Energy Consumption Modelling for 5G Networks

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Abstract

5G, as the next-generation cellular technology, has undeniably revolutionized the telecommunication landscape with its superior data transfer capabilities and reduced latency. However, this enhanced performance comes at a price: increased energy consumption. As the global push towards sustainability intensifies, balancing the benefits of 5G's advanced transfer performance with its energy demands becomes paramount. Accurate prediction of energy consumption can inform optimization strategies, ensuring that the advantages of 5G are harnessed without undue environmental and economic costs.

This paper introduces a novel energy consumption modeling framework that captures the dynamic and multifaceted nature of 5G networks. This analysis integrates machine learning, data analytics and mathematical modeling techniques to predict energy usage under varying network conditions and scenarios.

1. Introduction

In this research paper, we systematically evaluate various machine learning models tailored to predict the energy consumption of 5G networks. The dataset under scrutiny encompasses time sequential tabular data, reflecting past energy consumption patterns, alongside detailed technical configuration data from 5G network stations. Our evaluation centers on average error metrics, providing a standardized measure for gauging the predictive accuracy of the assessed models.

By prioritizing average error as our evaluative benchmark, we aim to offer an objective comparison of the performance of the various ML models in predicting 5G energy consumption. This metric-centric approach ensures that the results are quantifiable, replicable, and directly tied to real-world implications. It is anticipated that the insights garnered from this research will aid telecommunication engineers, data scientists, and ML practitioners in refining 5G operations. Ultimately, the goal is to strike an equilibrium between harnessing the full potential of 5G's transfer capabilities and maintaining sustainable energy consumption patterns.

Upon obtaining the dataset, our first task involved a systematic familiarization with its structure and attributes. This initial stage was crucial to comprehend the dataset's inherent characteristics, potential inconsistencies, and any nuances that might impact subsequent analysis.

Following this, data cleaning was undertaken. Given the intricate nature of real-world datasets, especially in the telecommunication sector, this step is of paramount importance. A comprehensive analysis revealed an uneven distribution of missing data across various attributes, which necessitated specialized treatment. Addressing such irregularities is critical to ensure that the subsequent modeling phase maintains both the integrity and the accuracy of the predictions.

This methodical approach to data preparation, ensuring both familiarity and thorough cleaning, provided a robust foundation for the ensuing modeling and evaluative processes. By addressing the challenges presented by the dataset in a structured manner, we aimed to optimize the predictive capabilities of our chosen machine learning models for 5G energy consumption.

2. Data analysis

The first step in the data mining process was to visualize all the basic information such as their distributions or correlation between input and output variables. The most crucial information we obtained during this process was capturing the dependencies between similar inputs that manifest in the form of "stripes" in the UMAP plot (Figure 1). That manifestation led us to believe, that the input vector should contain the energy from previous time steps and that a recurrent/autoregressive model would perform the best.

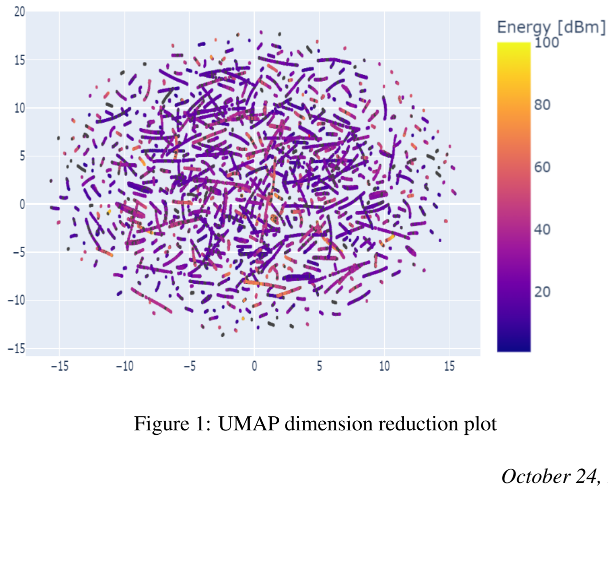

Figure 1: UMAP dimension reduction plot

When observing the attribute distribution of training and prediction data, we noticed that the **Hour** histogram is almost evenly scattered and seems to be the most balanced input (Figure 2 and Figure 4).

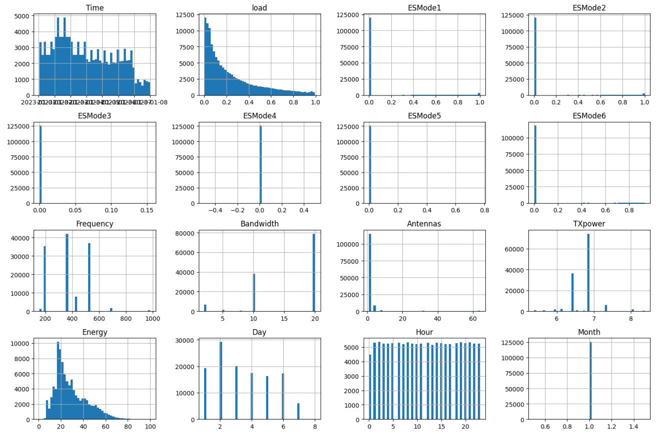

Figure 2: Distribution of attributes in training data

That observation led us to the conclusion that filling the missing samples with values from different day's corresponding hours of the same base station is most likely to provide enough information to padd all the missing data volume. This method emerged as an alternative to scaling each known sample input attribute to the interval: (0, 1] and filling the missing values with 0's. Our further exploration of the dataset led us to the termination of **cell2** and **cell3** attributes as network inputs, since there where only 48 occurrences of them (Figure 3).

