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Novel Mobility Prediction-Based Autonomous Energy-Aware Framework using ML and RL Techniques

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Abstract*: The approach delivers two separate results through an innovated energy-conscious framework which conducts RL-based Q-learning analysis for energy conservation with CO2 measurements followed by ML-based KNN algorithm application with distance metrics for classification accuracy. A three-fold benchmark evaluates the first part of the results using NS and ES and Greedy approach and the second part verifies its performance through KNN alongside SVM, DA, NB, DT, and ANN.*

Keywords: KNN, SVM, ANN

I. INTRODUCTION

The essential challenge of rising CO2 emissions prevents network densification from achieving the required 5G cellular capacity along with maintaining environmental sustainability. The 5G era requires immediate attention to energy consumption because it addresses operational reactivity and delay as well as scout.INVALID CELL error detection and SONs systemic functionality. The proposed model uses a mobility prediction-based autonomous energy-aware framework to analyze bus passengers' ridership through statistical ML and proactive energy savings combined with CO2 emissions in Het Net architecture through RL. The research implements ML algorithm analyses of London Over ground (LO) dataset to study bus passenger ridership.

1.1. Contributions

A framework (Fig. 1) addresses these limitations through its implementation of multi-tier self-organizing HetNets for bus passenger ridership analysis in Central London area that includes one MC and nine SCs [1]. The research objective anticipates the movement patterns of passengers aboard buses traversing HetNet structures which enables autonomous and intelligent function of involved SCs. The artificial intelligence would create a new ES optimization issue by managing motion to plan ahead for SC offloading scheduling while accomplishing QoS requirements. This research provides the following key points as its main contributions:

1. The work presents a mobility prediction framework that uses statistical KNN analysis to develop modern ES solutions to overcome conventional limitations.
2. The research establishes a new method to anticipate passenger positions which uses multiple K-values in the KNN model for next cell spatiotemporal HO prediction.
3. Another novelty of this proposal is; based on the future cell load information and CIOs as optimization variables for load balancing among SCs, a proactive ES optimization problem is formulated to reduce, power and energy consumption by switching OFF lightly loaded, idle or underutilized HetNet SCs. Intelligence in load balancing would exploit specifically lightly loaded SCs to be switched OFF while satisfying QoS.
4. Based on the information achieved from mobility prediction of passengers ridership and ES awareness, a novel scheme of CO_2 reductions is also quantified.

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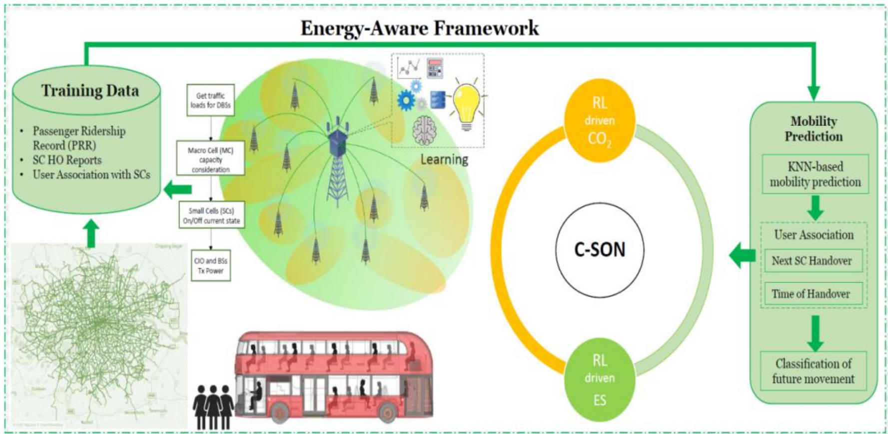

Figure 1: Network model comprising a 1 MC and 9 SCs (Data Base Stations - DBS) in HetNets deployment with CDSA. Energy-aware framework with bus passenger ridership dataset as an input.

II. SYSTEM MODEL

Here the analytical model explores the energy-aware framework through its essential components which will be discussed.

• Statistical KNN-based Passengers Mobility Prediction.
• Passengers Future Location Estimation.
• Proactive ES, and CO2 Reduction.

