

# LSTM-Based Forecasting of Power Demand and Dynamic Pricing in Norway

Vishnu Vardhan Reddy Gurram  
*Computer Science*  
*Blekinge Tekniska Högskola*  
Karlskrona, Sweden  
vegu23@student.bth.se

Jyothi Madhurya Nalam  
*Computer Science*  
*Blekinge Tekniska Högskola*  
Karlskrona, Sweden  
jyna23@student.bth.se

## I. INTRODUCTION

Forecasting of electricity consumption is essential to ensure efficient resource planning, maintain grid stability, and enable sustainable energy management. Accurate forecasting not only supports energy providers but also allows governments and industries to make informed decisions in the face of increasing consumption demands and environmental constraints. In Norway, the unique combination of extensive hydroelectric resources, high per capita electricity usage, and growing interest in dynamic pricing policies creates an ideal setting for advanced forecasting techniques [8] [3].

Recent developments in machine learning and neural networks have significantly improved the ability to predict short- and long-term electricity usage. In particular, the integration of feature engineering, ensemble methods, and deep learning models such as LSTM (Long Short-Term Memory) has shown superior performance in modeling electricity consumption across varied contexts [2]. These models address the limitations of traditional statistical approaches, which often fail to capture non-linear dependencies, seasonality, and consumer behavior in energy data [7].

Given the importance of accurate demand prediction to support dynamic pricing, carbon reduction goals, and renewable energy integration, Norway offers an ideal use case to evaluate advanced forecasting frameworks built on LSTM-based models [5] [6]. This project proposes a dual-model LSTM-based approach: one model predicts hourly electricity demand, while the other forecasts dynamic electricity pricing. Both models leverage smart meter data, incorporating temporal and contextual features to support real-time energy management and pricing optimization.

## II. AIM

This project aims to develop machine learning models for forecasting hourly power consumption and electricity price signals using smart meter data. The models will incorporate external factors such as weather conditions and calendar-based effects to improve predictive accuracy. The ultimate goal is to provide insights into consumption patterns and enhance demand-side flexibility.

## III. OBJECTIVES

- 1) **Develop LSTM-based forecasting models** for electricity demand and dynamic pricing at both national and regional levels in Norway using smart meter data.
- 2) **Evaluate the influence of temporal patterns** (daily cycles, weekday-weekend differences) and environmental factors (especially temperature) on electricity consumption and pricing.
- 3) **Identify regional variations** in electricity consumption patterns across different Norwegian regions (Oslo, Bergen, and Stavanger).
- 4) **Develop and assess feature engineering strategies** that effectively capture historical patterns, cyclical variations, and environmental influences for improved forecasting accuracy.
- 5) **Validate model performance** using appropriate evaluation metrics and optimize hyperparameters to enhance predictive power.

## IV. EXPECTED OUTCOME

- 1) **24-hour ahead predictions** demonstrating daily consumption cycles and pricing trends that can support short-term operational planning for energy providers.
- 2) **Quantified regional differences** in electricity usage patterns identifying significant variations between Norwegian regions.
- 3) **Identified temporal patterns** distinguishing between weekday and weekend consumption behaviors, revealing how human schedules impact electricity demand.
- 4) **Effectiveness assessment of feature engineering** determining which data transformations and feature combinations most significantly improve forecasting accuracy.

## V. ETHICAL, SOCIETAL AND SUSTAINABILITY ASPECTS

**Ethical** The use of smart meter data within this project raises important privacy concerns. Special precautions were taken to ensure data anonymity and adherence to ethical principles. Forecasting models were developed with fairness being a key consideration in order to avoid results that might unnecessarily disadvantage particular user groups.

**Societal:** Accurate demand and price prediction can enhance

energy reliability and inform fairer pricing policies. Dynamic pricing, however, needs to be implemented carefully to avoid inflicting damage on low-income families with limited consumption flexibility.

**Sustainability:** Improved forecasting enables the integration of renewable energy sources, streamlines grid management, and reduces carbon emissions. The development is in support of Norway's long-term sustainability goals and promotes responsible consumption of energy.

