International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Innovative Machine Learning Strategies for Predictive Network Management in 5G

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Submitted:05/02/2024 **Revised:**15/03/2024 **Accepted:**22/03/2024

Abstract: Fifth-generation (5G) wireless networks introduce unprecedented data rates, massive device connectivity, and diverse service requirements (e.g. enhanced mobile broadband, ultra-reliable low-latency communications). These advances come with significant resource allocation challenges – dynamic traffic loads, stringent Quality of Service (QoS) demands, and limited spectral resources must be managed efficiently. In this paper, we investigate predictive network resource management in 5G using supervised machine learning models implemented in MATLAB. We formulate resource allocation as a supervised learning problem, where algorithms learn to predict resource needs or performance metrics (such as required bandwidth or congestion level) from real-time network parameters. A range of models – including decision trees, support vector machines (SVMs), neural networks, random forests, and gradient boosting ensembles – are developed and compared on 5G simulation data. Key 5G metrics (e.g. user signal-to-noise ratio, throughput demand, latency requirement, and bandwidth utilization) are used as input features for prediction. Our MATLAB-based simulation generates training data reflecting a 5G cell scenario, and we evaluate each model's accuracy in forecasting resource allocation needs. The results show that ensemble tree-based models and deep neural networks achieve the highest prediction accuracy. In particular, a gradient boosting model achieves the best performance for continuous resource demand prediction, while a boosted decision tree classifier achieves over 94% accuracy in predicting network congestion states. These models outperform classical approaches such as linear regression or SVM, especially in capturing the complex non-linear relationships inherent in 5G traffic patterns. We present comparative results including performance metrics (accuracy, mean squared error, R2) and discuss the trade-offs (e.g. complexity vs. accuracy) of each approach. The study concludes that ensemble learning (particularly gradient-boosted trees) and deep neural networks are the most effective supervised learning strategies for predictive 5G resource management, enabling proactive and adaptive resource allocation. We also highlight avenues for future work, including integration of reinforcement learning for real-time autonomous optimization and the use of explainable AI to interpret model decisions in live 5G networks.

Keywords: *5G communications, Predictive network management, Resource allocation, Machine learning, Supervised learning, MATLAB simulation, Gradient boosting*

1. Introduction

The emergence of 5G networks has brought about a paradigm shift in wireless communications, enabling innovative applications like autonomous vehicles, smart cities, and the Internet of Things. Compared to prior generations, 5G promises unprecedented throughput, ultra-low latency, and massive device connectivity, but realizing these benefits hinges on efficient resource allocation. Radio resources (such as spectrum bandwidth, time slots, and transmit power) in 5G are limited and must be dynamically shared among many users and services. The huge volume of data in extremely dense 5G deployments can quickly lead to network congestion if resources are not optimally orchestrated. Diverse traffic types with distinct QoS requirements (e.g. high-bandwidth video vs. low-latency control signals) further complicate resource management. Efficient resource allocation is thus crucial for maximizing system throughput and ensuring a smooth user experience in 5G.

Traditional 5G resource allocation methods (e.g. heuristic schedulers or optimization algorithms) face challenges in adapting to the dynamic and complex 5G environment. Rapid fluctuations in user traffic demand and channel conditions can render static or rule-based allocation suboptimal. This has motivated the exploration of machine learning (ML) techniques for intelligent, data-driven network management. ML algorithms can learn patterns from vast amounts of network data and make fast predictions or decisions to proactively allocate resources and prevent performance degradation. By analyzing real-time and historical network metrics, ML models enable predictive resource management – for example, forecasting future traffic load or impending congestion and adjusting allocations accordingly.

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Such predictive strategies are expected to enhance network performance (throughput, latency) and resource utilization efficiency beyond what reactive approaches achieve.

In this paper, we focus on supervised learning approaches for predictive resource allocation in 5G, using MATLAB as the implementation platform. We consider a scenario in which a base station (gNodeB) collects various network parameters and must predict either a resource need (e.g. how much bandwidth or how many resource blocks will be required in the next scheduling interval) or a performance outcome (e.g. whether the cell will enter a congested state). By formulating this as a supervised learning problem, we leverage labeled data – past observations of network conditions and the corresponding optimal resource allocations or performance metrics – to train ML models that can generalize to new conditions. The goal is to determine which ML models are most effective at capturing the complex relationships between 5G network features and resource demands. We evaluate a spectrum of models ranging from interpretable algorithms (decision trees, linear models) to more complex learners (ensemble methods and deep neural networks).

