IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 18 November 2022, accepted 29 December 2022, date of publication 10 January 2023, date of current version 26 January 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3235882

RESEARCH ARTICLE

Mitigating Trade-Off in Unlicensed Network Optimization Through Machine Learning and Context Awareness

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This work was supported by the National Institute of Information and Communications Technology (NICT), Japan, under the commissioned grant 222C03 for the Research and Development of Information and Communication Technologies that Contribute to Countermeasures against Infectious Diseases.

ABSTRACT Unlicensed cellular networks are being deployed worldwide by cellular operators to meet the rising data demands. However, the unlicensed band has existing incumbents such as Wi-Fi and radar systems. This creates a highly dynamic environment, making harmonious unlicensed coexistence difficult. Consequently, conventional optimization techniques are not sufficient to offer latency-critical applications and services. A data-driven hybrid optimization approach is necessary for optimal network performance with low convergence times. However, a largely unexplored problem in dense unlicensed network optimization is the accuracy-speed trade-off, that is, achieving high accuracy in optimization objectives with minimal time costs. This work seeks to address this problem through a hybrid optimization approach that combines machine learning and network optimization. It investigates the use of more precise higher-order network feature relationships (NFRs) in optimization formulations and the consequent trade-off that arises between the increase in convergence time (Speed) and the nearness to optimal results (Accuracy). In addition, it demonstrates the relevance of context awareness of network conditions and the traffic environment to mitigate the trade-off. To that end, a context-aware network feature relationship-based optimization (CANEFRO) approach is proposed and validated through decision matrix analysis. The experiments were carried out on a coexistence testbed consisting of both unlicensed LTE standards (LTE-U & LAA) and two Wi-Fi standards (802.11n/ac) on multiple channel bandwidths. In addition, LTE-U & LAA are contrasted on signaling and user data traffic data models and resource block allocation performance. More importantly, CANEFRO demonstrates the impact of the network context on the degree of feature relationship (2^{nd} & 3^{rd} degree polynomials), objective of optimization (SINR and Capacity), and the network use case (Accuracy vs. Speed). CANEFRO is also used to contrast LTE-U & LAA optimization performance. In particular, the decision matrix analysis demonstrates a higher decision score for LAA by as much as 42% compared to LTE-U.

INDEX TERMS Unlicensed networks, machine learning, network optimization, context awareness, LAA, LTE-U, 5G NR-U, data analysis, network measurements.

I. INTRODUCTION

There has been a consistent increase in latency-critical data traffic from services such as augmented reality (AR) and

The associate editor coordinating the review of this manuscript and approving it for publication was Paulo Mendes.

on-the-go video streaming [1]. The inability of existing LTE/LTE-A (Long Term Evolution/Long Term Evolution-Advanced) networks to meet the Quality of Service (QoS) requirements for uplink-heavy and bursty flows of AR applications deny the end-user a seamless experience [2].

To address these challenges cellular operators have taken recourse to harnessing the potential of the unlicensed spectrum through operation of LTE in the 5GHz band in coexistence with Wi-Fi. Two unlicensed cellular standards were put forward, *viz., LTE in unlicensed spectrum* (LTE-U) and *LTE license assisted access* (LTE-LAA). The adoption of these standards has led to a rapid deployment of LAA/LTE-U small cells in the 5GHz band where 500 MHz has been allocated for unlicensed LTE operation in coexistence with Wi-Fi access points (APs) [3], [4].

However, dense deployment of LTE/LTE-A, LAA, and 5G small cells (SCs), magnifies the scale and complexity of cellular networks. This leads to increased computational costs and longer convergence times to arrive at optimal solutions [4], [5]. From the perspective of ultra-low-latency augmented reality (AR) applications and high-speed vehicular networks, this is extremely undesirable. A typical LTE/LTE-A network already contributes about 30% to end-to-end latency in mobile AR [2]. Network densification will exacerbate the latency problem and undo the enhancement in network throughput achieved through the utilization of unlicensed spectrum. Thus, an important expectation from optimization techniques is low convergence times, so that dense unlicensed networks can seamlessly facilitate latency-critical services to end-users [6]. To meet this expectation, data-driven optimization is a hybrid optimization technique that is quickly gaining prominence, especially in the unlicensed band [7], [8].

A. MOTIVATION

In the unlicensed band, cellular operators must co-exist with existing incumbents, such as Wi-Fi, radar operation, fixed satellite transmission links, and Broadcast Auxiliary Services (BAS) [3]. This increases the probability of transmission conflicts making the environment highly dynamic. Although conventional optimization techniques have been the bedrock of wireless network performance enhancement, a data-driven optimization approach is more suitable for unlicensed band optimization [9]. A data-driven optimization approach combines the power of machine learning and traditional optimization to better support applications such as mobile AR and autonomous vehicles that need low end-to-end delays (typically $\leq$ 10ms).

However, machine learning-based optimization is context-specific and application-dependent. Applications such as mobile AR and autonomous vehicles require low association times and fast handovers. These constraints make optimizing performance and resource allocation **time-critical** for these applications. This work refers to it as the "Speed" of network optimization model. However, some applications and services such as VR-enabled telesurgery are resource intensive and require the highest priority QoS Class Identifier for satisfactory end-user QoS. To ensure maximal resource allocation, data-driven time-critical optimization solutions must be close to theoretical optimal solutions. This nearness to optimal solutions is referred to as the "Accuracy" of the model.

In [9], the proposed data-driven optimization solution focuses on reducing convergence times for time-critical services. However, the challenge of Accuracy-Speed trade-off was not investigated. This involves selecting the network feature relationship (NFR) learned from the network data to be used in the optimization model. Typically, multiple feature relationships with varying polynomial degrees can be learned using machine learning algorithms. Thus, selecting a suitable NFR is a non-trivial problem. Further, the network context was not considered in the data-driven optimization solution presented in [9]. The context typically comprises the network configuration, the ambient network environment, the priority of the application for Accuracy or Speed, the goal of optimization, the degree of learned feature relationships, etc. [10], [11]. For example, only signaling data and user-plus-signaling data would create two different network contexts.

Furthermore, since the network context is extremely dynamic, the context-aware solution should be validated through an appropriate methodology. Therefore, this work explores a context-aware data-driven approach that combines machine learning and network optimization. It reduces the time-cost of dense unlicensed network performance optimization while ensuring high accuracy vis-a-vis baseline optimization models.

B. CONTRIBUTIONS

This work utilizes Network Feature Relationships (NFRs) learned from machine learning algorithms to accelerate network optimization. NFRs are also a suitable indicator of the network context. Further, in comparison to [9], this work examines the performance of higher-order feature relationship models. It analyzes the trade-off involved in the use of higher-order NFRs with high R-sq in data-driven optimization. Specific contributions of this work are listed below.

- Conducted experiments for multiple dense LTE-WiFi coexistence combinations and bandwidth variations on an experimental testbed.
- Evaluated LTE-U and LAA network performance through feature relationship analysis (e.g., SINR-Capacity relationship) using machine learning (ML) algorithms.
- Demonstrated importance of network context through difference in ML model parameters such as R-sq, residual error (RSD), outliers, etc.
- Utilized network feature relationships (NFR) to optimize performance through four state-of-the-art network capacity and signal strength optimization formulations.

- Analyzed Accuracy-Speed trade-off in using higher-order NFRs in optimization models for different coexistence configurations.
- Validated context-aware data-driven optimization through decision matrix analysis.

This work expands on the data-driven optimization solution proposed in [9], through: (a) 8 additional test scenarios, (b) analysis of context using signaling vs. user data and resource block allocation for LAA & LTE-U, (c) analysis of trade-off in data-driven network optimization using higher-order feature relationships, and (d) validation of data-driven context-aware optimization through decision matrix analysis.

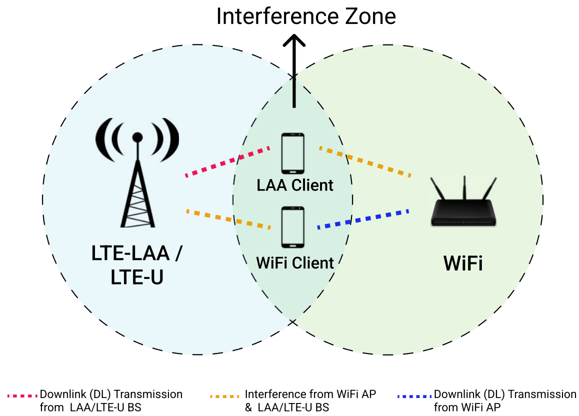


FIGURE 1. Interference in the unlicensed band.

II. A REVIEW OF RELATED WORKS

A brief overview of recent studies relevant to the analysis and solutions proposed in this work is presented in the following subsections.

A. UNDERSTANDING NETWORK CONTEXT THROUGH FEATURE RELATIONSHIP ANALYSIS

Understanding the interplay between various network parameters is crucial for analysis and modeling of wireless network performance. The network context is governed by these metrics such as throughput, signal plus interference and noise ratio (SINR), resource block allocation, modulation coding scheme, etc.

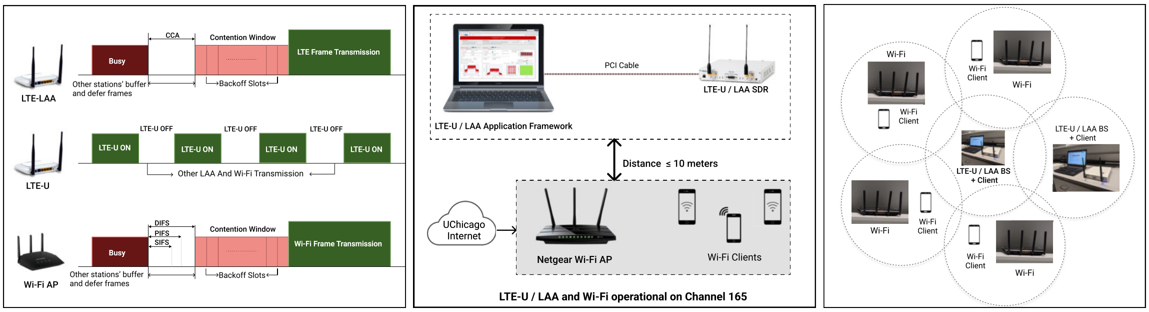
Conventionally, relationships between network parameters were determined through abstract theoretical models. For example, capacity interference relationship (CIR) analysis and modeling has been the focus of numerous works [12], [13], [14], [15]. Theoretical solutions invariably require additional prior network related information, e.g., the network layout, location of the nodes, etc. Further, due to the complexity of the problem (e.g., determining CIR is NP-hard), often assumptions are made about wireless network parameters such as the expected traffic load or expected mobility patterns of nodes in dynamic scenarios [13], [15]. However, context is highly spatio-temporal and can be adequately represented only through actual network data. Theoretical models and assumptions cannot offer a true measure of the actual context of the network. Thus, a better approach of understanding network context is to learn the relationships between the network variables through data analysis. In recent state-of-the-art studies, the most common machine learning techniques used to learn *network feature relationships* include family of regression algorithms, decision trees, and random forests [16], [17], [18], [19], [20]. This approach is empirical and data-driven, compared to the abstract theoretical solutions discussed earlier. Training models on network data also does away with the need for assumptions, approximations, and prior network information typically required in theoretical models [14], [21]. Further, the algorithms used in learning NFRs are not only reliable but also computationally less expensive, compared to both conventional solutions and more advanced machine learning techniques, such as deep learning. These advantages have encouraged the application of NFR analysis to learn context even in large-scale networks [18], [19].