## VI. RESEARCH QUESTIONS

This study addresses two primary research questions:

**RQ1:** How can machine learning models be applied to accurately forecast hourly electricity consumption using smart meter data?

**RQ2:** How do weather conditions and time-based patterns affect electricity consumption?

## VII. RELATED WORK

Traditional statistical methods like ARIMA and regression have been widely used for electricity forecasting, but they often fall short in handling the complexity and variability of modern energy systems [9]. Hybrid and ensemble approaches have improved accuracy, with Tan et al. introducing a hybrid LSTM model using Bagging, Boosting, and Random Subspace techniques to better capture peak demand patterns [11]. Similarly, Abbasimehr et al. showed that multi-layer LSTM networks outperform ARIMA and other models in real-world settings, highlighting their scalability and effectiveness [1].

## VIII. CRISP-DM METHODOLOGY

Our methodology follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, which provides a structured approach to data science projects. Here we describe how we implemented each step, highlighting technical choices made and the reasons why.

### A. Business Understanding

The business understanding phase established clear objectives for electricity demand and price prediction. Through accurate forecast models, energy businesses can anticipate demand shifts, optimize power distribution, and enforce effective pricing. We aimed to enhance grid stability, analyze consumption patterns, and assess the efficacy of dynamic pricing as a demand management strategy.

### B. Data Understanding

Our dataset originated from the iFlex Dynamic Pricing Experiment in Norway [4]. It contains a total of 583 unique user IDs, distributed across three regions: Oslo (396 users), Bergen (167 users), and Stavanger (20 users). This regional distribution enables both national- and region-level forecasting. The dataset is composed of two main files:

**Hourly Data:** Over 1 million rows of hourly smart meter readings, containing electricity consumption, temperature, and price information.

**Participants Data:** Originally expected to cover six Norwegian regions (Oslo, Bergen, Stavanger, Trondheim, Bodø, and Tromsø). However, upon data exploration, we discovered that the dataset only includes participants from three regions: Oslo (396 participants), Bergen (167 participants), and Stavanger (20 participants).

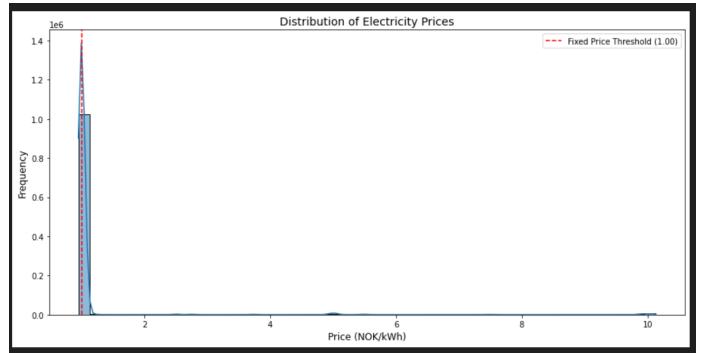


Fig. 1. Distribution of electricity prices (Figure 1). The overwhelming majority of prices are concentrated at 1.0 NOK/kWh (flat rate), reflecting the prevalence of control-group data.

The initial analysis revealed that the control group, which was not subjected to dynamic pricing, accounted for around 95% of missing price points. This is indicated by the distribution of electricity prices (Figure 1), where the overwhelming majority of prices are concentrated at 1.0 NOK/kWh (flat rate) with very few instances of actual dynamic pricing.

After loading the data using pandas, we did an exploratory analysis of key variables (Experiment\_price\_NOK\_kWh, Demand\_kWh, and Temperature) and plotted the distribution of the price using Seaborn's histplot function. That revealed the prevalence of constant prices at 1.0 NOK/kWh.

This was an important insight into the data and served to clarify why our models subsequently forecast low price variability levels. The forecasts accurately reflected the underlying market structure, rather than being constrained by model limitations.