2.1. Energy-Aware Framework

The proposed framework examines downlink service that contains 1 MC along with 9 SCs in Fig. 2. The framework consists of direction-controlled antennas at the MC station while all antennas at the SC stations possess uniform gain with omnidirectional patterns. All cells share identical bands of frequencies throughout the framework while using a frequency re-use factor equal to one. The centralized C-SON system operates with proactive-energy saving optimization to lower CO2 emissions while supplying constant bit rate service with full buffer data utility network-wide. The C-SON server receives historical traces about mobility which comprise times and locations together with number of passengers as well as cell IDs and power level reception (RSRP). A Proactive- energy saving optimization based CO_2 reduction scheme is designed for the two-tier HetNet model which contains nine active SCs and one live MC alongside traffic management in exclusive control and data planes. Signaling takes place at the MC which operates low data rate services yet high capacity services become available through the MC-connected SCs. The SCs automatically switch off and send their traffic to the MC when they meet both conditions of detecting minimal traffic levels and finding suitable MC capacity available to accept the offloading load.

2.2. Statistical KNN-based Passengers Mobility Prediction

The non-parametric KNN classifier uses simultaneous parameter adaptations to find best results and deliver complete comparison ability. The KNN classifier possesses training data storage capabilities for which parameters need adjustment and modeling to perform re-substitution predictions. The model provides two different classification options either through re-substitution prediction or through application of the predict method in alternative instances. The modified equation defines the procedure as follows [2]:A simplified version of the algorithm for passenger location prediction can be achieved by transforming its language into basic terminology.

Algorithm: Simple Passengers Future Location Estimation

Input:

- Current location parameters: \(M_k \), \(M_u \), \(T_u \), \(M_{M_u} \)
- Maximum sojourn time: \(SojournTime_{max} \)

Output:
The predicted next move will be $M_{k+\bar{k}}$.
Procedure:
1. For each passenger u in the set U:
2. Check if either:
The sojourn time duration for passenger u (u(SojournTime - time)) exceeds or matches the maximum allowed time (SojournTime_max).
A lack of training data $M_{M_u} = \emptyset$ or the time spent sojourn exceeds the maximum $SojournTime_{max}$ will be the two conditions checked.
3. If either condition is true:
The future mobility prediction $M_{k+\bar{k}}$ receives the value of current location M_k.
4. Otherwise:
Run Equation (4.4) to produce an estimation for the upcoming mobility movement.
5. End the loop.

III. PROPOSED APPROACH

3.1. ML-driven Classification Accuracy

The above section included RL but this research also proposes ML-driven methods to estimate when passengers will travel in peak or off-peak times within HetNet systems. The invention of ML started with pattern detection to create automatic machine learning capabilities for intelligent decision systems which process historical data for adaptation during testing scenarios [3, 4]. The authors in [3, 5, 6, 7] introduced ML approaches to create models which identify traffic streams and link users to base stations for developing moving pattern classifications.

KNN serves as the classification mechanism because it functions as a non-parametric classifier that searches among K training sets points nearest to test inputs. During the calculation process it counts the members from its classes then delivers estimated observational fractions as its output values [8, 2]. The paper provides an extensive review of distance-based approaches used in KNN algorithms. Second identifies DA as its classification method that uses independent variables to perform two functions: new input classification through predictive equations and individual variable prediction for relationship understanding [8, 2].

SVM functions as a large margin classifier to carry out high dimensional input classifications using linear and non-linear mapping. Support vectors form a subset of training data that determines output results in SVM [8, 2]. The model bases its decisions through boundaries which generate hyper planes for nearest training samples within specified distances. The fourth mechanism implements DT via classification and regression trees (CART) to partition the input space of local models that generate new regions. The model presents itself as a tree framework that has one terminal node for each region area [9, 39]. The classification mechanism known as NB constitutes another mobility classification algorithm that enables the classification of features with discrete values [8, 2]. The training classes consisting of peak and off-peak passengers demonstrate their product using the artificial model concept NB. The sixth classification mechanism relies on ANN technology to process interconnected nodes and neurons between input and output layers. The neurons acquire training data by themselves while lacking predefined rules for specific tasks. The learning process for neural nets requires on-the-job training of numeric weights to achieve optimal outcomes [8, 2].

