

Integrating Explainable AI for Energy Efficient Open Radio Access Networks

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Abstract—The Open Radio Access Network (Open RAN) is an emerging idea — transforming the traditional Radio Access Networks (RAN) that are monolithic and inflexible into more flexible and innovative. By leveraging open standard interfaces, data collection across all RAN layers becomes feasible, paving the way for the development of energy-efficient Open RAN architectures through Artificial Intelligence / Machine Learning (AI/ML). However, the inherent complexity and black-box nature of AI/ML models used for energy consumption prediction pose challenges in interpreting their underlying factors and relationships. This work presents an integration of eXplainable AI (XAI) to understand the key RAN parameters that contribute to energy consumption. Furthermore, the paper delves into the analysis of RAN parameters — *airtime, goodput, throughput, buffer status report, number of resource blocks*, and many others — identified by XAI techniques, highlighting their significance in energy consumption.

Index Terms—Radio Access Network (RAN), Open RAN, eXplainable AI (XAI), Energy consumption.

I. INTRODUCTION

The United Nations (UN) aims at achieving the seventeen Sustainable Development Goals (SDGs) to create a better future for the generations to come by 2030 [1]. Among industries, Information and Communication Technologies (ICT), including wireless networks, plays a key role in achieving SDG-13:Climate Action. The ongoing development of Beyond 5G (B5G) networks aligns with SDGs, focusing on reducing energy consumption and carbon footprint. Given the ICT sector's commitment to sustainability, there is a need to reduce energy consumption and enhance network performance. Recent studies have highlighted that the ICT sector contributes between 1.8% and 2.8% of global greenhouse gas emissions, with a significant increase in energy consumption observed in 2020 [2].

The emergence of B5G networks has brought about a diverse range of data-hungry applications that consume more energy. The Radio Access Network (RAN) faces the challenge of accommodating diverse use cases and devices while meeting stringent Quality of Service (QoS) demands. The growth in data traffic, coupled with the increasing number of connected devices and resource-intensive computations are causing more energy consumption. RAN itself contributes over 75% of the total energy consumption by service provider networks [3].

Energy consumption can be measured as power consumption over a period. To reduce energy consumption, a strategic

focus on power reduction over shorter intervals emerges as a viable and effective solution. Efficiently managing power consumption while maintaining high performance is important in light of the increasing demand for B5G services. The existing literature on RAN energy or power measurement includes various platforms, methods, and tools, all aiming to improve RAN performance while minimizing energy consumption.

Alongside, 3rd Generation Partnership Project (3GPP) offers energy-saving mechanisms —on/off strategy of base station, core network functions optimization and others — for Mobile Network Operators (MNOs), however, these mechanisms need access of RAN data for optimization. In this context, the O-RAN Alliance's RAN Intelligent Controllers (RICs): the Non-Real-Time (Non-RT) RIC and the Near-Real-Time (Near-RT) RIC [4] plays a crucial role in enabling this optimization by providing enhanced data access and control in B5G networks.

The Near-RT RIC supports applications to run as xApps, whereas Non-RT RIC supports rApps. For example, rApps are used to push the policies related to the energy efficiency when to apply the energy schemes and xApps perform the corresponding actions for the required energy efficiency schemes by utilizing the AI/ML techniques.

The work on optimizing power consumption in the RAN includes theoretical models, heuristic approaches, hardware and software tools, and Artificial Intelligence/Machine Learning (AI/ML) based solutions [5]. AI/ML approaches predict traffic patterns and network conditions, enabling dynamic resource allocation and power adjustment. AI/ML detects anomalies, optimizes resource allocation, and activates sleep modes during idle periods. AI/ML based load balancing distributes traffic efficiently, reducing power consumption while maintaining network performance. AI/ML driven power optimization in RAN ensures significant energy savings and network efficiency enhancements.

However, due to the AI/ML models complexity, black-box nature, and model bias, it is difficult to interpret AI/ML outputs for operators when considered to oversee a decision. The advent of eXplainable AI (XAI) techniques into RAN, enables the transparency and interpretability for each prediction of RAN power/energy consumption. XAI in the realm of RAN energy consumption offers network operators, regulators, and end-users, clear and understandable explanations for the energy-saving strategies.

