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AI/ML for 5G-Energy Consumption Modelling by ITU AI/ML in 5G Challenge

Predicting energy consumption of different 5G products?

Presenters

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Agenda

INTRODUCTION

- Problem Understanding
- Data Understanding
- Data Pre-Processing
- Model Building & Evaluation
- Application of Learnings

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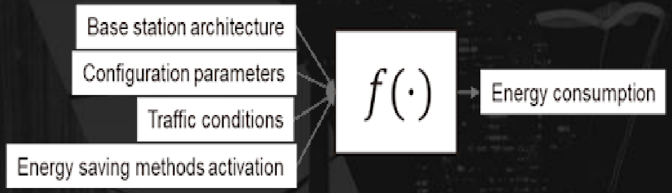
Problem Understanding

Challenge

Base station energy consumption depends on multiple factors, such as specific architecture configuration parameters (e.g., number of operated carriers, bandwidth, transmit power), traffic conditions (e.g., number of allocated physical resource blocks), and the activation of energy-saving methods. To reduce network energy consumption, it is crucial to optimize base station parameters and energy-saving methods. This requires a deep understanding of how these parameters and methods impact the energy consumption of different base stations.



Objectives

Energy Consumption Estimation

Estimation of the energy consumed by different base station products.

Generalization Across Product

Generalization across different base station products. It must estimate the energy consumption of a new base station based on measurements collected from existing ones

Generalization Across Configs

Generalization across different base station configurations It must predict the energy consumption of newly configured parameters real network configuration parameters

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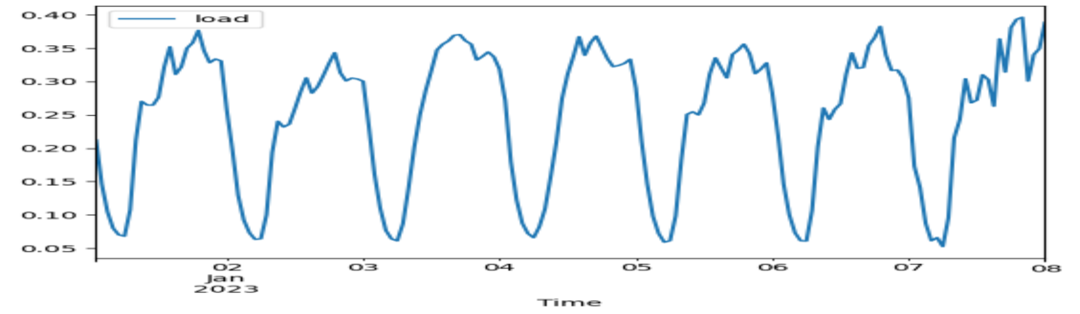
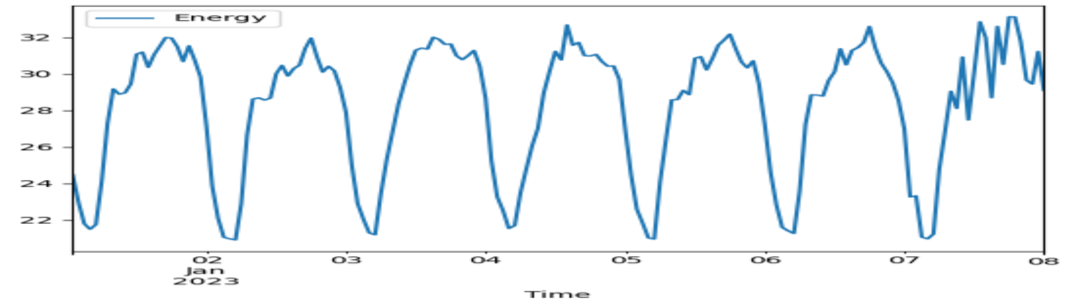
Data Understanding & EDA

Raw Features	load, Timestamp, ESMode1, ESMode2, ESMode3, ESMode5, RUType, Mode, Frequency, Bandwidth, Antennas, TXpower
Target Variable	Energy





It pronounced relationship between load and energy consumption, particularly concerning the hour of the day. This suggests the presence of seasonal components associated with these variables, warranting a closer examination of temporal patterns

