affecting the consumers' usage patterns.

4.7.4 Temperature Variant Components

To illustrate the breakdown of temperature-independent and temperature-dependent components among the district heating, numerous machine learning methods have been employed.

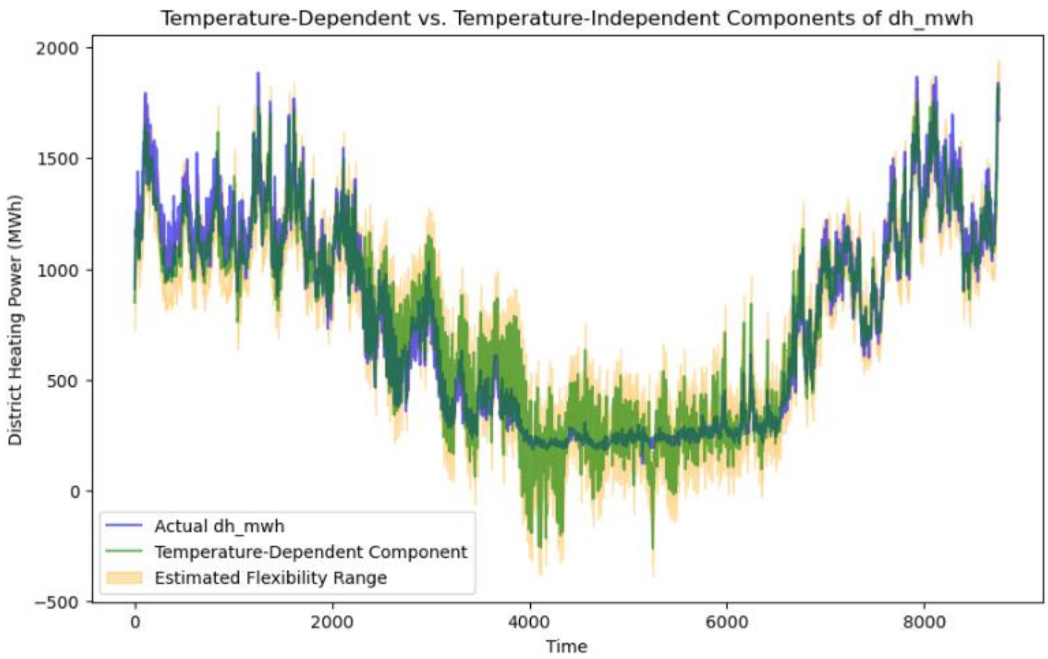

Figure 13. Temperature-independent vs temperature-dependent components of DH_MWh

As shown in Figure 13, the temperature-dependent term compares closely with the actual energy demand, which is correlated to the temperature within the surrounding air in outdoor temperatures. The temperature-independent term defines the possible fluctuation of energy demand where temperature is not accountable. The analysis of both components highlights the amount of district heating demand that is adjustable, and this leads to promoting the incorporation of demand-side management techniques into energy systems.

4.7.4.1 Comparison Using Lasso

A regression analysis (Lasso and Ridge) is used to deconstruct the district heating demand (dhmwh) into temperature-independent and temperature-dependent components. Unlike other linear regressions, Lasso makes an adjustment to the absolute values of regression coefficients, which helps to mitigate the overfitting. This also helps to improve the model's reliability in noisy and high-dimensional data. Lasso forecasts the temperature-dependent component, and this portion of district heating demand fluctuates with outdoor temperature, mostly referring to space heating.

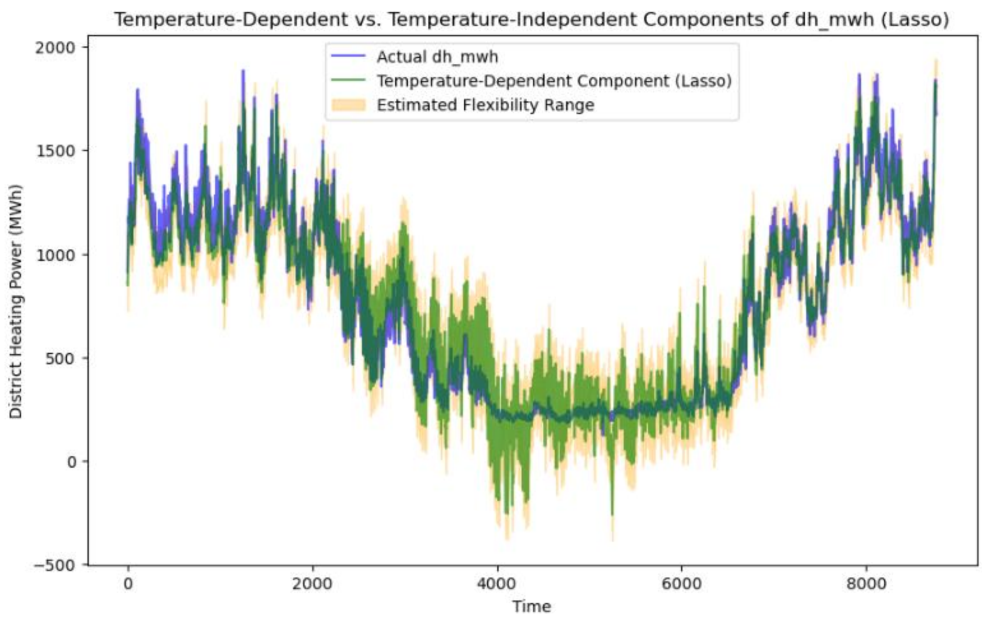

Figure 14. Temperature-independent vs temperature-dependent components of DH_MWh using Lasso

The Lasso residuals of temperature-independent component, which are covered in their residual, include baseline consumptions, which consist of hot water consumptions and industrial heating processes. Mean and standard deviation calculations provide an expected range of flexibility that can be modified according to demand. Lasso provides a stable and reasonable breakdown than other linear regression methods. Figure 14 shows the graphical representation of temperature-dependent and temperature-independent components of DH in MWh by use of Lasso.