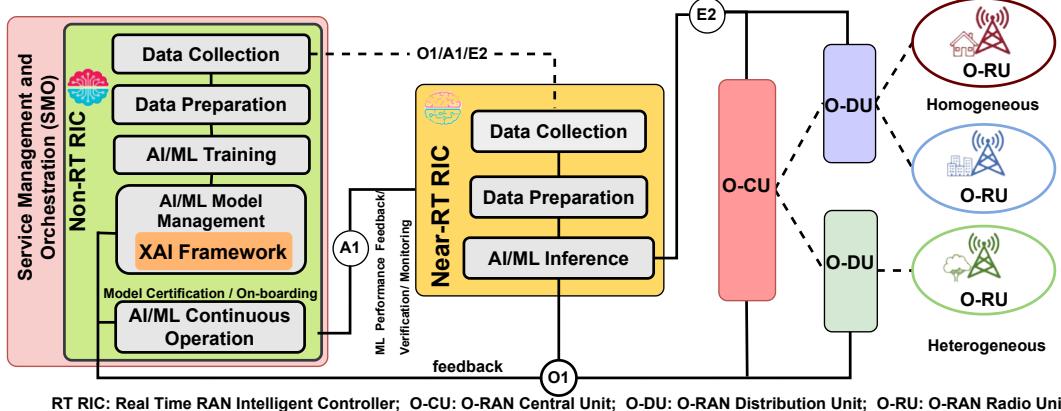


Fig. 1: System Model

This paper focuses on exploiting various RAN parameters that contribute to RAN energy consumption by utilizing the XAI. The main contributions of this paper are as follows:

- Exploring two XAI techniques by understanding their advantages and challenges in the context of Open RAN.
- Elaborating how the various RAN parameters consume more energy by utilizing the XAI techniques.
- Evaluating the considered XAI techniques by using the real-time RAN dataset.

II. RELATED WORK

[6] presents the theoretical models and heuristic approaches that aim to optimize the power consumption at the RAN. Theoretical models — linear models and frameworks — face the challenge of achieving practical solutions within reasonable time frames. Hardware and software approaches [7] enable detailed power measurement and monitoring in various RAN scenarios. The tools offer granular insights into component power usage, facilitating thorough energy pattern analysis. At the hardware level, tools provide detailed insights into each of the RAN components power usage. Various software algorithms and tools facilitate power profiling and monitoring, encompassing the measurement of energy footprints for applications and processes. However, the sub-optimal solutions and a focus on specific power measurement levels results in limited real-time monitoring capabilities.

In [8], Genetic Algorithms (GAs) are utilized to optimize the power. GAs iteratively improve solutions towards optimal or near-optimal outcomes, making them useful for effective resource allocation. Evaluating each individual in a population is time-consuming, which limits their applicability for real-time scenarios or latency sensitive use cases.

AI/ML solutions [9], [10] are increasingly used to optimize energy efficiency, building models for power prediction and other energy related parameters. The AI/ML models excel due to their ability to predict the power consumption patterns and employ the operators to build energy-efficient networks. However, due to the complexity of AI/ML models, interpreting predicted outputs poses challenges for operators.

III. SYSTEM MODEL

Fig. 1 shows the O-RAN architecture that enables *intelligence* through two RICs: Non- and Near-RT, operates at different components of the RAN with various time scales. O-RAN architecture introduces interfaces — O1, A1, and E2 — for facilitating data collection from the RAN components. O1 orchestrates components, A1 provides policy-driven guidance and AI/ML feedback, and E2 controls RAN functions via E2 control messages.

The AI/ML model management block inside the Non-RT RIC is responsible for training and deploying an AI/ML model as an x/r App. All the collected data is stored inside the Non-RT RIC, and the AI/ML model management takes care of the AI/ML model training with the available data. The adoption of XAI could help to interpret the predictions of r/x Apps and RICs can optimize the energy at RAN through E2 control message by fine tuning the parameters that consume energy.

This work investigates two popular XAI techniques — SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) — and their integration into the Open RAN. SHAP [10] and LIME [11] are techniques utilized for explaining the interpretability of AI/ML models, known for their model-agnostic nature — can be applied to any type of model. Both methods assess the impact of various parameters on model predictions.