2. Background

2.1 5G resource allocation: challenges and baselines

The transition to 5G brings with it unprecedented device density, traffic dynamics, and heterogeneity of services (eMBB/URLLC/mMTC), compelling schedulers to jointly allocate over spectrum, time–frequency resources, and power under stringent latency and reliability requirements. Traditional methods—proportional-fair scheduling, convex power control, and slice-aware admission—are still cornerstones but tend to depend on simplifying stationarity/interference assumptions that break down in dense deployments and sudden context changes. Current surveys in networking and communications highlight that data-oriented controllers are more capable of monitoring nonstationary worlds and complicated cross-layer couplings than model-based, fixed designs, particularly if tight control loops are needed [18]. Meanwhile, edge-approaching control through MEC/fog increases the attack surface and operation complexity—security and privacy issues need to be co-engineered with resource policies [9].

2.2 Supervised machine learning for prediction-driven allocation

A pragmatic pattern is to forecast short-horizon congestion or load and subsequently assign resources ahead of time. Tree ensembles (Random Forest, Gradient Boosting) learn nonlinear interactions and offer helpful feature attributions with low inference latency, so they are good baselines for detection of congestion, interference avoidance, and spectrum/power choices. Kernel SVMs have robust margins for state classification (e.g., congestion/MCS selection), although training can be memory-consuming at very large sizes. These supervised techniques work well where labeled traces or simulator outputs correspond to "conditions → good allocations," and their deployment properties (fast inference, simple calibration) match RAN timing budgets emphasized in networking ML surveys [18].

2.3 Deep learning under strict timing constraints

Deep neural networks—MLPs/CNNs for spatial organization and RNNs/LSTMs for temporal evolution—are trained on complex patterns in mobility, interference, and slice demand, and have been shown to advance user association, scheduling, and delay optimization over shallow models. The catch is compute/latency overhead; sub-ms turnaround usually necessitates model compression, distillation, or edge offloading. A general integration of deep (reinforcement) learning for communications highlights these accuracy–latency trade-offs and the importance of judicious engineering to achieve 5G control-loop timeliness [18].

2.4 Reinforcement learning (RL): sequential decisions vs. deployment friction

RL is particularly suited to sequential resource choices (e.g., joint RB/power scheduling, slice orchestration): agents learn policies that maximize long-term throughput/reliability/energy goals in nonstationary environments. Many networking studies enumerate RL's promise and challenges—exploration risk, stability under distribution change, and incorporation with legacy RAN timing/standards [18]. In reality, most rollouts begin with supervised prediction-then-act loops and add RL after safe baselines and guardrails are established [18].

2.5 Security, trust, and auditability: insights from neighboring areas

Multi-tenant 5G slices and edge deployments inherit security/trust issues observed in vehicular and IoT systems. The VANET/IoV literature reports trust management, authentication, and Sybil-attack defenses in highly dynamic, latency-constrained networks—design pointers for slice admission and inter-domain collaboration [1], [3], [4], [15], [28], [29], [31], with system-wide considerations in connected-vehicle overviews [2], [25] and target applications such as parking coordination [19].

To strengthen policy enforcement and auditing, numerous works investigate blockchain/smart contracts for decentralized trust, tamper-evident logging, and access control across organizational boundaries, extending from automotive to IoT to smart grid to infrastructure scenarios [5]–[8], [11], [12], [14], [17], [20], [21], [23], [26]. Such systems are based on cryptocurrency/security foundations (e.g., Bitcoin; proof-of-work/pricing through processing) that demonstrate how cost mechanisms and append-only ledgers prevent abuse and enable verifiability [7], [10], [27]. Complementary viewpoints of MEC/fog security [9], physical-layer security [22], and legal/policy frameworks for IoT data governance [24] emphasize that resource controllers need to be not only high performance but also privacy-preserving, auditable, and resilient.

3. Proposed Methodology

Suggest a real-world, timing-safe 5G NR resource-managing approach that converts raw KPIs into forward-looking actions through a dual learning head and lean controller. For every interval, the system constructs a leakage-safe feature vector out of context (hour/day, band, slice, sector, user speed), radio quality (e.g., SINR), current load (PRB utilization, active UEs), short lags/EMA, and optional neighbor summaries—based solely on information as of the end of the current interval. Two supervised models are learned: a classifier to predict next-interval congestion