### C. Data Preparation

#### Handling Missing Values

For the large missing values for price data (95%), we adopted a multi-level imputation approach:

- Forward-fill and backward-fill to handle sequential gaps, preserving time-series trends. We did this using pandas' ffill() and bfill() functions on the Experiment\_price\_NOK\_kWh column.
- Pattern-based imputation based on hour and weekend status for the rest of the gaps, understanding that prices follow temporal patterns. This was accomplished by specifying a groupby operation over ["Hour", "Weekend"] to find typical values per period.
- Median imputation by group is the last resort to impute any remaining missing values.

For lag features and rolling metrics, we employed linear interpolation with forward-fill and backward-fill. This ensured

temporal consistency without compromising the integrity of the time series data.

## Outlier Detection and Treatment

Interquartile Range (IQR) method was used to identify and manage outliers in our data. This non-parametric approach possesses resistance to non-normality and is particularly suited for electricity consumption data with rare extreme values. By using the `detect_and_handle_outlier` function, we calculated the IQR limits and flagged values outside the range. For power demand data, outliers were values outside the range [-2.70, 7.28] kWh, and for temperature data, outliers were values outside [-5.20, 11.60]°C. Rather than remove these data points, we clipped them to boundary values using pandas' `clip()` function. This approach preserved the total volume of data but prevented model training from being distorted by outliers. We also preserved the original unclipped values in separate columns (e.g., `Demand_orig` and `Temperature_orig`) for referencing and analysis.

## Feature Engineering

Feature engineering was essential to enhance model performance by allowing temporal patterns and contextual dependencies to be learned. We started by generating **time-based features**, including the hour of the day, day of the week, and a weekend indicator. To accurately represent the cyclical nature of time, where, for example, hour 23 is more similar to hour 0 than to hour 12, we applied sine and cosine transformations using NumPy's trigonometric functions. This resulted in features such as '`hour_sin`', '`hour_cos`', '`day_sin`', and '`day_cos`', which allow the model to interpret time not as a linear sequence but as a repeating cycle, more accurately reflecting real-world consumption and pricing behaviors.

To incorporate historical trends, we developed **lag features** at multiple time intervals using Pandas' '`shift()`' function. These included 1-hour, 3-hour, 24-hour, and 168-hour lags. The 1-hour lag captures immediate past behavior, the 3-hour lag reflects short-term trends, the 24-hour lag links to the same hour on the previous day, and the 168-hour lag captures weekly seasonality. Together, these lag features allow the model to learn from patterns that occur at different temporal resolutions.

We also calculated **rolling statistics** to capture smoothed behavior over time. Rolling means were calculated across 3-hour, 24-hour, and 168-hour windows to detect underlying trends while reducing noise. In addition, we calculated 24-hour rolling standard deviations for both demand and pricing (e.g., `demand_rolling_std_24`) to quantify volatility, which is an important factor in energy forecasting models.

To account for how environmental factors interact with temporal cycles, we introduced **interaction features**, such as '`temp_hour_interaction`', which represents how the effect of temperature varies depending on the hour of the day. This helps the model distinguish between the impacts of tempera-

ture during different parts of the day, such as cold mornings versus warm afternoons.

Finally, we included **difference features** by calculating first-order changes in demand over 1-hour and 24-hour periods using Pandas' '`diff()`' function. These features ('`lag_diff_1`' and '`lag_diff_24`') measure the rate of change in consumption, allowing the model to detect acceleration or deceleration in demand trends over time.

## Data Transformation

Before feeding data into the LSTM models, we performed several transformations:

- **Normalization:** We used `MinMaxScaler` from scikit-learn to normalize all features in the range [0,1]. This uniform scaling is crucial for neural networks to ensure that all features contribute proportionally to the learning process and prevent features with larger magnitudes from dominating training.
- **Sequence Creation:** We transform the data into sequences of length 24 using our custom `create_sequences` function to capture daily patterns. Each sequence contained 24 consecutive hours of features, the target being the value for the hour immediately following this window. This sliding window approach is fundamental to time series forecasting with LSTMs, allowing the model to learn patterns across a full day cycle. Item textbf{Train-Test Split}: We implemented an 80/20 temporal split for training and testing. Unlike traditional random splits used in other machine learning contexts, we maintained the temporal order of the data to ensure the model was tested on future data points. This approach provides a more realistic evaluation of the forecast's performance.

