Toward Energy-Efficient 5G: A Machine Learning-Based Prediction Approach

Hamdi Barkous

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Abstract

5G networks, while promising increased energy efficiency, also bring with them heightened energy consumption challenges, particularly due to more cells for coverage and augmented processing needs. A considerable part of this energy is consumed by base stations, whose consumption is affected by various factors. Traditional models have found it challenging to capture the intricate relationships between these parameters. This study introduces a machine learning-based approach to predict the energy consumption of these base stations under varying conditions. Using cell-level traffic statistics from 5G sites, we sought to understand how different parameters influence base station energy consumption. Our results indicate a high accuracy of our predictive model with a Weighted Mean Absolute Percentage Error (WMAPE) of 7.7% for the test set. Density plot analyses further confirmed the model's capability to closely match the training data's energy density, though minor refinements are suggested for tail-end deviations. This research underscores the effectiveness of machine learning in predicting and managing energy consumption in 5G networks and hints at areas for future refinement.

1 Introduction

The fifth generation of radio technology, 5G, has ushered in a new era of services, technologies, and networking paradigms, offering numerous societal benefits Tan et al. (2022). However, the energy consumption associated with these new network deployments has become a significant concern. While 5G networks promise enhanced energy efficiency, their actual energy consumption is considerably higher due to the need for more cells to provide the same coverage at elevated frequencies and the increased processing required for broader bandwidths and additional antennas Lorincz et al. (2021). The operational expenditure (OPEX) of networks, which constitutes a significant portion of the total operator's cost, is primarily driven by substantial energy bills. A significant chunk of this energy is consumed by the radio access network (RAN), especially the base stations (BSs) Frenger and T. (2019). The energy consumption of these base stations is influenced by various factors, including their architecture, configuration parameters, traffic conditions, and the activation of energy-saving methods Gupta et al. (2020). To achieve energy-efficient network deployments, it is imperative to understand and optimize these parameters and methods, necessitating accurate energy consumption modeling.

While there has been significant research on understanding the energy consumption patterns and underlying influential factors of base stations, there remains a gap in creating accurate predictive models that adapt to dynamic scenarios and changing parameters. Leveraging machine learning techniques can address this gap, providing insights that can be used for proactive network management, efficient resource allocation, and, ultimately, optimized energy consumption.

In this report, we present a machine learning-based approach to predict the energy consumption of base stations under varied scenarios. Each scenario is characterized by specific attributes, such as the number of antennas, traffic load, operating frequency, and maximum transmit power. This approach is especially pertinent given the varied nature of 5G deployments, where different network configurations may be employed to cater to specific service needs. Traditional static models may not capture the intricacies and relationships between the various parameters; hence, a more adaptive and flexible modeling approach is required.

To build our predictive model, we have utilized cell-level traffic statistics of 5G sites. This data, collected on different days, provides an hourly granularity, allowing us to explore the diurnal patterns and fluctuations in energy consumption. Through this work, we aim to offer a comprehensive understanding of how different parameters impact the energy consumption of base stations, and how machine learning can be a powerful tool in predicting and managing this consumption more efficiently.

2 Methodology

2.1 Data Preprocessing

In the foundational stages of our data science journey, understanding and preparing the data for our predictive model was of paramount importance. The nuances, quality, and relevance of the dataset directly influence the accuracy and robustness of our predictions.

Data Selection: Our initial foray involved meticulously selecting and curating the data tailored for our analysis. Our attention was especially drawn towards the 'Base Station' and 'Cell Level' datasets. Our primary objective was to sieve out the most informative predictors that would eventually guide our energy consumption prediction model.

Revised Data Structures: Understanding the intricate nature of the base stations, where multiple cells can operate simultaneously, prompted us to refine the structure of the 'cell_level_data' and 'base_station_info' datasets.

For the 'base_station_info', new columns were introduced to elaborate on the properties of the primary cell, such as 'RUType_1', 'Mode_1', among others. However, given the sporadic appearances of 'cell2' and 'cell3', we strategically decided against their inclusion to avoid dimensionality inflation, which can inadvertently steer the model towards overfitting.