SHAP [10] values assess the significance of a feature by contrasting model predictions with and without the considered feature. However, because the sequence in which a model encounters features can influence its predictions, this comparison is conducted in every conceivable order to ensure a fair comparison of features. Consequently, our approach involves evaluating all potential combinations of feature values, both with and without a particular feature, to precisely compute the SHAP value.

LIME [11] calculates values through local sub-sampling of the dataset, whereas SHAP calculates values by removing specific features and evaluating their importance. LIME approximates the mapping function $f(x)$ of the ML model by sampling instances, referred to as input perturbation. It generates synthetic samples x_0 closely resembling the orig-

inal instance x , passes them to the original model f , and records the predictions. The perturbation process helps LIME to understand how different input fluctuations affect the model output. Ultimately, LIME can explain a particular prediction by identifying which features contribute most significantly to it.

Regarding interpretability scope, LIME offers localized insights ideal for simpler models. SHAP provides both global and local interpretability. Both LIME and SHAP are model-agnostic and adaptable to various AI/ML models. LIME generates local approximations through perturbing input data, while SHAP computes Shapley values, prioritizing model-specific characteristics. LIME is better suited for simpler models, while SHAP handles tasks with varying complexity due to its comprehensive understanding of feature contributions. Regarding the stability, LIME may be unstable due to random sampling, while the SHAP tends to be more stable and consistent, ensuring reliability across multiple runs. The integration of XAI for Open RAN is evaluated for a real-time dataset and obtained results are discussed in the following section.

IV. EXPERIMENTAL RESULTS

A real-time dataset [12] from the O-RAN testbed is considered to evaluate the XAI techniques and understand the key parameters of the RAN that contributes energy consumption.

The dataset comprises two sets of energy measurement data: *dataset_ul* and *dataset_dlul*. The former captures performance and power consumption metrics of a next-generation evolved NodeB (gNB) solely utilizing the uplink channel, whereas the later includes both uplink and downlink channels. Configurations within each dataset detail essential parameters — timestamp, CPU platform, Long Term Evolution (LTE) interface bandwidth, transmission mode, and traffic load, among others. Additionally, measurements includes a comprehensive range of indicators including Modulation and Coding Scheme (MCS), Block Error Rate (BLER), throughput, power consumption, Signal-to-Noise Ratio (SNR), and clock speed. Both *dataset_ul* and *dataset_dlul* offers a valuable insights into the complexities of energy consumption and performance in virtualized base station deployments, enhancing the efficiency and reliability of 5G networks.

A. Analysis and Comparison of the considered AI/ML models

The AI/ML models that are considered are *Gradient boosting*, *Random Forest (RF)*, and *eXtreme Gradient Boosting (XGBoost)* due to their robust performance in predictive analytics and their ability to handle complex, high-dimensional data effectively.

Gradient boosting [13] is a sequential AI/ML technique that constructs predictive models iteratively to minimize prediction error. *Gradient boosting* sets target outcomes for each model iteration based on how changes in predictions affect overall error. By adjusting predictions for individual cases, *Gradient boosting* iteratively improves model performance, aiming to minimize error for each training case.

Random Forest (RF) [14] is an ensemble learning method comprising decision trees, constructed using random samples

drawn with replacement from the training data. By employing bagging and feature randomness, *RF* creates a set of uncorrelated decision trees.

eXtreme Gradient Boosting (XGBoost) [15] is an efficient, flexible, and scalable AI/ML technique that extends gradient boosting. XGBoost follows the principles of traditional gradient boosting, sequentially constructing a predictive model by aggregating the predictions of weak learners, often decision trees. XGBoost employs a regularized learning objective function, combining a loss function to measure prediction errors with regularization terms to manage model complexity, thus preventing overfitting and enhancing generalization performance. While traditional gradient boosting methods use first-order optimization techniques, XGBoost can optionally utilize second-order optimization techniques, such as Newton's method, to further improve convergence speed and model accuracy.

