This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking

A Data-Driven Self-Optimization Solution for Inter-Frequency Mobility Parameters in Emerging Networks

Muhammad Umar Bin Farooq*, Marvin Manalastas*, Waseem Raza*, Syed Muhammad Asad Zaidi*,
Ali Rizwan†, Adnan Abu-Dayya‡ and and Ali Imran*
*AI4Networks Research Center, University of Oklahoma-Tulsa, USA
†Qatar Mobility Innovations Centre, Qatar University, Doha Qatar
‡Department of Electrical Engineering, Qatar University, Doha Qatar
{umar.farooq,marvin,waseem,asad,ali.imran}@ou.edu,
arizwan@qmic.com,adnan@qu.edu.qa

***Abstract*—Densification and multi-band operation means inter-frequency handovers can become a bottleneck for mobile user experience in emerging cellular networks. The challenge is aggravated by the fact that there does not exist a method to optimize key inter-frequency handover parameters namely A5 time-to-trigger, A5-threshold1 and A5-threshold2. This paper presents a first study to analyze and optimize the three A5 parameters for jointly maximizing three key performance indicators that reflect mobile user experience: handover success rate (HOSR), reference signal received power (RSRP), and signal-to-interference-plus-noise-ratio (SINR). As analytical modeling cannot capture the system-level complexity, we exploit a data-driven approach. To minimize the training data generation time, we exploit shapley additive explanations (SHAP) sensitivity analysis. The insights from SHAP analysis allow the selective collection of the training data thereby enabling the easier implementation of the proposed solution in a real network. We show that joint RSRP, SINR and HOSR optimization problem is non-convex and solve it using genetic algorithm (GA). We then propose an intelligent mutation scheme for GA, which makes the solution 5x times faster than the legacy GA and 21x faster than the brute force search. This paper thus presents first solution to implement computationally efficient closed-loop self-optimization of inter-frequency mobility parameters.**

***Index Terms*—Mobility Management, Handover Optimization, 5G, 6G, Machine Learning**

I. Introduction

Spectrum scarcity means densification and operation at higher frequency bands cannot be avoided in emerging and future networks [1]. In addition, operating at higher frequency bands also requires reducing cell sizes and concurrent operation at multiple frequency bands [2]. However, one caveat of dense base stations (BSs) operating on a motley of frequency ranges, is the increase in the complexity of the mobility management as well as a more pronounced effect of sub-optimal mobility parameters on user experience and resource efficiency. This is due to the proportional increase in the number of handovers (HO), with the decrease in cell size. As discussed in [3], a wide range of key performance indicators (KPIs) including user experience (RSRP), throughput (SINR), HOSR as well as network signaling overhead hinge on mobility management parameter configurations. A poor HO management leads to the degradation in several KPIs including data rates, latency, retainability, and user quality of experience (QoE). Optimal HO performance is also vital to support the ultra-reliable low-latency communication (URLLC) use case in 5G and beyond [4].

The current industrial practice of optimizing mobility-related KPIs involves the manual tuning of HO related configuration and optimization parameters (COPs) [5]. These COPs are tuned by leveraging human experience based hit and trial and sometimes using vendor defined gold standards. These gold standards are based on one-value-fits-all scenarios without considering varying network deployment, user densities and mobility patterns. Hence, this manual tuning is often sub-optimal and even degrades KPIs in some cases. Moreover, the human intervention based tuning process is not suitable for rapidly changing network conditions. In addition to a large number of BSs, an increase in the number of COPs per site in emerging networks compared to legacy networks makes the mobility COP optimization problem even more complicated and expensive to manage manually. Therefore, the current hit and trial based approach used in industry, is not viable for emerging (5G) and future networks (6G).

State of the art self organizing network (SON) solutions do provide some automation in COP tuning and KPI optimization [6]–[9]. For instance, mobility robustness optimization (MRO) is one of the SON functions, which deals with HO parameter management [10]. MRO automatically adjusts HO related parameters based on the past HO performance between two neighboring BSs. Though one step ahead of the manual tuning, the current SON solutions do not meet the ambitious performance requirements of emerging and future networks because of being reactive and relying on only past observations instead of complete system behavior models [11]. In addition, current SON solutions use a very limited number of mobility COPs, i.e. cell individual offset (CIO), event A3 related time to trigger (TTT), HO margin (HOM) and hysteresis etc., to optimize the KPIs. An optimal and robust HO management can only be devised if the COP-KPI relationship can be quantitatively modeled. Despite the recent efforts on analytical modeling of HO process with certain assumptions and limited

COPs [12], [13], a tractable analytical COP-KPI model is not feasible due to the system-level dynamics and complexity of the cellular network involving mobile users. This calls for investigating the data-driven models instead.