## D. Model Selection

We chose LSTM [10] neural networks because they are well-suited for time series forecasting. They can remember long-term patterns, handle multiple features like time and weather, and capture complex relationships between inputs. LSTMs have also been proven effective in previous energy forecasting studies.

## Model Architectures

We implemented three different LSTM model architectures for various forecasting tasks. The first, a standard LSTM model, was designed for regional forecasting. It consists of two LSTM layers with 50 units each and employs a dropout rate of 0.2 to prevent overfitting. This simpler structure was well-suited for the smaller regional data size. The second model, a more advanced one for national dynamic pricing, contains three LSTM layers with 100, 75, and 50 units, features a higher dropout rate of 0.3, and includes additional dense layers. This design effectively captured the pricing data's more complex and subtle patterns. The third model, created to forecast national electricity demand, is the most complex. It comprises three LSTM layers with 128, 64, and

32 units, also utilizing dropout (up to 0.3), creating a funnel-like shape that efficiently discards noise while preserving the essential patterns. This more capable model was better suited for processing lengthy and complicated consumption patterns. Each architectural choice was meticulously made to balance the model's complexity, the volume of data, and the overall prediction objective.

### Hyperparameter Tuning

We chose our hyperparameters based on theoretical understanding and practical testing. The sequence length was set to 24 to capture the full daily cycles in electricity consumption and pricing since electricity usage typically follows strong 24-hour patterns. For the LSTM units, we used a bottleneck pattern with progressively decreasing units to create an information funnel, helping the model focus on the most important features and reduce noise, which also prevents overfitting. We applied dropout rates between 0.2 and 0.3 to prevent neurons from co-adapting and to improve generalization, with higher rates used in deeper models to counter overfitting. A batch size of 32 was selected to strike a balance between computational efficiency and model stability, providing enough gradient averaging while allowing faster updates during training. We chose the Adam optimizer for its adaptive learning rate, which helps it to perform well on time series tasks where the magnitude of the gradient can vary. The Mean Squared Error (MSE) loss function was used because it works well for regression tasks, especially in energy forecasting, where larger errors can have significant operational consequences. Finally, we applied early stopping with a patience of 3 to stop training when validation loss stops improving, saving computational resources while ensuring the model performance is optimized.

### Model Training

We trained separate models at both national and regional levels to effectively capture broad consumption trends as well as region-specific variations. The training process included feeding data through the network, calculating loss using Mean Squared Error (MSE), updating model weights through back-propagation, and applying early stopping to prevent overfitting. For both price and demand forecasting, we used Keras' 'fit()' method with a validation split to track model performance during training. Regional models were trained on data subsets specific to each region, enabling them to learn localized patterns that might be overlooked in a national model. This distinction is important because electricity consumption can vary widely across regions due to differences in weather, infrastructure, and population demographics. To ensure consistent testing and manage execution time during development, all models were initially trained using only one epoch. This allowed us to validate the end-to-end pipeline efficiently. However, for academic evaluation, we recommend increasing the number of training epochs to between 3 and 5, which gives the models more opportunity to learn effectively while still taking advantage of early stopping to avoid overfitting.

### Next 24Hrs forecasting

For practical forecasting, we used a recursive prediction approach to generate 24-hour forecasts. Starting with the most recent sequence of observations, the model predicted the next hour's value. This prediction was then added to the input sequence, and the process was repeated one hour at a time for the full 24-hour horizon. This method reflects real-world forecasting conditions, where future values must be predicted based only on past and current data. Once all predictions were made, we applied inverse transformations using our MinMaxScaler to convert the results back to their original units (kWh or NOK/kWh), making them easy to interpret for stakeholders.

### Interpretability

To enhance transparency and interpretability, the models utilize intuitive features such as an hour of the day, day of the week, lagged consumption values, and temperature forecasts. These features align with known patterns in electricity usage, allowing stakeholders to understand how predictions are influenced by time, weather, and historical demand. This design supports more explainable forecasting outputs, which is critical for building trust in data-driven energy systems.