Meanwhile, the 'cell_level_data' dataset was also augmented to encapsulate additional columns like 'load_1', 'ESMode1_1', etc. It's pertinent to highlight that parameters such as 'Rutype' and 'Mode' are invariant across cells for a given base station. Consequently, redundant columns like ‘Rutype_1‘ and ‘Mode_1‘ were pruned from our dataset.

Handling of CellName Values: An instrumental phase in our data preprocessing was managing the ’CellName’ values. Notably, ’CellName0’ and ’CellName1’ surfaced as the dominant unique identifiers. Data stemming from these two cells was retained, while other ’CellName’ instances were harmoniously amalgamated into our train and test sets.

Feature Engineering: To bolster the predictive capacity of our model, we ventured into feature engineering. New variables were birthed from existing ones by harnessing operations like summation and multiplication. For instance, in the ‘cell_level_data‘ dataframe, a novel column ‘load_sum‘ was fashioned to store the aggregate of ‘load‘ and ‘load_1‘ values. Similarly, a ‘load_mult‘ column was introduced to encapsulate their product. These freshly minted features were architected to unearth pivotal patterns and relationships embedded within the data.

The ensuing segments of this report will navigate through other salient dimensions of our methodology, encompassing exploratory data analysis, model fine-tuning, and subsequent post-processing maneuvers.

2.2 Exploratory Data Analysis

The exploratory data analysis aims to offer an in-depth understanding of the dataset’s characteristics, revealing patterns, correlations, and insights essential for building our predictive model. The analysis is structured into four primary segments: Univariate Analysis, Bivariate Analysis, Correlation Analysis, and Time Series Analysis.

2.2.1 Univariate Analysis

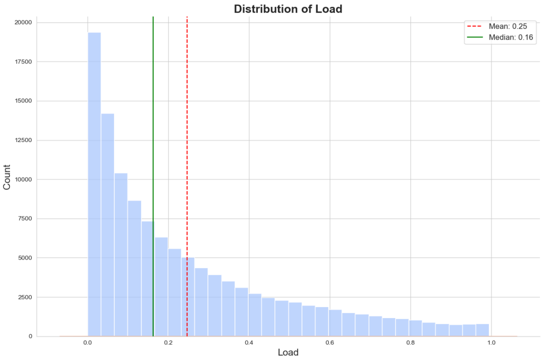
Univariate Analysis provides insights into the distributions of individual variables in the dataset. We delve into the characteristics of essential columns such as ’Load’, ’ESModes’, ’Frequency’, ’Antennas’, ’TXpower’, and ’Energy’.

From these visualizations, key observations include:

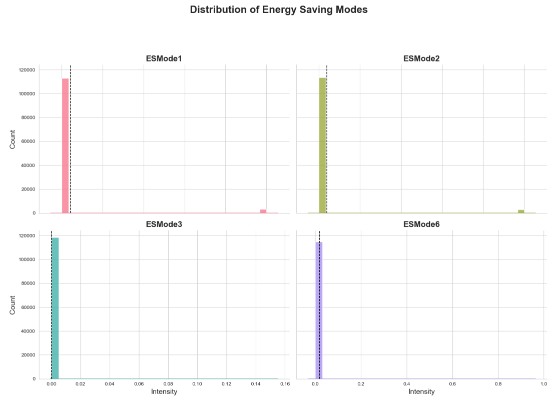
- The majority of base stations typically operate at lower load capacities, with few reaching full capacity.
- Several energy-saving modes, like ’ESMode3’ and ’ESMode6’, showcase bimodal activations.
- The 365 MHz frequency is predominantly utilized.
- A majority of base stations come equipped with 4 antennas, while the maximum transmit power distributions are inclined towards higher values.
- Energy consumption is right-skewed, with many instances consuming lower energy levels.