3.2. RL-driven Energy Savings

An energy-aware framework operates SC On-Off switching through the implementation of an RL algorithm which enables the MC to sense and take actions depending on reward or penalty according to environmental conditions. The choice of RL for supporting SC On-Off switching is due to its capability to handle multiple strategic decisions from limitless alternatives. The network environment interaction process enables MC to acquire user association criteria along with SC traffic information before decision-making. Through learning and adaptation RL obtains dynamic environmental capabilities to determine the necessary actions that preserve QoS. The Q-learning algorithm serves as a solution for the identified constraints according to [9, 10, 11]. Q-learning represents a well-known RL algorithm known for operating effectively in changing environments according to research from [12,13]. As an off-policy methodology

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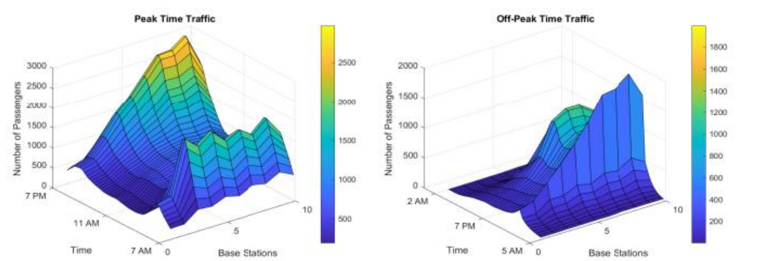
QL uses distinctive policies to determine future action states during its simultaneous update of action-value tables. The Q-learning approach consists of six integral components which include agent and environment and additionally action state reward/penalty and action-value table.

The agent performs environmental interaction through specific actions to reach the maximum reward level and minimum penalties. The agent performs actions which trigger evaluations of both current situation and received rewards/penalties [10]. Analysis uses a basic HetNet simulation model that features one MC together with 9 SCs located throughout a central London busy street. The model will utilize a basic look up table (Q table) because its state space remains small. The Q table updates its entries through every processed state action pair. The primary objective when designing the SC switching mechanism involved selecting the most efficient switching strategy which combines reduced ECR alongside CO2 emission performance while determining the optimal set of SCs that should be switched off from all available options.

IV. PERFORMANCE EVALUATION

Two parts comprise the proposed energy-aware framework for analyzing peak and off-peak dataset originating from Central London bus passenger ridership. How the generated bus passenger distributions thrive through three 3GPP standard compliant RL-based QL and ML-based six classification algorithms for various functions according to Section 4.2. Bus passenger numbers continuously shift because of the busy operational conditions of the environment. The 21-hour time period extending from 05:00 am to 02:00 am represents the peak and off-peak travel intervals according to Fig. 2. The initial portion of this model identifies the best possible On-Off switching and overloading technique by distributing bus passengers in HetNet cells. The complete power usage for the HetNet architecture is assessed. During the second model stage bus passengers are subjected to different ML algorithms for classification purposes which results in identifying the optimal approach for mobility prediction within dense mobile networks. The simulation runs in MATLAB utilize the network topology design and Table 1 provides the necessary simulation parameters for both parts.



(a) Peak Time. (b) Off-Peak Time.

Figure 2: Simulation results for Peak and Off-Peak travel for 10 Base Stations. Plotted dataset is from 05:00 AM to 02:00 AM (21-hours) by different buses.

Table 1: Simulation Scenario and Settings (M = millions, hrs = hours)

Data type	Value
Number of BS	10 (1 MC and 9 SCs)
Bandwidth	20 MHz
Frequency	2.6 GHz
Physical Resource Blocks (PRBs)	100
Number of iterations for RL	100
Number of iterations for ML	100
Total bus routes	673
Total number of passengers (Peak)	0.5 M
Total number of passenger (Off-Peak)	0.2 M
Number of classes	2

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Area of passenger movement probability	100%
Total simulation duration	21hrs

4.1. Classification Prediction Accuracy

Among the six Machine Learning classifiers in the MATLAB libraries the KNN classifier achieves highest accuracy through its nearest neighbor distance metric of K = 1 known as Mahalanobis which surpasses other metrics (Figure 3) according to Section 4.2. The algorithm demonstrates ease for classifying new data points using the similarity principle. Similar to the K = 1, when K = (2, 3, 4, ..) the output value stays closer to the K = 1 results, meaning test points from the training dataset, the classifier have memorized the last movement to the correct label and the classifier will achieve minimal error rate response; DA classifier with linear function being used; SVM classifier with default RBF kernel parameters settings but kernel size used is 200; DT classifier with maximum splits set to 50; NB classifier with normal function; ANN classifier with neurons set to multiple values to train weights and layers in each k intervals; and rest of the values are set to default.