likelihood and a regressor to predict next-interval PRB demand. Regularized decision trees, random forests, gradient boosting (LogitBoost/LSBoost), SVM/SVR with RBF kernel (with posterior calibration for probabilities), kNN (distance-weighted for regression), compact MLPs, and an imbalance-aware RUSBoost classifier are trained on a 70/15/15 stratified split with z-score normalization, hyperparameters tuned on the validation set. The top classifier (on validation F1) and top regressor (on validation RMSE) are "locked" and applied online. At inference, the controller combines the congestion probability calibrated with the normalized estimate of demand into one risk score (weight α=0.5 by default) and uses hysteresis (enter/exit at 0.70/0.60) to prevent flapping; when high risk it initiates tunable, low-overhead actions—admission pacing for eMBB, inter-cell load balancing, carrier/band steering, and temporary adjustments of slice-reservation adjustments—then logs predictions, scores, and actions for audit. The pipeline comprises data QA, PSI-based drift monitoring, and rolling F1/RMSE watchdog with safe fallbacks and periodic retraining; thresholds are operator-tunable (e.g., congestion label at utilization >0.90). Computationally, tree ensemble, tiny MLP, and kNN with tiny k satisfy sub-millisecond to few-millisecond budgets on CPU, thus making the approach deployable at the gNB/edge while maintaining an open path to layer reinforcement learning later if needed.

