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Prediction of Power Loss in Grid Using Neural Network

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ABSTRACT- This Paper proposes a data-driven approach for grid loss prediction in power systems. It utilizes a comprehensive dataset with relevant features such as grid load, temperature forecasts, and calendar data. The dataset is pre-processed by handling missing values, normalizing features, and encoding cyclic calendar features. A Long Short-Term Memory (LSTM) recurrent neural network is employed for the prediction model, capturing temporal dependencies and generating forecasts of grid loss two hours ahead. The model is trained using mean absolute error (MAE) as the loss function and optimized through hyperparameter tuning. Evaluation metrics like MAE and root mean squared error (RMSE) assess the model's accuracy. Visualization techniques compare predicted and actual grid loss values. The Paper concludes with analysis, future research suggestions, and highlights the potential of the Prophet data-driven approach for efficient and reliable power distribution.

KEYWORDS- Loss prediction, power loss, LSTM, prophet model

I. INTRODUCTION

With the increasing integration of renewable energy sources in the electricity markets worldwide, the dynamics of power grid operations are undergoing significant changes. These changes pose challenges for accurately predicting grid losses, particularly as existing methods often struggle to incorporate local weather conditions into their models. In the context of India, with its diverse climate and complex grid infrastructure, reliable power grid loss prediction becomes even more critical.[1]

The background of this Paper lies in the need to address the limitations of current prediction methods and develop a more robust approach that considers local weather conditions. The accurate prediction of power grid losses is crucial for grid operators, utility providers, and policymakers to effectively plan and optimize grid operations, reduce losses, and enhance energy efficiency. Additionally, accurate predictions enable proactive maintenance planning, resource allocation, and cost optimization.[2]

The motivation for this Paper stems from the potential of Long Short-Term Memory (LSTM) recurrent neural network models to overcome the shortcomings of traditional methods. LSTM models have demonstrated their effectiveness in capturing long-term relationships and temporal dependencies in time series data, making them suitable for power grid loss prediction. By incorporating hourly time series data from electricity markets, local weather conditions, and the calendar, LSTM models can better capture the complex dynamics of grid losses, especially in the context of the Indian power grid.

The unique characteristics of the Indian power grid, including its vast geographical spread, diverse climatic zones, and evolving renewable energy landscape, require tailored prediction models. By developing an LSTM-based predictive model specifically for the Indian context, this Paper aims to contribute to the advancement of grid loss prediction capabilities in India. Accurate and localized predictions can empower grid operators to take proactive measures to mitigate losses, improve grid stability, and optimize resource allocation.[3]

Furthermore, this research aligns with the increasing emphasis on renewable energy integration and grid modernization efforts in India. As the country strives to expand its renewable energy capacity and enhance grid reliability, accurate power grid loss prediction becomes even more critical. By leveraging LSTM models and considering local weather conditions, this Paper seeks to address the specific challenges faced by the Indian power grid and provide practical insights and recommendations for improved grid loss prediction.[4]

Overall, the background and motivation for this Paper lie in the significance of accurate power grid loss prediction in India, the limitations of existing methods, and the potential benefits of leveraging LSTM neural networks to address these challenges. By developing an advanced predictive model, this research aims to contribute to the enhancement of grid reliability, efficiency, and sustainability in India's evolving energy landscape.[5]

II. LITERATURE REVIEW

"Power Loss Analysis and Estimation in Power Transmission Systems" by S. G. Srivani and B. V. Sanker Ram [6] Srivani and Sanker Ram present a detailed analysis of power loss in power transmission systems. The authors investigate the factors that contribute to power losses in transmission lines, including line resistance, reactance, and load characteristics. They discuss various loss estimation techniques, such as the use of power flow analysis and mathematical models. The paper emphasizes the significance of accurate loss estimation for assessing system efficiency and optimizing transmission network design. Moreover, the authors highlight the impact of power loss on system stability and the economic operation of power grids. The comprehensive coverage of power loss analysis in transmission systems provided in this work serves as a valuable resource for researchers and practitioners in the field of power system engineering.

"Power Losses in Power Systems: An Overview" by S. Chatterjee and B. Gupta: Chatterjee and Gupta [7] present a comprehensive overview of power losses in power systems, encompassing both transmission and distribution networks. The authors provide insights into the sources of power losses, including resistive losses in conductors, losses in transformers, and losses due to reactive power flow. They discuss the various methods employed for estimating power losses, ranging from basic calculation approaches to more advanced modeling techniques. The paper highlights the importance of accurate loss estimation in assessing system performance, optimizing operation, and implementing energy-saving measures. Furthermore, the authors shed light on the economic implications of power loss and the potential benefits of loss reduction strategies. This comprehensive overview offers a valuable foundation for understanding power loss phenomena and their impact on power system operation and efficiency.