### Model Evaluation

To evaluate model performance, we used several metrics including MAE, MSE, R<sup>2</sup>, MAPE, and RelMSE. These metrics together provide a well-rounded view of accuracy, capturing both average error and variance explained, while also accounting for percentage errors and error magnitude relative to data variability.

### E. Deployment

Although this project focuses primarily on modeling and evaluation, the proposed LSTM-based forecasting models can be integrated into operational dashboards used by energy providers or grid operators. These models can support near real-time electricity demand and dynamic pricing forecasts, enabling smarter scheduling, better load balancing, and more adaptive pricing strategies in line with consumer behavior and market signals.

## IX. RESULTS, ANALYSIS, AND DISCUSSION

Our LSTM forecasting models demonstrated strong predictive performance for electricity demand and dynamic pricing in Norway. The national dynamic pricing model achieved an R<sup>2</sup> of 0.8865, MAE of 0.0330 NOK/kWh, and MAPE of 1.67%, while the power demand model yielded an R<sup>2</sup> of 0.7985 and MAE of 0.4781 kWh. Table I summarizes the evaluation metrics.

Figure 2 shows that the predicted electricity demand closely follows actual patterns but tends to underpredict sudden peaks above 6 kWh. This smoothing suggests our model may miss some atypical consumption events influenced by factors outside our input features. Particularly noticeable is how the model captures the overall trend and cyclical patterns in the

TABLE I  
EVALUATION METRICS FOR NATIONAL FORECASTING MODELS

Metric	Dynamic Pricing Model	Power Demand Model
R <sup>2</sup>	0.8865	0.7985
MAE	0.0330	0.4781
MSE	0.0690	0.5147
MAPE	1.67%	789624.51%*
Relative MSE	0.0384	0.0947

\*High MAPE due to near-zero actual values in the dataset

time series while maintaining accuracy during periods of relatively stable consumption, demonstrating its strength in predicting typical usage scenarios.

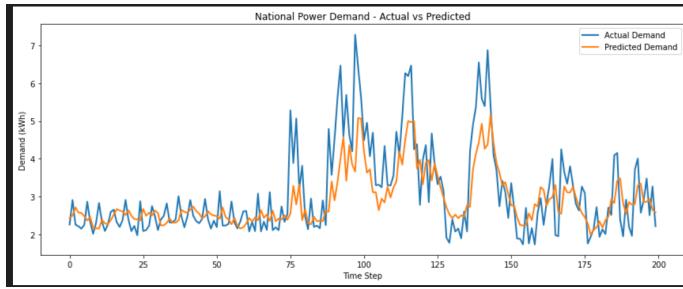


Fig. 2. National Power Demand - Actual vs Predicted

The dynamic pricing model (Figure 3) reflects that most of the dataset is based on fixed pricing (1.0 NOK/kWh), which results in a horizontal actual price line. The predicted prices, while fluctuating slightly, captured time-based variation patterns that would be typical under dynamic pricing conditions.

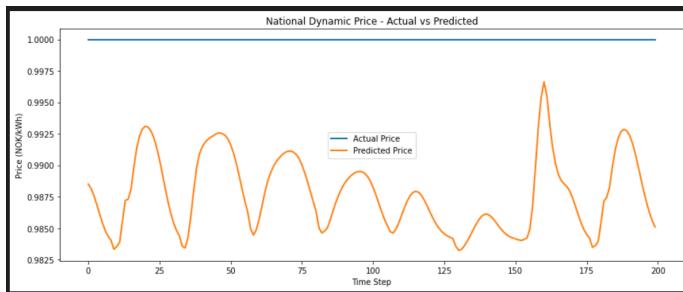


Fig. 3. National Dynamic Price - Actual vs Predicted

## Forecast Results

Forecasts for the next 24 hours show average per-household electricity consumption ranging from 4.75–5.44 kWh. Peak consumption is predicted in the early morning hours (e.g., 5.44 kWh at 2:00 AM), dipping during midday, and increasing again in the evening, consistent with expected residential usage patterns.

