ORAN-MAP: A Hybrid Approach to Mobility-Aware Power Optimisation in Open Radio Access Networks (ORAN)

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***Abstract*—This paper presents a novel framework for optimising energy consumption in ORAN networks using machine learning (ML) models integrated with realistic mobility and spatial data aggregation techniques. The proposed approach leverages real-time Key Performance Metrics (KPMs) to dynamically manage the power states of Radio Units (RUs), ensuring energy efficiency while maintaining network performance. A dense urban simulation environment with realistic mobility patterns, based on a Poisson Point Process and Dijkstra's Algorithm, models user movement and traffic dynamics. To address the challenges of large-scale dataset management, an H3 spatial indexing system aggregates data into hexagonal grids, reducing data size by 74% without sacrificing spatial accuracy. Five ML-based classifiers, including ensemble and regression-based methods, were trained and evaluated using the aggregated dataset based on actual data from the city of Leeds. The results demonstrate high accuracy for optimal power plans, with models achieving up to 97.8% accuracy. Network performance metrics, including throughput and energy efficiency, highlight significant improvements over a Full Power Baseline (FPB), with energy consumption reduced by up to 33.88% using the proposed models. These findings underscore the potential of ML-driven approaches to optimise energy usage in ORAN networks, providing a scalable and effective solution for sustainable network operations.**

***Index Terms*—Energy Saving, ORAN, Network Optimisation**

I. Introduction

In the current 5th generation of telecommunication networks, the densification of infrastructure and the deployment of additional radios in new frequency bands have increased overall energy demands while offering enhanced coverage and capacity features. Next-generation wireless networks face a dual challenge: they must meet the ever-growing data requirements while also addressing significant energy consumption associated with their operation [1]. Specifically, RAN accounts for approximately 70% to 85% of the total energy usage [2]. This underscores the importance of focusing on RAN components and its flexibility when implementing energy-saving strategies in mobile networks. Currently, traditional RAN base stations (BSs) rely on monolithic network architectures and proprietary hardware [3]. As a result, it is challenging to apply reconfigurations and energy-saving strategies due to the legacy architecture with limited interoperability. ORAN, as defined by the O-RAN ALLIANCE [4], replaces the traditional RAN framework with a disaggregated base station architecture featuring open, interoperable interfaces. By decoupling hardware from software, virtualizing functions, and leveraging cloud-based management, ORAN enhances flexibility and fosters innovation [5], [6]. The RAN Intelligent Controller (RIC) utilizes AI/ML-driven solutions on near-real-time and non-real-time platforms to optimize energy efficiency and network performance. Additionally, xApps, operating via the E2 interface, enable efficient Radio Resource Management (RRM) [7], offering promising solutions for improved energy efficiency.

Recent research efforts have focused on improving energy efficiency (EE) in ORAN systems through intelligent control mechanisms. One notable approach is presented in [8], where a DRL model is proposed to optimise the activation and deactivation of the front ends in 5G BSs. The proposed method achieves significant energy savings while maintaining network performance. In [9], a quantum-inspired load-balancing approach leverages entanglement theory to optimise the selection of distributed unit (DU) servers, reducing energy consumption. The study demonstrates considerable energy efficiency gains by applying advanced optimisation techniques, including sequential quadratic programming (SQP). The works in [10] and [11] propose energy consumption models utilising scheduling algorithms inspired by biological genetics to reduce energy usage. The study in [2] explores power consumption models and energy-saving techniques for ORAN, identifying key challenges and future research directions. However, these approaches rely on simulations, often neglecting realistic user mobility and the computational demands of large-scale data processing. To our knowledge, no study has evaluated ORAN's energy efficiency using real spatial and network data. This paper addresses these gaps, bridging the divide between simulation-based insights and real-world deployment challenges.