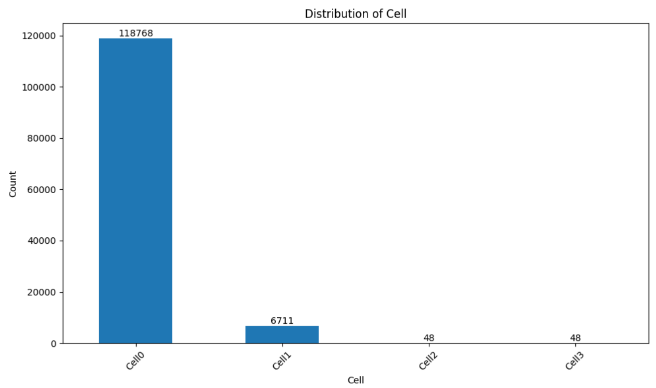

Figure 3: Distribution of cells

2.1. *Data handling*

The final algorithm consists of two independent networks - the first one was trained on all one-cell base station samples i.e. **B_1, B_100**, etc. and it's sole purpose is to model energy consumption for those base stations only. Second network handles the rest of the base stations.

2.2. *Input examples*

In our final machine learning model, we employ data from three consecutive time stamps (hours) as inputs. Each time stamp provides a set of features in the form of a vector, encompassing parameters such as **Bandwidth**, **ESMode1** through **ESMode6**, **Frequency**, **TXpower**, **load** for all cells as well as **Mode**, **Antennas**, **Day**, **Hour**, **RUType0** through **RUType11**, and **Energy** from previous time steps. A singular vector of length 3 would contain all the information listed above for 3 consecutive hours (padded or not). These features capture the temporal dynamics and nuances of the system, allowing our model to recognize patterns over the span of the three time frames. This design decision aids in enhancing the model's capability to make more accurate and informed predictions based on the historical context provided by the three consecutive vectors.

3. Pre-processing

The first step in preparing the data was to exclude all the columns containing the data from **cell2** and **cell3** which we deemed irrelevant. The next step was to fill the missing values with values from settings and load of the same base station during the same hour of a different day. The previous energy level was passed in non-padded samples. In the case of missing samples the energy level from previous time steps was simply passed on from the last sample.

All of this required us to implement a dataloader which is responsible for forming input vectors of a given sequence length, while ensuring that consecutive samples in any given vector come from the same base station and that the previous energy levels are correctly passed.

Classical zero-padding method with bias in the input layer disabled provided similar but slightly worse results, thus it is not a part of our final model implementation.

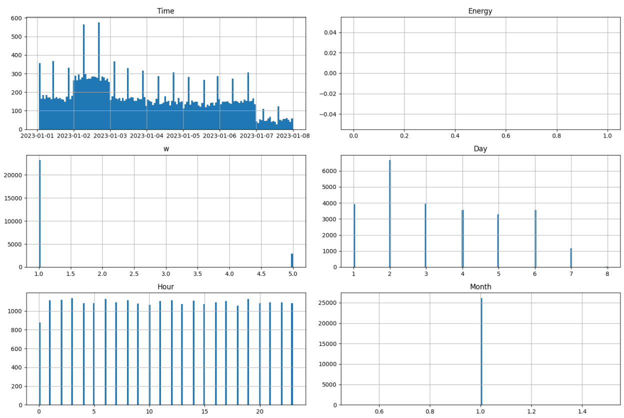

Figure 4: Distribution of attributes in prediction file

4. Model selection

The use of both static and recurrent neural network architectures have their justification.

4.1. Static networks

Static models perform really well when it comes to filling the gaps even in a time series problem [1]. In a time series problem, where the values that are to be predicted come after all the training data, a static neural network would produce very poor results and the use of dynamic models would be an obvious approach. In this case the testset consists of samples that were ”taken out” of the middle of the whole dataset which makes a case for the use of neural networks such as CNNs. Unfortunately CNNs performed poorly on this particular problem, MLPs provided similar, but slightly inferior results as our best recurrent models.

4.2. Recurrent models

Even though, the static modelling approach seems to be a good idea, the mentioned before UMAP plot signifies, that there exist strong dependencies between adjacent dBM values and that their are highly reliant on starting conditions, which is highlighted by the presence of multiple ”stripes” that occupy different areas instead of a long, singular stripe.

Multiple tests and score comparisons on validation dataset (which consisted of 5-10% of train dataset) provided evidence that a GRU neural network is going to be out architecture of choice. Other tested recurrent models were LSTMs and RNNs.

5. Conclutions

Within the context of 5G technological advancements, the imperative of optimizing energy consumption is increasingly evident. This research embarked on a meticulous evaluation of several machine learning models, aiming to derive precise predictive capabilities for energy consumption within 5G networks. A methodical protocol involving data familiarization and intricate data preprocessing — particularly emphasizing the rectification of non-uniform missing data distributions — ensured the reliability of the foundation upon which the predictive analyses were based.

To encapsulate, the research findings elucidate the prominence of the GRU model as an optimal instrument for professionals in telecommunications. Its demonstrated proficiency in forecasting energy consumption can serve as a linchpin for future strategies aiming to synergize 5G's high-throughput capabilities with sustainable energy practices. As the telecommunication sector navigates the evolving terrains of 5G, the insights derived from this investigation are poised to be indispensable, emphasizing the need for the adoption of advanced, data-centric models in shaping industry-standard methodologies.

References

[1] Md. Mijanur Rahman, Mohammad Shakeri, Fatema Khatun, Sieh Kiong Tiong, Ammar Ahmed Alkahtani, Nurul Asma Samsudin, Nowshad Amin, Jagadeesh Pasupuleti, Mohammad Kamrul Hasan. **A comprehensive study and performance analysis of deep neuralnetwork-based approaches in wind time-series forecasting**, 2021