The Mean Squared Error (MSE) is considered as model metrics for *Gradient Boosting*, *Random Forest*, and *XGBoost*. The train MSE and test MSE of each model are as listed in Table I and II for both DL/UL and UL datasets. Here, train MSE indicates how well a model fits the training data and the test MSE shows how well a model performs on unseen data. The proportions of training and test datasets are 80% and 20% respectively.

TABLE I: Model Performance Metrics for DL/UL dataset

Model	Train MSE [W]	Test MSE [W]
Gradient Boosting	0.05733	0.06710
Random Forest	0.00897	0.06806
XGBoost	0.01672	0.07021

TABLE II: Model Performance Metrics for UL dataset

Model	Train MSE [W]	Test MSE [W]
Gradient Boosting	0.0290	0.0307
Random Forest	0.0020	0.0143
XGBoost	0.0085	0.0191

B. The influence of RAN parameters on Energy Consumption

- *airtime* : The duration of time a base station is actively transmitting data over the air.
- *number of Radio Blocks (nRB)* : The quantity of radio resource units allocated for data transmission in a wireless network to determine the amount of bandwidth used per subframe, affecting network performance and resource utilization.
- *Buffer Status Report (bsr)* : Amount of data waiting to be sent from a user's device to the base station.
- *Goodput (gput)* : Measures the amount of useful data successfully delivered to the destination per unit of time, excluding any retransmitted or corrupted packets.
- *selected_airtime* : The specific amount of time during which a wireless communication channel is actively used for transmitting data.
- *throughput (thr)* : The rate at which data is successfully transmitted over a network, usually measured in bits per