III. OBJECTIVES

- To develop a predictive model for power loss in grids using LSTM, incorporating historical measurements of grid load, temperature forecasts, and predictions from the Prophet model.
- To investigate the relationship between grid load, temperature, and the components of the Prophet model (trend, daily, weekly, and yearly) in predicting grid loss accurately.
- To incorporate the cyclic nature of calendar features into the LSTM model architecture for improved prediction performance.
- To evaluate the effectiveness of the Prophet LSTM model in predicting power loss for three grids in Norway with varying data availability and grid characteristics.
- To compare and analyze the performance of the LSTM model in predicting power loss against alternative prediction methods and traditional approaches

IV. METHODOLOGY

The chosen model for our application is the Long Short-Term Memory (LSTM) recurrent neural network. LSTM is widely utilized in various fields such as text and language processing, as well as time-series modeling. It stands out due to its ability to handle sequential data and capture complex, non-linear relationships that evolve over time. Figure 1 shows the prophet model.

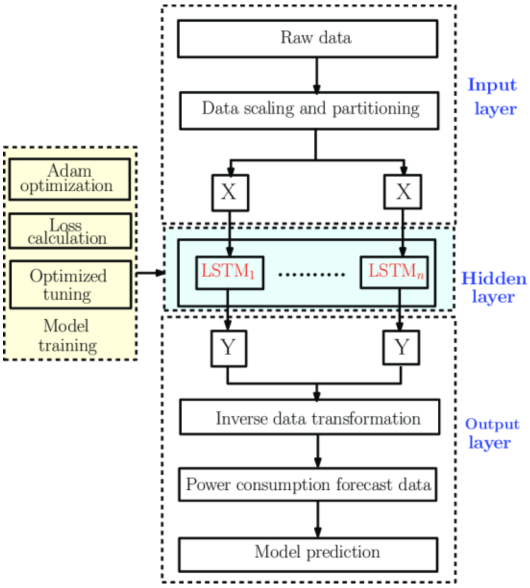

Figure 1: Prophet Model

Our proposed Prophet model is specifically tailored for forecasting total grid losses in an intra-day market, like the Norway market. In this market, there is a lead time of two hours between the forecasting moment and the forecasting horizon, as the gate closes one hour before the traded hour. To address this, our model is designed to predict grid losses two hours ahead with a one-hour forecasting horizon. This allows the model to be updated and run every hour, utilizing up-to-date weather forecasts to provide accurate forecasts for the market two hours in advance [8].

The computational graph of our model processes a sequence of 70 past observations (x1, x2, ..., xt-1, xt), as well as one- and two-hour ahead forecasts (x^t+1, x^t+2), which are the 54 selected variables used as inputs to the model.

At each step of processing, the recurrent neural network (RNN) updates its hidden states (h) and passes them as inputs to the next iteration. In the final processing step, the hidden states are combined linearly to compute the model output, which is desired to closely approximate the predicted grid loss (y^t+2) two hours ahead. To evaluate the performance of the model, we utilize the mean absolute error (MAE) as the loss function.

The MAE is calculated by taking the average absolute difference between the predicted grid loss (y^τ) and the true value ($y\tau$) at each time step τ, as shown in Equation (1) presented below:

$$MAE = (1 / T) * \Sigma|y\hat{}\tau - y\tau| \quad (1)$$

In this equation, $y\hat{}\tau$ represents the predicted grid loss, and $y\tau$ represents the true value of the grid loss at time τ. The mean absolute error is chosen as the loss function due to its robustness in handling potential outliers and providing a reliable measure of prediction accuracy [9].

A. Dataset Description

The dataset in question focuses on the complex power grid system, which plays a vital role in transmitting electricity from producers to consumers. However, not all the electricity generated reaches its intended destination due to losses that occur during the transmission and distribution processes. In Norway, grid companies are responsible for reporting these grid losses to the authorities overseeing the national transmission networks. Forecasting the anticipated grid losses a day in advance is crucial for determining electricity prices [10].

Although the underlying principles governing grid losses are well understood, their calculation is not straightforward due to the dynamic and uncertain nature of these losses. The dataset contains various features that are considered relevant for accurately predicting grid loss. It provides hourly measurements of these important features. Specifically, for each grid, the dataset includes the following information::

The dataset contains detailed historical measurements of grid loss, representing the electricity lost during transmission and distribution processes, measured in megawatt-hours (MWh). Additionally, it includes measurements of grid load, which represents the total power within the grid, also in MWh.

The dataset also provides temperature forecasts expressed in Kelvin. Temperature has a significant impact on power consumption, and therefore, it influences the grid load and subsequently affects grid loss.

Moreover, the dataset includes predictions obtained from an alternative forecasting model, which are presented in MWh. These predictions can be valuable additional features in predicting grid loss accurately.

Furthermore, the alternative forecasting model generates distinct components, including trend, daily, weekly, and yearly patterns associated with grid loss. These components derived from the alternative model can serve as important features within the prediction model, enhancing its ability to forecast grid loss effectively.