2.2.2 Bivariate Analysis

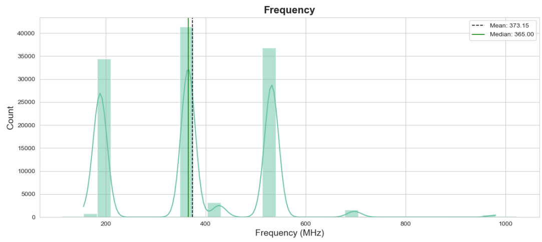
The Bivariate Analysis evaluates how variables correlate with energy consumption. Key variables such as ’Frequency’, ’Antennas’, ’TXpower’, and ’RUType’ are cross-examined



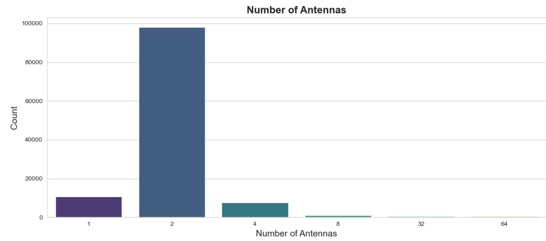
(a) Distribution of 'Load'



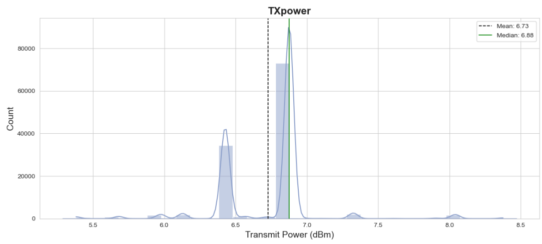
(b) Distributions for different 'ESModes'



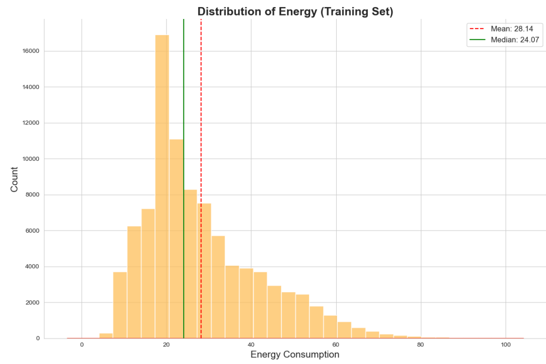
(c) Distributions of 'Frequency'



(d) Distributions of 'Antennas'



(e) Distributions of 'TXpower'



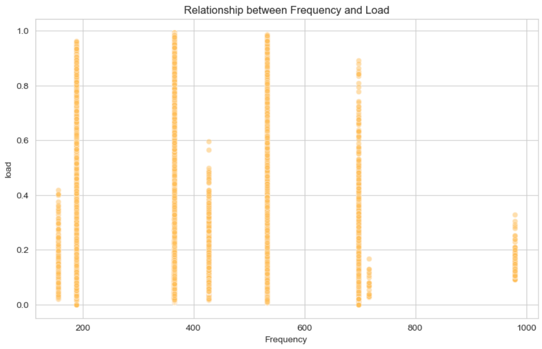
(f) Distribution of 'Energy'

Figure 1: Distribution plots for various columns

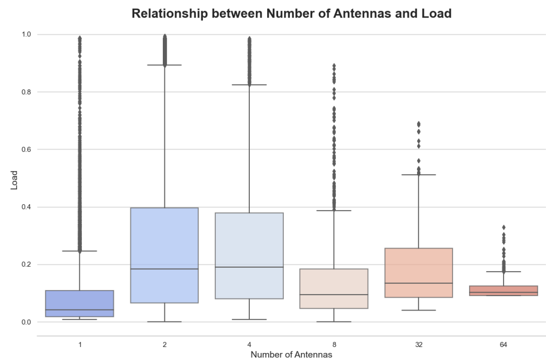
against 'Load' to deduce their influence on energy consumption.

Insights from these analyses include:

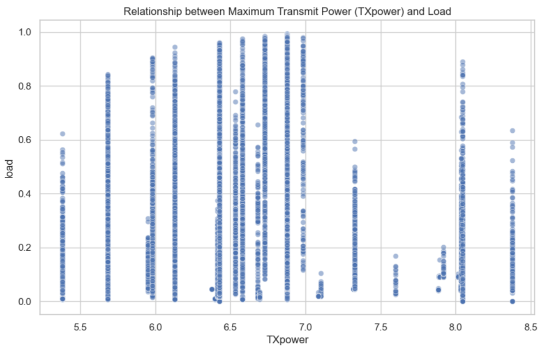
- A lack of clear linear relationship between frequency and load.
- Stations with more antennas demonstrate a wider load range, with some having higher median loads.
- The relationship between transmit power and load lacks a linear pattern.
- Different radio unit types contribute varied load levels, with specific types showing distinctive median loads.