The performance metric mobility prediction accuracy assessments were conducted with a total of 840 observations for peak and off-peak time travel using six ML classifiers which were presented in Table 2. The results show that ANN yielded poor accuracy during classification which placed it last in the table with accuracy at 73.09%. The NB achieved an overall accuracy rate of 86.94% but DA, SVM and DT algorithms showed nearly equivalent performance with overall accuracies of 97.00% and above. The KNN classifier in the Energy-Aware framework produced a final classification accuracy of 98.82% which exceeded performance of all five other classifier results.

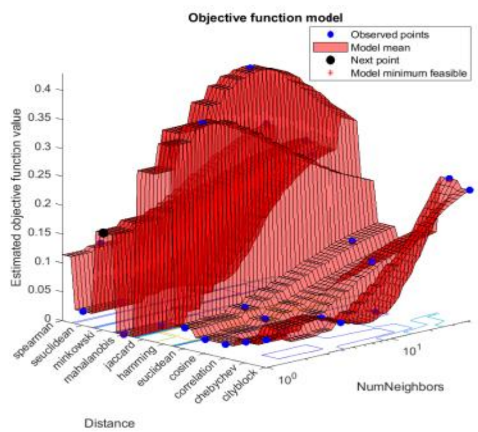

Figure 3: KNN Functional Model with the observed optimal values and next point classification.

Table 2: Classification of Mobility Prediction Accuracies

Machine Learning Algorithm	Accuracy
K-Nearest Neighbor (KNN)	98.82%
Discriminant Analysis (DA)	98.75%
Support Vector Machine (SVM)	98.75%
Decision Tree (DT)	97.78%
Naive Bayes (NB)	86.94%
Artificial Neural Network (ANN)	73.08%

4.2. Energy Saving, Benchmarking and Metrics

The evaluation process of the QL-based cell switching algorithm happens through assessment of live BSs in this phase. The value of learning rate at λr equals 0.3 and the discount factor stands at ϕ=0.9 [14]. The proposed QL assisted approach obtains energy efficiency performance assessments against the NS switching method and the Greedy approach followed by ES.

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The SCs stay active throughout the evaluation period in no-switching while Greedy disables the SCs whether the MC offers ample capacity or not. ES analyzes every available network switching alternative to identify the configuration that achieves maximum power savings without violating the MC power capacity. Fig.4 illustrates the power utilization for all the approaches.

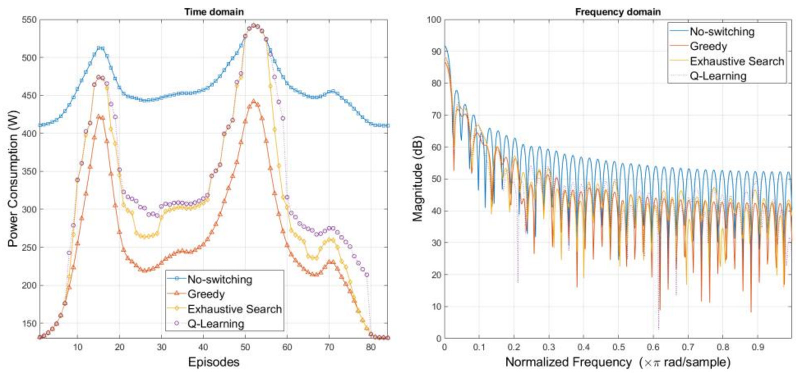
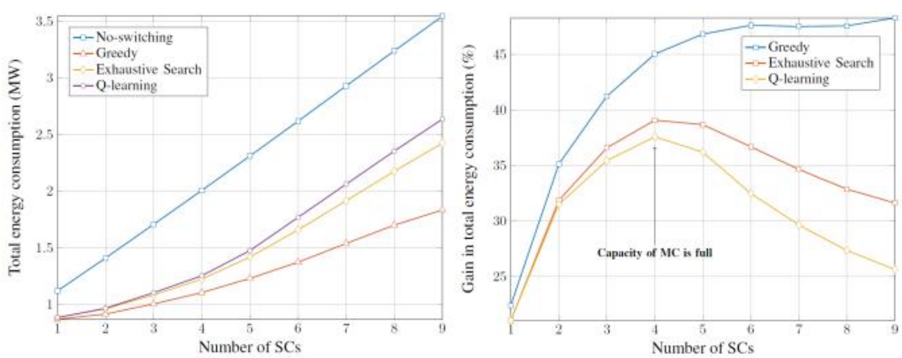


Figure 4: Power consumption of various approaches when the number of SCs is 9. Episodes refers to the instances in the network.