4.7.4.2 Comparison Using Ridge

Ridge is a form of regularized linear regression method that includes an L2 penalty on the magnitude of coefficients. Lasso shrinks the coefficients precisely to zero when Ridge shrinks them proportionally and ensures a more stable estimation where data contains variance and multicollinearity.

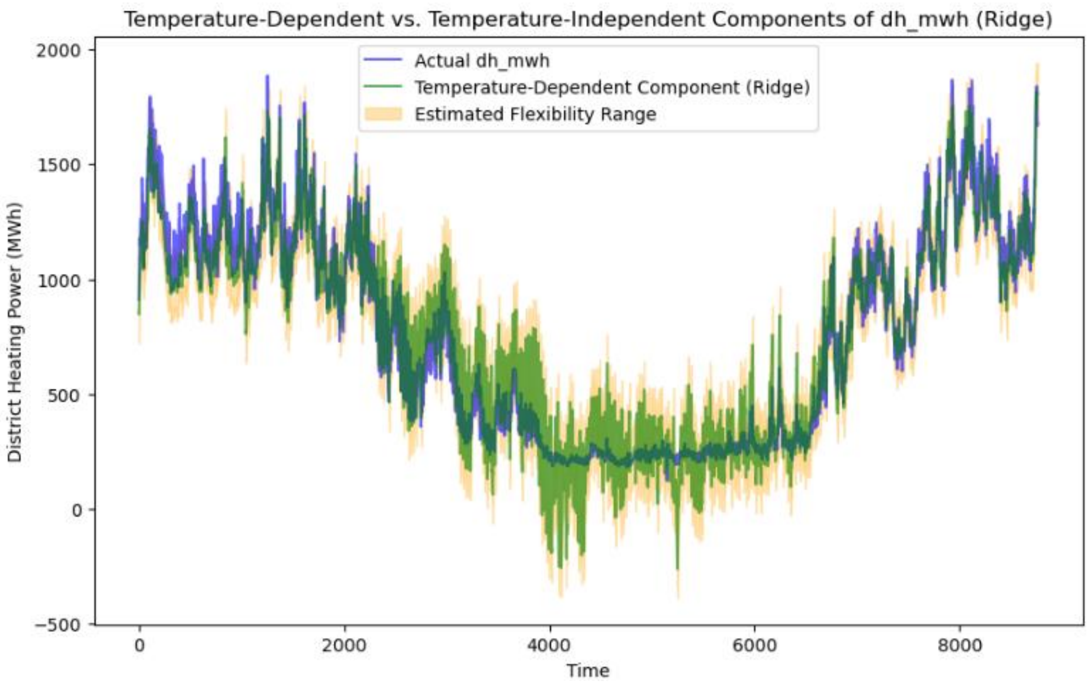

Figure 15. Temperature-independent vs temperature-dependent components of DH_MWh using Ridge

Calculating the mean and standard deviation of the temperature-independent component, Ridge provides a flexibility estimation of -125.80 MWh to 125.80 MWh. Contrary to other linear regressions, Ridge fosters extra robustness in the malleability, in the case where the condition is high-noise, allowing an efficient approach to demand-side flexibility. Figure 15 demonstrates the comparison between temperature-dependent vs. temperature-independent components of DH in MWh using Ridge.

4.7.4.3 Comparison Using XGBoost

XGBoost (Extreme Gradient Boosting) is a strong tree-based algorithm that can generate many decision trees sequentially and combine them to reduce the prediction error. In contrast to linear techniques like Lasso and Ridge, XGBoost can identify the nonlinear and complicated correlations among variables.

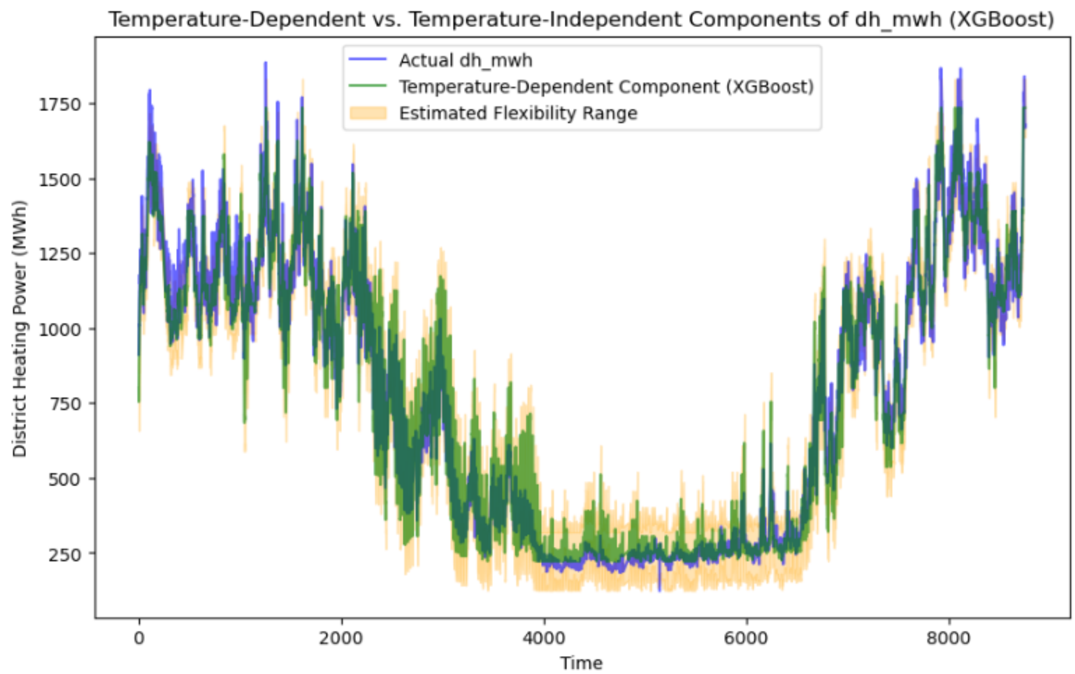

Figure 16. Temperature-independent vs temperature-dependent components of DH_MWh using XGBoost