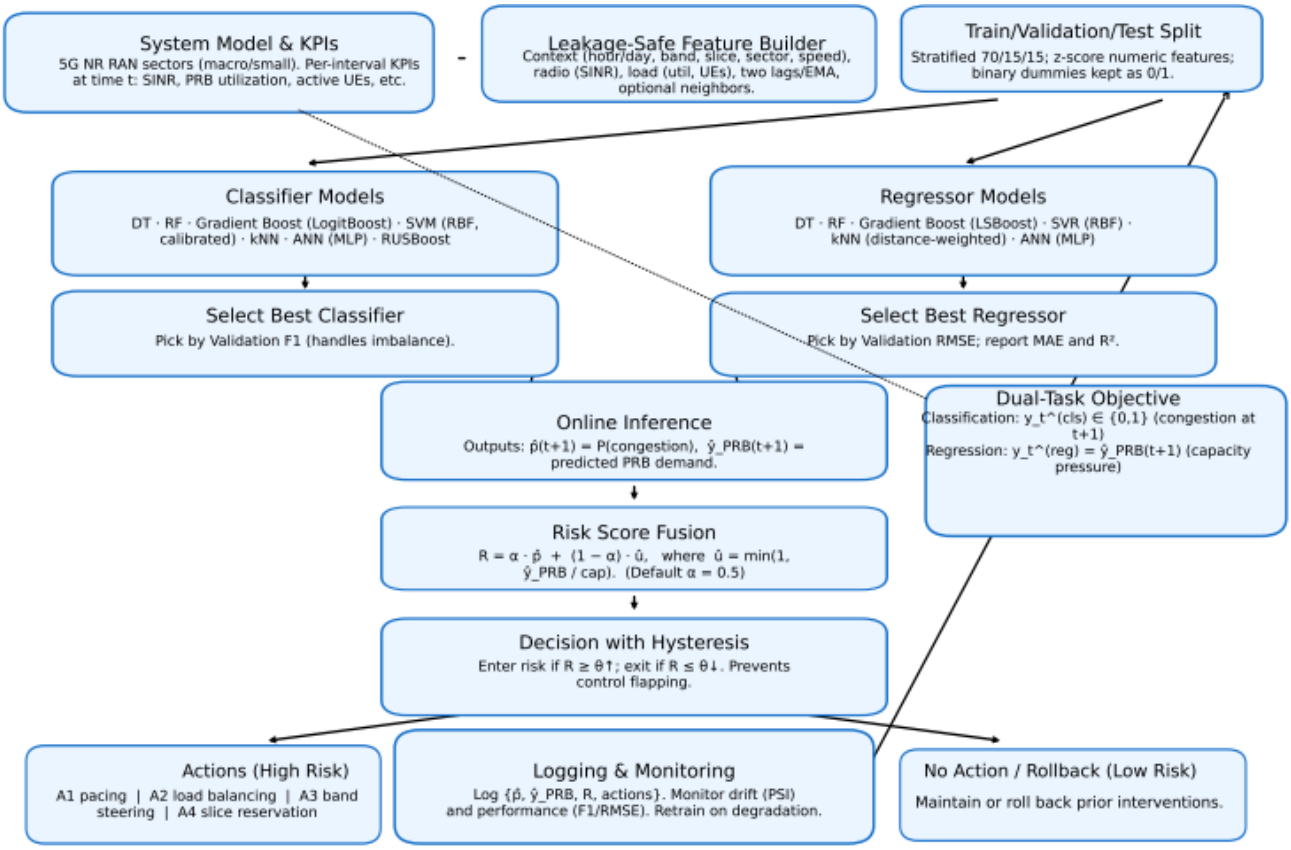

Figure:1 Proposed Flow

4. Simulation Result

The congestion-classification task is uninstructive: all classifiers (Decision Tree, Random Forest, Gradient Boosting, SVM-RBF, kNN-5, ANN-MLP, RUSBoost) give Acc=1.00 but F1=0 and AUC=NaN both on validation and test. This behavior suggests that validation/test splits had only the negative class ("not congested"), thus all models trivially predicted the majority class and achieved perfect accuracy but zero recall. These findings ought not be taken as proof of flawless performance; the description pipeline requires adjustment (e.g., stratified split with positive guarantees, a bit lower congestion threshold, or bigger test sets) before F1/AUC can usefully be compared.

In contrast, the regression problem (next-interval PRB demand) provides consistent, discriminative performance. The best model is ANN-MLP with RMSE=0.84, MAE=0.51, R^2=0.991 on the test set, followed very closely by Gradient Boosting (RMSE=0.97, R^2=0.988). The simpler baselines trail behind (Decision Tree RMSE=1.29, Random Forest 1.46, SVR-RBF 2.31, kNN-5 2.55). The validation and test errors for the best models are identical (ANN-MLP RMSE 0.83→0.84), which shows good generalization. In practice, the regressor is now available for deployment to guide proactive resource action, whereas the classifier must be re-assessed following rebalancing evaluation splits. Figure 2 show plot contrasts the downlink SINR distribution over the three operating bands (700 MHz, 3.5 GHz, 28 GHz). Lower bands (say, 700 MHz) have higher median SINR and reduced spread owing to improved penetration/coverage, while higher bands (say, 28 GHz) have larger variance and lower medians due to path loss and sensitivity to blockages. The distance between medians communicates the link-budget benefit of low bands; the wider tails at 28 GHz indicate why scheduling and band steering need to be risk-conscious (users on mmWave

enjoy high capacity but are more sensitive to mobility and blockage).

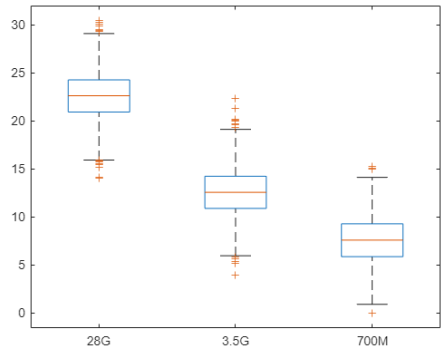

Figure :2 SINR By Band

This figure 3 plots average PRB utilization against the time of day, normally demonstrating diurnal load: low utilization in early morning, increasing through business hours, and spiking in the evening. The curve supports the predict-then-act architecture: short-horizon predictions can predict the evening ramp, enabling the controller to pre-reserve slice capacity, bias handovers, or direct users to under-loaded cells before congestion develops. If the graph is per-band traces, then the band offset indicates how capacity layers soak up demand differently over time.