The relevance of network context in the unlicensed spectrum can be demonstrated through the NFR analysis of unlicensed LTE standards, viz., LAA & LTE-U. The existing research literature on the comparative performance of the two LTE unlicensed standards is characterized by three features. First, experiments are conducted primarily through simulations and often make assumptions or relaxations [22], [23]. Second, the comparative analysis and the conclusions drawn rely on *measurements*, *i.e.,* through the comparison of important network parameters such as network capacity, signal plus interference and noise ratio (SINR), resource block (RB) allocation, modulation coding scheme (MCS), latency, number of retransmissions, *etc.* Third, there is a limited focus on learning the network context. For example, the variation in performance of LTE unlicensed variant with the variation in the coexisting Wi-Fi standard is rarely studied. Similarly, the network context is influenced by factors such as bandwidth allocation and signaling data.

While measurement-based studies are a great first step in network performance evaluation, learning and utilizing the network context is highly desirable for the optimal performance of dense unlicensed networks [10], [11]. Thus, network *feature relationship analysis* of network variables is the logical next step. It facilitates learning the network context through machine learning models trained on network data.

NFR analysis unlocks deeper insights into various dimensions of network context such as the strength of the relationship between network variables (R-sq or accuracy), precision in the prediction of the response variable (residual error), presence of significant fluctuation in parameter values (Outliers), etc. In addition, NFR analysis can also reveal associations between network parameters such as dependence, correlation, causation, *etc.*

Furthermore, as shown in Figure 1, the adverse impact of interference on the LTE-WiFi coexistence networks will exacerbate and pose additional challenges with network



(a) Channel Access Mechanisms (b) Representative Testbed (c) Representative Topology

FIGURE 2. Testbed design.

densification. Although it may lead to an initial gain in unlicensed system capacity, network performance eventually deteriorates with increasing network density [24]. However, the impact of factors relevant to network performance and context, *viz.,* unlicensed LTE variant, Wi-Fi standard, allocated bandwidth, and signaling data remains unexplored. For example, the analysis presented in [25] is limited to demonstrating how the SINR-Capacity relationship differs in regular and dense/ultra-dense networks and does not explore the impact of these factors.

Therefore, we focus on these aspects of performance and context in dense unlicensed coexistence networks. The importance of network context is demonstrated through a comparative performance analysis of LAA & LTE-U networks. The feature relationship between interference and network capacity is analyzed in a dense coexistence network by considering a variety of network configurations.

B. DATA-DRIVEN NETWORK OPTIMIZATION

Several challenges in network management are solved through optimization *viz.,* dynamic allocation of resources, energy efficiency, interference management, and efficient spectrum sharing [6]. Although efficient solutions to many of these problems are available for sparse wireless networks, they assume new dimensions in dense unlicensed networks. Interestingly, the decrease in inter-AP/inter-SC distance does not necessarily lead to gains in network capacity due to increased interference in dense coexistence networks [24]. With increased spatial colocation of small cells and APs in coexistence deployments, the complexity of formulations, and consequently, the convergence time of optimal solutions, increases significantly [26]. Due to the complex network topology, detailed network information is required for unlicensed network optimization [5]. The cumulative impact of these factors results in NP-hard mixed integer non-linear formulations [6], which lead to higher computational overheads and longer convergence times.

To overcome these challenges and reduce convergence times in unlicensed network optimization, some measures can be taken. First, instead of complex theoretical constraints, constraints rooted in ground truth that are learned from network data should be considered. Second, simplistic constraint relaxation techniques should be avoided. For example, linearizing complex theoretical constraints by making context-specific assumptions or considering specific scenarios [27]. Such reductionist approaches lead to sub-optimal results, and a better solution for dense unlicensed networks is network-data-driven optimization.

Consequently, several recent studies have used machine learning to optimize vital network metrics, e.g., rate adaptation [16], link adaptation [19], and network throughput [17]. In particular, the learned feature relationships can be utilized to improve network performance. For example, learning 802.11n feature relationships can facilitate improved configuration selection and enhanced rate adaptation [16]. Likewise, they can be used to design link adaptation algorithms and improve network throughput [17], [19].

However, the impact of the degree of feature relationship equations on optimization goals and performance is not studied. In [9], we show that strong NFRs are characterized by high R-sq, low fluctuations in R-sq, and low mean squared error. These NFRs lead to high Accuracy, i.e., nearness to baseline optimal formulations. But the solution is restricted to only second-order polynomial NFRs and the Accuracy-Speed Trade-off involved in higher-order NFRs is not investigated. Further, a methodology for mitigating this trade-off based on the network context and the use case (application/service) is not explored either.

This work addresses these challenges. It focuses on the relationship between interference and network throughput or the capacity-interference relationship (CIR), since interference is a serious bottleneck to network performance management.

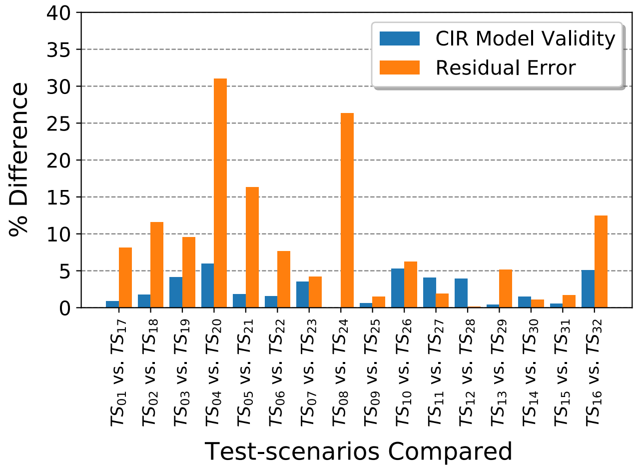
III. FEATURE RELATIONSHIP ANALYSIS METHODOLOGY

This work seeks to leverage network feature relationships to analyze network context and optimize network performance. To that end, this section contains a discussion on LTE-WiFi experimental textbeds (LTE-U and LTE-LAA), the ML algorithms considered for feature relationship analysis, and the test scenarios considered in the comparative context analysis of LTE-U and LAA.

TABLE 1. Experiment parameters.

Parameter	Value
Number of nodes	6
Transmission Power	23 dBm
Operating Frequency	5 GHz
LTE-U/LAA RF Transmission	Loopback
LTE Transmission Channel	PDSCH, PDCCH
Data Traffic	Full buffer
WiFi Channel Access Protocol	CSMA
LAA Channel Access Protocol	LBT

*PDSCH - Physical Downlink Shared Channel



(a) LTE-LAA vs. LTE-U

FIGURE 3. Test scenario specific comparative analysis.

A. NETWORK DESIGN CONSIDERATIONS

For efficient utilization of the unlicensed band, LTE and Wi-Fi coexistence must be fair and cooperative. To achieve fair coexistence between the two radio access technologies, two standards for unlicensed LTE were released, viz., LTE-U and LTE-LAA. However, the two standards employ different mechanisms for medium sensing and access, illustrated in Figure 2(a). While LTE-U has a load-dependent duty-cycle mechanism, LTE-LAA relies on a Listen-Before-Talk (LBT) mechanism. LAA's LBT is compatible with the CSMA/CD MAC protocol of Wi-Fi, ensuring a more fair coexistence with 802.11 WLANs compared to LTE-U.

Testbed Design LAA/LTE-U testbed are created using the National Instruments *NI RIO* platform, shown in Figure 2(b). The NI Labview system provides 3GPP prescribed PHY implementation and supports flexible configuration of system parameters such as transmission power, LAA transmission opportunity (TXOP), LTE-U duty cycle ON & OFF, etc. The Wi-Fi platform comprises of Netgear wireless routers which support both 802.11n and 802.11ac in the 5 GHz band. The Wi-Fi testbed allows easy configuration of MAC and PHY layers parameters such as channel bandwidth, transmission power, CW_{min}, CW_{max}, etc. Relevant technical specifications related to the testbed are presented in Table 1.

The experiments were performed in an indoor setting at the University of Chicago. Multiple coexistence configurations were implemented through combinations of LAA-LTE/LTE-U, 802.11n/802.11ac, and varying bandwidths (5, 10, 15, & 20MHz) to account for cross-talk interference. The interference from LAA was kept below Wi-Fi's clear channel assessment (CCA) threshold by regulating LAA's power spectral density (PSD). Further, as shown in Figure 2(c), random dense coexistence networks were created by maintaining an internodal distance $\leq 10m$ between nodes in the testbed. SINR and Capacity data was gathered through the experiments. It is noteworthy that apart from the dense scenario, multipath fading due to obstacles such as walls and furniture, makes this experimental setup suitable for studying CIR in coexistence networks.

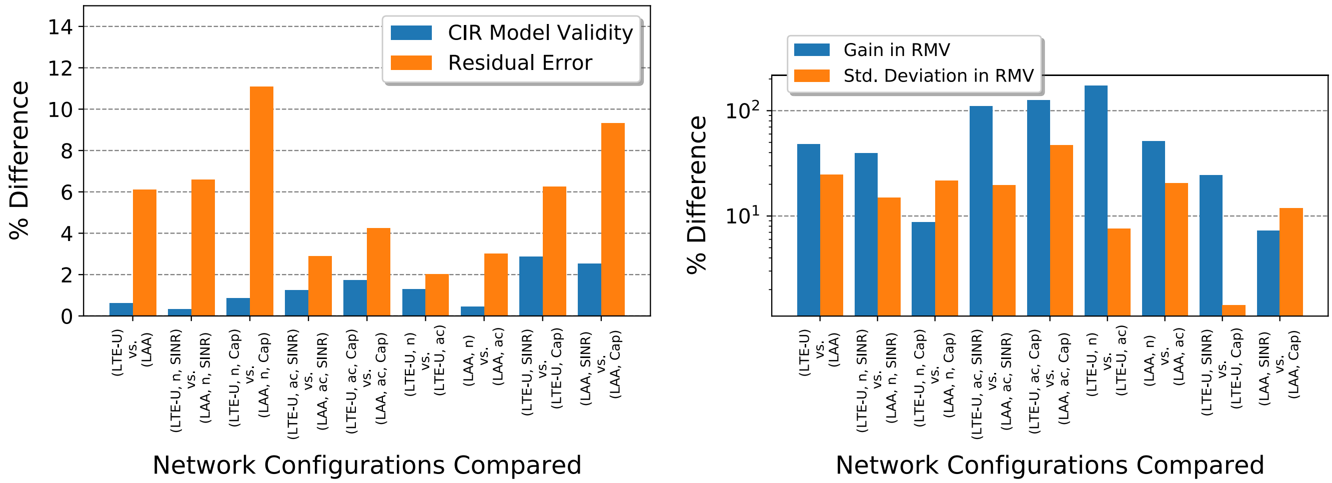
B. MACHINE LEARNING ALGORITHMS FOR RELATIONSHIP ANALYSIS

Next, the feature relationships in the LTE-WiFi coexistence data gathered from the experimental testbed are modeled as a regression problem.