In a nonlinear situation, XGBoost provides a more accurate relationship between heating demand and temperature, along with more flexibility than other linear models. XGBoost counts all small changes within heating patterns throughout different temperature ranges; hence, the potential flexibility identified by XGBoost is more accurate. Figure 16 demonstrates the comparison between temperature-dependent vs. temperature-independent components of DH in MWh using XGBoost.

4.7.4.4 Comparison Using GRU

In particular, the Gated Recurrent Unit(GRU) is a special form of the recurrent neural network (RNN) that involves a gating mechanism to explicitly recollect and discard information, allowing the capture of time dependencies in the sequential data. GRU is more appropriate compared to linear and other tree-based models when forecasting a time series because it relies on both long-term and short-term implications of heating demand.

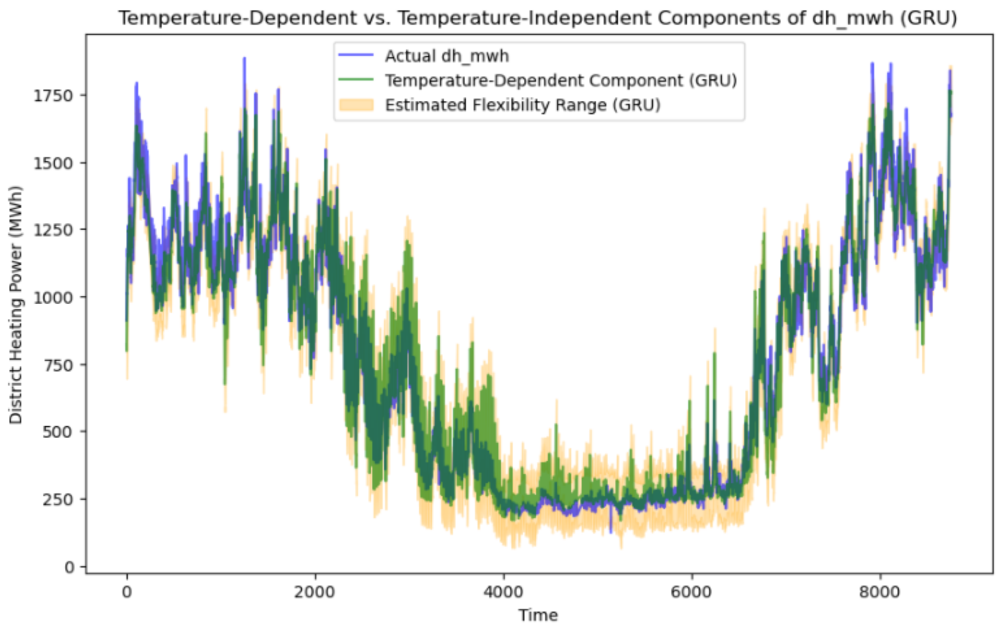

Figure 17. Temperature-independent vs temperature-dependent components of DH_MWh using GRU

GRU offers a more agile and flexible reflectivity between demand and temperature than Ridge, Lasso, and XGBoost, which are linear models. Capturing nonlinear patterns and temporal variation where demand is measured by both being temperature-driven and time-dependent, the best fit to a real-world district heating system is capturing that demand. In MWh, the comparison between temperature-dependent and temperature-independent components of DH was given in Figure 17 through GRU.

4.7.4.5 Comparison Using LSTM

Long-Short Term Memory (LSTM) is a sophisticated RNN type to recognise long-term dependencies in sequential data by using its memory and gating mechanism. LSTM efficiently stores and applies information for a long time, which makes it the best fit for time-series-based energy consumption predictions.

For modeling linear, dynamic, and time-dependent correlation between temperature and heating demand, compared to other tree-based algorithms like XGBoost and linear algorithms like Linear Regression, Ridge, and Lasso, LSTM offers a more comprehensive framework. Comparison of the temperature-dependent and independent components of DH in MWh with LSTM is shown in Figure 18.