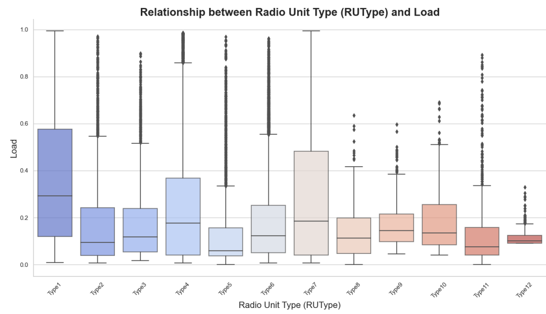
(a) Relationship between 'Frequency' and 'Load'



(b) Relationship between 'Antennas' and 'Load'



(c) Relationship between 'TXpower' and 'Load'



(d) Relationship between 'RUType' and 'Load'

Figure 2: Relationship plots for various features against 'Load'

2.2.3 Correlation Analysis

The Correlation Analysis quantifies the relationships between variables, particularly focusing on correlations with energy consumption.

From this visualization, we can deduce certain relationships between variables, emphasizing their influence on energy consumption.

2.2.4 Time Series Analysis

This section delves into the temporal aspects of the data, specifically focusing on energy consumption's temporal variation. A time series analysis is essential for understanding how energy consumption fluctuates over time, which can be instrumental in developing a robust predictive model.

Time Series Plot: Key observations from the time series analysis include:

- Identification of cyclical patterns, indicating daily fluctuations in energy consumption.
- Recognition of peaks and troughs at regular intervals, likely corresponding to daily high and low usage periods.