Predicted dynamic prices for the same period ranged narrowly between 0.983–0.988 NOK/kWh, a deviation of less than 0.5% from the fixed base price, indicating the model has picked up subtle time-of-day effects despite the prevalence of fixed rates.

Regional forecasts revealed large variation in household power usage, as shown in Table II.

TABLE II  
REGIONAL FORECAST RESULTS FOR THE NEXT HOUR

Metric	Bergen	Oslo	Stavanger
Power Demand	0.55	0.62	4.88
Dynamic Price	1.0063	1.0015	0.9973

In the Stavanger region, although the sample size is relatively small, the results indicate a tendency toward higher average household electricity consumption compared to Oslo and Bergen. While this may point to regional usage patterns, the limited sample size prevents drawing firm conclusions. Meanwhile, dynamic price variations remained small and consistent across all regions throughout the observed period.

## Weekly Consumption Patterns

A comparison of weekday and weekend electricity demand revealed key behavioral differences. Weekday consumption patterns typically exhibited distinct peaks during morning and evening hours, reflecting standard workday routines. In contrast, weekend demand was more evenly distributed throughout the day, with higher overall usage during daytime hours. This indicates the influence of daily human behavior, such as staying home more on weekends, on electricity consumption profiles.

## Temperature vs. Demand

The relationship between temperature and demand (Figure 4) was not linear, but temperature features improved model accuracy, implying interaction effects and non-linear impacts.

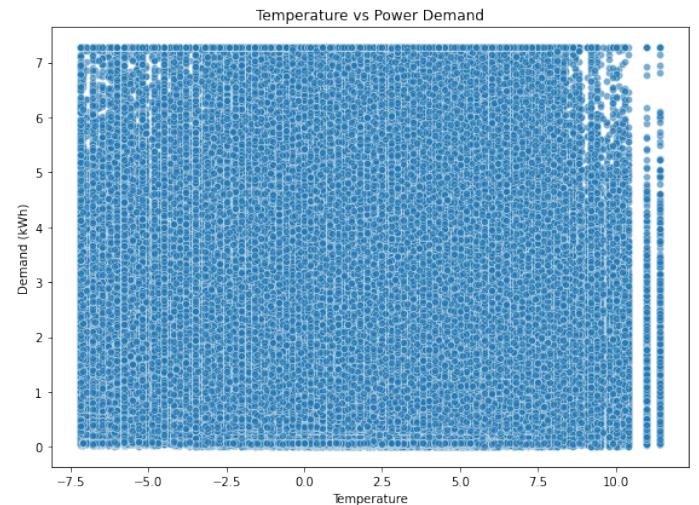


Fig. 4. Temperature vs. Electricity Demand

Our feature engineering, including lag features at 1, 3, 24, and 168 hours, effectively captured both short-term variability and weekly trends. This reinforced the importance of historical consumption in forecasting electricity usage. Time-of-day

patterns remained the dominant predictors, with distinct daily and weekly cycles modeled.

The regional differences reinforce the need for localized approaches to energy management, and the complex interaction with temperature underscores the importance of sophisticated modeling methods able to identify subtle and conditional impacts. The model's capacity to recognize possible temporal price trends, even with the prevalence of fixed rates in our sample, implies that our method can facilitate the transition towards more dynamic price structures as they gain popularity in the electricity market in Norway.

These findings have important implications for energy providers that are trying to improve the stability of the grid and maximize resource allocation. By accurately forecasting demand patterns, providers can better control generation resources, reduce costs, and decrease environmental footprints.

## X. CONCLUSION

This study successfully implemented LSTM-based forecasting models for electricity demand and dynamic pricing in Norway, achieving  $R^2$  values of 0.7985 and 0.8865 respectively. Analysis revealed that time-based factors with significant regional variations primarily drive consumption patterns, while temperature exhibits complex, non-linear relationships with demand. Effective feature engineering, notably lag features at multiple intervals, proved crucial to capture short-term fluctuations and seasonal patterns. These insights provide energy providers with valuable tools to improve grid stability, optimize resource allocation, and develop more targeted energy management strategies for a more efficient and sustainable electricity system.