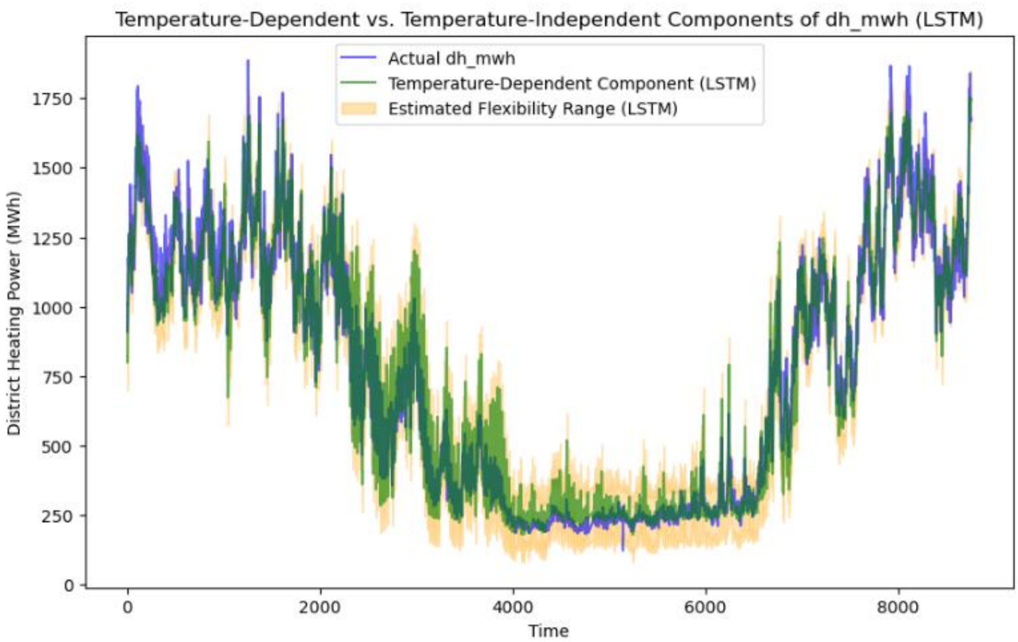

Figure 18. Temperature-independent vs temperature-dependent components of DH_MWh using LSTM

4.7.4.6 Comparison Using LightGBM

Light Gradient Boosting Machine (LightGBM) is a swift and accurate gradient boosting algorithm framework that generates leaf-wise decision trees. Compared to Ridge and Lasso, LightGBM can address nonlinear correlation, and fragile threshold impacts between temperature and heating demand. LightGBM has the capabilities to make an appropriate balance between accuracy and interpretability for large-scale district heating flexibility. Figure 19 demonstrates the comparison between temperature-dependent vs. temperature-independent components of DH in MWh using LightGBM.

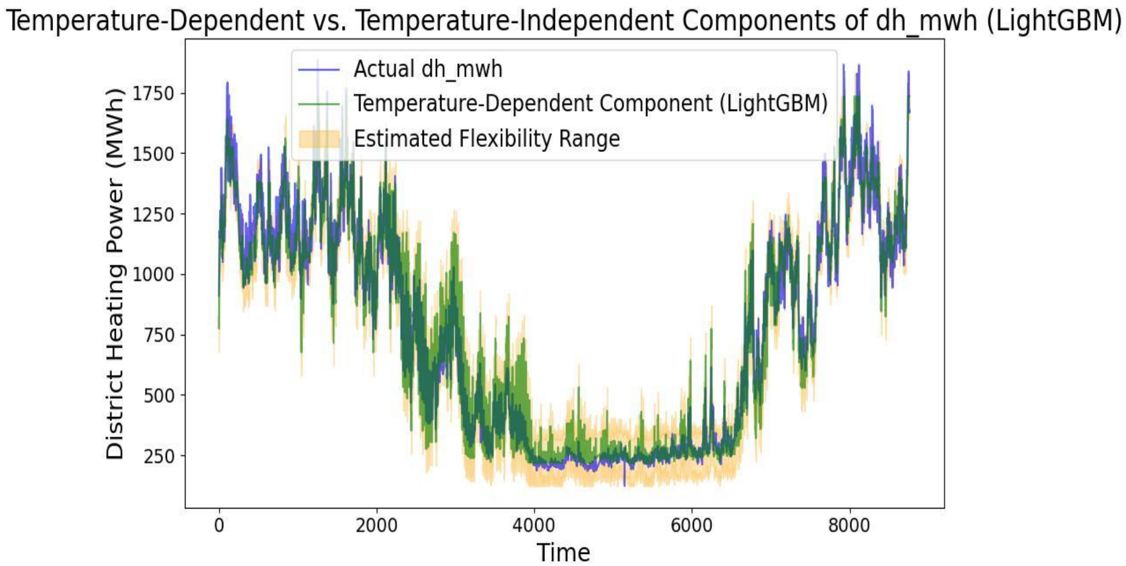

Figure 19. Temperature-independent vs temperature-dependent components of DH_MWh using LightGBM

5 Flexibility Estimation Discussion

After estimating the temperature-independent component, the next step is to calculate the flexibility of DH power consumption. The term flexibility refers to the ability of the system to adjust to temperature changes independently, which is one of the important factors for a DH system to integrate with the smart grid and market-based pricing mechanisms. Flexibility estimation typically involves a statistical assessment of the rapid speed and duration of divergence of baseline operation where the DH system can withstand.

5.1 Temperature-Dependent Demand Performance Analysis

To identify the most accurate and reliable flexibility estimation, comparison of several models, for instance, Lasso, Ridge, XGBoost, GRU, LSTM and LightGBM has done using error metrics. The result shows that –

(1) All the traditional models (Linear Regression, Ridge, Lasso) have similar performance with an RMSE ≈ 125.97 and $R^2 \approx 0.9233$. Compared to more advanced models, these models are incapable of detecting nonlinear connections in data, resulting in larger errors.

(2) Compared to traditional models, tree-based models performed significantly better, where RMSE of XGBoost is ≈ 96.96, and $R^2 \approx 0.9544$ and for LightGBM RMSE is ≈96.52 with $R^2 \approx 0.9548$.

(3) Deep learning models GRU and LSTM performed strongly with RMSE ≈ 112.78 and $R^2 \approx 0.9383$ and for LSTM, RMSE ≈ 117.89 and $R^2 \approx 0.9326$. GRU, as well as LSTM, proved effective in dealing with changes over better than linear regression, and yet they are slightly less accurate than XGBoost and LightGBM.