Data Understanding & EDA

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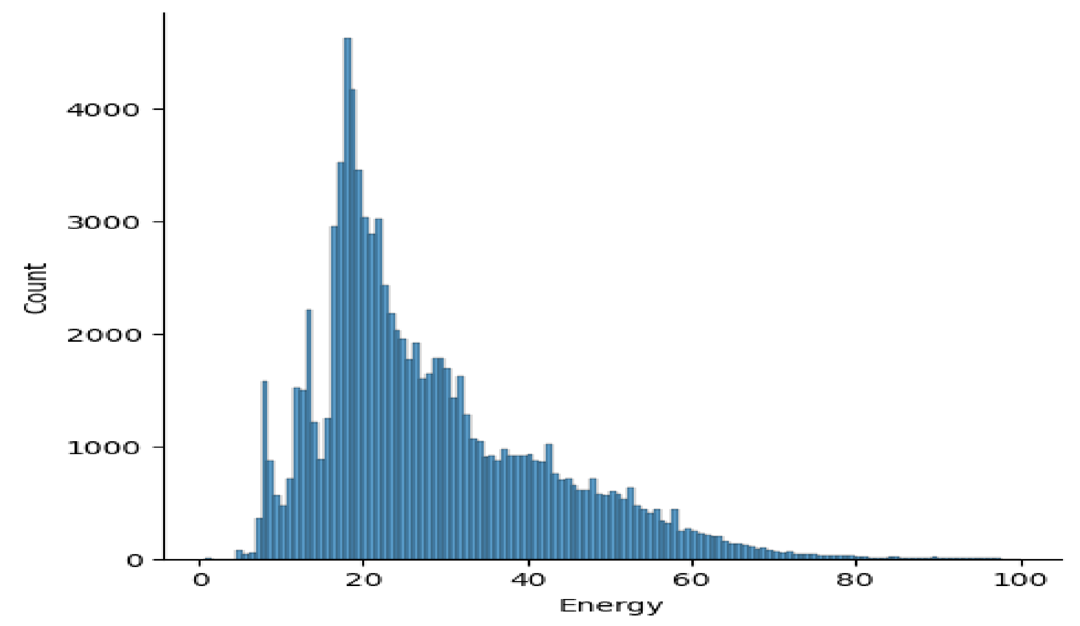

It exhibits notable skewness in the distribution of energy values, hinting at the need for potential data transformations to enhance model performance.

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Data Understanding & EDA

Raw Features	load, Timestamp, ESMode1, ESMode2, ESMode3, ESMode5, RUType, Mode, Frequency, Bandwidth, Antennas, TXpower
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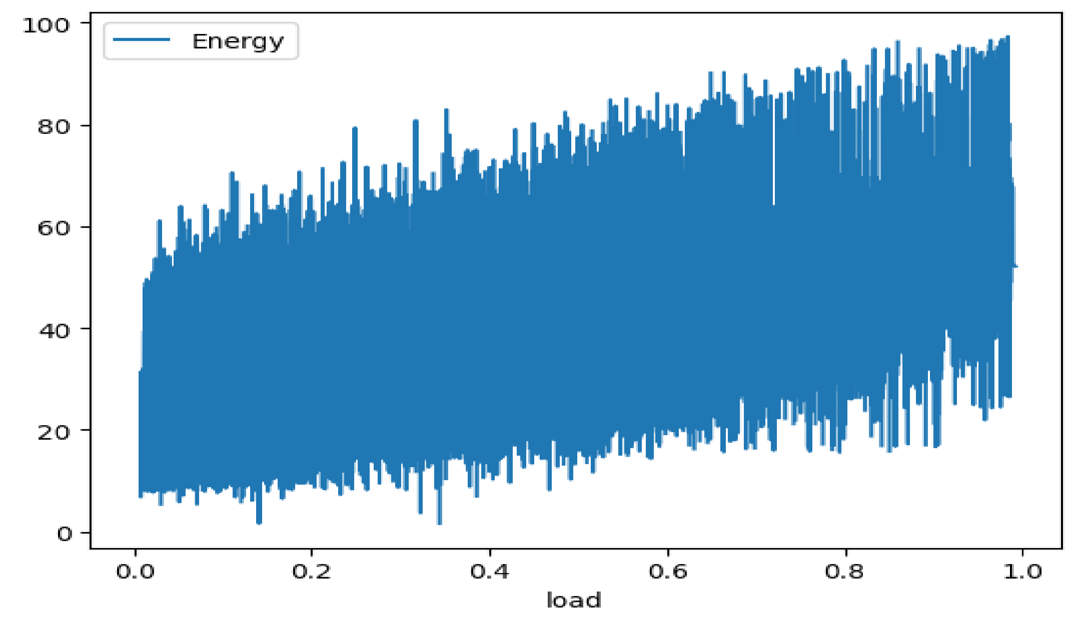

It illustrates a linear relationship between load and energy, offering further insights into the dynamics governing these crucial factors.