This paper proposes a framework to quantify and improve ORAN's EE in urban deployments. It introduces an EE xApp that minimises ORAN power consumption by dynamically controlling RU transmitting power. Leveraging spatial modelling, real-time analytics, and ML, the xApp optimises energy use while maintaining Quality of Service (QoS). A key contribution is a realistic user mobility model for dense urban networks, replicating pedestrian movement and traffic dynamics to evaluate connectivity and throughput over time. The framework incorporates H3 spatial indexing to reduce computational costs associated with large-scale datasets and is validated using spatial and network data from Leeds city centre, UK.

The remainder of this paper is organised as follows. Section II introduces the System Model, which includes three subsections: Section II-A, detailing the simulation environment and network configuration; Section II-B, describing the novel framework for simulating realistic user behaviour; and Section II-D, which outlines the ML-based optimisation approach and its implementation. Section III discusses the results, analysing the performance of the proposed models in terms of energy efficiency, throughput, and power savings. Finally, Section IV concludes the paper, summarising key findings and proposing directions for future research.

II. System Model

In this section, we formulate a systematic approach to study the EE in ORAN based on the spatial orientation and mobility of users. The interaction between the near-RT RIC, E2 nodes, key performance metrics (KPMs), and user equipment (UE) mobility forms the basis for evaluating energy efficiency and network performance.

A. Spatial Model

The model environment represents an ORAN deployment in a dense urban scenario to evaluate energy optimisation strategies under realistic conditions. The network consists of a total number of UEs donated as N_{UE}, and N_{BS} small-cell base stations (gNBs), each equipped with a number of RUs where the total RUs in the network defined as α. Each RU operates in one of the configurable power modes P_{Modes}= $\{P_F, P_M, P_S\}$, where (P_F) is full transmitting power mode, (P_M) is mid transmitting power mode, and (P_S) is the sleep mode. These modes allow dynamic adaptation to varying traffic conditions. They are controlled via real-time KPMs received through the E2 interface to the near-RT RIC. The network operates over a carrier frequency (f_c), ensuring compliance with 3GPP specifications.

A Poisson Point Process (PPP) is used to model the spatial distribution of users, ensuring randomness in their placement within a square grid area of size $|A|$. The number of points M in this area is given by:

$$M \sim \text{Poisson}(\lambda \cdot |A|),$$

where λ represents the intensity parameter (average number of points per unit area). The generated points represent the users' deployments within the urban topology.

The connectivity between UEs and BSs is governed by the Signal-to-Interference-plus-Noise Ratio (SINR), defined as [12]:

$$\gamma_j(t) = \frac{pl_j(t) P_{Tj}(t)}{N_0 + \sum_{k \neq j}^{N_{\text{BS}}} pl_k(t) P_{Tk}(t)}, \tag{1}$$

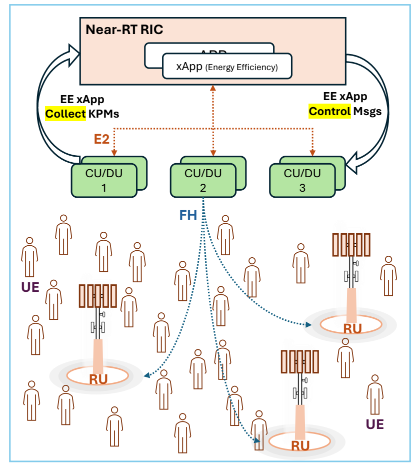

Fig. 1. The layout of our energy efficiency using ORAN architecture

where P_{Tj} and $P_{Tk} \in P_{Modes}$ are the transmit powers of the serving and interfering RUs, respectively, $pl_j(t)$ and $pl_k(t)$ represent the channel path loss between the UE and the RUs, and N_0 denotes the noise power density.