Let N represent the number of training points and let dimensionality of the feature vector be denoted by D. Then, the unlicensed network data can be represented as $\{\mathbf{x}_i, y_i\}_{i=1}^{N}$, where $\mathbf{x}_i \in \mathbb{R}^D$ is the feature vector and $y_i \in \mathbb{R}$ is the ground truth value for i^{th} training point. The goal is to learn a mapping $f : \mathbf{x}_i \rightarrow y_i$ where x_i is the predictor (SINR or Capacity) and y_i is the response (Capacity or SINR). This work considers the following basket of learning algorithms for the regression analysis:

Linear Regression: This group of algorithms learns a linear relationship by solving $\arg\min_{\mathbf{w},b} \sum_{i=1}^{N} ||(\mathbf{w}^\top \mathbf{x}_i + b) - y_i||_2^2 + \alpha \mathbf{w}^\top \mathbf{w}$ [28]. Here, the weight vector is denoted by $\mathbf{w} \in \mathbb{R}^D$ and the bias term is $b \in \mathbb{R}$. Further, the weightage (importance) of the l_2-regularization term is controlled by the hyperparameter denoted by α, which is set to zero for Ordinary Least Squares Linear Regression (OLS). However, for Ridge Regression (RR), α is set through k-fold cross validation (kCV).

Kernel Ridge Regression: A non-linear mapping is expected to be more suitable for the SINR-Capacity relationship, especially with respect to optimization [21]. Therefore, we use Kernel Ridge Regression [28] that employs non-linear transformations such as polynomial and radial basis function (RBF). Its goal is to solve $\arg\min_{\mathbf{w},b} \sum_{i=1}^{N} ||K(\mathbf{w}, \mathbf{x}_i) + b - y_i||_2^2 + \alpha \mathbf{w}^\top \mathbf{w}$. Here, $\mathbf{w} \in \mathbb{R}^D$ is the weight vector, $b \in \mathbb{R}$ is the bias term, and α is a hyperparameter defined above. It should be reiterated that α is the weightage of the regularization term that can help us avoid overfitting and lead to better performance on test data, especially in case of non-linear kernels. The experiments are performed for both radial basis function (RBF) and polynomial kernel (MPR).



(a) Avg. RMV and Residual Error

(b) Avg. % Gain & Std. Deviation in RMV

FIGURE 4. Configuration-level comparative analysis.

C. TEST SCENARIOS AND MODEL SELECTION

Experiments were performed and data was recorded for CIR analysis for 40 Test Scenarios, represented as TS_i, where $i \in \{1 \dots 40\}$. A TS_i denotes a unique unlicensed coexistence configuration which is a combination of the unlicensed LTE standard (LTE-U/LTE-LAA), the Wi-Fi variant (802.11n/ac), bandwidth allocation (5, 10, 15, &20 MHz), and the response variable (SINR/Capacity). Eight new test scenarios (TS_i where $i \in \{33 \dots 40\}$) are considered, which involve experiments only for control and signaling data transmission in LTE-U and LAA, 802.11n/ac, for the 20 MHz band. These scenarios are compared with the respective control-plus-data transmission test scenarios. Further, the CIR selection for each TS_i is carried out through the following ML model selection scheme. Feature relationships that are 1–3 degree polynomials are learned and validated through k-fold cross validation (kCV). Further, higher-order terms are ensured to be statistically significant to avoid overfitting. To remove outliers, the local outlier factor (LOF) algorithm is used, which is an unsupervised technique that determines the deviation in the density of a sample with respect to its k neighbors.

Using this methodology, the context and performance of LAA & LTE-U networks is studied and a comparative analysis is presented in the next section.

IV. RELEVANCE OF CONTEXT IN UNLICENSED COEXISTENCE NETWORKS

To delineate the network context, the parameters of the CIR model are observed and a comparative analysis of LTE-U & LAA is performed. The results are presented for scenario-specific comparisons in Figure 3, and configuration-level trends in Figure 4. Please note that only for Figure 4(b), a logarithmic scale is used to show "% Difference" due to a high variation in values. Relevant aspects that shape unlicensed coexistence network context, such as outliers, are also discussed.

A. UNLICENSED COEXISTENCE: LTE-U VS LAA

We begin with measurement-based observations on average network capacity, as most comparative studies focus primarily on this metric [23]. In 75% of the test scenarios, LTE-LAA outperforms LTE-U in coexistence with the corresponding Wi-Fi variant (n/ac). Likewise, in 87.5% scenarios, 802.11ac outperforms 802.11n in coexistence with the corresponding LTE variant (LTE-U/LAA). Further, LTE-LAA in coexistence with 802.11n/ac offers a higher SINR on average than LTE-U in all scenarios save one.

The LBT mechanism of LAA is quite similar to the CSMA channel access protocol of Wi-Fi and leads to a higher network capacity on average in LTE-LAA. LAA nodes sense the energy level on the medium (−72 dBm) prior to transmission, which mitigates co-channel interference from Wi-Fi and other LAA APs, ensuring higher SINR on average than LTE-U. On the contrary, LTE-U has a duty-cycle-based channel access mechanism which leads to inefficient transmissions and packet collisions in both the LTE-U and Wi-Fi components of the coexistence system.

1) R-sq OR REGRESSION MODEL VALIDITY (RMV)

LAA and LTE-U models perform equally well, in a scenario-specific comparison with $\leq$5% difference in RMVs in 13/16 comparisons (26/32 scenarios). CIR in LAA seems to be only slightly better, as it outperforms LTE-U in the remaining 3 scenarios. In terms of average RMVs across all 32 scenarios, LAA and LTE-U are comparable, although LAA has a slight edge (<1%). Likewise, in LAA-WiFi-Predictor configuration combinations, LAA has a slight edge (0–2%). Prima facie, based solely on RMV, CIR does not appear to be impacted by the unlicensed LTE variant. However, RMV cannot be considered to be the only goodness-of-fit measure for feature relationships. A higher RMV is an indicator of the variation in the dependent variable explained by the model, but it does not indicate how far the data points lie from the regression line. Moreover, the standard deviation of the RMV with kCV for a specific scenario must also be low. The analysis ahead explores these dimensions.

2) RESIDUAL STANDARD DEVIATION (RSD)

The ability of a feature relationship model to make accurate predictions is highly desirable for the model to be deployed in real-world network performance management. Thus, residual error, or RSD, is a measure of precision of the model's predictions and should ideally be low for a robust CIR.

A higher residual error is observed in twice as many LTE-U scenarios compared to LAA scenarios (5% margin of error). On average, LTE-U scenarios have a 6% higher RSD than LAA. Further, average residual error in all LTE-WiFi-Predictor network configurations is lower for LAA when compared to LTE-U. Thus, LAA models seem to be more precise in their ability to predict coexistence network performance, regardless of the response variable (Capacity or SINR).

3) GAIN AND STANDARD DEVIATION IN RMV

It is important to note the standard deviation (SD) in the validity of the CIR model when subjected to kCV, especially after LOF outlier removal. While outlier reduction yields higher RMVs, the Gain in RMV should be accompanied with low SD in RMV, averaged across all kCV runs. Thus, we consider high Gain and low SD as characteristics for stable CIR models.

LTE-U fares much worse than LAA in terms of both Gain and SD. LAA outperforms LTE-U by 47.67% in Gain and registers a 24.5% lower SD, averaged across all scenarios. A similar trend can be observed in LTE-WiFi-Predictor combinations as well. Thus, LAA has a higher gain after outlier removal along with a lower SD, which demonstrates the robustness of the LAA CIR models.

4) OUTLIERS

For a network system, the outlier % may be considered to be a good indicator of the degree of fluctuation in network performance, and consequently the ability of a network to deliver the promised Quality of Service (QoS). However, selecting the outlier detection algorithm is a subjective choice. Although this work steers clear of making inferences based on outliers, we compare the outliers in the LTE-U and LAA data detected by the LOF algorithm with the outliers detected by "Minitab," a standard tool for data analysis [29]. Minitab's outlier detection algorithm labels samples with extreme "leverage points" and "large residuals" as outliers. As expected, the percentage of data points labeled as outliers is different in LOF and Minitab. However, LTE-U has a higher fraction of outliers compared to LAA in both LOF (by 9.11%) and Minitab (by 5.14%).

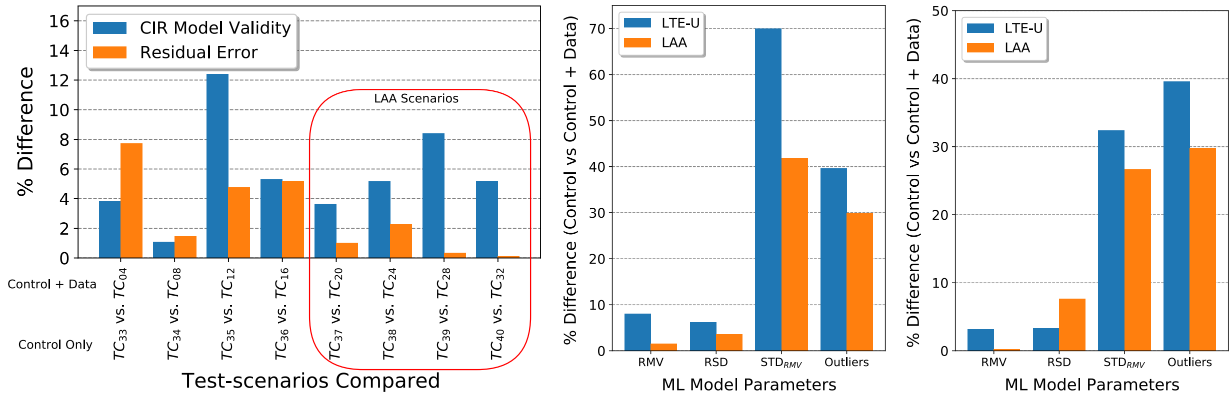
The reason for the high fluctuation in LTE-U can be attributed to the greater susceptibility of an LTE-U node to the unpredictable interference from Wi-Fi APs in its proximity. This primarily occurs during the LTE-U ON state, as there are no energy detection thresholds in LTE-U. Unlike LTE-U, Wi-Fi considers the energy threshold as −62 dBm and the preamble detection threshold as −82 dBm. Similarly to Wi-Fi, the LBT mechanism in LAA has an energy threshold of −72 dBm, making it less vulnerable to interference from Wi-Fi APs, and ensuring fewer extreme network performance fluctuations. Thus, LAA seems to offer more reliable performance from the perspective of end-user QoS experience.