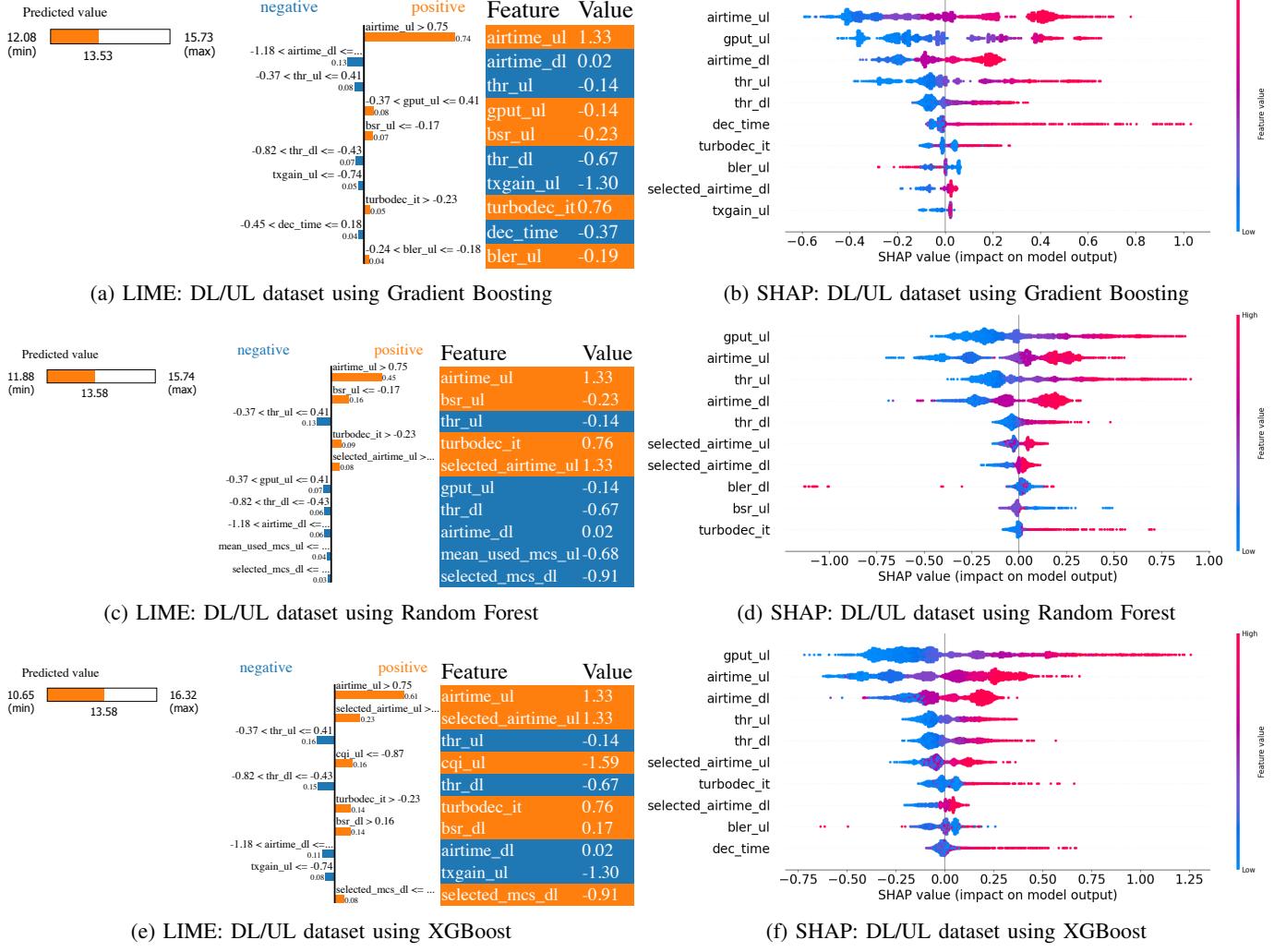


Fig. 2: LIME and SHAP analysis for DL/UL RAN parameters influence on power consumption

second (bps) — Megabits per second (Mbps) or Gigabits per second (Gbps).

- *Decoding time (dec_time)*: The time required to decode data blocks in a wireless communication system.
- *Block Error Rate (BLER)*: A measure of the reliability of data transmission, indicating the percentage of data blocks that are received with errors and require retransmission.
- *Transmission Gain (tx_again)*: The amplification level applied to a signal before it is transmitted by an antenna in a wireless communication system.
- *turbodecoder iterations (turbodec_it)*: The number of iterations performed by the turbo decoder during the error correction process.

Fig. 2 and Fig. 3 show the impact of various parameters of the RAN and their power consumption for both DL/UL and UL datasets. The obtained influencing parameters between SHAP and LIME are different due to differences in their algorithms, approaches to handling feature interactions, and sensitivity to data perturbations and noise. However, the considered models provide insights into the parameters influencing energy

consumption.

Both LIME and SHAP in all the considered AI/ML models report that (i) *airtime*; (ii) *Average Buffer Status Report (bsr)*; (iii) *Average Goodput (gput) uplink*; and (iv) *selected_airtime* are top-4 key parameters that could influence energy consumption of the RAN for the DL/UL dataset as shown in Fig. 2.

As shown in Fig. 2a, the predicted value for the specific instance is reported in the top-left corner (13.53W). The middle section shows how different features contribute to the model prediction by dividing it into negative and positive contributions. The positive contribution of each feature — the length of each feature bar represents the influence of feature contribution in energy consumption — a longer bar means the feature exhibits a strong contribution to energy consumption. The positive contributed features are represented in orange color and the negative contributed features are represented in blue color.

The middle section values are ordered by their significant contributions. For example, longer *airtime* indicate higher network activity (i.e., active radio transceivers), leading to elevated energy consumption. The top right corner table shows