During testing the Greedy solution proved better than all other approaches because it fails to assess MC resource availability. A power-efficient connection occurs through the MC capacity reduction which decreases QoS because unconnected users remain when service capacity is full. The proposed ES approach establishes optimal power-saving equilibrium with MC capacity constraints and the QL assisted method consequently reaches this equilibrium.

The QL assisted proposed method manages to decrease network power usage while maintaining original QoS metrics. Total energy consumption rates (ECR) of all considered HetNet approaches are demonstrated in Figure 6a and Fig. 6b illustrates NS, Greedy and ES method performance. The following data shows the results presented in Fig. 4 and Fig. 5.



(a) Total HetNet energy consumption. (b) Gain for different methods compared to the NS approach.

Figure 5: Results for total ECR of the HetNet and the Gain provided by different switching approaches.

The number of SCs determines the greatest influence on conserving power as well as energy. The total network energy consumption displays an almost direct relation with the number of SCs according to Fig. 5a. The upscaled component numbers are anticipated to directly enhance ECR values. CIO maintenance stands significant because it enables the system to maintain Quality of Service capabilities while keeping power consumption low. The energy efficiency grows in line with random service center (SC) quantities until it reaches its maximum when SC number equals four. Energy consumption from SCs reaches higher significance when their quantity rises so that ECR enhances through SC power-off strategies. Energy consumption gain shows a descending trend after the number of SCs reaches a specific point which equals 4 based on the proposed model simulation results. When the MC reaches its capacity limit additional SCs cannot be turned off since there is no more available space. When the MC capacity has maximal utilization its switching capacity restriction reaches maximum because too many SCs cannot be shut off. The additional SCs exceed the maximum capacity of the MC which results in increasing network energy consumption while diminishing relative gain since more energy is required to operate the network. Fig. 6 represents the direct relationship between ECR and CO2 emissions while the ratio increase results in continuous ECR growth. The HetNet energy usage along with CO2 reduction presents 45.63% gains between the NS and Greedy approach and 31.83% gains between NS and QL and 35.60% gains between NS and ES. Results indicate that the proposed statistical framework lowers energy consumption and resulting CO2 emissions extensively.

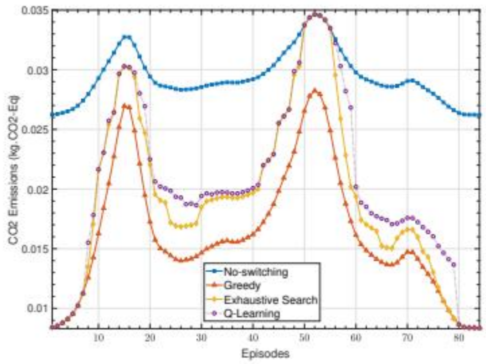


Figure 6: Total CO emissions of the HetNet for various numbers of SCs.

V. CONCLUSION

The autonomous energy-aware framework employs mobility prediction-based ML and RL techniques to solve peak and off-peak time passenger ridership problems alongside the estimation of future locations while ensuring accurate predictions and HetNet energy consumption analysis to calculate two-tier CO2 emission impacts through cell On-Off switching and offloading strategies.

The first part of ML-based analysis focused on comprehensive assessment and optimal mapping of classification prediction accuracy that achieved 98.82% accuracy with KNN classifier. The analysis between peak and off-peak periods and predictions about future locations demonstrate sufficient operational reliability. Through the second part of the proposed framework an RL-based QL algorithm executes an optimal methodology for switching underutilized cells Off along with reducing SCs that produce unnecessary CO2 emissions. The proposed framework demonstrates a total energy saving amounting to 31.83% together with a corresponding reduction in carbon emissions level.

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