The dataset used in this study includes various grid-specific features as well as cyclic calendar features. These calendar features capture important time-based attributes such as year, season, month, week, weekday, and hour. To accurately represent the cyclic nature of time, these features are encoded using cosine and sine functions. Additionally, the dataset indicates whether a specific time period corresponds to a holiday.

It's worth noting that Grid 3 has a smaller amount of training data compared to Grid 1 and Grid 2. This difference in data availability suggests potential variations and disparities in historical data accessibility for each grid.

The data for this study was sourced from the Norway transmission system operator. It encompasses different types of information, including historical hourly electricity market data, local weather data, calendar data, and data specific to the power grid system under investigation. A careful selection process was carried out, resulting in 54 variables with sufficient availability and satisfactory data quality.

The electricity market data includes metrics such as electricity demand, wind power generation, and physical flows from different regions. The calendar data consists of indicators for weekdays, public holidays, and years, encoded in a one-hot format. A two-dimensional sine-cosine representation of the daily cycle is also included. The power-grid data includes the aggregate grid loss with a 24-hour delay, a moving average of the aggregate grid loss with a 24-hour delay, and electricity flow between different parts of the grid system with a 2-hour lag. These variables were chosen based on their availability in real-time operation.

The data covers the period from 2011 to 2019 and is divided into three segments: training, validation, and testing. The training dataset spans 6 years, the validation dataset covers 1 year, and the testing dataset also encompasses 1 year. Prior to inputting the data into the model, a quantile transformation is performed to convert the features into a uniform distribution ranging from 0 to 1. The target values used for the model outputs are scaled to have a mean of zero and a standard deviation of one [11].

B. Data Pre-processing and Feature Engineering

In the process of preparing the dataset for predictive modelling, several data pre-processing and feature engineering steps are employed to ensure the data is in a suitable format and to extract meaningful features. The following techniques can be applied:

Firstly, missing values in the dataset, particularly in the grid-specific features, are identified. The appropriate strategy to handle missing values is chosen based on their extent. This may involve removing rows or columns with insignificant missing values, imputing missing values using methods like mean, median, or interpolation, or employing advanced imputation techniques such as regression imputation or multiple imputation as shown in figure 2

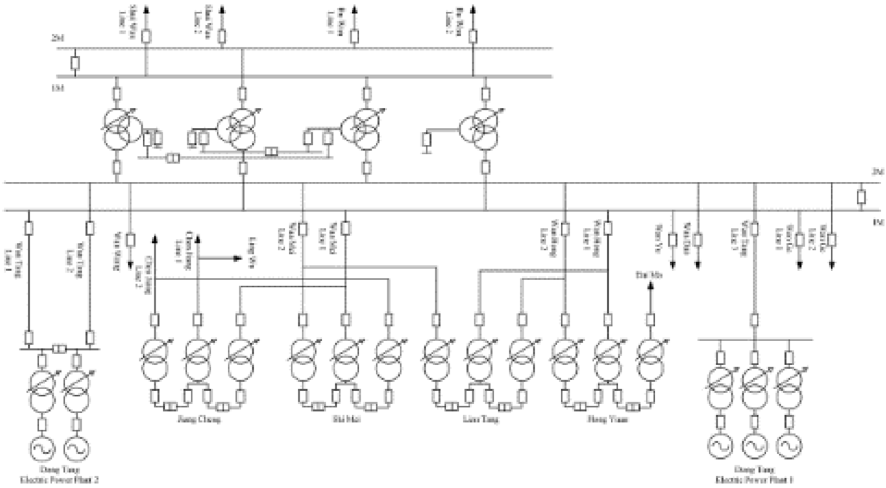

Figure 2: Primary electrical system in Norway above 110 kv, including electric power plants, transmission buses, converting stations, and user loads.

Finally, the pre-processed dataset is split into training and testing sets. The training set covers a significant period to allow the model to learn patterns and relationships, while the testing set is used to evaluate the model's performance on unseen data.

By following these data pre-processing and feature engineering steps, the dataset can be transformed into a suitable format for training a predictive model that accurately forecasts grid loss

C. LSTM Architecture

The Long Short-Term Memory (LSTM) is a specialized type of recurrent neural network (RNN) architecture that excels in capturing long-term dependencies in sequential data. Unlike traditional RNNs, LSTM networks overcome the issue of vanishing gradients, enabling them to retain and utilize information from earlier sequences more effectively.

The LSTM architecture as shown in figure 3 comprises a unique memory unit called the cell state (Ct) and three types of gates: the forget gate (ft), the input gate (it), and the output gate (ot). These gates play a crucial role in controlling the information flow within the LSTM cell, allowing it to selectively remember or forget information from previous time steps.

The forget gate evaluates the significance of the information stored in the previous cell state. It takes inputs from the previous hidden state (ht-1) and the current input (xt) and generates a forget gate activation (ft) ranging between 0 and 1. A value of 0 signifies complete forgetting, indicating that the LSTM cell should discard all previous information. Conversely, a value of 1 signifies retaining all information for future use..