The data-driven handover models become more essential in a multi-band heterogeneous networks due to the handovers between different frequency bands. These handovers between BSs operating at different frequency bands, known as inter-frequency HO, are increasing as the number of frequency bands increase, which is the case in 5G. With 6G expected to support even larger number of frequency bands, the inter-frequency handover management will become a more complex and cumbersome task. To deal with this complexity brought by multi-band operations in the current 5G and future 6G networks, data-driven models provide a viable solution. However, a practical data-driven solution should possess two qualities: 1) it should converge quickly to deal with the time sensitive nature of handovers and to keep up with the rapidly changing network conditions; 2) it should build on 3GPP standardized handover procedures for rapid industrial uptake.

Data-driven models can be leveraged to quantify the COP-KPI relationships. However, an efficient data-driven model needs training data with the following two underlying conditions: 1) data should be sufficiently large and 2) data should be representative. Although, massive data can be mined from a real network meeting the first condition efficiently, the real challenge lies in the representativeness of that data because operators cannot afford to try all possible combinations of COPs on the live network due to the inherent risk of performance loss during the process. Secondly, such data cannot be shared with academia for privacy and business protection reasons. Even if painstakingly gathered and shared, irrespective of the volume, experience shows in case of cellular networks that real data alone is not representative enough to train reliable models, and it has to be augmented with authentic synthetic data anyway. To address the issue, in this study, we generate and exploit reliable synthetic data to solve the important problem of key mobility parameters optimization for inter-frequency HOs. We propose a framework to optimize three COPs namely A5-threshold1, A5-threshold2 and A5-TTT. Event A5 is the most widely used event to trigger inter-frequency HO in industry. The proposed framework works in tandem with the current 3GPP standardized methods and does not require new HO standardization efforts. enabling the swift uptake of the proposed solution by network vendors and operators alike. The major novelties in the proposed framework include: 1) the first framework to perform multi-objective optimization of RSRP, SINR and HOSR as a function of relatively less explored A5 inter-frequency HO parameters; 2) the framework addresses the training data scarcity challenge by leveraging a reliable 3GPP compliant simulator [14]; 3) performance improvement of machine learning (ML) algorithms utilizing SHAP-based smart COP sampling; and 4) SHAP-based intelligent mutation scheme for GA (IMGA) to accelerate convergence.

A. Related Work

A HO is triggered by pre-defined events called "Measurement Events". 3GPP release 16 [15] has defined standard events for 5G NR, which can aid HO decisions. Most of the existing studies optimize HO related parameters of event A3 to improve certain KPIs [16]–[30]. A simulated model for LTE HOs was presented in [16], which showed the variation in HO failures and HO frequency with varying mobility parameters (offset, TTT and filter coefficient) and different user speed. However, this study lacked rigorous parameter optimization. Authors in [17] extended the work by optimizing a weighted sum of three KPIs, HO failure ratio, ping pong HO ratio and radio link failure (RLF) ratio, with two COPs, hysteresis and TTT. The optimization algorithm performs an iterative search over hysteresis and TTT pairs to find the optimal combination. However, the proposed optimization algorithm has a high convergence time. The convergence time of this optimization algorithm is improved in [18].

The impact of system load and the user speed with different TTT and HOM values of A3 for long-term evolution (LTE) was studied in [19]. The study presented a fuzzy logic controller that modifies HOM to optimize call dropping ratio and HO ratio. Authors in [20] followed a different approach and categorized users based on the speed and traffic type. They presented an algorithm to tune TTT and HOM of A3 independently for each user category and optimized two KPIs, RLF and ping-pongs. In contrast, users were categorized using clustering in [21]. This study jointly optimized HO failure rate, ping pong rate, achievable data rate and number of HOs and assigned a different TTT and offset of A3 for each cluster. A different set of inputs was used in [22] and the study presented a fuzzy logic based algorithm to determine hysteresis margin of A3. The fuzzy logic based algorithm decides the value of hysteresis margin from the user velocity, RSRP and RSRQ. The study showed improvement in number of handovers, RLF and ping-pongs. In contrast to the previous studies, authors in [23] optimized energy efficiency and SINR along with ping-pong ratio. They presented an algorithm which tunes TTT and hysteresis margin of A3 to optimize KPIs.

CIO as COP was used to develop a context-aware MRO solution for reducing connection failures using A3 in [24]. In contrast, authors in [25] used hysteresis and TTT of A3 as COPs to develop a Q-learning based MRO solution and optimized number of RLFs and ping-pongs. The idea was extended in [26] by using three COPs; TTT, offset of A3 and CIO, to develop a distributed MRO algorithm to minimize RLF. The analysis was expanded to 5G settings in [27] and the study used HOM and TTT as COPs while considering user speed and RSRP. The authors proposed an auto-tuning algorithm to optimize the number of HOs and HO failure ratio using A3. A study on the real network using A3 instead of simulations was done in [28]. The authors tuned CIO as COP for each problematic cell-pair and showed improvement in late HO rates, early HO rates and RLF rates. However, this study did not consider any parameters of A3 for optimization.