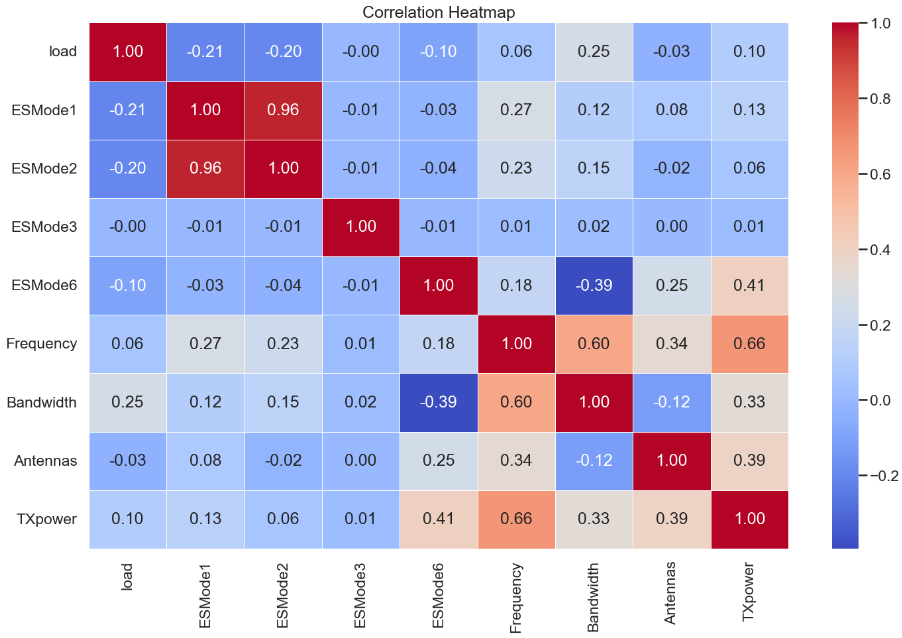


Figure 3: Heatmap of Correlations

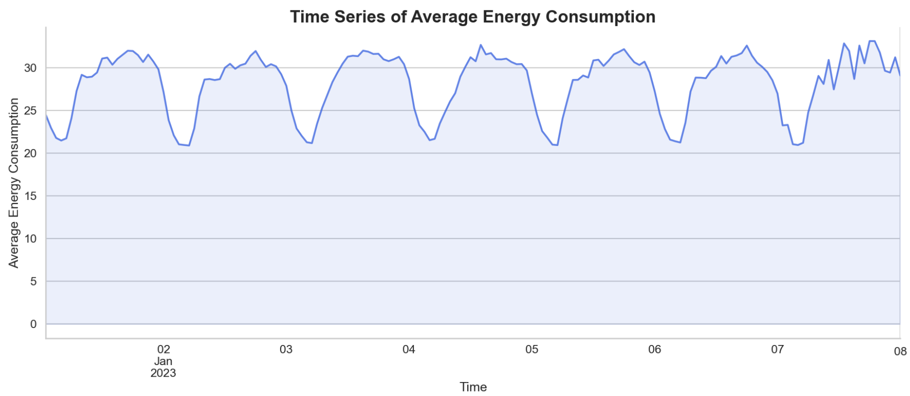


Figure 4: Time Series Analysis of Energy Consumption

- Interpretation of the cyclical pattern, which is typical for many utilities, where consumption rises during certain hours (e.g., daytime or evening) and drops during off-peak hours (e.g., late at night).

Concluding the exploratory analysis, it is evident that the dataset's patterns, dependencies, and correlations will significantly influence subsequent modeling and prediction stages.

2.3 Feature Engineering

2.3.1 Temporal Feature Engineering

To enhance our model's predictive power, several time-related features are introduced. Specifically, we derive the following:

- **Hour**: Extracted from the 'Time' column.

- **Hour_sin** and **Hour_cos**: Conversion of hours into cyclic features via sine and cosine transformations.
- **hour_class**: Categorization of hours into predefined classes.
- **Day_of_week**: Recognizing the day of the week.
- **Is_weekend**: Ascertainment if the day falls on a weekend.
- **Day_of_month**: Extraction of the day from the 'Time' column.

We further compute the power utilization ratio for each record and assess the energy-saving intensity by aggregating specific energy-saving modes. These temporal and aggregative methodologies enhance our model's overall predictive accuracy.

2.3.2 Aggregative Feature Engineering

Here, we focus on aggregative feature engineering, emphasizing on generating statistical features by grouping data by specific variables. This facilitates a deeper insight into the data. By clustering data based on the unique 'BS' (Base Station) identifiers, we empower the model to generalize across various base stations, learning from the behaviors of multiple stations to predict energy consumption for unseen ones.

2.3.3 Encoding Categorical Features

We employ ordinal encoding to convert categorical columns, specifically 'BS', 'Mode', and 'RUType'.

2.3.4 Power Utilization and Energy Saving Intensity

The power utilization ratio for each record is computed, ensuring robust handling of potential division by zero cases. In parallel, the energy saving intensity is determined by summing specific energy-saving modes.

2.3.5 Function Overview: 'predict_next_load'

This function harnesses the power of **XGBoost** to forecast the subsequent load value based on historical data. Due to constraints from the competition host that prevent the use of future values, a strategy was devised to forecast these values relying solely on past data.

Key steps include:

1. Chronologically sorting data via the 'Time' column.
2. Iteration over each unique Base Station to manage data extraction and interpolation.
3. Data preparation for XGBoost model training.
4. Load value predictions and dataframe updates.

Usage:

```
merged_data = predict_next_load(merged_data)
```

To finalize preprocessing, columns of the 'merged_data' DataFrame are filtered to retain only those with more than one unique value, ensuring they offer variability for downstream analysis.

2.4 Model Development and Validation

In the quest to develop a predictive model for energy consumption, the following methodology was employed to ensure robust training, validation, and ultimately, a model with strong generalization capabilities across various base station products.

2.4.1 Grouping by Base Station

The first step in the modeling process was grouping the data based on unique values of the feature denoted as 'BS' (presumably representing Base Station). This grouping ensured that data from the same base station is consistently placed together, paving the way for representative validation during cross-validation.