5) CONTEXT IN LTE-LAA VS LTE-U: A FEATURE RELATIONSHIP PERSPECTIVE

The analysis of various parameters of the data model underscores the relevance of the network context. The residual error, standard deviation in RMV, and % of outliers in LTE-U is higher than LAA, while the gain in RMV after outlier removal is lower. This is true for the majority of test scenarios regardless of the choice of Wi-Fi variant, predictor variable, and bandwidth allocated. Thus, CIR in LTE-LAA networks is qualitatively better in terms of the spread of data along the expected curve fit. This implies that LAA offers greater consistency in network performance and lower fluctuations in system variables, such as signal strength or throughput at the end-user device.

The impact of the network context has a strong correlation with macrolevel industry trends as well. The Global Mobile Suppliers Association (GMSA) report states that 38 operators in 21 countries have made investments in LAA compared to only 11 operators investing in LTE-U. In terms of global deployments, 30 operators are planning to deploy or are actively deploying LAA networks in 18 countries, in contrast to LTE-U, which is being deployed in only 3 countries. Furthermore, LTE-U deployments are designed with an upgrade path to LAA and eLAA [30]. Clearly, LAA is the preferred choice of industry for LTE unlicensed networks. From the perspective of network data analysis, this appears to be reasonable as LAA machine learning models indicate a more robust network performance and context than LTE-U.

A detailed data-driven network context analysis is presented in [9]. It includes a comparative analysis of coexisting Wi-Fi standards and the impact of factors such as network bandwidth, the choice of predictor, and the optimization goal. The findings in [9] had hinted at three aspects that are relevant to the context and performance of unlicensed coexistence networks. These are resource block allocation, physical cell id (PCI), and control vs. user data. The impact of PCI on network performance and context has already been extensively demonstrated [7], [8], [31]. In the next section, we focus on the two remaining unexplored factors that influence the context and performance of an unlicensed network.



(a) Signaling vs User Data (b) Capacity as Response (c) SINR as Response

FIGURE 5. Impact of signaling data on network feature relationships.

V. ADDITIONAL FACTORS THAT IMPACT CONTEXT

Feature relationships between networks variables are shaped by several other factors. In a public unlicensed cellular deployment, parameters such as Physical Cell ID, Resource Block (RB) allocation, Channel Quality Indicator, etc. often lead to more reliable data-driven network models. This is demonstrated in recent works on performance analysis and optimization of LAA operator deployments [7], [8]. However, these recent studies have not explored the impact of RB allocation. Additionally, while both [7], [8] present data-driven cell selection solutions, the impact of control signaling is not evaluated. Thus, this section expands on the comprehensive analysis of CIR presented in Section IV. It investigates two additional dimensions unique to this work, which are (a) variation of CIR in control signaling compared to control-plus-data transmission, and (b) impact of resource allocation on CIR. These aspects are explored ahead through data analysis and ML-based modeling of data gathered through 8 new test scenarios (TS_i, where $i \in \{33 \ldots 40\}$).

A. NFRs IN CONTROL VS Control+Data

In the recent data-driven cell selection solutions presented for LAA deployments [7], [8], [31] both control data and user data are considered, referred to as D_{C+U}. It remains to be seen whether the NFRs differ in the scenario in which only control signaling data packets are transmitted (D_C). Furthermore, it is pertinent to study the variation of LAA and LTE-U NFRs in the two scenarios, namely, D_{C+U} and D_C. Because a significant variation in the parameters of the ML model can render the solutions derived from D_{C+U} less effective for cell attachment and handover.

1) RESULTS AND ANALYSIS

To investigate these two challenges, additional experiments were conducted for both LTE-U and LAA. The experiments are run with coexisting Wi-Fi 802.11n/ac for the 20MHz band. The new eight control-only scenarios (TS_i, where $i \in \{33 \ldots 40\}$) are compared with the respective D_{C+U} test scenarios.

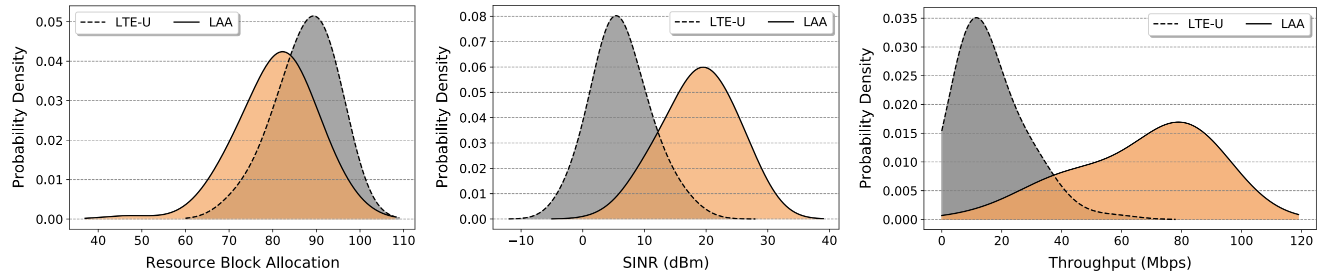
The scenario-specific comparative analysis is presented in Figure 5(a), with LAA scenarios highlighted to contrast with LTE-U scenarios. It is evident that signaling-only and signaling-plus-user data models are qualitatively different, leading to feature relationships that differ significantly. This variation is quite prominent in terms of RMV, for both LTE-U and LAA. However, for LTE-U there is a greater fluctuation in the difference in RMV between the D_{C+U} and D_C models. In addition, the difference in residual error is also higher for most test scenarios compared to LAA.

Network configuration level analysis for ML models with Capacity and SINR as the response variable is presented in Figures 5(b) and 5(c), respectively. The comparative analysis of LAA and LTE-U further consolidates the findings presented in Section IV. The difference between ML model parameters such as RMV, standard deviation in RMV, residual error, and outliers, between the D_{C+U} and D_C models, is much more pronounced in LTE-U than in LAA. Further, for both SINR and Capacity models, LAA NFRs show lower variation between signaling-only and signaling-plus-user data.

2) EXPLANATION AND RELEVANCE

Both LTE-U and LAA transmit the control channel information over PUCCH, PDCCH, and PBCCH. Typically, LTE-U requires less control signaling than LAA. Due to its ON-and-OFF duty cycle mechanism, there is a lesser need for signaling information in PUCCH because there is no need to sense the medium for load, interference, etc. On the other hand, LAA needs to sense the medium for contention through CW_{min} and CW_{max} which vary, depending on the nature of the traffic.

Channel sensing in LAA ensures fair transmission and limited interference, enabling an operator to identify a better interface and select the ideal PCI for transmission. The fact that the signaling vs. signaling-plus-data feature relationships



(a) Resource Blocks (b) SINR (c) Throughput

FIGURE 6. Probability distribution of network variables.

TABLE 2. Distribution analysis of network variables.

	Resource Blocks			SINR			Capacity		
Unlicensed Standard	Mean	Mode	Std Dev	Mean	Mode	Std Dev	Mean	Mode	Std Dev
LAA	81	84	8.3	18.9	18	5.4	66.9	89	20.5
LTE-U	87.5	93	6.5	6.2	5	4.3	16.4	10	10.6

in LAA are comparable is desirable for data-driven cell selection. In sharp contrast, LTE-U experiences more interference with WiFi transmissions. The LTE-U ON message will interfere with nearby unlicensed band transmissions such as Wi-Fi or other LTE-U, leading to more retransmissions at the MAC layer (in terms of resource allocation) and RLC (in terms of queue and HARQ) by using additional radio resources. This explains a greater variation in network feature relationship parameters in signaling vs. signaling-plus-data compared to LAA transmission.

B. RESOURCE ALLOCATION IN UNLICENSED COEXISTENCE

Resource Block (RB) allocation is an important network parameter that can influence network feature relationships such as CIR. In unlicensed LTE (LTE-U or LAA), the 20 MHz channel consists of 100 RBs, which are transmitted in the sub-frame within an interval of 1ms duration. Depending on the nature of traffic, the scheduler allocates the number of RBs necessary to satisfy the QoS/QoE. To investigate the distribution and impact of resource allocation two experiments were conducted for LTE-U and LAA, respectively. Thereafter, the probability density function (PDF) of the RB, SINR, and Throughput distributions in LTE-U and LAA is generated using kernel density estimation with a bandwidth estimator of 0.8. The results are presented in Figure 6.

We begin by exploring the characteristics of the distributions of the three network variables. It can be ascertained that except for SINR, the other two distributions for both unlicensed variants are skewed. For LTE-U, the RB distribution is left-skewed, while the Throughput distribution is right-skewed. In contrast, for LAA, both RB and Throughput distributions are left skewed. Thus, in LTE-U the SINR distribution seems to be influencing the Throughput distribution more than RB allocation.

Statistical analysis of the distribution is presented in Table 2. It is discernible from the statistics that the RB allocation is higher in LTE-U than in LAA. Taking into account the probability distribution, 87.53% samples in LTE-U have an RB allocation of 80 and higher, i.e., $P(RB \geq 80)$, compared to 54.70% in LAA. However, there is a drastic difference between the two standards and LAA performs much better. For example, $P(SINR \geq 15dBm)$ or SINR equal to or greater than 15dBm is true for only 2% of the LTE-U samples compared to 67.3% samples in LAA. When combined, these results lead to an interesting Capacity distribution. Despite a higher allocation of RB, LTE-U offers much lower throughput values compared to LAA, with only 9.9% samples above 30Mbps compared to 96.4% samples in LAA.

A possible explanation is that, despite better RB allocation, high interference with coexisting Wi-Fi signals during the LTE-U On mode leads to increased packet retransmission. Corrupted symbols/bits over the air transmission render the RB utilization inefficient. Thus, poor SINR causes the LTE-U small cell to transmit a lower number of bits at a lower modulation coding scheme (MCS). Poor SINR combined with lower MCS results in a low overall system throughput or network capacity. Inefficient resource utilization may pose additional challenges in the fair sharing of the spectrum in the unlicensed band. On the other hand, LAA small cell are able to leverage the RB allocation more effectively to maximize network capacity.