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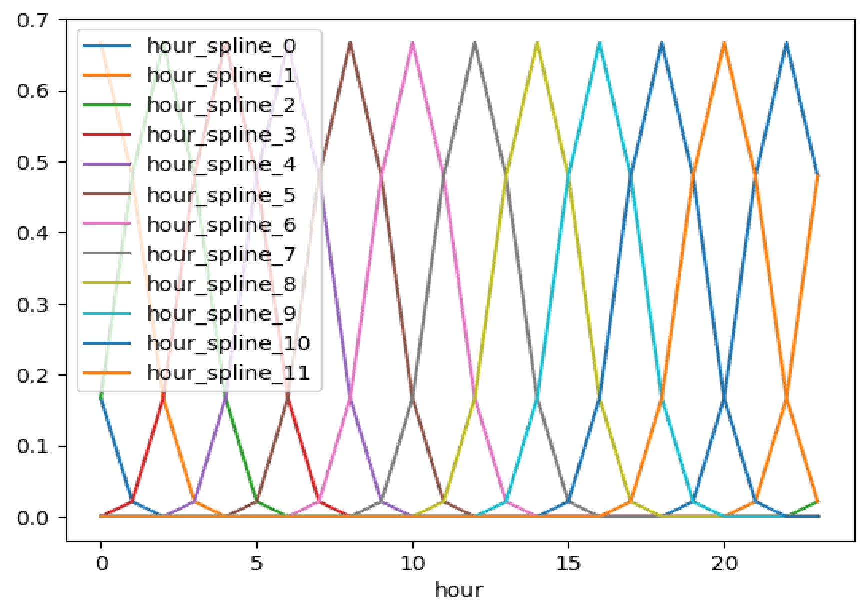
Data Understanding & EDA

Time Stamp derived Features

day, weekday_number, hour, hour_spline_0, hour_spline_1, hour_spline_2, hour_spline_3, hour_spline_4, hour_spline_5, hour_spline_6, hour_spline_7, hour_spline_8, hour_spline_9, hour_spline_10, hour_spline_11



We utilized features like **Hour** to generate their corresponding spline representations. This approach not only contributes to the refinement of feature encoding but also introduces periodicity into the expanded feature set

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Data Understanding & EDA

Historical Lags features for each BS

load_T-1, ESMode1_T-1, ESMode2_T-1, ESMode3_T-1, ESMode6_T-1, Energy_T-1, load_T-2, ESMode1_T-2, ESMode2_T-2, ESMode3_T-2, ESMode6_T-2, Energy_T-2, load_T-3, ESMode1_T-3, ESMode2_T-3, ESMode3_T-3, ESMode6_T-3, Energy_T-3, Time_T-1_hours_elapsed, Time_T-2_hours_elapsed, Time_T-3_hours_elapsed

To address the challenge of **Target Leakage,** we meticulously engineered lag features that inherently exclude the use of **future data**. The **shift function with respect to time (T-1, T-2 and T-3), effectively mitigated the risk of leveraging future data values.**

The time-based lagging, implemented via the shift function with respect to time (T-1, T-2 and T-3), effectively mitigated the risk of leveraging future data values. We selected till T-3 window based on ACF and PCF function