Table 1. Model Performance Metrics for Temperature-Dependent

Model	RMSE (MWh)	(R^2)	Residuals Flexibility Range in MWh
Linear Regression	125.79	0.9233	-125.80 MWh to 125.80 MWh
Lasso	125.79	0.9233	-125.80 MWh to 125.80 MWh
Ridge	125.79	0.9233	-125.80 MWh to 125.80 MWh
XGboost	96.96	0.9544	-96.96 MWh to 96.96 MWh
LightGBM	96.52	0.9548	-96.53 MWh to 96.53 MWh
GRU	112.78	0.9383	-105.94 MWh to 119.25 MWh
LSTM	117.89	0.9326	-89.01 MWh to 141.00 MWh

5.2 Optimize Model for Temperature-Dependent

After analysing all the models' performance, LightGBM provides the overall performance with the lowest RMSE (96.52 MWh) and highest R^2 (0.9548). This proves that LightGBM generated the lowest prediction errors and covered the most variance in the data. Figure 20 shows the comparison between the temperature-dependent predictions of various models in the plot.

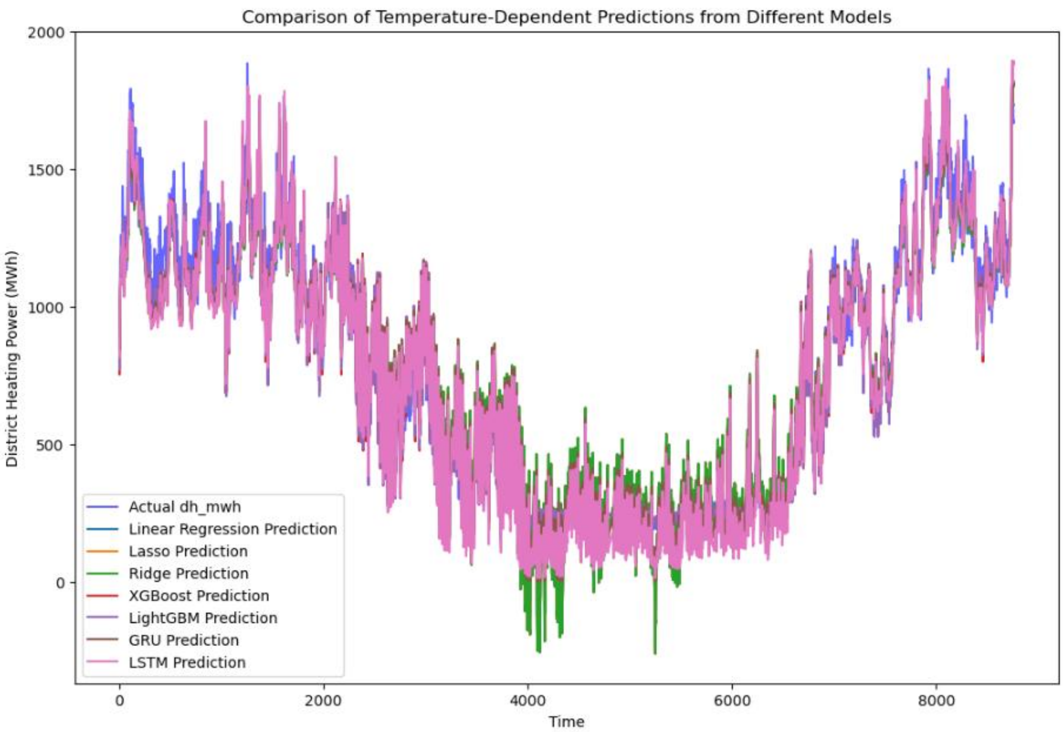

Figure 20. Comparison of different models' temperature-dependent predictions

(1) The reason for the effective performance of LightGBM and XGBoost, compared to comparatively deep learning models, can be defined as their ability to effectively describe nonlinear patterns in data without requiring considerable feature engineering or larger datasets.
(2) GRU and LSTM tended to perform well with long-term dependencies in time and highly detailed sequence data.
(3) This means that LightGBM is the most effective for implementing this task, achieving an ideal balance of accuracy, interpretability, and computational performance.

5.3 Performance for Temperature-Independent Demand Analysis

To separate the temperature-independent element from district heating demand from temperature-independent residuals, various models have been evaluated to achieve prediction efficiency. This was carried out by training different models using air temperature as the main predictor and considering the remaining residuals as the unexplained portion of energy demand. The result of the temperature-independent analysis is shown below –

(1) Linear Regression, Ridge, and Lasso provide almost identical results (RMSE ≈ 125.79 MWh), and ($R^2 \approx 0.9233$), and these models can detect the linear correlation between heating and air temperature but are inappropriate for detecting nonlinear relations. The flexibility range seems comparatively wider (±125.80 MWh), which is not suitable for precise prediction.
(2) XGBoost shows the (RMSE ≈ 96.96 MWh) and ($R^2 \approx 0.9544$), indicating a better improvement since it can identify nonlinearities. It is an important indicator of heating demand, which is nonlinear. LightGBM has (RMSE ≈ 96.52 MWh) and ($R^2 \approx 0.9548$), which is better than XGBoost and can detect nonlinearities and fluctuations. Compared to XBoost, it has a smaller flexibility range (±96.53 MWh), whereas XGBoost has (±96.96 MWh). This makes the LightGBM more consistent for temperature-independent demand prediction.

(3) Compared to Linear models, GRU performs better but is not capable of withstanding boosting models. It has (RMSE ≈ 115.02 MWh) and ($R^2 \approx 0.9358$) and it can detect temporal dynamics better in sequential data series. LSTM has (RMSE ≈ 133.07 MWh) and ($R^2 \approx 0.9141$), providing poor performance, and it requires more variance in data to be outperformed. Table 2 shows all the comparative metrics among all the methods.