Thus, features such as RB allocation and MCS have a clear impact on network feature relationships and, in turn,

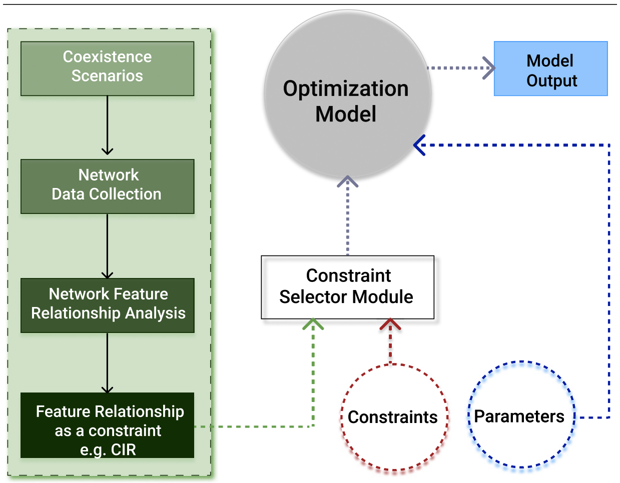


FIGURE 7. Network feature relationship based optimization.

on the network context. Including these features in the data models is likely to offer improved feature relationships and greater gains in optimization accuracy [9]. However, application to network optimization must be done with caution, as constraints with additional features may lead to longer convergence times. Thus, accuracy-speed trade-off is a crucial aspect that must be considered in NFR-based optimization. This paper covers it at length in Section VII.

VI. UTILIZING FEATURE RELATIONSHIPS FOR NETWORK OPTIMIZATION

Optimal performance or resource allocation in a wireless network can be achieved through three broad frameworks, which are (a) optimization models, (b) machine learning techniques, and (c) a hybrid approach that combines the two called data-driven optimization [20], [32]. Although machine learning algorithms are commonly used for prediction and classification problems, feature relationships are particularly useful to reduce the computational overhead of unlicensed network optimization [33], [34].

A. NETWORK FEATURE RELATIONSHIP BASED OPTIMIZATION

This work leverages the NFRs to enhance network performance, through the proposed ***Network Feature Relationship based Optimization*** (NeFRO) technique [9].

NeFRO is a data-driven approach which adopts the hybrid optimization methodology. As illustrated in Figure 7, NFRs learned from the network data serve as constraints in a model that aims to optimize dense unlicensed networks.The NeFRO framework overcomes the reliance on arbitrary assumptions and heuristics to relax complex theoretical constraints. NeFRO uses ML-based network feature relationship equations that reflect the ambient state of a wireless network.

The first step entails collecting data from network deployments at predetermined epochs. Next, low-cost machine learning algorithms are used to learn NFRs for each epoch. Robust NFRs from relationship models with high R-sq (RMV) are fed to *constraint selector module*, which chooses the constraints necessary for optimization formulation. Typically, the selector module is designed to compare the NFR learned for a feature vector $\{f_1, f_2, \ldots, f_n\}$ with the theoretical constraints associated with the feature vector. The rationale behind this step is that since the NFRs capture the ambient network environment, they can be used "as is" in the model, doing away with the need for arbitrary constraint relaxations. Despite its suitability, an NFR is tested for *convergence time viability*, by comparing its complexity and expected run-time vis-a-vis the theoretical constraint. Owing to its data-driven optimization approach, NeFRO is able to significantly reduce time costs of optimization while delivering results that are close to the values derived from theoretical constraints.

Although the illustration highlights the process-flow for a coexistence network, the NeFRO approach will apply similarly to network optimization in all wireless networks, with minor modifications, if required.

Benefits of the NeFRO Approach The proposed NeFRO framework offers several advantages over conventional network optimization. First, NFRs are learned from empirical data through ML algorithms for a given epoch. Thus, they reflect the ambient network environment better than theoretical constraints that involve similar network variables. Second, NFRs can be used "as is" in optimization without making any assumptions, unlike theoretical constraints, which often require context-specific relaxations and assumptions. Finally, if the data-driven NFRs are less complex than the corresponding theoretical constraints, the problem of arbitrary or forced relaxation of theoretical constraints is automatically solved. Even when the learned NFRs result in computational overheads comparable to theoretical constraints, they ensure an informed network optimization process grounded in network data.

B. IMPLEMENTATION AND VALIDATION OF NeFRO

1) EVALUATION OF NEFRO

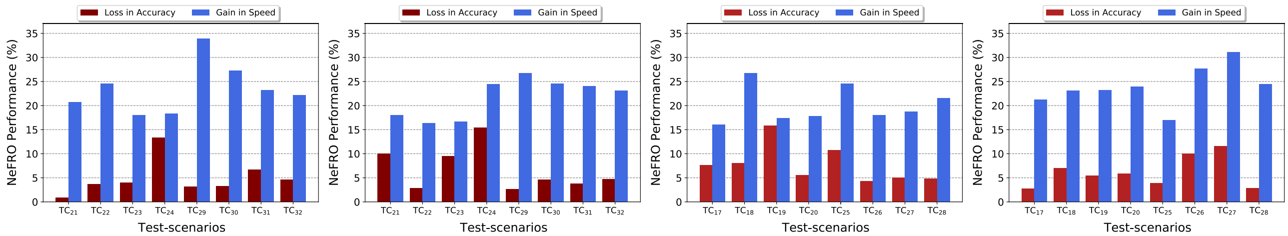
This work improves the metrics used for evaluation in [9]. Three simplified metrics are considered to evaluate NeFRO, viz., "Accuracy", "Speed", and "Optimization Gain". Accuracy of the NeFRO model demonstrates the closeness of the "NeFRO-optimal output" to the optimal value generated by the baseline optimization model. Thus,

2) LOSS IN ACCURACY

can be defined as the *"(%) difference in the optimal value generated by the baseline model and the NeFRO-optimal value"*. The second parameter is the reduction in convergence time achieved by the NeFRO model to arrive at the NeFRO-optimal value. It is named **Speed**. Thus,

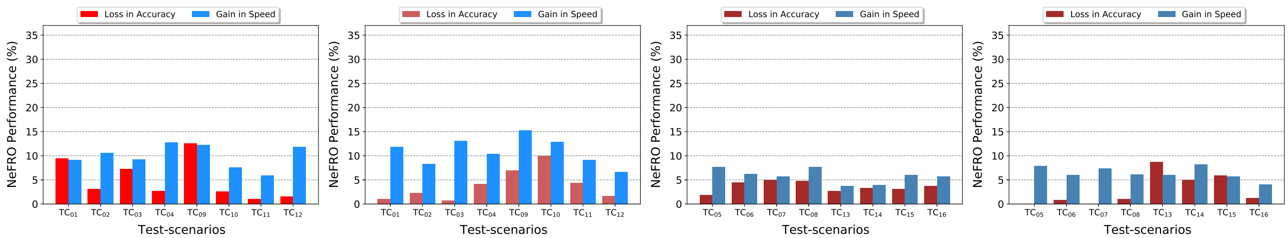
3) GAIN IN SPEED

can be defined as the *"(%) reduction in convergence time achieved by NeFRO compared to the baseline model's*



(a) NeFRO vs. COM_1 (b) NeFRO vs. COM_2 (c) NeFRO vs. SOM_1 (d) NeFRO vs. SOM_2

FIGURE 8. NeFRo performance in LAA capacity and SINR optimization.



(a) NeFRO vs. COM_1 (b) NeFRO vs. COM_2 (c) NeFRO vs. SOM_1 (d) NeFRO vs. SOM_2

FIGURE 9. NeFRO performance in LTE-U capacity and SINR optimization.

TABLE 3. Performance trends in test scenarios.

NeFRO Parameter	LTE-LAA Scenarios (%)				LTE-U Scenarios (%)			
	COM_1	COM_2	SOM_1	SOM_2	COM_1	COM_2	SOM_1	SOM_2
Gain in Speed	23.54	21.75	20.11	23.98	9.9	10.95	5.83	6.4
Loss in Accuracy	4.96	6.69	7.72	6.18	5.03	3.88	3.62	2.84

convergence time". Together, the first two indicators are used to derive the "Accuracy Speed Trade-off" (Trade-off). In, this work *Trade-off* is defined in terms of *Optimization Gain*, where,

$$\text{Optimization Gain } (\%) = \text{Gain in Speed } (\%) - \text{Loss in Accuracy } (\%)$$

For example, if the baseline model outputs an optimal solution of 100 and takes 10*ms* to converge, and the NeFRO generates 95 as the optimal solution and requires 9*ms* to arrive at the NeFRO-optimal value, then the Optimization Gain is 5%, and the Trade-off is acceptable.

A positive Optimization Gain justifies the Trade-off involved, especially when faster convergence time is highly desirable, such as an AR service communicating on an LAA or LTE-U channel. However, the lower the Loss in Accuracy, the lower the Trade-off, and more suitable is the optimization formulation. Thus, NeFRO uses data-driven NFRs to achieve the twin objectives of gain in Speed through *convergence time reduction* and high *Accuracy* with respect to the baseline optimization model. Please note that the Accuracy Speed Trade-off in dense network performance optimization is a major challenge in itself [26], and is addressed at length in Section VII. Next, the baseline optimization models and the validation methodology are discussed.

4) BASELINE UNLICENSED NETWORK OPTIMIZATION MODELS

The proposed NeFRO framework is validated through four recent state-of-the-art studies that seek to optimize coexistence network performance. These include two studies that optimize end-user throughput or network capacity, and the remaining two works attempt to provide optimal signal strength to end-user equipment (UE). The LAA capacity optimization model presented in [35], is based on optimal resource allocation in an unlicensed coexistence network [35]. An LBT-compliant channel access solution is proposed in [36] for both LTE-U/LAA in the 5GHz band with the aim of maximizing network capacity through interference mitigation in the LTE-WiFi system. The two baseline capacity optimization models are denoted as COM_1 and COM_2, respectively in the discussion ahead. Regarding signal strength, the optimization solution proposed in [37] improves network signal quality through strategic placement of nodes in the LTE-U and LAA networks. Next, the solution presented in [38], considers efficient spectrum usage of Wi-Fi

APs along with optimal placement of nodes, for enhanced signal strength. The signal strength optimization models are henceforth denoted as SOM_1 and SOM_2, respectively.

5) MODELING OF UNLICENSED NETWORK OPTIMIZATION

The General Algebraic Modeling Language (GAMS) [39], tool effectively models an unlicensed coexistence environment through the use of constraints. The SINR-related constraints account for the impact of LAA/LTE-U transmission on Wi-Fi APs and vice versa. Constraints concerning the number of active users connected to the LAA/LTE BS or Wi-Fi AP prevent the network from overloading. Similarly, constraints with respect to the user association threshold, such as an RSRP of −108 dBm, limit packet loss. Constraints concerning the placement of the BS or APs ensure that there are no blind spots or coverage holes in the network. Finally, resource allocation constraints are vital for modeling fairness in the coexistence system. For LAA and Wi-Fi, these include the sensing duration of LTE-LAA (LBT) and Wi-Fi (CSMA), ED thresholds (−62 dBm for Wi-Fi and −72 dBm for LAA) and the corresponding opportunities for data transmission. Similarly, for LTE-U, the duty cycle ON and OFF constraints are based on the number of contending nodes in the network.