The channel model incorporates path loss and fading effects based on the 3GPP Urban Micro (UMi) specifications [13]. Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) conditions are modelled probabilistically, with the probability of a LoS link given by:

$$Prob_{\text{LoS}} = \begin{cases} 1, & \text{if } d_{\text{2D}} \leq d_{\text{th}} \\ \frac{d_{\text{th}}}{d_{\text{2D}}} + \left(1 - \frac{d_{\text{th}}}{d_{\text{2D}}}\right) \exp\left(-\frac{d_{\text{2D}}}{36}\right), & \text{if } d_{\text{2D}} > d_{\text{th}} \end{cases} \tag{2}$$

where d_{2D} is the horizontal distance between the UE and the BS, d_{th} is the threshold distance for guaranteed LoS.

The wireless channel path loss (pl) is calculated as:

- For LoS conditions:

$$pl_{\text{LoS}} = 32.4 + 21 \log_{10}(d_{\text{3D}}) + 20 \log_{10}(f_c), \tag{3}$$

where d_{3D} is the 3D distance between the UE and the BS.

- For NLoS conditions:

$$pl_{\text{NLoS}} = \max(pl_{\text{LoS}}, pl'_{\text{NLoS}}), \tag{4}$$

with

$$pl'_{\text{NLoS}} = 35.3 \log_{10}(d_{\text{3D}}) + 22.4 + 21.3 \log_{10}(f_c) - 2.55.$$

The network operates with a time resolution of Δt, corresponding to the periodicity of KPM updates for a full run time donate as T_{time}. For each time step, data is collected for all power modes across the UEs, resulting in a dataset of size proportional to $N_{\text{UE}} \times \alpha \times T_{\text{time}}$. This scale increases significantly with larger networks, highlighting the computational challenges associated with training energy optimisation models.

To address the challenges of processing and managing large-scale datasets generated by user mobility and network measurement reports, spatial aggregation techniques are employed using H3 indexing [14]. H3 is a geospatial indexing system that partitions the geographical area into a hierarchy of hexagonal grids, each uniquely identified by an H3 index. This hexagonal tessellation provides consistent spatial coverage, eliminating the distortions introduced by traditional square grids, particularly in large-scale areas. The indexing system enables efficient data aggregation while maintaining spatial accuracy by grouping users based on their locations within these hexagonal cells.

B. Users Mobility Model

This subsection introduces the user mobility model designed to mimic the movement patterns of UEs within an urban environment. The model considers various factors, including spatial user distribution, stochastic mobility behaviour, and urban features like intersections and road networks. These elements are critical for generating realistic trajectories and supporting accurate network performance evaluation.

We consider UEs passing by nodes within the network by taking the shortest path using Dijkstra's Algorithm [15] at a constant speed v_u. For each user u_i, the mobility model randomly assigns a starting node n_s and a destination node n_d from a graph $G = (N, E)$. The graph G is defined as a network layout where N represents nodes, and E represents edges (roads) in the network. To ensure realistic travel behaviour, the distance between the start and destination nodes must exceed a predefined threshold d_{min}, enforcing a minimum route length:

$$d(n_s, n_d) > d_{\text{min}},$$

where $d(n_s, n_d)$ represents the Euclidean path distance. Moreover, a bias is introduced in the edge cost function $C(e)$ as follows:

$$C(e) = \text{length}(e) - \beta \cdot \text{junction\_count}(n), \tag{5}$$

where $\text{length}(e)$ is the physical edge length, $\text{junction\_count}(n)$ represents the number of roads converging at a node, and β is a tunable parameter that adjusts the influence of junction density. This approach biases user routes toward high-density intersections, reflecting realistic traffic flows. The details of this approach are outlined in Algorithm 1, which describes the procedure for user route assignment.

C. KPM Measurements

KPM reports are generated at DU for each user at Δt intervals based on their trajectories, including metrics such as SINR, received power, and throughput. These reports are critical for evaluating energy optimisation strategies but result in large datasets, particularly in scenarios with numerous UEs and BSs.