Table 2. Model performance metrics for temperature-independent

Model	RMSE (MWh)	(R^2)	Residuals Flexibility Range in MWh
Linear Regression	125.79	0.9233	-125.80 MWh to 125.80 MWh
Lasso	125.79	0.9233	-125.80 MWh to 125.80 MWh
Ridge	125.79	0.9233	-125.80 MWh to 125.80 MWh
XGboost	96.96	0.9544	-96.96 MWh to 96.96 MWh
LightGBM	96.52	0.9548	-96.53 MWh to 96.53 MWh
GRU	115.02	0.9358	-104.28 MWh to 124.87 MWh
LSTM	133.07	0.9141	-69.93 MWh to 174.73 MWh

5.4 LightGBM, the Optimized Model for Temperature-Independent

In Figure 21, the different models used in DH MWh compare their temperature-independent predictions. The LightGBM demonstrated a lower RMSE value, higher R^2 and the narrowest flexibility range, which makes it the best fit model. The metrics in this case determine how well this prediction of air temperature (dh_MWh) can be predicted. The residual, followed by the forecasting result, is the temperature-independent part. Reasons LightGBM stands out as the optimised model, followed by:

(1) Due to the lowest RMSE value, LightGBM can provide more accuracy.

(2) The reason LightGBM is the optimised model is that a Higher R^2 explains most of the data variation and shows that the flexibility range can be as useful by having a steadier estimation of the temperature-sensitive demand.

(3) LightGBM is classified as the optimised model due to the better prediction ability of the nonlinear temperature response, leading to an accurate residual that represents the temperature-independent demand.

(4) By capturing the major portion of the temperature-dependent component, LightGBM generates the residual. These residuals reduced in variance, showed no correlation with temperature, and were indicative of more temperature-independent consumption.

LightGBM perfectly captures the correlation between DH demand and outdoor temperature. The residual part offers an accurate illustration of the temperature-independent component, which can shift and modify, and is the key flexibility indicator.

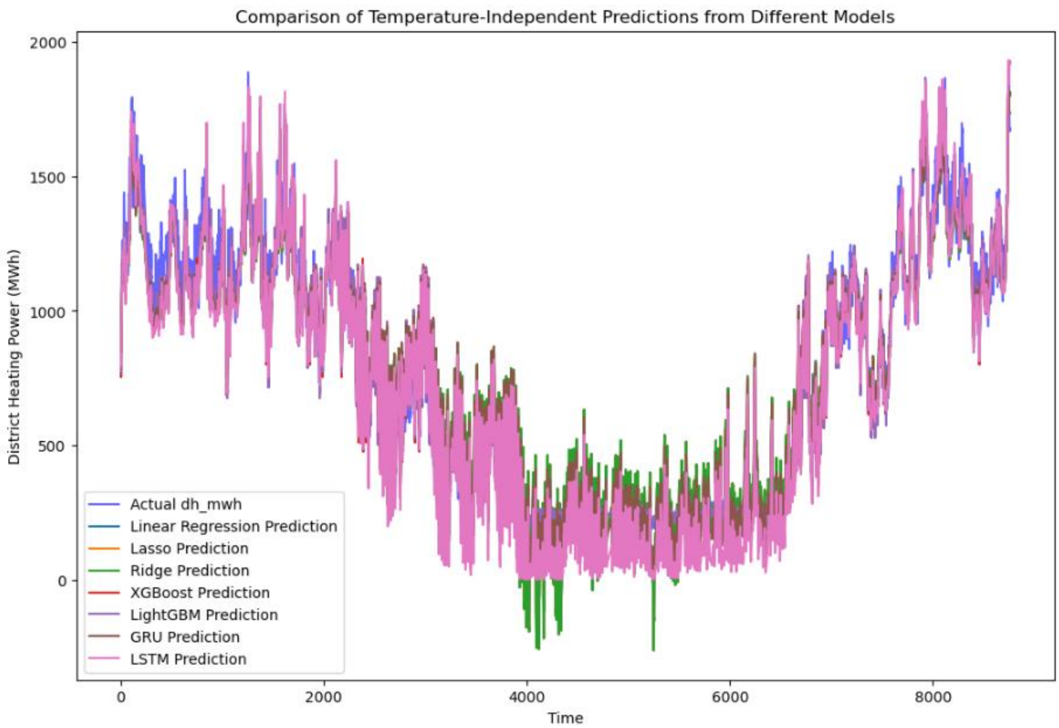

Figure 21. Comparison of temperature-independent predictions from different models

5.5 Result Discussion

The result demonstrated that, predicting the temperature-independent components of district heating demand, a combination of boosting models (LightGBM and XGBoost) performed better than traditional linear regression models (Linear, Ridge, Lasso), and Neural Network (GRU and LSTM). Among all the models, LightGBM obtained the lowest RMSE value (≈ 96.5MWh) and a higher ($R^2 \approx 0.9548$), making this model outperform the most reliable predictor. Due to limited features in data sets, LSTM (RMSE $\approx$ 133.07 MWh, $R^2 \approx 0.9141$) and GRU (RMSE $\approx$ 115.02 MWh, $R^2 \approx 0.9358$) have shown poor performance. As the air temperature was the sole input, the RNN could not properly utilize its sequential advantages. RNN functions effectively with multivariate, sequential datasets which connected with latent demand, structural characteristics, and variables related to weather.

The portion of the expected flexibility range that is temperature-independent in the DH system does not affect the external temperature fluctuations. As boosting models showed smaller RMSE, they can efficiently isolate the temperature-independent component, and the wider flexibility range of LSTM is associated with unstable flexibility estimation. The potential of flexibility is important in DH energy demand as it acts as an indicator of how much energy should be shifted or altered without affecting the end-users' side.