6) VALIDATION METHODOLOGY

The methodology adopted to validate NeFRO entails the following steps. First, the four baseline unlicensed network optimization models are implemented in GAMS [39], for each of the test scenarios. That is, the implementations conform to the system configurations and network specifications considered. Second, *baseline optimal value* of the network parameter (SINR or Capacity) and the *convergence time* taken by the optimal baseline solution are recorded. The third step applies the NeFRO process to the baseline solutions. Thus, the complex theoretical constraints related to signal strength and/or network capacity in a baseline formulation are replaced with the data-driven CIR equations learned through ML algorithms. It is worth mentioning that baseline network capacity optimization formulations viz., COM_1 and COM_2, are considered for test scenarios where SINR is the predictor in the network ML model, and vice versa. Fourth, *NeFRO-optimal values* and *NeFRO convergence time* are recorded. In the fifth step, the NeFRO performance indicators are determined, viz., Gain in Speed, Loss in Accuracy, and Trade-off, from the observations made for baseline models (step two) and NeFRO models (step four),

Finally, NeFRO is assessed for its ability to reduce convergence time while ensuring a high Accuracy vis-a-vis the baseline optimization models. Therefore, *a high Gain in Speed, a low Loss in Accuracy, and a positive Trade-off will validate the NeFRO hypothesis*.

C. OPTIMIZATION RESULTS AND NeFRO EVALUATION

The NeFRO validation is performed through second-degree non-linear CIR models as the SINR-Capacity relationship in wireless networks is shown to be quadratic [21].

The results of the optimization simulations run in GAMS are presented in Figure 8 and Figure 9, for the LAA and LTE-U test scenarios, respectively. Further, Figures 8(a), 8(b), 9(a), and 9(b), present results for test scenarios where the objective is to optimize network capacity. The remaining figures show results for signal strength optimization test scenarios.

It can be discerned that NeFRO performs remarkably well by reducing the required convergence times while delivering NeFRO-optimal values very close to the optimal results of the respective baseline models. A scenario-specific evaluation of NeFRO can be performed by observing the difference in the length of bars of "Loss in Accuracy" and "Gain in Speed" for a particular test scenario. The greater the difference, the lower the Trade-off and the better the NeFRO performance. Two points are noteworthy. First, in LAA scenarios, NeFRO offers a significant reduction in convergence time, while in LTE-U scenarios, the Gain in Speed is somewhat subdued. Network optimization in LTE-U is inherently more challenging due to its channel access mechanism. Hence, it is more computationally intensive and requires a longer convergence time. Second, for LAA scenarios, the difference in NeFRO performance for capacity optimization and SINR optimization is negligible.

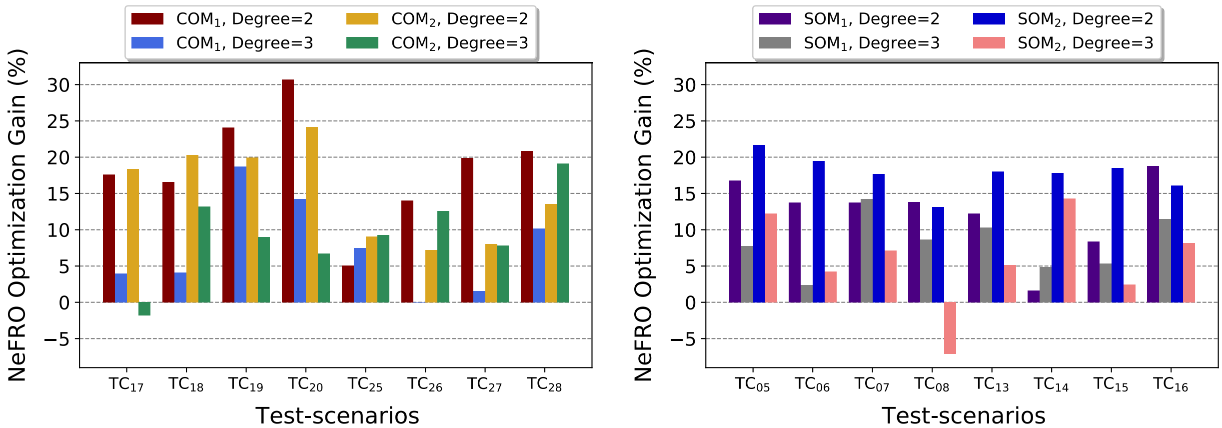
However, in LTE-U, there appears to be a noticeable difference in NeFRO performance for these two objectives. In particular, the Gain in Speed for SINR optimization in LTE-U is rather low, and for two specific SOM_2 test scenarios viz., TS_{13} and TS_{15}, it is lesser than the Loss in Accuracy, leading to a negative Trade-off. The average performance of NeFRO across all test scenarios for the four optimization models is presented in Table 3. Despite these specific instances, for both SOM_1 and SOM_2, the average Gain in Speed of NeFRO is higher than its average Loss in Accuracy, leading to an overall positive Trade-off.

In general, NeFRO outperforms the baseline model across all test scenarios and both unlicensed LTE variants by significantly reducing the convergence time (large Gain in Speed). The average Loss in Accuracy, as shown in Table 3, is also very low. Further, NeFRO seems to perform better in LTE-LAA scenarios compared to LTE-U, which can be expected based on the discussion and findings presented in this work. Thus, the NeFRO framework stands validated.

Please note that these state-of-the-art optimization models are implemented for small-scale dense unlicensed coexistence scenarios on an experimental testbed. We expect that in a real-world network of much higher scale and density, the performance enhancement demonstrated by NeFRO will be far more pronounced.

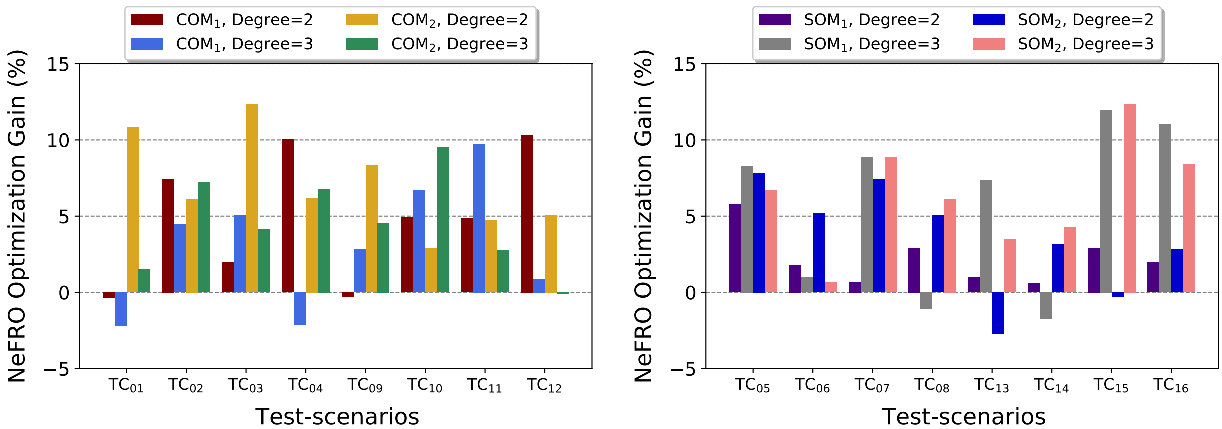
VII. ACCURACY SPEED TRADE-OFF IN DATA-DRIVEN OPTIMIZATION

The primary contribution of this work is context-aware data-driven optimization. Developing an understanding of the Accuracy-Speed Trade-off is the first step in that direction.



(a) NeFRO vs COM$_1$ & COM$_2$ (b) NeFRO vs SOM$_1$ & SOM$_2$

FIGURE 10. Impact of the degree of NFR on LTE-U capacity and SINR optimization.



(a) NeFRO vs COM$_1$ & COM$_2$ (b) NeFRO vs SOM$_1$ & SOM$_2$

FIGURE 11. Impact of the degree of NFR on LTE-U capacity and SINR optimization.

Within the hybrid optimization paradigm that leverages machine learning, *Accuracy-Speed Trade-off* implies that it is challenging to achieve high Accuracy while delivering results at high Speed. Although NeFRO is designed to deliver optimal results with high Accuracy and high Speed, essentially overcoming the Trade-off, its performance is invariably linked to the NFRs used as constraints. Multiple relationship models can be learned for a set of network features, depending upon objective criteria such as R-sq, outlier threshold, higher-order terms, *etc*. For example, a polynomial NFR of n^{th} degree with statistically significant higher-order terms (no overfitting) may represent the relationship more accurately through a higher R-sq. Strong NFRs lead to better results when used in tasks such as rate adaptation or throughput enhancement [16], [20]. Thus, the R-sq of an ML model trained on network data can be considered to be an indicator of its ability to optimize network performance. However, the use of a higher-order feature relationship in NeFRO may lead to a significantly longer convergence time. Hence, not all relationship models for a given feature-set are suitable for dense unlicensed optimization through NeFRO.

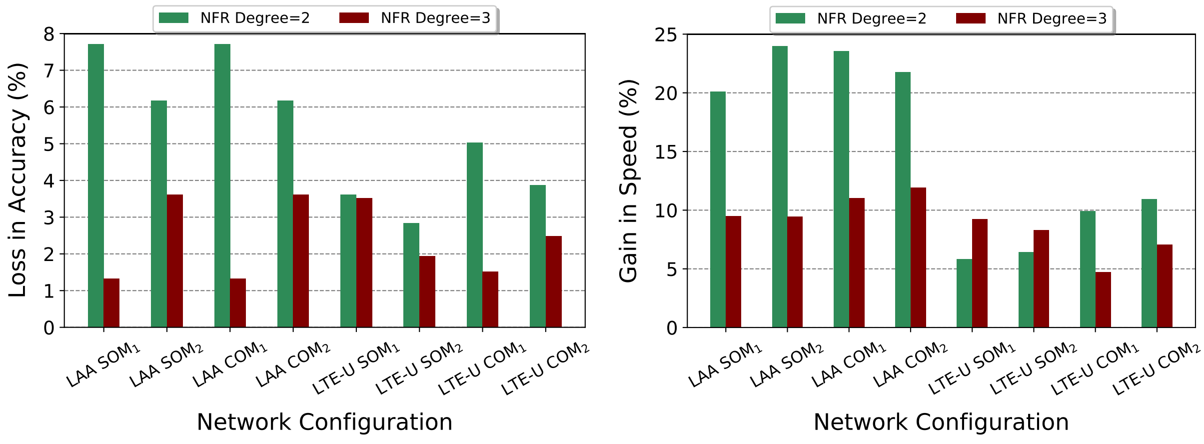
These factors make the selection of an appropriate NFR for ML-based optimization a challenging problem. Thus, a prime objective of this work is to study *convergence time and accuracy trade-off* in using feature relationships of different degrees in data-driven optimization. In addition, it proposes a practical context-aware approach to selecting the appropriate NFR for the right use case.