Algorithm 1 User Route Assignment Algorithm

```
Input: Target area A, intensity λ
Output: Shortest path routes for all users
Generate user points P ~ PPP(λ · |A|)
for each point p_i ∈ P do
    Assign coordinates (x_i, y_i) uniformly in A
    Map p_i to nearest intersection n_j using n(p_i) = argmin_{n_j ∈ N} d(p_i, n_j)
end for
for each user u_i do
    Select start node n_s and destination node n_d such that d(n_s, n_d) > d_min
    Compute shortest path using C(e) = length(e) − β · junction_count(n)
end for
```

Instead of tracking individual users and generating separate measurement reports for each, the framework aggregates data within each hexagonal cell. H3 indexing is employed to reduce data complexity while preserving essential metrics for model training. The spatial distribution of users across the H3 indices is modelled using a Poisson distribution, ensuring realistic traffic patterns that align with urban population densities. For each cell, metrics such as SINR, received power, and throughput is averaged, significantly reducing the volume of data without sacrificing the granularity required for accurate analysis. This adaptability ensures the scalability of the proposed framework, accommodating scenarios with varying numbers of UEs and BSs. Figure 2 illustrates the mapping of user routes onto the H3 indexing grid, highlighting how the system captures the spatial dynamics of the simulation environment.

By integrating H3 indexing into the mobility model, the framework enhances computational efficiency and ensures that spatial relationships among users and network elements are preserved. This integration supports evaluating energy-efficient strategies at scale, bridging the gap between realistic mobility modelling and practical data management in 5G ORAN networks.

Consequently, KPMs are collected for all configurations in P_{Modes} to train and optimise the energy-saving ML models introduced in the next section.

D. Model Implementation

The proposed system leverages ML to optimise power consumption in a 5G ORAN network by dynamically selecting the most suitable power plan for the network's BSs. The system is designed to integrate a trained machine learning classifier as an xApp within the near-RT RIC, enabling near real-time decisions based on current network conditions. To determine the best power configuration within the set P_{Modes} for network RUs, a Power Plan ID (Pow_{ID}) has been introduced. Each Pow_{ID} represents a specific power configuration for the network RUs. For example, the first

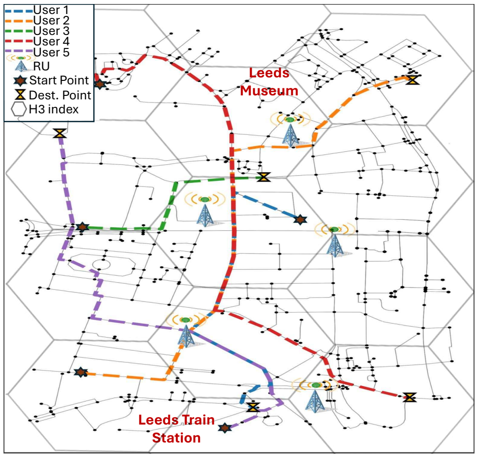

Fig. 2. Mapping user routes onto an H3-indexed area.

Pow_{ID} corresponds to all BSs' RUs operating at full power (P_F), while the last Pow_{ID} represents all BSs' RUs in sleep mode (P_S). The training dataset was generated by simulating all possible Pow_{ID} configurations.

The input features used for training include the number of users and their corresponding H3 index, the received power (P_{rx}), the SINR for each user, the network throughput, the serving BS ID for each user, the total power consumption of the network, and the selected Pow_{ID}. The total power consumption of the network (P_{total}) is included as an auxiliary metric and is computed as:

$$P_{\text{total}} = \sum_{j=1}^{\alpha} P_{\text{T},j} \tag{6}$$

The target variable for the machine learning models is the optimal Pow_{ID} that minimises power consumption while maintaining acceptable network performance.

Several models are introduced in this work, each employing a distinct technique to balance energy efficiency and throughput.