5.6 Implications

The study contributes a comprehensive understanding of the portion of potential flexibility. Isolation of this component carries significant meaning, as based on this, policy makers can estimate the extent of DH flexibility through predicting the temperature-independent DH power. From the results, it is evident that boosting models are appropriate for the practical applications of DH forecasting procedures. Boosting models quantify with precision excellence along with computational efficiency and are adaptive to the systems. The effectiveness of flexibility estimation has an inherently conditioning influence over grid management, RES integration and peak load management; to reach the sustainability wherein the objective is to reduce the reliance on fossil fuels.

6 Conclusion

The goal of this thesis was to assess the efficiency of different models and their prediction capabilities of DH demand, and the extent of flexibility potential based on the temperature-independent component. The study provides fresh insights into procedures of different statistical methods and how they work in DH flexibility in comparison with standard statistical methods, machine learning methods, and deep learning algorithms.

6.1 Summary of Findings

From the findings, LightGBM and XGBoost become the most accurate for predicting with the lowest RMSE (≈ 97 MWh) and highest R^2 (≈ 0.95). These models can generate the narrowest and most stable flexibility range (±96 MWh), which demonstrates the capabilities of capturing nonlinearities between DH demand and air temperature. Linear models such as the Ridge, Lasso, or Linear Regression demonstrated acceptable results, but they were not yet accurate. On the other hand, GRU and LSTM showed poor results as they are inappropriate for this kind of environment, where only one variable exists, as they require complex and large datasets.

6.2 Features Influence on DH Demand Prediction

Temperature was playing a key dominating factor of DH demand, and spot price had less contribution to model effectiveness, as from both Pearson and Spearman, the correlation was nearly zero. Models until 2023 used the effects of temperatures and seasons to provide forecasting accuracy. However, starting from 2023, the prediction curve started to change. The rising Pearson (0.36) and Spearman (0.42) correlations indicate that the hourly spot price started to have an impact on DH demand. Incorporating the spot price along with time and temperature allowed the prediction to be more accurate. This indicates DH demand is now influenced by both economic factors and weather conditions.

The result can contribute to the academic purpose of selecting the right model for prediction and isolating the portion of DH systems that is not temperature dependent. For improving demand-side management and short-term demand forecasting, boosting models can be a reliable source for the DH operators and policymakers. These sorts of findings promote demand-side management, incorporating RES and developing techniques to mitigate the peak loads in DH.

6.3 Limitations

Several limitations were identified during this study.

- **Data Constraints:** Air temperature was the sole predictor variable in the analysis, as this was considered one of the main factors for heating demand prediction. Other factors like wind velocity, solar exposure, space utilisation, and socio-economic behaviour were overlooked. Considering these factors can add an advantage for NN, which can help to enhance the precision method.
- **Limited Timeframe:** The study was conducted on a specific region based on historical data, where it is important to take into consideration the vast array of areas with seasonal and extensive weather patterns. Only specific regional historical data-based predictions can not give insights into unusual scenarios in extreme conditions like heat waves or snowstorms.
- **Model Speculation**: Boosting models depend on hyperparameter optimization, and traditional regression models depend on linearity. Boosting model provides outstanding optimization, but the outcome varies because of the datasets.
- **Flexibility Estimation:** Only the statistical method was employed to estimate the potential flexibility, which can be helpful, but this can not take into account operational or behavioural limits from the real demand perspective.

6.4 Future Work

Based on the findings of this work, there are a few possible possibilities for the future.

- **Integrating with Multi-variate and High-resolution Datasets:** For this study, air temperature was the only variable, and other parameters like solar radiation, wind speed, and humidity should be taken into consideration as larger datasets for prospective work. By using complex and high-resolution datasets, GRU and LSTM will be empowered by their capacity to exploit their temperature dependencies. In more realistic and complex environments, it can be observed whether RNN can do better than boosting algorithms.
- **Consider Hybrid Modeling:** In this thesis, boosting models were appropriate for the prediction accuracy, but they cannot capture the sequential dynamics naturally. The GRU and LSTM, on the other hand, were trained to learn and observe over time, but they need more complicated and varied inputs to work well. Utilizing hybrid models may result in a convergence of the interpretability and reliability of boosting models with the sequential learning abilities of neural networks.
- **Flexibility Validation:** The estimated flexibility range was determined through residual analysis, and to validate these results, prospective work should be included to run this analysis against the actual demand response in an operational DH network.
- **Identify Seasonal and Regional Differences:** Potential flexibility estimation can be applied in all conditions, such as all seasons and all regions. It may be adjusted and changed in relation to factors such as climate change, heating, and user behaviour. To make the analysis precise and accurate, different aspects should be explored.

In summary, LightGBM outperformed in this case, demonstrating a high level of results when only a limited amount of data is available as input. As the data setup was simple, the neural network could not withstand. The study supports previous findings in the literature and denotes the feasible incorporation of flexibility estimation into DH design.