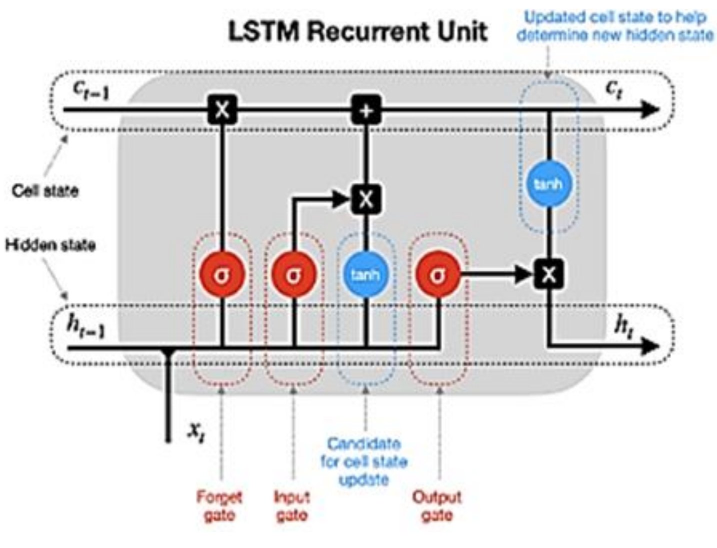

Figure 3: LSTM Architecture

D. Input Sequence

The LSTM architecture is designed to process sequential data, where each data point represents a specific time step. This could be any type of sequential data, such as text, audio, or numerical values. The input sequence is structured as a matrix, where the rows represent different time steps, and the columns represent the various features or dimensions of the data.

Within the LSTM cell, there are several key components that work together to process the input sequence. These components include the cell state, input gate, forget gate, output gate, and hidden state. The input gate determines which new information should be stored in the current cell state, allowing the LSTM to selectively incorporate relevant information. The forget gate decides which information from the previous time step should be discarded, ensuring that the LSTM focuses on the most important aspects of the sequence. The output gate regulates the influence of the current hidden state on the final output, enabling the LSTM to capture and retain the most relevant information for prediction or classification tasks.

E. LSTM Cell

The LSTM cell utilizes three types of gates, namely input gates (it), forget gates (ft), and output gates (ot), to regulate the flow of information within and outside the cell state. These gates employ sigmoid activation functions, which generate values ranging from 0 to 1.

The input gate (it) assesses the relevance of the current input (xt) and the previous hidden state (ht-1) in relation to power loss prediction. By computing an activation value, the input gate determines how much of the candidate cell state (C~t) should be incorporated into the cell state (Ct) at the given time step.

The forget gate (ft) governs whether the previous cell state (Ct-1) should be retained or forgotten. It takes into account the previous hidden state (ht-1) and the current input (xt), generating an activation value. This value is multiplied element-wise with the previous cell state, enabling the LSTM cell to selectively preserve or discard information..

F. Hidden State

In an LSTM model, the hidden state acts as a memory and learned representation of the input sequence. It encapsulates the information and patterns extracted by the LSTM cell from the sequential data. The hidden state is not only utilized within the LSTM cell itself but also plays a crucial role in generating predictions and transmitting information to subsequent time steps or other model layers.

Following each time step, the LSTM cell updates its hidden state (ht) based on the current input (xt) and the previous hidden state (ht-1). This update process involves the activation of input gates, forget gates, and output gates, which control the flow of information and determine the relevance of the input and previous hidden state.

The hidden state (ht) serves various purposes. In subsequent time steps, the hidden state from the previous step (ht-1) is fed as input to the current LSTM cell, allowing the model to build upon the knowledge it has accumulated thus far. This recurrent nature empowers the LSTM model to capture long-term dependencies and retain memory of relevant patterns over extended sequences.

Overall, the hidden state in an LSTM model plays a vital role in connecting time steps, capturing and preserving the learned information from the input sequence. It enables the model to make predictions, build upon past knowledge, and provide valuable representations for different downstream tasks. Leveraging the hidden state enhances the LSTM model's capacity to capture temporal dependencies and extract meaningful insights from sequential data, making it a powerful tool in power loss prediction and other time series applications..

G. Multiple LSTM Layers

Stacking multiple LSTM layers in an architecture enhances the model's ability to learn complex patterns and dependencies in the data. Each layer in the stack builds upon the representations learned by the previous layer, creating a hierarchical structure that captures increasingly abstract information.

In a multi-layer LSTM architecture, the output of one LSTM layer serves as the input to the next layer. This sequential flow of information allows the model to learn representations at different levels of abstraction. Each layer focuses on capturing specific temporal patterns and relationships, leveraging the knowledge acquired by the previous layers.

The bottom layer of the stacked LSTM architecture receives the input sequence, which represents historical observations of power loss. Using its LSTM cell and gating mechanisms, this layer processes the input and generates a hidden state. This hidden state is then passed to the next layer, which performs a similar operation. This process continues through each layer until reaching the top layer, which produces the final hidden state representation.