TABLE III  
RISKS AND POTENTIAL SOLUTIONS

Risk	Severity	Solution
Fixed-rate pricing prevalence	High	Incorporate variable pricing data sources
Limited regional scope	Medium	Expand to additional Norwegian regions
Extreme peak under-prediction	Medium	Develop specialized event models with contextual features
Temperature correlation ambiguity	Medium	Implement non-linear modeling approaches
Training iteration constraints	Low	Optimize epoch count with early stopping

- [3] M. Hamlehdar and A. Aslani, "Analysis of Energy System in Norway with Focus on Energy Consumption Prediction," *Management of Sustainable Development*, vol. 9, no. 1, pp. 5–14, Jun. 2017. [Online]. Available: <http://archive.sciendo.com/MSD/msd.2017.9.issue-1/msd-2017-0008/msd-2017-0008.pdf>
- [4] M. Hofmann and T. Siebenbrunner, "A rich dataset of hourly residential electricity consumption data and survey answers from the iFlex dynamic pricing experiment," Mar. 2023. [Online]. Available: <https://zenodo.org/records/8248802>
- [5] M. Irandoust, "The renewable energy-growth nexus with carbon emissions and technological innovation: Evidence from the Nordic countries," *Ecological Indicators*, vol. 69, pp. 118–125, Oct. 2016. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1470160X16301558>
- [6] S. Jaipuria and A. Chaurasia, "Energy Price Prediction Using LSTM," in *2024 3rd International Conference for Advancement in Technology (ICONAT)*, Sep. 2024, pp. 1–6. [Online]. Available: <https://ieeexplore.ieee.org/document/10775084?denied=1>
- [7] A. Manowska, "Using the LSTM Network to Forecast the Demand for Electricity in Poland," *Applied Sciences*, vol. 10, no. 23, p. 8455, Jan. 2020, number: 23 Publisher: Multidisciplinary Digital Publishing Institute. [Online]. Available: <https://www.mdpi.com/2076-3417/10/23/8455>
- [8] R. Nesbakken, "Price sensitivity of residential energy consumption in Norway," *Energy Economics*, vol. 21, no. 6, pp. 493–515, Dec. 1999. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0140988399000225>
- [9] L. N. Nyakundi, "PREDICTING ELECTRICITY CONSUMPTION IN NORWAY: A COMPARISON OF MACHINE LEARNING MODELS," Master's thesis, Norwegian University of Life Sciences, 2024, accepted: 2024-08-23T16:32:32Z. [Online]. Available: <https://nmbu.brage.unit.no/nmbu-xmlui/handle/11250/3148115>
- [10] R. C. Staudemeyer and E. R. Morris, "Understanding LSTM – a tutorial into Long Short-Term Memory Recurrent Neural Networks," Sep. 2019, arXiv:1909.09586 [cs]. [Online]. Available: <http://arxiv.org/abs/1909.09586>
- [11] M. Tan, S. Yuan, S. Li, Y. Su, H. Li, and F. He, "Ultra-Short-Term Industrial Power Demand Forecasting Using LSTM Based Hybrid Ensemble Learning," *IEEE Transactions on Power Systems*, vol. 35, no. 4, pp. 2937–2948, Jul. 2020, conference Name: IEEE Transactions on Power Systems. [Online]. Available: <https://ieeexplore.ieee.org/abstract/document/8946642?casatoken=0agnNH26dJcAAAAAA:6BvbHpx6K7C7Np9KMWZ2DvewyilJDqukRm>

## REFERENCES

- [1] H. Abbasimehr, M. Shabani, and M. Yousefi, "An optimized model using LSTM network for demand forecasting," *Computers & Industrial Engineering*, vol. 143, p. 106435, May 2020. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0360835220301698>
- [2] E. Choi, S. Cho, and D. K. Kim, "Power Demand Forecasting using Long Short-Term Memory (LSTM) Deep-Learning Model for Monitoring Energy Sustainability," *Sustainability*, vol. 12, no. 3, p. 1109, Jan. 2020, number: 3 Publisher: Multidisciplinary Digital Publishing Institute. [Online]. Available: <https://www.mdpi.com/2071-1050/12/3/1109>