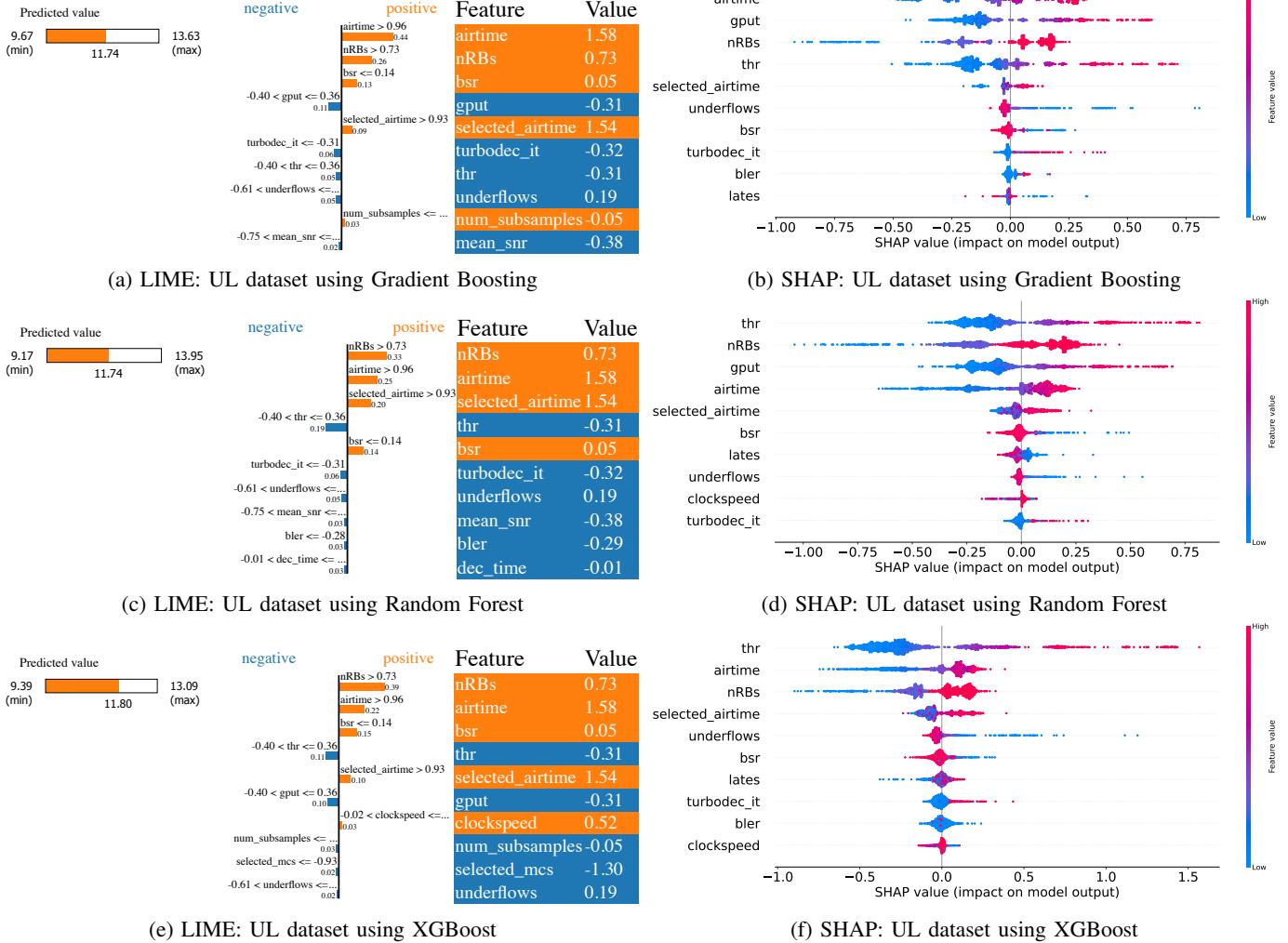


Fig. 3: LIME and SHAP analysis for only UL RAN parameters influence on power consumption

the exact values of the considered instance.

Fig. 2b shows the SHAP values plot generated from the Gradient Boosting model, the features *dec_time*, *airtime_ul*, *thr_ul*, *gput_ul*, *thr_dl*, and *turbodec_it* have a significant positive impact on energy consumption. This indicates that higher values of these features lead to increased energy consumption. In addition, *selected_airtime_dl* and *txgain_ul* also contribute to energy consumption, to a lesser extent. However, *bler_ul* negatively impacts energy consumption, meaning that an increase in *bler_ul* results in a reduction in energy consumption.

Also, Fig. 2c and 2d demonstrate the RAN energy consumption for the DL/UL dataset using *Random Forest*. The parameters such as *airtime*, *BSR*, *thr*, *gput*, significantly influence the RAN power consumption. Fig. 2c shows longer *airtime* and higher *BSR* indicate increased network activity, demanding more energy. Higher *throughput* and *Goodput* imply efficient data transfer, potentially lowering power consumption per data unit as they are on the negative side.