2.4.2 GroupKFold Cross-Validation

Traditional K-Fold cross-validation risks scattering data from a single base station across both training and test sets, potentially compromising the quality of validation. To circumvent this, we employed the 'GroupKFold' cross-validation. This approach ensures that all data from a single base station is exclusively in either the training set or the test set. This validation methodology closely aligns with real-world scenarios, wherein the objective is to predict energy consumption of unseen base stations based on data from known stations.

2.4.3 Model Training with XGBoost

For model training, we leveraged the XGBoost Regressor with the following hyperparameters:

- Objective: 'reg:gamma'
- Number of estimators: 2100
- Learning rate: 0.05
- Column sample by tree: 0.7
- Subsample: 0.8
- Maximum depth: 8
- Regularization lambda: 5

The choice of the ‘reg:gamma‘ objective was influenced by our observation that the distribution of energy consumption resembled a Gamma Distribution. This insight, combined with the specified hyperparameters, ensures our model is finely tuned to capture the nuances of our data’s distribution, potentially enhancing prediction accuracy.

2.4.4 Model Evaluation

To gauge the model’s performance, the mean absolute error (MAE) was computed between the actual values and predictions on the test set. This metric serves as a transparent measure of the model’s ability to make precise energy consumption forecasts across diverse base stations.

2.4.5 Iterative Training and Validation

The model underwent rigorous training and evaluation for each fold in the cross-validation process. This iterative approach ensures the model’s exposure to varying combinations of training and test data. Once all folds were evaluated, an average loss was calculated to provide a comprehensive assessment of the model’s performance across the entire dataset.

In summary, our methodology, comprising of GroupKFold cross-validation, strategic feature engineering, and a tailored XGBoost model, aspires to simulate the real-world challenge of forecasting energy consumption for unseen base stations, based on historical data from known products.

2.5 Post-Processing

A keen observation of our dataset revealed that despite its considerable size, approximating 90,000 records, it encompasses merely around 600 unique values. This characteristic suggests a significant portion of the dataset might have been synthesized. To address this, a post-processing strategy tailored to ensure consistent and relevant energy predictions was devised.

2.5.1 Differentiating Base Stations

Our strategy bifurcates the predictions into two distinct categories:

1. **Known Base Stations**: These are base stations that have previously been encountered in the training dataset. For such stations, we align the predicted energy value from the test set with the nearest energy value observed for the respective base station in the training set. This approach is grounded in the rationale of ensuring continuity and relevance in the predicted energy values based on historical data.

2. **Unknown Base Stations**: These represent base stations that are uniquely present in the test dataset, with no prior records in the training data. For these stations, the initial energy predictions are preserved, as no reference data from the training set is available to make adjustments.

This strategy is fundamentally designed to uphold the integrity and relevance of the predicted energy values, while concurrently accommodating for both familiar and unfamiliar base stations in the test dataset.

Your write-up provides a clear and detailed account of the model's performance. However, I can offer some refinements and further insights based on the image and the content provided:

2.6 Results

This section comprehensively examines the outcomes from our predictive model. Using quantitative metrics, along with the visual display of predictions, we can discern the model's proficiency.

2.6.1 Quantitative Assessment

The primary yardstick for the model's assessment is the Weighted Mean Absolute Percentage Error (WMAPE). It quantifies the error percentage while factoring in the magnitude of the actual values. This ensures that substantial deviations on smaller values don't go unnoticed.

For the test set, the model returned a WMAPE of 0.077 or 7.7%. In simpler terms, our predictions, on average, veer from the true values by a margin of 7.7%. In the realm of energy consumption forecasting, such precision underscores our model's commendable predictive prowess.

2.6.2 Density Distribution Visualization

To dive deeper into the model's capabilities, a density plot is employed. It visually contrasts the distribution of energy consumption from the training dataset with the predictions for the test dataset.