A. TRADE-OFF EVALUATION IN METHODOLOGY

The first step in this process is the evaluation of the Trade-off in data-driven optimization. To that end, the analysis in this section considers multiple network models for capacity-interference relationship (CIR) of different degrees (influences Speed) and R-sq (influences Accuracy).

1) GENERATING CIRS OF VARYING DEGREES

Kernel functions are varied in the ML algorithms discussed in Section III-B, to generate feature relationship models of



(a) Loss in Accuracy (b) Gain in Speed

FIGURE 12. **Trade-off analysis at the level of network configuration.**

multiple degrees. A kernel function $K(\mathbf{x}, \mathbf{x}')$ allows us to compute the dot product in an arbitrary large space without the need to explicitly project features in high-dimensional space. In particular, $K(\mathbf{x}, \mathbf{x}')$ is defined as $exp(-\gamma||\mathbf{x} - \mathbf{x}'||^2)$ and $\gamma(\mathbf{x}^\top\mathbf{x}' + r)^d$ for radial basis function and the polynomial kernel, respectively. Here, γ, r, and d are kernel-specific parameters. In particular, d controls the complexity of the decision function f, *i.e.,* setting $d = 1, 2, 3$ corresponds to learning a linear, quadratic, and cubic boundary in the case of the polynomial kernel. In practice, we prefer the polynomial kernel, as it can be easily plugged into the optimization routine, whereas the RBF kernel would require certain modifications. Nevertheless, the results are reported with both radial basis function (RBF) and polynomial kernel (MPR) for completeness.

SINR-Capacity relationship has been theoretically shown to be non-linear [12], [21], hence the analysis presented considers CIR polynomials of degrees 2 and 3. Please note that data-driven CIRs can also be linear for specific network scenarios, e.g., when only a relatively linear section of the overall non-linear CIR curve is applicable to a system. In such scenarios, linear CIRs can have a high RMV or R-sq and may yield a better optimization performance, i.e., a lower Trade-off [20]. Since the experiments in this study were performed for the entire SINR range, linear models are not considered in the Trade-off analysis.

2) EVALUATION METHODOLOGY

A comparative Trade-off analysis is performed for 2^{nd} and 3^{rd} degree polynomial CIRs through the baseline models that seek to maximize coexistence network performance through network capacity optimization (COM_1 and COM_2) and signal strength optimization at the UEs (SOM_1 and SOM_2). Next, as previously described (Figure 7), the theoretical constraints in the baseline models are replaced with the 2^{nd} and 3^{rd} NFRs learned from the feature relationship analysis. The NeFRO-optimal values and the convergence times are noted for the optimization objectives. Finally, the NeFRO-optimal and baseline-optimal values are compared to determine (a) Loss in Accuracy and (b) Gain in Speed.

B. RESULTS AND ANALYSIS

The optimization simulation experiments are run in GAMS and the results are evaluated at the level of individual test scenarios and at the level of network configuration.

1) SCENARIO-SPECIFIC TRADE-OFF EVALUATION

The scenario-specific results are presented in Figure 10 and Figure 11, for LAA and LTE-U, respectively. For each test scenario, the "Degree" shows the order of the polynomial CIR used in NeFRO.

It is evident from the scenario-specific assessment that for NFRs of both polynomial degrees, NeFRO reduces run times while converging on NeFRO-optimal values that are extremely close to the baseline-optimal values. This is true for most test scenarios. Except in a few cases, even NFRs with "Degree=3" offer better overall performance than the baseline optimization models. In LAA scenarios, generally the magnitude of Optimization Gain decreases as the degree of the non-linear NFR increases from 2 to 3. Further, there is no unfavorable Trade-off in 2^{nd} degree polynomials and negative Optimization Gain in only two scenarios for 3^{rd} degree CIR.

Comparing 2^{nd} and 3^{rd} degree CIRs, the relative performance trends seem different for Capacity and SINR optimization models. In the former, as shown in Figure 10(a), 2^{nd} degree CIRs seem more suitable than 3^{rd} degree CIRs, except in one instance, TC_{25}. Since 3^{rd} degree CIRs perform slightly better for both optimization models in TC_{25}, the "context" of the scenario seems important. For signal strength optimization models (Figure 10(b)), the case is somewhat similar. In 6 of 8 test scenarios, 2^{nd} degree CIRs appear to be the better choice. However, for TC_{07} and TC_{14}, 3^{rd} degree CIR SOM_1 outperforms 2^{nd} degree. This, too hints at the fact

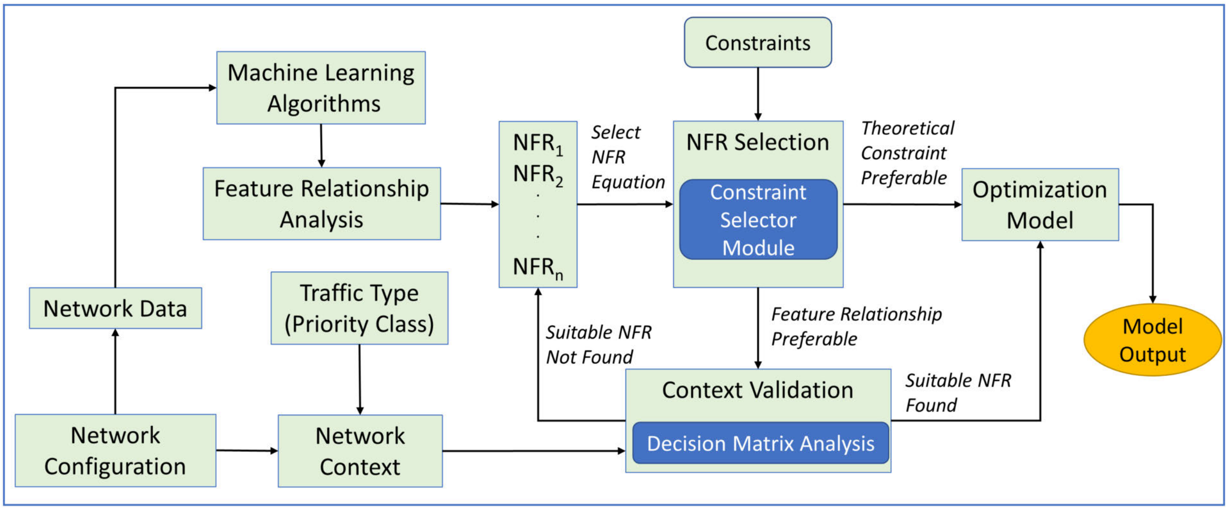


FIGURE 13. **Context aware network feature relationship based optimization.**

that for a specific "context," network configuration, and the optimization objective, a higher degree CIR may offer a lower Trade-off.

In contrast to LAA, LTE-U optimization Trade-off trends are significantly different. Although NeFRO offers a positive Optimization Gain for both capacity and signal strength models for most scenarios, the distinction between CIR of 2^{nd} and 3^{rd} degrees is not very pronounced. In capacity optimization (Figure 11(a)), 2^{nd} degree CIRs seem slightly more suitable and have a negative Optimization Gain for half the number of test scenarios. However, in LTE-U SINR optimization, the performance of CIRs of 2^{nd} and 3^{rd} degrees varies depending on the network configuration and optimization formulation. A possible reason for this could be that network optimization in LTE-U is often more complex owing to its duty-cycle-based channel access mechanism, leading to longer convergence times, regardless of the degree of NFR.

These findings highlight the importance of the network context and choosing the right NFR based on that context.

2) NETWORK CONFIGURATION LEVEL EVALUATION

To investigate the relevance of context, it is important to see if the above Trade-off patterns are reflected at the macrolevel. Thus, the results of the network configurations are presented in Figure 12. It is evident that, averaged across all test scenarios, NeFRO always ensures a positive Trade-off, for both LTE-U and LAA and all four baseline models, i.e., Gain in Speed is invariably higher than the Loss in Accuracy. On average, the Loss in Accuracy, is higher for LAA than it is for LTE-U, e.g., 2.98% and 4.7% for LTE-U and LAA SINR optimization, respectively. However, the average Gain in Speed, and as a result, the magnitude of average positive Trade-off, is higher for LAA than it is for LTE-U.

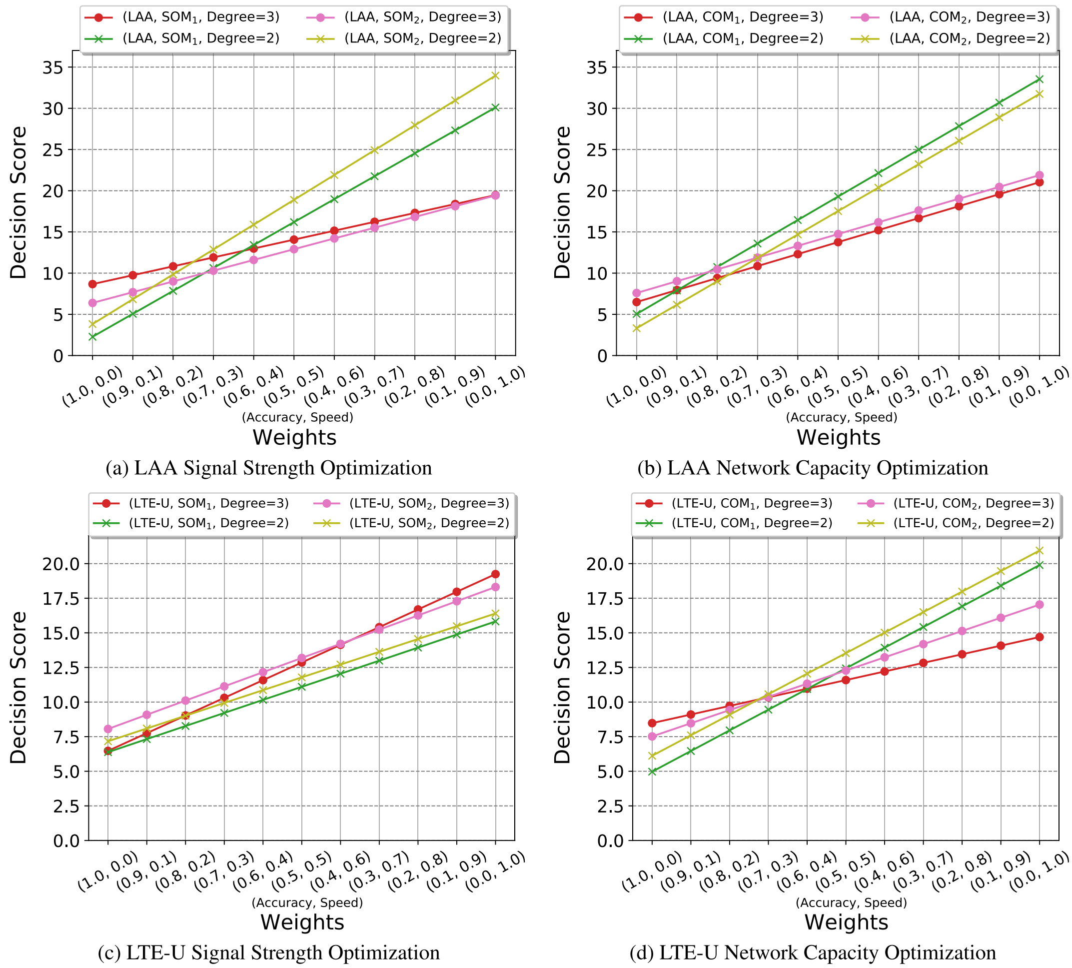
A comparison of 2^{nd} and 3^{rd} degree CIRs, offers great insight into the role of network context in NeFRO performance. The *network context*, as conceptually applied to this work, can be defined as "the sum total of the ambient network environment, network configuration, and the optimization objective." Looking at LAA optimization models in Figure 12, it is discernible that 2^{nd} degree CIRs offer a somewhat lower Accuracy but a much higher Speed, leading to a much higher overall Trade-off. Thus, at the configuration level, 2^{nd} CIRs lead to a higher Optimization Gain than 3^{rd} degree CIRs. However, considering Loss in Accuracy alone, the 3^{rd} degree CIRs perform much better, e.g., they offer one fifth the loss for LAA SOM_1, compared to 2^{nd} degree CIRs. Thus, navigating the Trade-off becomes highly contextual. In scenarios where high Accuracy is important, despite the overall higher Optimization Gain, 2^{nd} degree CIRs may not be suitable.