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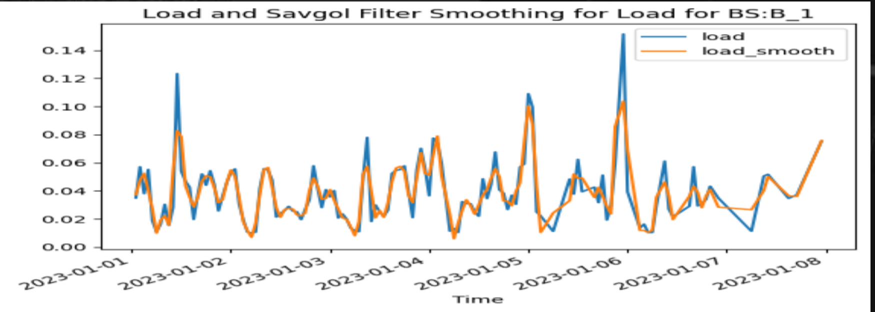
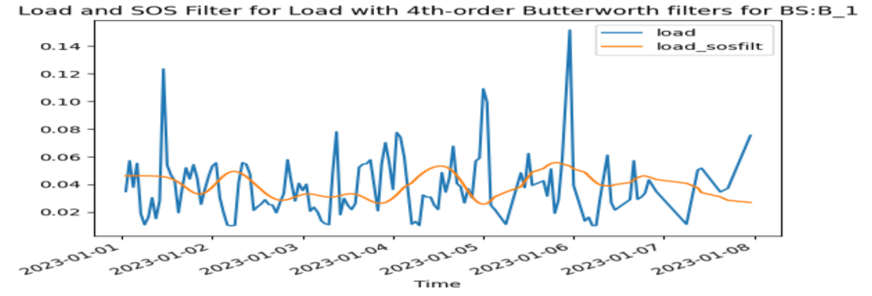
load_smooth, load_diff, load_diff2, load_diff3, load_sosfiltfilt, load_sosfilt





Signal Processed Features

Our feature engineering endeavors extended into the realm of signal processing like **Savitzky-Golay Filtering & Second-Order Section (SOS) Filtering**

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Data Pre Processing

Raw Initial Data →

Pre-Processing

- Data Cleaning
- Ordinal encoding of Base Station Specific Information
- Cell Name information and other attributes
- Creation of static Date Time Features from Time

→

Feature Engineering

- Data Transformation for Time Stamp features
- Periodic Spline Transformation of Hour to get expanded set of features
- Feature Bins of Time specific attribute such as Load
- Lag Features for Load, ESModes and other Base station specific variables such as Bandwidth etc
- Signal Processing for Load using Savitzky-Golay Filtering & SOS Butterworth Filtering to capture signal dynamics while capturing causality in Time Series

→

Cross Validation

- **GroupKfold** Using Base Station Grouping
- Best Suited Strategy to target Base stations with History and new Base Station considering its attributes considering all objectives

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Data Pre Processing

Feature Engineering

Data Transformation for Time Stamp features

Periodic Spline Transformation of Hour to get expanded set of features

Feature Bins of Time specific attribute such as Load

Lag Features for Load, ESModes and other Base station specific variables such as Bandwidth etc

Signal Processing for Load using Savitzky-Golay Filtering & SOS Butterworth Filtering to capture signal dynamics while capturing causality in Time Series

No Future Data

To address the challenge of **Target leakage**, we took a strategic approach to feature creation. We meticulously engineered time-based features that inherently exclude the use of future data.

Cross Validation

GroupKfold Using Base Station Grouping

Best Suited Strategy to target Base stations with History and new Base Station considering its attributes considering all objectives

Model Building and Evaluation

Cross Validation

GroupKfold Using Base Station Grouping

Best Suited Strategy to target Base stations with History and new Base Station considering its attributes considering all objectives

FAST AI ANN Model

Local CV MAE (0.68) + MAPE (0.031)

- 5 Layers (256 x 512 x 1024 x 512 x 256)
- 54 final features
- MAE + MAPE
- ReLU

Private WMAPE 0.0549

Keras ANN Model

Local CV MAE (0.67) + MAPE (0.026)

- 5 Layers (256 x 512 x 1024 x 512 x 256)
- 54 features (3 Embedding Layers + 51 Dense Features
- SiLU
- MAE + MAPE

Private WMAPE 0.0435

Final Thoughts

We tried various Models out of which finally, we selected **Keras ANN model** was selected as the final model due to its better performance in the local Group K Fold cross validation and public leaderboard.

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Model Explainaibility

EXISTING

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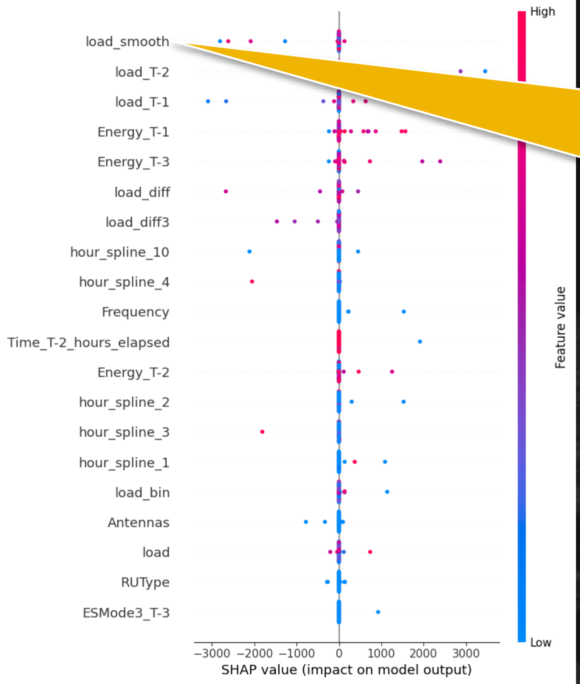
Understanding SHAP for NEW & EXISTING Base Stations