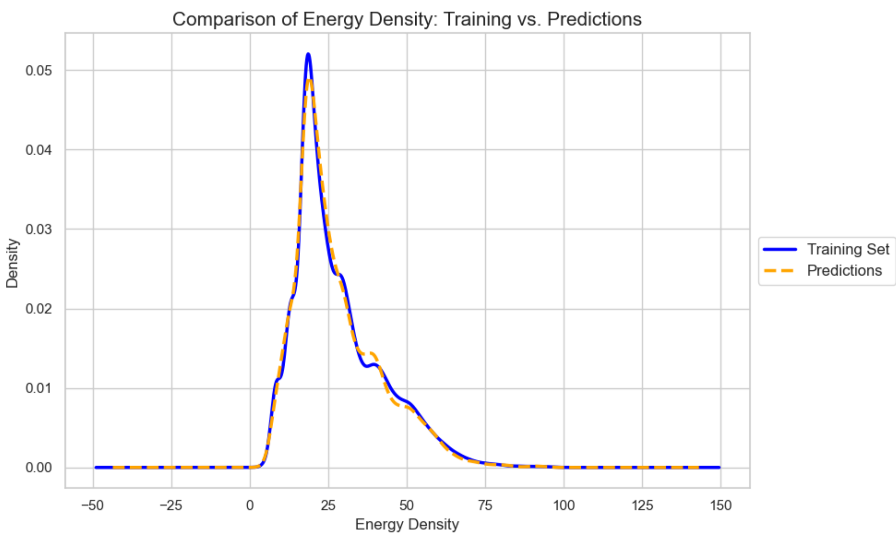


Figure 5: Comparative density plot highlighting energy consumption in the training dataset against predictions for the test dataset.

Upon scrutinizing the graph, it's evident that the test predictions closely mirror the training set's energy density, especially around the peak values. This overlap speaks volumes about the model's capacity to emulate the training data's inherent characteristics when forecasting. However, some deviations are noticeable at the tail ends, suggesting areas where model refinements could further improve predictions.

2.6.3 Conclusion

Both the quantified WMAPE score and the illustrative density plot mutually corroborate the model's substantial effectiveness in predicting energy consumption across diverse base stations. The outcomes emphasize the potency of our chosen modeling and validation strategies. Nonetheless, future endeavors will aim to bridge the observed gaps, striving for even greater accuracy.

3 Discussion

The utility of machine learning in predicting energy consumption for 5G base stations has been showcased through our research. While our results indeed portray a promising performance of our predictive model, it is important to understand potential limitations and explore further enhancements.

3.1 Limitations

1. **Data Granularity**: Our dataset's hourly granularity, useful for capturing broader diurnal patterns, might omit short-lived fluctuations in energy consumption. Variations within the hour that could be influential remain undetected at this granularity.
2. **Model Simplifications**: Every machine learning model introduces some level of simplifications and assumptions. Decisions related to the number of layers, choice of algorithm, or the training technique can influence prediction accuracy. The discrepancies observed at the tail ends of the density plot could be outcomes of these model simplifications.

3.2 Future Work

1. **Finer Data Granularity**: To obtain a more detailed understanding of energy consumption patterns, future research might consider data at finer granularities, such as every few minutes. This could reveal short-term variations that the hourly granularity might overlook.
2. **Exploring Advanced Modeling Techniques**: Incorporating advanced techniques such as deep learning, ensemble methods, or hybrid models could enhance prediction accuracy. Addressing the reasons behind the deviations observed in the density plot could further refine the predictive capabilities.

In conclusion, our model, while effective, serves as a testament to the continuous nature of scientific exploration. The pursuit of energy-efficient network deployments remains a key focus, with further refinements and advancements anticipated in subsequent iterations.

References

Frenger, P. and T., M. (2019). More capacity and less power: How 5g nr can reduce network energy consumption. *VTC Conference*.

Gupta, A., S., R., F., T., and T., M. (2020). Apt-ran: A flexible split-based 5g ran to minimize energy consumption and handovers. *IEEE Transactions on Network and Service Management*.

Lorincz, J., K., D., and B., M. (2021). Modeling and analysis of data and coverage energy efficiency for different demographic areas in 5g networks. *Sensors Journal*.

Tan, X., S., Y., F., Z., Z., W., and W., X. (2022). Energy saving technologies and best practices for 5g radio access network. *IEEE Access*.