Fig. 2d shows the SHAP values plot generated from the *Random Forest* model — *thr_ul*, *gput_ul*, *turbodec_it*, *airtime_dl*,

time_ul, *thr_dl*, and *airtime_dl* — have a significant impact on energy consumption, indicating that higher values of these features lead to increased energy usage. The *selected_airtime_ul* and *selected_airtime_dl* have a smaller impact on energy consumption. Initially, *bler_dl* negatively impacts energy consumption, but as *bler_dl* increases, it starts to positively impact energy consumption. On the other hand, *bsr_ul* consistently has a negative impact on energy consumption. The intensity on the graph indicates regions where more data points are concentrated.

Fig. 2e shows the LIME values plot generated from the *XGBoost* model. Here, the *airtime_ul* has a significant impact on energy consumption. In contrast, *selected_airtime_ul*, *turbodec_it*, *bsr_ul*, and *selected_mcs_dl* have minimal impact on consumption. All other parameters have a negative impact on energy consumption. Whereas, Fig. 2f shows the SHAP values plot generated from the *XGBoost* model, the parameters — *gput_ul*, *dec_time*, *airtime_ul*, *turbodec_it*, *thr_dl*, *thr_ul*, *airtime_dl*, and *selected_airtime_ul* — exhibit a significant impact on energy consumption, indicating that higher values

of these features lead to increased energy usage. However, *selected_airtime_dl* shows minimal impact on energy consumption. Understanding how different features affect energy consumption helps in designing energy-efficient network systems. For example, here airtime ul has a significant positive impact on power consumption which can urge to design protocols that minimize unnecessary airtime usage.

Fig. 3a and 3b depict the RAN key parameters for the UL data using *Gradient Boosting*. As similarly observed in Fig. 2, the UL-only data also shows *airtime*, *selected_airtime*, *nRBs* has a significant impact on energy consumption. In contrast, *gput*, and *num_subsamples* have minimal impact on consumption. Most of all other parameters negatively affect energy consumption. Fig. 3b shows the SHAP values plot generated from the *Gradient Boosting* model, *thr*, *gput*, *turbodec_it*, *airtime*, *nRBs*, and *selected_airtime* show a significant impact on energy consumption. Initially, *bler* has a negative impact, but as it increases, its impact turns positive. *Underflows*, *bsr*, and *lates* consistently have a negative impact on energy consumption.

Fig. 3c and 3d depict the RAN key parameters for the UL data using *Random Forest*. Fig. 3c shows the LIME values plot generated from the Random Forest model, *nRBs*, *airtime*, *selected_airtime*, and *bsr* positively impact energy consumption, while all other parameters negatively affect energy consumption. Fig. 3d shows the SHAP values plot generated from the Random Forest model, *thr*, *gput*, *nRBs*, *turbodec_it*, *selected_airtime*, and *airtime* exhibit a significant impact on energy consumption, whereas *clockspeed* shows minimal impact.

Finally, Fig. 3e and 3f depict the RAN key parameters for the UL data using *XGBoost model*. Fig. 3e shows the LIME values — *nRBs*, *airtime*, *bsr*, and *selected_airtime* — have a positive impact on energy consumption, whereas *clock speed* has minimal impact. Fig. 3f shows the SHAP values plot generated from the XGBoost model, *thr* has a very high impact on energy consumption. Following *thr*, *turbodec_it*, *selected_airtime*, *nRBs*, and *airtime* demonstrate a high impact on energy consumption. Conversely, *underflows*, *bsr*, *bler*, and *clockspeed* all show a negative impact on energy consumption.

In summary, the analysis of RAN energy consumption highlights key parameters — *airtime*, *BSR*, *Goodput*, *selected_airtime* — as significant influencers. Longer *airtime* indicate higher network demand and energy usage, while higher *BSR* values suggest congestion. Conversely, improvements in *Goodput* efficiency can reduce energy per unit of data. This work serves as a benchmark for further research into reducing the carbon footprint of networks. By establishing a clear connection between network parameters and power consumption, it sets the stage for developing more energy-efficient network architectures and protocols.