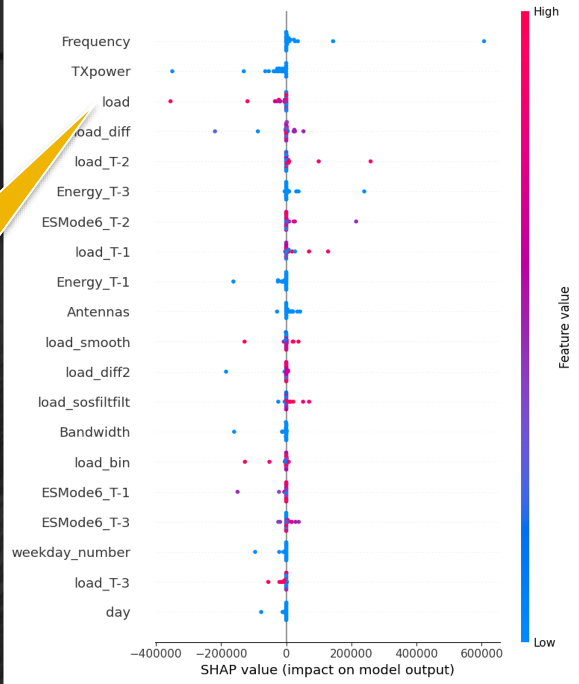
BS -1016

NEW



HIGH impact on the model, since **load_smooth** with high and low values

HIGH values of Load tend to have **LOW** impact (though good importance), but HIGH values of **load_T-2** and **load_diff** have a very impact on model output



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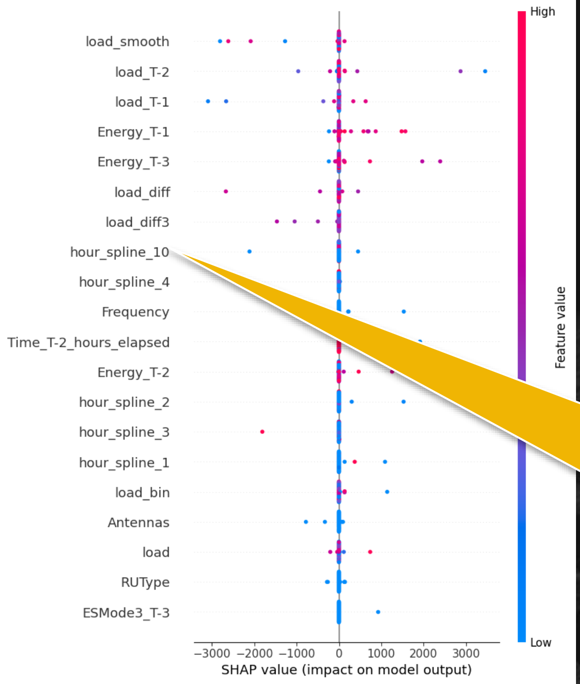
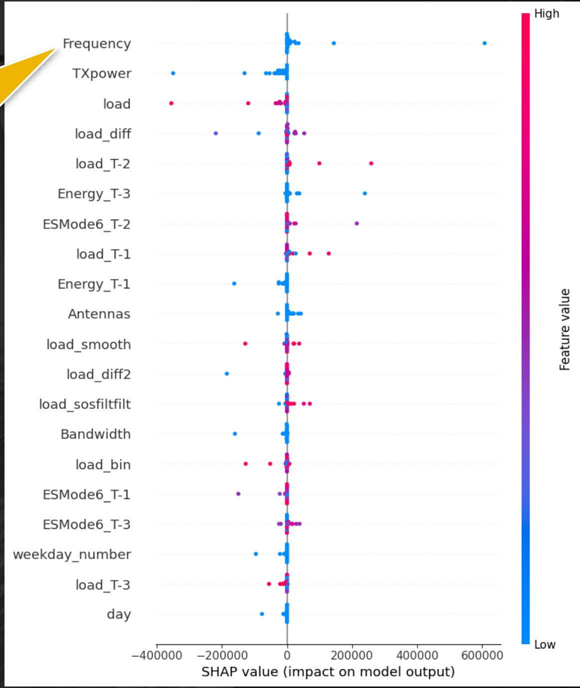