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Appendix 1. Code snippets

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression, Lasso, Ridge
import xgboost as xgb
import lightgbm as lgb
from sklearn.metrics import mean_squared_error, r2_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import GRU, LSTM, Dense
from sklearn.preprocessing import StandardScaler

***Define the predictor (air_temp) and target (dh_mwh)***
X = df[['air_temp']]
y = df['dh_mwh']

***Models to compare (including GRU and LSTM)***
models = {
    'Linear Regression': LinearRegression(),
    'Lasso': Lasso(alpha=0.1),
    'Ridge': Ridge(alpha=0.1),
    'XGBoost':              xgb.XGBRegressor(n_estimators=100,
learning_rate=0.1, max_depth=3, objective="reg:squarederror"),
'LightGBM':                lgb.LGBMRegressor(n_estimators=100,
learning_rate=0.1, num_leaves=31, objective='regression')
}

***Define GRU and LSTM models***
def create_gru_model(input_shape):
    model = Sequential()
    model.add(GRU(50,                       activation='relu',
input_shape=input_shape))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model

def create_lstm_model(input_shape):
    model = Sequential()
    model.add(LSTM(50,                      activation='relu',
input_shape=input_shape))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model

***Rescale the data for neural network models (GRU, LSTM)***
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

***Reshape data for GRU and LSTM (time-series data shape***
X_reshaped    =    X_scaled.reshape((X_scaled.shape[0],    1,
X_scaled.shape[1]))  # 1 time step for each sample
```

*****Add GRU and LSTM models to the models dictionary*****

```
models['GRU'] = create_gru_model((X_reshaped.shape[1], X_reshaped.shape[2]))
models['LSTM'] = create_lstm_model((X_reshaped.shape[1], X_reshaped.shape[2]))
```

*****Store results*****

```
results = {}
```

*****Fit each model and calculate performance metrics*****

```
for model_name, model in models.items():
    residuals = []
    if model_name in ['GRU', 'LSTM']:
***Neural network models (GRU, LSTM) need to be trained on reshaped data***
        model.fit(X_reshaped, y, epochs=10, batch_size=16, verbose=0)
        y_pred = model.predict(X_reshaped)
    else:
***Classical models***
        model.fit(X, y)
        y_pred = model.predict(X)
    df[f'dh_mwh_pred_{model_name.lower()}'] = y_pred
***Calculate residuals (temperature-independent component)***
df[f'temperature_independent_component_{model_name.lower()}'] = df['dh_mwh'] - df[f'dh_mwh_pred_{model_name.lower()}']
***Performance metrics***
    mse = mean_squared_error(y, df[f'dh_mwh_pred_{model_name.lower()}'])
    r2 = r2_score(y, df[f'dh_mwh_pred_{model_name.lower()}'])
    results[model_name] = {'MSE': mse, 'R2': r2}
***Calculate mean and standard deviation of temperature-independent component***
    mean_flexibility = df[f'temperature_independent_component_{model_name.lower()}'].mean()
    std_flexibility = df[f'temperature_independent_component_{model_name.lower()}'].std()
***Estimate flexibility range***
    flexibility_min = mean_flexibility - std_flexibility
    flexibility_max = mean_flexibility + std_flexibility

    print(f"{model_name} - MSE: {mse:.4f}, R^2: {r2:.4f}")
    print(f"Estimated flexibility range: {flexibility_min:.2f} MWh to {flexibility_max:.2f} MWh\n")
***Plot all models' predictions for comparison***
plt.figure(figsize=(12, 8))
***Plot actual dh_mwh***
plt.plot(df.index, df['dh_mwh'], label='Actual dh_mwh', color='blue', alpha=0.6)
***Plot each model's predictions***
```

```
for model_name in models.keys():
    plt.plot(df.index, df[f'dh_mwh_pred_{model_name.lower()}'],
label=f'{model_name} Prediction')
plt.xlabel("Time")
plt.ylabel("District Heating Power (MWh)")
plt.title("Comparison of Temperature-Dependent Predictions from
Different Models")
plt.legend()
plt.tight_layout()
plt.savefig('Comparison_of_Temperature_Dependent_Predictions.j
pg', format='jpg', bbox_inches='tight')
plt.show()
***Print comparison of MSE and R^2 for each model***
print("\nComparison of models' performance:")
for model_name, metrics in results.items():
    print(f"{model_name}: MSE = {metrics['MSE']:.4f}, R^2 =
{metrics['R2']:.4f}")
***Create a dictionary to store flexibility metrics***
flexibility_metrics = {}
***Add flexibility calculations to the results***
for model_name, model in models.items():
    residuals = []
    if model_name in ['GRU', 'LSTM']:
***Neural network models (GRU, LSTM) need to be trained on
reshaped data***
        model.fit(X_reshaped, y, epochs=10, batch_size=16,
verbose=0)
        y_pred = model.predict(X_reshaped)
    else:
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    r2 = r2_score(y, df[f'dh_mwh_pred_{model_name.lower()}'])
    results[model_name] = {'MSE': mse, 'R2': r2}
***Calculate mean and standard deviation of temperature-
independent component***
    mean_flexibility =
df[f'temperature_independent_component_{model_name.lower()}'].
mean()
    std_flexibility =
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std()
***Estimate flexibility range***
    flexibility_min = mean_flexibility - std_flexibility
    flexibility_max = mean_flexibility + std_flexibility
```

```
    print(f"{model_name} - MSE: {mse:.4f}, R^2: {r2:.4f}")
    print(f"Estimated flexibility range: {flexibility_min:.2f}
MWh to {flexibility_max:.2f} MWh\n")
```
*****Add the flexibility metrics to the dictionary*****
```
    flexibility_metrics[model_name] = {
        'mean_flexibility': mean_flexibility,
        'std_dev': std_flexibility,
        'flexibility_range': (flexibility_min, flexibility_max)
    }
```
*****Convert flexibility metrics into a DataFrame*****
```
results_df =
pd.DataFrame(flexibility_metrics).T.sort_values('std_dev')
```
*****Plot the standard deviation of the temperature-independent component*****
```
plt.figure(figsize=(10, 6))
results_df['std_dev'].plot(kind='bar', color='skyblue')
plt.title('Temperature-Independent Flexibility
Comparison\n(Standard Deviation of Residuals)')
plt.ylabel('Standard Deviation (MW)')
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.savefig('Temp_independent_flexibility_comparison.jpg',
format='jpg', bbox_inches='tight')
plt.show()

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```

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{metrics['R2']:.4f}")
```