V. CONCLUSIONS AND FUTURE WORK

This study explores various eXplainable AI (XAI) techniques such as LIME and SHAP and analyzes the impact of different RAN parameters on energy consumption. The

considered XAI techniques are evaluated within a real-time RAN dataset and reports that variations in RAN parameters — *airtime*, *goodput*, *throughput*, *subframe decoding time*, *buffer status report*, *number of resource blocks* — could impact the RAN energy consumption. In future work, efforts may focus on refining XAI techniques, integrating them into O-RAN testbed for XR use case, and conducting further experiments to validate their effectiveness in optimizing energy usage and improving network performance as r/xApps.

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REFERENCES

- [1] V. Gudepu, B. Pappu, T. Javvadi, R. Bassoli, F. H. Fitzek, L. Valcarenghi, D. Devi, and K. Kondepudi, “Edge Computing in Micro Data Centers for Firefighting in Residential Areas of Future Smart Cities,” in *IEEE ICECCMCE*. IEEE, 2022, pp. 1–6.
- [2] C. Freitag, M. Berners-Lee, K. Widdicks, B. Knowles, G. S. Blair, and A. Friday, “The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations.” *Patterns*, vol. 2, no. 9, 2021.
- [3] L. M. Larsen, H. L. Christiansen, S. Ruepp, and M. S. Berger, “Toward Greener 5G and Beyond Radio Access Networks—A Survey,” *IEEE Open Journal of the Communications Society*, vol. 4, pp. 768–797, 2023.
- [4] V. Gudepu, V. R. Chintapalli, P. Castoldi, L. Valcarenghi, B. R. Tamma, and K. Kondepudi, “The Drift Handling Framework for Open Radio Access Networks: An Experimental Evaluation,” *Computer Networks*, vol. 243, p. 110290, 2024.
- [5] V. Gudepu, R. R. Tella, C. Centofanti, J. Santos, A. Marotta, and K. Kondepudi, “Demonstrating the Energy Consumption of Radio Access Networks in Container Clouds,” in *NOMS2024, the IEEE/IFIP Network Operations and Management Symposium*, 2024.
- [6] M. Okhovvat, M. T. Kheirabadi, M. R. Okhovvat, and A. Nodehi, “Joint Time and Energy-Optimal Approach to Allocate Task to Actors in Wireless Sensor Actor Networks,” *Computer Networks*, p. 110018, 2023.
- [7] V. Gudepu, B. Chirumamilla, R. R. Tella, A. Bhattacharyya, S. Agarwal, L. Malakalapalli, C. Centofanti, J. Santos, and K. Kondepudi, “EARNEST: Experimental Analysis of RAN Energy with Open-Source Software Tools,” in *16th IEEE/ACM COMSNETS*. IEEE, 2024, pp. 1148–1153.
- [8] M. Ilbeigi, M. Ghomeishi, and A. Dehghanbanadaki, “Prediction and Optimization of Energy Consumption in an Office Building Using Artificial Neural Network and a Genetic Algorithm,” *Sustainable Cities and Society*, vol. 61, p. 102325, 2020.
- [9] H. Ma and A. Ding, “Method for evaluation on energy consumption of cloud computing data center based on deep reinforcement learning,” *Electric Power Systems Research*, vol. 208, p. 107899, 2022.
- [10] M. K. M. Shapi, N. A. Ramli, and L. J. Awalin, “Energy consumption prediction by using machine learning for smart building: Case study in Malaysia,” *Developments in the Built Environment*, vol. 5, p. 100037, 2021.
- [11] J. Dieber and S. Kirrane, “Why model why? Assessing the strengths and limitations of LIME,” *arXiv preprint arXiv:2012.00093*, 2020.
- [12] J. X. Salvat Lozano, J. A. Ayala-Romero, L. Zanzi *et al.*, “O-RAN Experimental Evaluatuin Datasets,” 2022. [Online]. Available: <https://dx.doi.org/10.21227/64s5-q431>
- [13] J. H. Friedman, “Stochastic Gradient Boosting,” *Computational statistics & data analysis*, vol. 38, no. 4, pp. 367–378, 2002.
- [14] L. Breiman, “Random Forests,” *Machine learning*, vol. 45, pp. 5–32, 2001.
- [15] T. Chen and C. Guestrin, “XGBoost: A Scalable Tree Boosting System,” in *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 2016, pp. 785–794.