- Energy-Driven Ensemble (**EDE**) model is based on Random Forest, utilising an ensemble of decision trees to achieve robust predictions by combining multiple weak learners. This approach is particularly effective in handling the complexity of multi-class classification in the presence of varied network conditions.
- Gradient Optimiser (**GO**) model, built on Gradient Boosting, incrementally refines its predictions by minimising errors at each stage. This technique effectively captures nuanced relationships between input features and the target Pow_{ID}, making it well-suited for energy optimisation tasks.
- Linear Efficiency Model (**LEM**) leverages Logistic Regression to provide a simple yet computationally efficient solution for predicting Pow_{ID}. By modelling the probability of each power plan as a function of the input features, LEM offers a probabilistic interpretation of network configurations.
- Support-Optimised Classifier (**SOC**) applies a Support Vector Machine (SVM) to classify optimal power plans. SOC utilises hyperplane separation in a high-dimensional space to find the best trade-off between energy efficiency and network performance.
- Proximity-Based Allocator (**PBA**) employs a K-Nearest Neighbors (KNN) approach, classifying power plans based on the proximity of similar historical network conditions. This technique relies on the assumption that similar states yield similar outcomes, making it effective for localised optimisations.

The output of each model is the predicted Pow_{ID} for a given network configuration, corresponding to the power plan that minimises energy consumption while maintaining acceptable connectivity levels. The reward function guiding the selection prioritises minimising the network outage, defined as the proportion of users experiencing SINR below a threshold (SINR_{th}). For a given Pow_{ID}, the outage $\mathcal{O}_{Pow_{ID}}$ is calculated as:

$$\mathcal{O}_{Pow_{ID}} = \frac{\sum_{i=1}^{N_{\text{UE}}} \mathbb{I}(\text{SINR}_i < \text{SINR}_{\text{th}})}{N_{\text{UE}}}, \tag{7}$$

where $\mathbb{I}$ is the indicator function. Among the power plans with the lowest outage, the one with the highest Pow_{ID}, indicating the most energy-efficient configuration, is selected as optimal.

III. Simulation and Evaluation Results

In this section, we assess the simulation configuration and the performance of our proposed models through extensive training and evaluation processes. The evaluation focuses on analysing the accuracy of the trained models in predicting the optimal power plan (Pow_{ID}) and the impact of these predictions on network performance metrics such as throughput, power consumption, and energy savings.

A. Simulation Settings

The simulation environment replicates a dense urban 5G ORAN network, uniquely grounded in real-world data collected from Leeds city centre, providing an accurate representation of user behaviour and ensuring the robustness of our model. The target area covers a rectangular area of $500\,\text{m} \times 1000\,\text{m}$ to evaluate energy efficiency and network performance. The network consists of five small-cell gNBs deployed at fixed locations, sourced from OpenCellID [16]. Each gNB is equipped with one omnidirectional RU that can operate in one of P_{Modes} where P_F operates with a transmit power of 24 dBm, P_M with 22 dBm, and P_S with 18 dBm. The network operates within the sub-6 GHz frequency band, specifically at 2 GHz, and utilises the 3GPP UMi channel model [13], incorporating both LoS and NLoS conditions. Path loss between UEs and BSs is calculated according to the channel model specifications, as detailed in Sec. II-A.

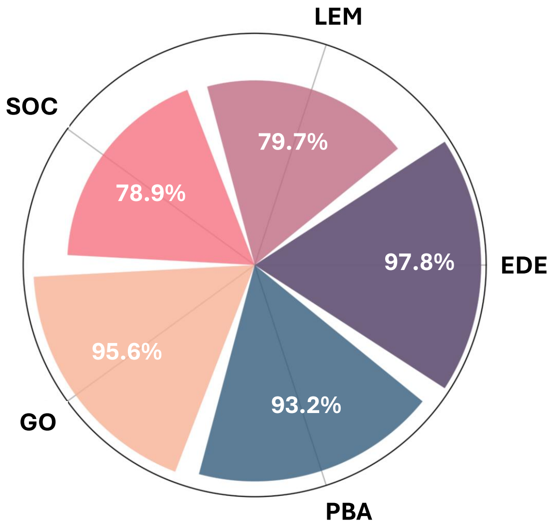

Fig. 3. Prediction Accuracy for the Selected Models.