By stacking multiple LSTM layers, the model becomes more adept at capturing intricate temporal patterns and can effectively learn complex relationships in the data. This hierarchical approach allows for improved representation learning and enhances the model's prediction capabilities for power loss...

H. Dense Layers and Output

After the LSTM layers in the model architecture, additional dense layers can be incorporated. These dense layers act as supplementary processing units that further refine and transform the features extracted by the LSTM layers. Comprising interconnected neurons, dense layers apply non-linear transformations to the input data.

The purpose of integrating dense layers following the LSTM layers is to enhance the model's ability to capture higher-level representations and intricate patterns within the input data. These layers are capable of learning and extracting more abstract features that are pertinent to the specific prediction task at hand. For instance, they can aid in classifying power loss incidents, predicting the magnitude of power loss, or generating a sequence of future power loss values.

I. Training

The training of the LSTM architecture, like other neural network models, involves optimizing its parameters to enhance its predictive capabilities. This training process utilizes labeled or unlabeled data, depending on the specific task.

For supervised learning tasks like power loss prediction, the LSTM architecture is trained using labeled data, where each input sequence is associated with a corresponding target output. The training dataset consists of historical observations of power loss and their corresponding true values.

During training, the LSTM model iteratively adjusts its internal parameters to minimize a defined loss function. This loss function quantifies the disparity between the predicted output values and the true target values. Common loss functions for regression tasks, such as power loss prediction, include mean squared error (MSE) and

mean absolute error (MAE), which measure the average squared or absolute difference between predicted and true values.
Through this iterative training process, the LSTM architecture learns to capture the intricate temporal dependencies and patterns present in the power loss data. By minimizing the loss function and updating its parameters, the model progressively enhances its ability to make accurate predictions on unseen data.
It is important to note that the training process of the LSTM architecture requires careful consideration of hyperparameters, such as the learning rate, batch size, and number of epochs. These hyperparameters impact the convergence speed and the quality of the trained model. Proper tuning of these hyperparameters is crucial to ensure optimal performance.

J. Prediction

Once the LSTM model is trained, it can be deployed for making predictions on new, unseen data. The model takes an input sequence and propagates it through the LSTM layers, producing the predicted output based on the learned patterns and dependencies captured during training.

V. RESULTS AND DISCUSSION

From the below graphs, we can interpret the following:
Time and Date: The "Unnamed: 0" column represents the date and time of the data entries. In this case, the data seems to be from December 1, 2019, with timestamps ranging from 00:00:00 to 04:00:00.
Demand: The "demand" column provides the recorded demand values at each specific date and time. The values range from 288.46 to 314.40. These values represent the energy demand during the corresponding time intervals.
Grid Load and Grid Loss: The "grid1-load" column indicates the load on grid1, which ranges from 392.90 to 407.68. The "grid1-loss" column represents the loss on grid1, with values ranging from 20.25 to 21.55. Higher load and loss values may indicate increased energy consumption and potential inefficiencies in the grid system.
Prophet Model: The columns "grid1-loss-prophet-daily," "grid1-loss-prophet-pred," "grid1-loss-prophet-trend," "grid1-loss-prophet-weekly," and "grid1-loss-prophet-yearly" correspond to predictions or trends generated by the Prophet model. These columns provide additional information about grid1 loss based on the specific forecasting model utilized.
Temperature: The "grid1-temp" column indicates the temperature data associated with each date and time. The temperature values range from 273.05 to 273.35.
Time-related Features: The columns "month," "monthly," "week," "weekly," "weekday," "weekday," "holiday," "hour," and "hourly" represent various time-related features. These features might be encoded values indicating specific characteristics associated with each date and time, such as the month, week, weekday, holiday status, and hour.
Incorrect Data: The "has incorrect data" column indicates whether the data in each row is flagged as incorrect or problematic. In this case, all the data entries are marked as "False," suggesting that there are no identified issues with the data quality. Training and testing accuracy can be seen in figure 4. Predicted loss and actual loss on test set for next 36 hours can be seen in figure 5. prediction of energy loss for '2019-12-06', '2019-12-13' is shown in figure 6. Figure 7 shows prediction testing over the years from '2020-01-15', '2020-01- . prediction testing over the years from '2017-01-27'. '2020-06-03' can be seen in figure 8.