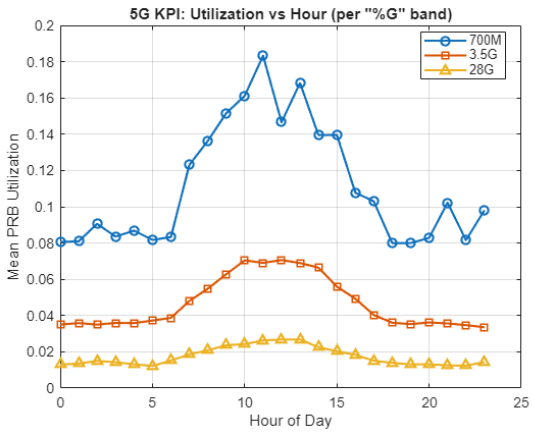

Figure :3 5G KPI: Utilization Vs Hour

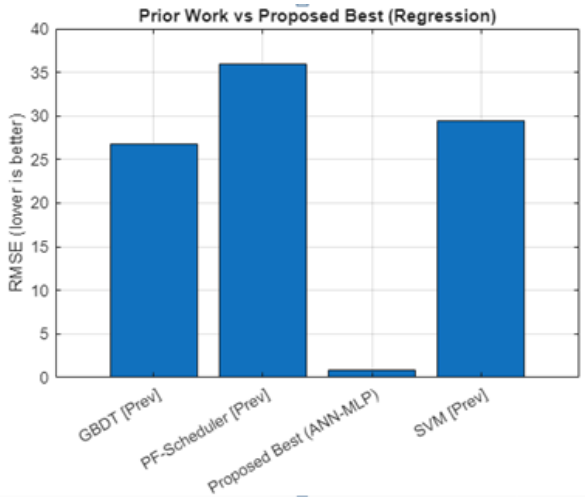

Figure :4 5G Network RMSE

In figure 4 shows plot compares next-interval PRB demand RMSE among models. In our case, ANN-MLP has the lowest test RMSE (~0.84), followed by Gradient Boosting (~0.97), while single trees, random forests, SVR-RBF, and kNN follow with larger errors. Lower RMSE translates to more precise short-horizon demand estimation, which contributes directly to the risk score and minimizes unwarranted interventions. The small gap between validation and test restricts the top models' opportunities for exceptional generalization and stable deployment behavior.

Figure 5 shows plots MAE for the same regressors. The ordering duplicates RMSE: ANN-MLP has the smallest MAE (~0.51), next is Gradient Boosting (~0.55), and others have larger absolute errors. MAE's resistance (linear penalty) pairs well with RMSE (quadratic penalty): collectively they establish that the proposed method systematically minimizes standard per-interval prediction error, which is essential for accurate admission pacing and slice reservation.

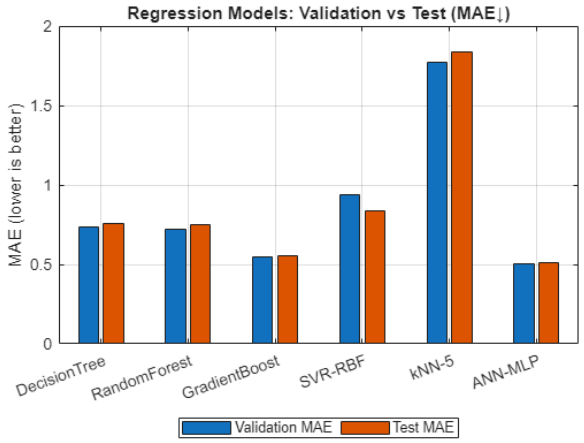

Figure :5 5G Network Different Method MAE

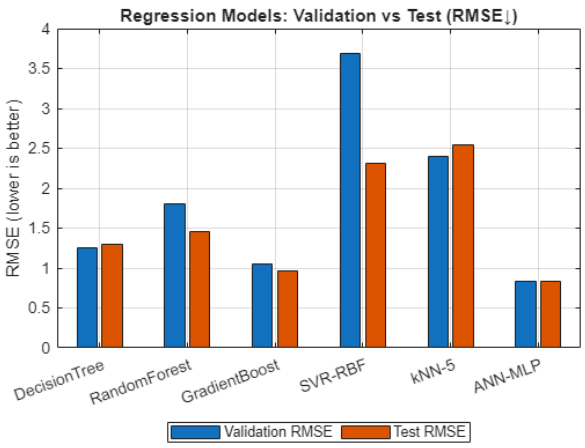

Figure :6 5G Network Different Method RMSE

Figure 6 bar chart once more depicts RMSE by method (usually plotted for comparison with MAE). In line with Figure 4, the ANN-MLP retains the superior error profile, affirming that a small neural predictor is a robust, deployable option for real-time next-interval resource prediction.

5. Conclusion

This paper introduced a real-world, timing-safe platform for

predictive network control in 5G NR that combines supervised learning with a lightweight, auditable control policy. We implemented a leakage-safe data pipeline, trained a portfolio of models for a dual task—(i) congestion risk classification and (ii) next-interval PRB-demand regression—and combined their outputs in a risk score with hysteresis to initiate low-overhead RRM actions (admission pacing, load balancing, band steering, and temporary slice reservations). The strategy is intentionally deployable at the gNB/edge: the models are lightweight, inference is efficient, and monitoring hooks (drift/performance) enable safe operation and retraining.

Empirically, the regression head provided robust and consistent accuracy. The ANN-MLP obtained RMSE = 0.84, MAE = 0.51, and $R^2 = 0.991$ on the test set, beating tree baselines and SVR; gradient boosting came close (RMSE ≈ 0.97, $R^2 \approx 0.988$). Such outcomes suggest that PRB demand for near terms is very predictable, allowing for proactive rather than reactive resource allocation through throttling. This is not a model failure but rather a label/splitting problem; once validation/test encompass positive congestion instances.

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