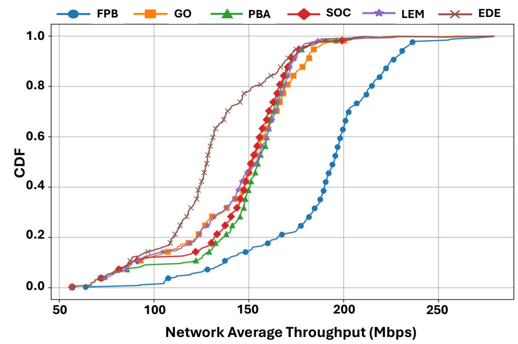

Fig. 4. CDF of Network Throughput (Mbps) for Different Models.

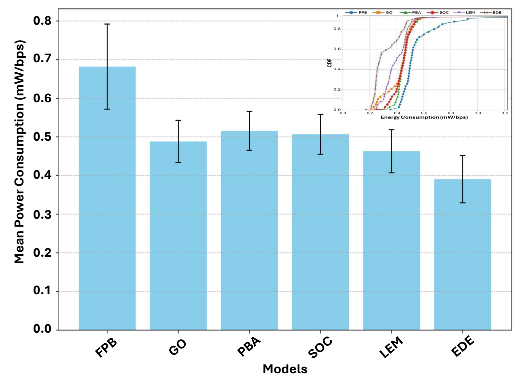

Fig. 5. Energy Consumption per Throughput Comparison.

The mobility model simulates the movement of 50 UEs distributed within the simulation area. The spatial distribution of UEs follows a PPP with an intensity parameter of $\lambda = 0.1\,\text{users/m}^2$. For each UE, n_s and n_d are selected from the road network, with d_{min} of $50\,\text{m}$ to ensure realistic travel behaviour. As obtained in Algorithm. 1, routes between nodes are generated. UEs traverse these routes at a constant speed of $1.5\,\text{m/s}$, typical of pedestrian movement in urban environments.

We considered Δt to be $100\,\text{ms}$ and v_u of $1.5\,\text{m/s}$ with total duration is $320\,\text{sec}$, resulting in 3200 time steps. To address the computational challenges posed by the large datasets, spatial aggregation is applied using H3 indexing at resolution 9. The simulation area is partitioned into 13 hexagonal cells, with measurement reports such as SINR, received power, and throughput aggregated at the cell level.

Hyperparameters of the models introduced in this work are tuned for each model to optimise performance. For example, the EDE was configured with $n_{\text{trees}} = 100$, a maximum tree depth of 10, and a minimum sample split of 10, while the GO employed a learning rate of 0.1 and 100 boosting stages. The LEM was trained with a maximum iteration count of 1000, ensuring convergence and the SOC was configured with probability estimation enabled for multi-class performance. The PBA used a dynamic selection of neighbours for optimal classification. The performance of each model was assessed based on classification accuracy and its impact on network metrics, such as energy savings and throughput.

B. Results and Discussion

The accuracy of each model in selecting the optimal Pow_{ID} is presented in Figure 3. Among the models, EDE and GO achieve the highest accuracy at 97.8% and 95.6%, respectively. PBA exhibits slightly lower accuracy at 93.2%, while LEM and SOC achieve 79.7% and 78.9%, respectively. These results highlight the effectiveness of ensemble-based models, such as EDE and GO, in handling complex multi-class classification tasks.

To evaluate the impact of these predictions on the network performance, we analyse key metrics, including throughput and EE. Figure 4 illustrates the Cumulative Distribution Function (CDF) of network throughput (Mbps) for the five proposed models along with the Full Power Baseline (FPB). PBA and SOC exhibit throughput distributions comparable to FPB, with average throughput values of 27.62 Mbps and 27.08 Mbps, respectively, demonstrating the highest throughput. GO and LEM achieve slightly lower averages at 26.95 Mbps and 26.79 Mbps, while EDE shows the lowest throughput at 23.9 Mbps, reflecting a trade-off between energy consumption and network performance.