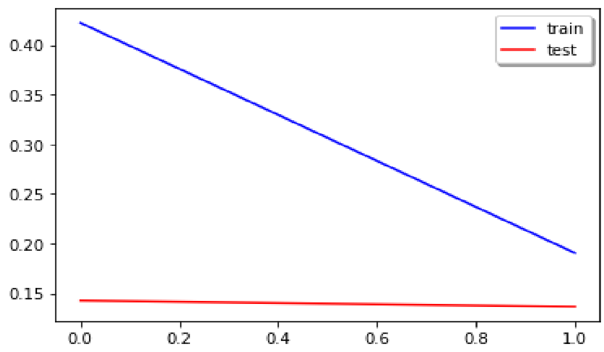

Figure 4: Training and testing accuracy

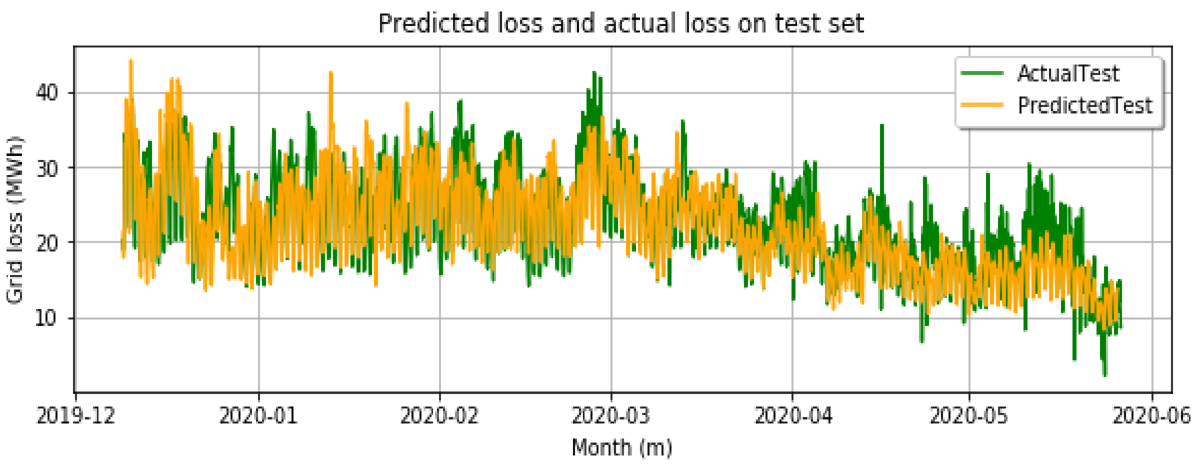

Figure 5: Predicted loss and actual loss on test set for next 36 hours.

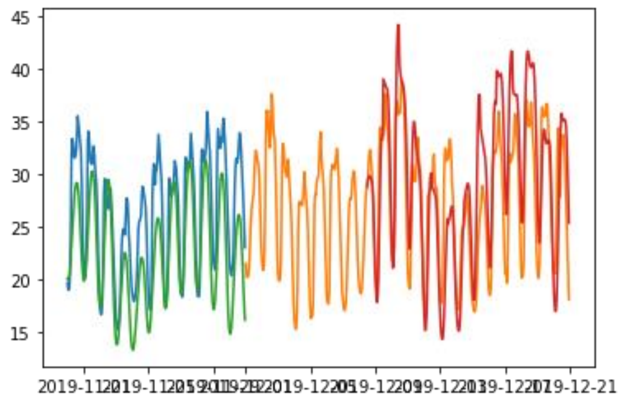

Figure 6: prediction of energy loss for '2019-12-06', '2019-12-13'

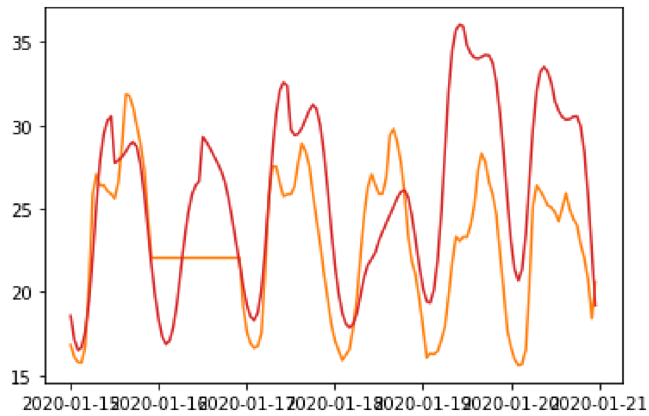

Figure 7: prediction testing over the years from '2020-01-15', '2020-01-

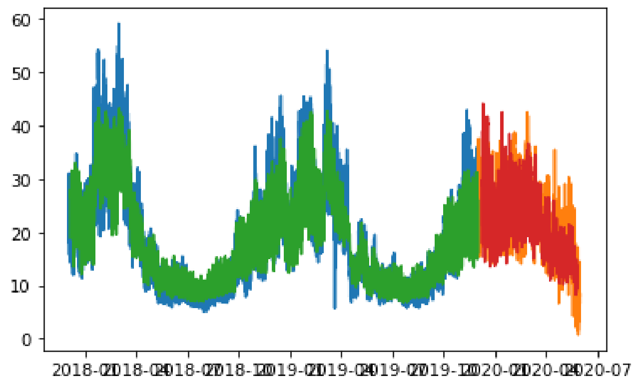

Figure 8: prediction testing over the years from '2017-01-27', '2020-06-03'