The impact of context with respect to network configurations is more clearly brought out in LTE-U signal strength optimization. Here, for both LTE-U SOM_1 and LTE-U SOM_2, the 3^{rd} degree CIRs show better Accuracy and higher Speed. Therefore, it seems to make more sense to use 3^{rd} degree CIRs for this network configuration and 2^{nd} degree CIRs for other configurations.

In general, it can be inferred that the NeFRO approach improves the baseline models regardless of the type or degree of the NFR. Furthermore, it seems to benefit the LAA-WiFi coexistence optimization more than LTE-U. Most importantly, the NFR for data-driven optimization must be chosen based on the network context. This finding underscores the importance of the awareness of network context, which is a nontrivial problem, and a practical solution is presented in the next section.

VIII. CONTEXT AWARE OPTIMIZATION

The findings of Trade-off analysis have highlighted that data-driven optimization of unlicensed coexistence network performance requires context awareness. The network context has several components. A major aspect of the network



(a) LAA Signal Strength Optimization
(b) LAA Network Capacity Optimization
(c) LTE-U Signal Strength Optimization
(d) LTE-U Network Capacity Optimization

FIGURE 14. **Accuracy-Speed Trade-off analysis in Data-driven optimization.**

context is the nature of the traffic requested by the UE, such as voice, video, live streaming, file download, etc. Each traffic type has a different QCI index, EPS bearers, and channel access priority. Mobile network operators distinguish between different types of traffic to ensure high QoS at the UE and prioritize data traffic based on these parameters. Thus, voice traffic has high priority, and the packets need to be transmitted more frequently to avoid performance degradation, e.g., voice quality. Similarly, a file download service/application demands higher resource block allocation at the MAC layer to maintain an excellent data rate. Another aspect of context can be the number of users connected to base station as that shapes the traffic load, congestion, and resource allocation.

The awareness of the context for network optimization is easily understood through cell selection mechanisms [31]. Data-driven cell selection is increasingly becoming the norm in industry [31], [40], [41] and solutions to improve the cell selection process have also been presented in recent academic studies [7], [8]. A context-aware optimization of signal strength would enhance the efficiency of the cell association process. For example, the context, i.e., ambient radio (LTE-U or LAA) condition and data demand, can guide the operator cell selection mechanisms in deciding which PCI needs to be enabled as an additional carrier for carrier aggregation or dual connectivity.

The discussion in this section proposes a context-aware NFR-based optimization framework (CANeFRO). The hypothesis is then validated through context-aware optimization choices made through *decision matrix analysis* [42].

A. CONTEXT AWARE NeFRO

A high-level schema of the context-aware NFR-based optimization framework (CANeFRO) is presented in Figure 13. CANeFRO introduces an element of context awareness in the NeFRO approach discussed in detail earlier. It also provides for an improved selection of NFR through context validation. In this work, decision matrix analysis (DMA) or the Pugh method is used to calibrate the network context on a weighted scale [42]. The important aspects of CANeFRO illustrated in Figure 13 are discussed below.

A strong network feature relationship is reflected in the high R-sq of the ML model and is likely to improve the performance of the data-driven optimization model [16], [20], [31].

Since the CIR is non-linear, a higher-order CIR often offers a better regression fit, thereby ensuring a higher RMV or R-sq. Therefore, it seems desirable to utilize it in a NeFRO model for enhanced accuracy. However, a higher-order CIR will also increase the time cost of the optimization model that utilizes it. Thus, the choice of NFR should be motivated by the context. For example, a high-performance use case, such as remote surgery using a virtualized digital twin will prefer Accuracy over Speed [43], while high Speed will be preferred in on-the-go video streaming.

To reflect a varying context, a decision matrix is considered. On the X-axis, weights are assigned to Loss in Accuracy and Gain in Speed for each individual test scenario. Thus, context can be defined as $C \rightarrow (X, \Upsilon) \mid X \rightarrow Weight_{Acc}, \Upsilon \rightarrow Weight_{Spd}$, where C is the network context, X is the weight assigned to Loss in Accuracy, Υ is the weight assigned to Gain in Speed, $\text{Weight}_{Acc} \in [1, 0]$, $\text{Weight}_{Spd} \in [0, 1]$. Thus, the context changes from the use case (e.g., remote surgery) where Accuracy takes the highest priority and Speed takes the lowest priority, i.e., $C \rightarrow (1, 0)$ to the use case (e.g., live streaming) where Speed takes the highest priority and Accuracy takes the least priority, i.e., $C \rightarrow (0, 1)$. All other network contexts or use cases fall between these two extremes.

Subsequently, the decision score $S(C_k)$ for a given context is computed as follows.

$$\mathbf{S}(C_k) = \frac{\sum_{i=1}^{n} X_{TS_i} \Delta_- \text{ Accuracy}_{TS_i} + \Upsilon_{TS_i} \Delta_+ \text{ Speed}_{TS_i}}{n}$$

where Δ_- refers to loss, Δ_+ refers to gain, C_k is the k^{th} network context, X is the weight assigned to Loss in Accuracy, Υ is the weight assigned to Gain in Speed, TS_i is the i^{th} test scenario, n is the number of test scenarios in a network configuration, and k is the number of contexts.

Finally, the decision scores for each network context are computed for LAA and LTE-U, for both optimization objectives, for CIRs of 2^{nd} and 3^{rd} degrees, and all four baseline optimization models.

B. EVALUATION OF CONTEXT AWARE NeFRO

The results of the decision matrix analysis for context-aware NeFRO are presented in Figure 14. It can be noticed that the context has an immense bearing on data-driven optimization and the choice of NFR. Given the multitude of test scenarios considered in this work, for simplicity, the decision scores are averaged across individual test scenarios for a single unlicensed coexistence standard, viz., LTE-U and LAA.

For both standards, the optimization objective, i.e., providing maximum SINR and Capacity to the UE, and the optimization formulation, viz., SOM_1, SOM_2, COM_1, and COM_2, determine the best NFR for the context, shaping the overall decision score. For example, 2^{nd} degree LAA SOM_2 CIR outperforms 2^{nd} degree SOM_1. However, the reverse is true for 3^{rd} degree CIRs in LAA signal strength optimization (Figure 14(a)). Moreover, the performance difference stays more or less constant for 2^{nd} degree NFRs for all use cases, but for 3^{rd} degree the decision scores converge for high-Speed use cases, viz., (0.1, 0.9) and (0.0, 1.0). Similar contextual variability can be observed in other plots as well.

We now focus on the performance variation between LTE-U and LAA. For LAA, the performance of the signal strength and capacity optimization models follows a similar pattern (Figures 14(a) & 14(b)). 2^{nd} degree NFRs outperform 3^{rd} degree NFRs as for all use cases where weight assigned to speed (faster convergence times) is $\geq$0.3. Furthermore, 3^{rd} degree NFRs are the clear choice in use cases where no compromise in optimization accuracy is tolerable.

In sharp contrast, LTE-U demonstrates different trends for signal and capacity optimization goals, and there is a greater contextual variation in the choice of NFR. The first point of marked difference is that the decision score for LTE-U models is lower than LAA by up to 42%. This holds true for all four NeFRO optimization models. Second, for both SINR optimization models (Figure 14(c)), 3^{rd} degree NFRs are a better choice, for all use cases. Thus, regardless of the priority class of the traffic type and latency requirements of the use case, 3^{rd} degree NFRs outperform 2^{nd} degree NFRs. Further, the trends in the decision score presented in Figure 14(d) reveal that both types of CIR perform better in capacity optimization models for almost equal number of use cases. Therefore, 3^{rd} degree NFRs are more suited in quadrant 3 use cases, where high accuracy is desirable and 2^{nd} degree NFRs are dominant in quadrant 2 use cases where high convergence speed is desirable.

From the above analysis, the impact of network context on data-driven optimization is evident. Thus, data-driven optimization solutions for real-world LAA deployments ought to consider the network context for a better end-user experience.

IX. CONCLUSION AND WAY FORWARD

Unlicensed cellular networks and spectrum-sharing mechanisms face new challenges that require data-driven solutions for network optimization. An unexplored problem in the data-driven optimization of unlicensed networks is the Accuracy-Speed trade-off. This work took advantage of machine learning to improve the performance of classical network optimization techniques in dense unlicensed networks. It highlighted the relevance of network context in mitigating the trade-off by considering multiple higher-order network feature relationships. A context-aware network feature relationship-based optimization framework (**CANEFRO**) was proposed and validated through decision matrix analysis. CANEFRO showed that the network context influences the choice of the feature relationship model and the optimization goal. It also demonstrated how network data and machine learning can be used to enhance the capabilities of classical network optimization. The next step would be to investigate the performance of mobile AR applications on cellular networks and apply CANEFRO at the application layer to enhance the end-user experience.

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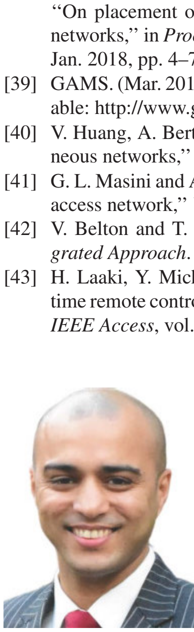

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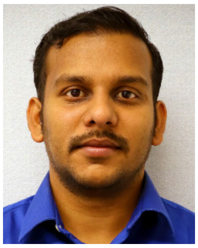

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