Figure 5 presents the CDF of energy consumption per throughput (in mW/bps) for all models. This metric demonstrates the EE achieved by each model. EDE significantly reduce energy consumption compared to FPB, averaging 0.39 mW/bps and then LEM and GO consume 0.46 mW/bps and 0.49 mW/bps, respectively. SOC and PBA consume slightly more energy at 0.51 mW/bps and 0.52 mW/bps, while FPB shows the highest energy consumption among the trained models at 0.68 mW/bps. These results underscore

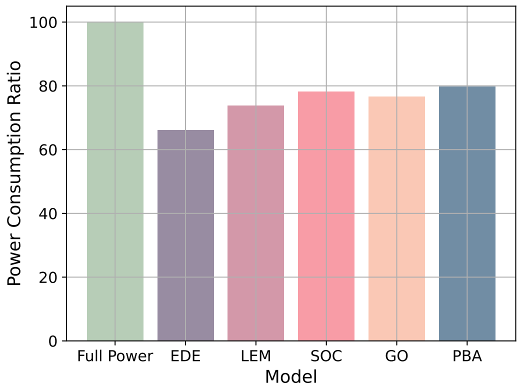

Fig. 6. Energy Consumption Ratio Compared to the Full Power Mode.

the potential of ensemble-based methods to optimise energy usage without sacrificing network performance.

Figure 6 highlights the power savings achieved by each model relative to FPB. EDE and LEM deliver the highest energy savings, reducing total power consumption by 33.88% and 26.18%, respectively. GO and SOC achieve moderate savings at 23.3% and 21.78%, while PBA exhibits the lowest savings at 20.27%. These findings illustrate the effectiveness of the proposed models in balancing energy efficiency and network performance, with EDE and GO emerging as the most robust approaches.

One notable contribution of this work is introducing a data aggregation technique based on H3 spatial indexing to address the scalability challenges posed by large datasets in 5G network simulations. The traditional approaches, each UE generates a row of data per time step, leading to an enormous dataset size (D_{raw}) proportional to the number of UEs and time steps. For $N_{\text{UE}} = 50$ UEs and $N_{\text{time}} = 3200$ time steps, the dataset size is: $D_{\text{raw}} = 50 \times 3200 = 160,000$ rows.

By aggregating data using our H3 spatial indexing approach, the simulation area is divided into a number of hexagons denoted as N_{H3}, where $N_{\text{H3}} = 13$ in our target area, and data is averaged across these hexagons. This reduces the dataset size (D_{H3}) required to train the ML models to: $D_{\text{H3}} = 13 \times 3200 = 41,600$ rows.

This approach achieves a data reduction ratio of 74%, significantly decreasing the computational burden while preserving spatial accuracy for training and evaluation purposes. All the classifiers trained in this work leverage the reduced dataset (D_{H3}), ensuring scalability without compromising performance.

IV. Conclusions

In conclusion, the results demonstrate that the proposed models can effectively predict the optimal Pow_{ID}, achieving significant energy savings while maintaining high throughput. Ensemble-based models (EDE and GO) outperform other methods in both energy efficiency and accuracy, making them ideal candidates for real-time deployment in the near-RT RIC. Other models, such as LEM, SOC, and PBA, offer simpler alternatives with moderate energy savings, showcasing the trade-offs between computational complexity and optimisation performance. The reduction in data volume by using H3 spatial indexing technique enables faster processing and more efficient training of the implemented ML models, which is critical for large-scale simulations. These findings highlight the potential of integrating machine learning-based energy optimisation into the near-RT RIC for real-time decision-making, enabling sustainable and efficient 5G ORAN deployments.

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