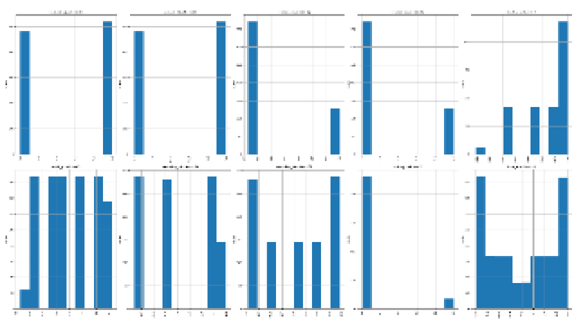

Figure 9: Plot per column distribution

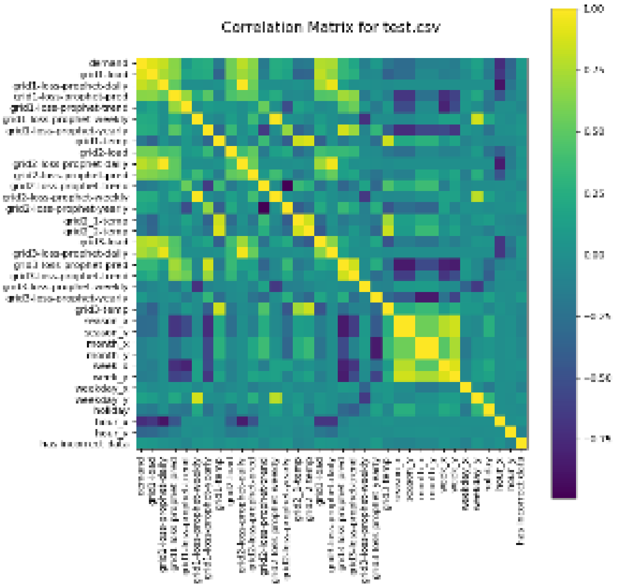

Figure 10: Correlation matrix for test

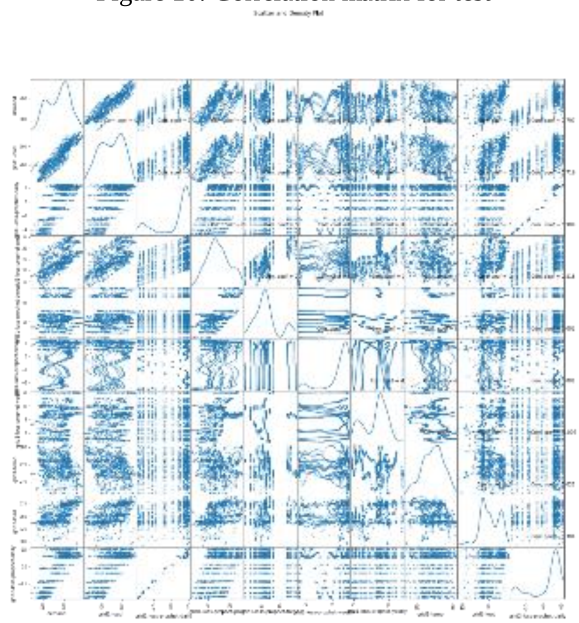

Figure 11: Scatter and Diversity plot

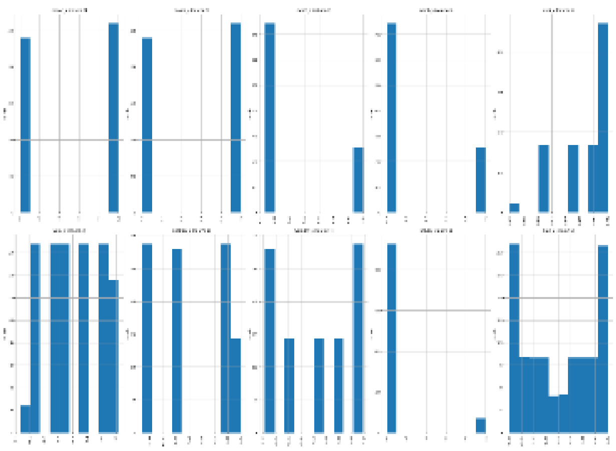

Figure 12: Plot per column

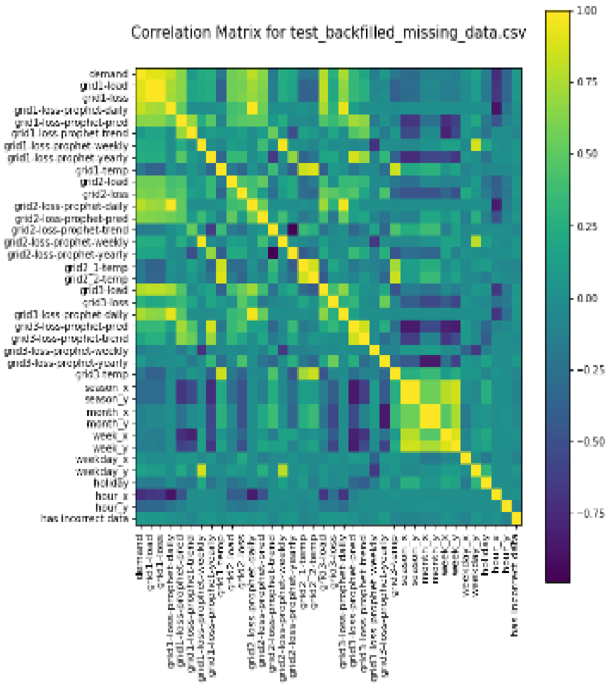

Figure 13: Correlation matrix for test backfilled missing data

Plot per column distribution can be seen from figure 9. Correlation matrix for test is shown in figure 10. Scatter and diversity plot is shown in figure 11 and plot per column can be seen in figure 12. In figure 13 Correlation matrix for test backfilled missing data is explained. The graphs represents various data points related to demand, grid load, grid loss, temperature, and other factors. Each row corresponds to a specific date and time. The "Unnamed: 0" column represents the date and time of the data entry. The "demand" column shows the recorded demand value at that specific date and time. The "grid1-load" column indicates the load on grid1, while the "grid1-loss" column represents the loss on grid1.

The data includes several columns related to a forecasting model called "Prophet," including "grid1-loss-prophet-daily," "grid1-loss-prophet-pred," "grid1-loss-prophet-trend," "grid1-loss-prophet-weekly," and "grid1-loss-prophet-yearly." These columns likely contain predictions or trends calculated by the Prophet model for grid1's loss.

Additional columns such as "grid1-temp" suggest the inclusion of temperature data. The table also contains columns related to time information, such as "month," "monthly," "week," "weekly," "weekday," "weekday," "holiday," "hour," and "hourly." These columns likely represent different time-related features or attributes associated with the date and time of the data entry.

The last column "has incorrect data" indicates whether the data in that row is flagged as incorrect or problematic. In summary, the table provides specific details about demand, grid load, grid loss, temperature, time-related features, and the accuracy of the data entries. Scatter and diversity plot can be seen in Figure 14.

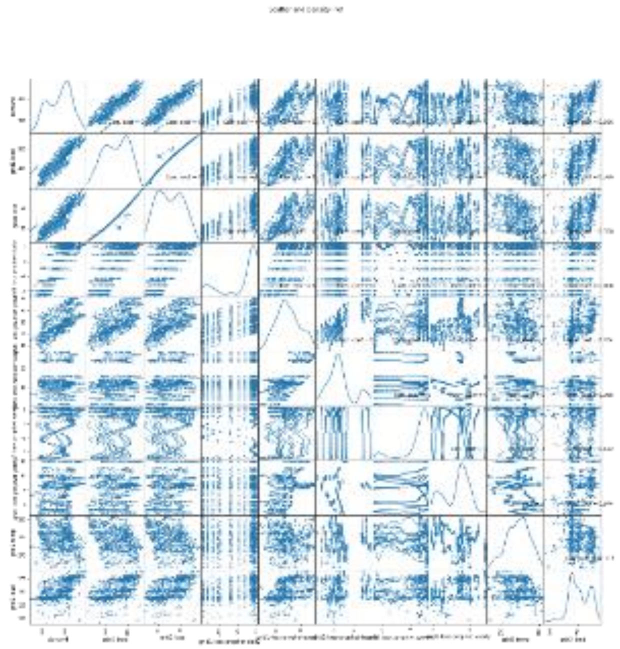