LOW values of **Frequency** have high impact on the model output,

hour_spline features which are also indicating good model insights



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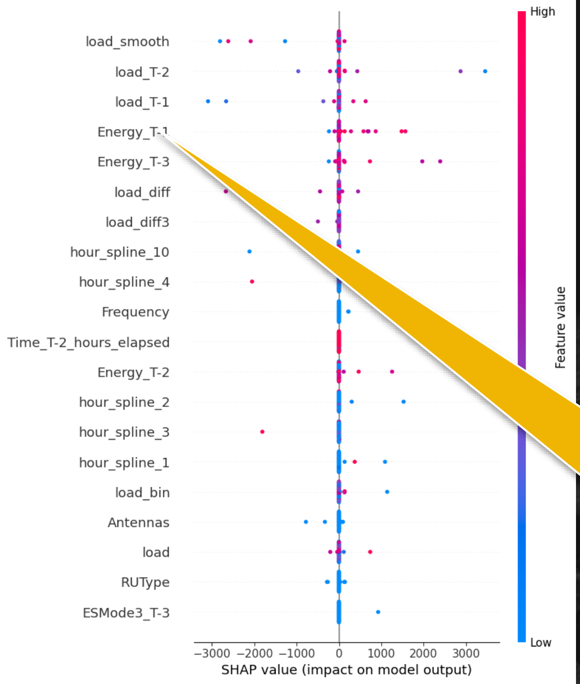
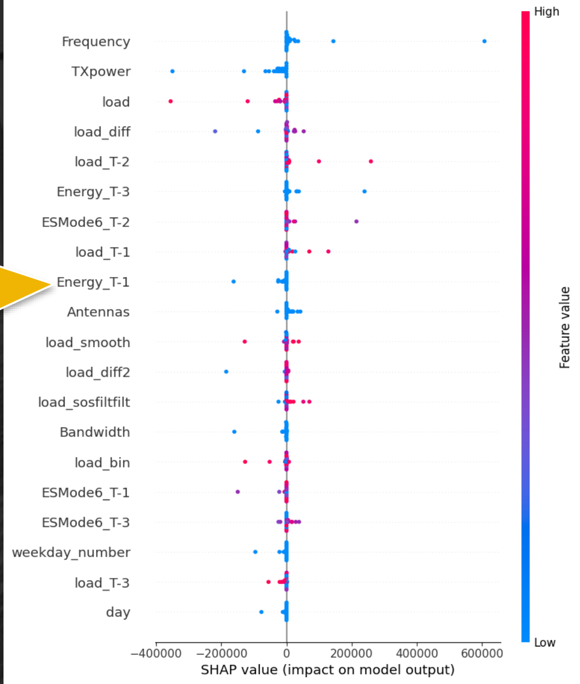


Energy consumption or (value=0 for Lagged Variables), therefore we can see that the values of all **Energy Lagged values such as Energy_T-1, Energy_T-2** and so on have very **low** Values

The interesting part of this analysis is the importance of **Energy_T-1, Energy_T-2 and Energy_T-3** for which **HIGH** values for **Energy_T-1** has a very good impact



Applications of Learning & Future Work

- Machine Learning Advancements
- Energy Efficiency Optimization
- Dynamic Network Configuration
- Resource Allocation Strategies
- Real-world Deployments and Testing
- Ethical and Societal Considerations

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Applications of Learning & Future Work

it would be use a generalized model for achieving the 3 objectives, irrespective of Base station/configuration or new or existing base stations which would be planted in future without any future values

Dynamic Network Configuration

Resource Allocation Strategies

Real-world Deployments and Testing

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Applications of Learning & Future Work

From the SHAP analysis which we had, Based on the feature importance we see that frequency, txpower, antennas, bandwidth, rutype etc with variations , as these are some of the top features. So for a new base station we can impute these values of a newer configuration to get new energy predictions, which help us in optimizing the energy consumption. We can build an optimizer on top of this model and choose different configurations. The objective of the optimizer will be minimizing energy

Energy Efficiency Optimization

Dynamic Network Configuration

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Thank You !!

Questions?