Figure 14: Scatter and diversity plot

VI. CONCLUSION

In summary, the Paper dataset contains hourly values of various features relevant to predicting grid loss. These features include grid loss measurements, grid load measurements, temperature forecasts, predictions from the Prophet model, and components of grid loss trends derived from the Prophet model. The dataset also includes calendar features such as year, season, month, week, weekday, hour, and holiday indicators. Additionally, the dataset provides estimated electricity demand for Trondheim.

The dataset is split into a training set and a test set. The training set spans two years, from December 2017 to November 2019, and includes all the aforementioned features. The test set covers six months, from December 2019 to May 2020, and contains the same features as the training set, with some occasional missing values. An additional version of the test dataset is provided, where the missing features are filled in using backfilling.

It is important to consider the cyclic nature of the calendar features. Representing weekdays as simple numbers from 0 to 6 does not reflect their proximity to each other. To address this, cyclic calendar features were created using cosine and sine functions. This ensures that the highest and lowest values of the features are positioned close to each other in the feature space. Although demand estimates are not available for all grids, predictions for Trondheim, the largest nearby city, were used as a substitute. Additionally, since grid load is directly proportional to grid loss, historical load measurements were predicted and included as a feature for grid loss prediction. While the Prophet model did not perform well as a standalone prediction tool for the dataset, it proved valuable for incorporating its predictions and other components as features in the model.

It is worth noting that Grid 3 has less training data compared to Grid 1 and Grid 2. This imbalance should be taken into consideration during the development and evaluation of the predictive model.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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