While all the previous studies considered a trade-off between ping pong and RLF, the authors in [29] extended the state of the art by proving that optimal settings of A3 exist for minimizing both ping pong rate and RLF. In contrast to the previous work, the implication of using the AHP-TOPSIS method from WiMax for target BS selection in LTE-Advanced

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking

TABLE I
USE OF MEASUREMENT EVENTS FOR INTER-FREQUENCY HO [36]

Function	Measurement Event	Vendor 1	Vendor 2	Vendor 3
Inter-Frequency HO	$A3$	Yes	No	Yes
	$A4$	No	Yes	No
	$A5$	Yes	Yes	Yes

cellular networks was done in [30]. The authors used Q-learning to find the optimal value of TTT and hysteresis of A3. Perhaps, the only study which ventured beyond A3 was performed in [31]. In [31], a weighted sum optimization of HO failure ratio, call drop ratio, and ping pong ratio using reinforcement learning is done. The study considered TTT and HOM for events A1, A2, A3, A4 and A5. However, this study considers the same TTT and HOM for all the events instead of optimizing distinct values of TTT and HOM for different events.

Several studies followed a different approach compared to the previously discussed literature and proposed new methods for handovers in cellular networks. For instance, authors in [32] proposed a reinforcement learning based handover policy called SMART that reduces the number of HOs in a millimeter wave (mmWave) network. SMART considered the mmWave channel and user's quality of service requirements for handover decision. The authors also proposed a reinforcement learning based BS selection algorithm. Meanwhile, an efficient handover mechanism for radio access network slicing using multi-agent reinforcement learning was proposed in [33]. The study proposed a two-layered approach to deal with the large action space and data sparsity. The study showed lower handover cost, outage probability and number of handovers. Authors in [34] proposed a proactive framework for handover timing optimization and data rate degradation prediction for mmWave networks. The study utilized camera images and deep reinforcement learning to predict obstacles that caused data rate degradation. Another study aimed to address the beam forming and handover challenges in mmWave network [35]. The authors utilized reinforcement learning to learn the optimal backup BS and show constant rate and reliability with smaller number of handovers. Although these studies show promising results, the proposed solutions require changes in the existing handover standards hindering a swift industrial uptake.

The aforementioned studies investigate the intra-frequency HOs using event A3. The second type of HOs called inter-frequency HOs are more challenging to manage and lead to more signaling overhead and quality of experience issues due to inter frequency cell discovery. Data collected from a leading operator in the United States, operating with 6 frequency bands, show that there are around 60% more inter-frequency HO attempts compared to intra-frequency HO [36]. This percentage is likely to increase as the number of bands being used increases e.g., due to co-existence of 4G and 5G at different bands. This signifies the importance of inter-frequency HO for current and future cellular networks. However, despite their significance and associated open challenges, the performance optimization of the inter-frequency HOs is not well explored in literature. Table I shows the allowed use of each measurement event for inter-frequency HO by the three major telecommunication vendors. It is clear that all the three vendors support event A5 for inter-frequency HO, making it the best choice for a self-optimization solution that will work across all the vendors.

To the best of the authors' knowledge, there does not exist a study in literature that investigates the optimal configuration of A5 parameters for inter-frequency HO. In addition, the main optimization KPIs in the discussed literature include RLF rate, HO failure rate and ping pong rate while some studies also look at data rates and energy efficiency. However, varying HO related COPs also impact core network KPIs such as serving RSRP and SINR. This motivates a joint optimization of core network KPIs in addition to HO related KPIs. Building on our prior work [37], we jointly optimize coverage (RSRP), capacity (SINR) along with HOSR to provide a holistic framework for inter-frequency HO management.

B. Contributions

Fig. 1 presents the proposed self-optimization framework for holistic mobility management in cellular networks. The optimization trigger block will start the handover closed loop self-optimization process. We have incorporated three types of optimization triggers in the framework namely KPI-based, event-based, and time-based. A KPI-based trigger is generated when any KPI falls below the expected KPI value. Meanwhile, any change in network deployment or any temporospatial community event generate an event-based trigger. The time-based trigger can be generated at pre-defined time intervals to deal with varying user densities at different time of the day or different days of a week. Once the optimization trigger is generated, the framework jointly optimizes three KPIs namely mean RSRP, mean SINR and HOSR as a function of key inter-frequency HO COPs namely A5 threshold1, threshold2 and TTT. As quantifying the COP-KPI relationship is essential for optimization, the framework leverages a data-driven approach to quantify the COP-KPI relationship in the absence of analytical models due to system-level complexity. To solve the training data scarcity challenge for data-driven COP-KPI relationship, the framework exploits a realistic 3GPP compliant simulator [14]. In addition, the framework utilizes a novel SHAP-based smart sampling approach to improve the performance of the ML models. We also integrate an intelligent mutation scheme for GA in the framework to accelerate convergence, which is particularly imperative in fast changing network conditions. The main contributions of this work are listed below:

1) This paper is the first study to quantitatively investigate the impact of key inter-frequency HO parameters namely A5 threshold1, threshold2 and TTT on three major KPIs that dictate user experience namely RSRP, SINR and HOSR. The analysis reveals three key insights: i) for a given network setting, there exist optimal parameter values for each KPI; ii) these optimal values do not necessarily belong to the current gold standard; iii)

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking

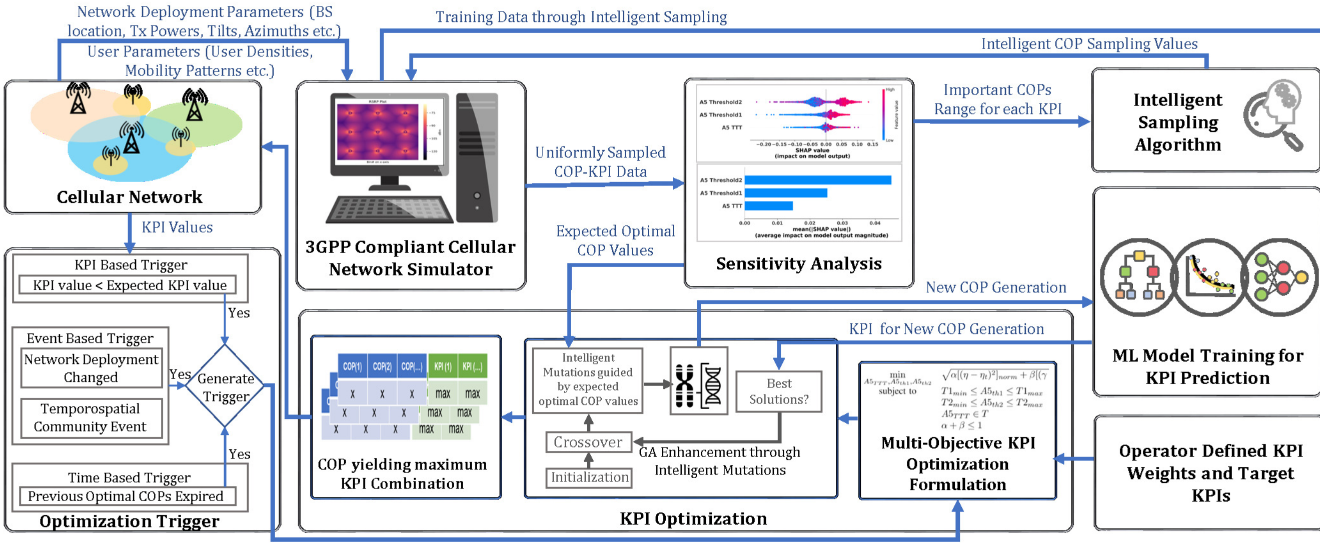


Fig. 1. Closed loop self-optimization framework for cellular networks.

the optimal parameter values for the three KPIs do not overlap. These insights call for a new method to determine the optimal values of the three parameters.

2) We formulate and solve a multi-objective optimization problem to determine the optimal values of threshold1, threshold2 and TTT. We design the objective function such that it not only allows joint maximization of all three KPIs, i.e., RSRP, SINR and HOSR but also ensures fairness among KPIs while achieving the desired operator defined goal for each KPI.
3) A key challenge in solving the said optimization problem is system level complexity that prohibits derivation of an analytical model. We address the challenge by exploiting data-driven modeling [2]. As operators do not allow experiments with A5 parameters outside the gold standard range, we generate and exploit synthetic training data using a realistic 3GPP compliant system level simulator [14]. Results show that the XGBoost based model outperforms other state of the art machine learning algorithms. Small root mean square error (RMSE) in predicting the KPI values for given COPs shows the ability of the models to accurately capture the complex COP-KPI relationship.
4) A key challenge in using data-driven approach in real networks is the difficulty of getting training data for a large number of COP combinations. To overcome this challenge, we leverage SHAP based sensitivity analysis that determines the important ranges of every COP for all the three KPIs by examining their rate of change. Drawing insights from SHAP analysis, we devise a smart sampling in which we collect more samples within the important ranges and only sparse samples in less important range. Results show that this sensitivity aware data collection approach improves the accuracy of the model compared to regular sampling.
5) We show that the joint optimization problem is non-convex and solve it using genetic algorithm (GA) that reduces the computational time by 4x compared to brute force based search. In addition, we exploit the SHAP sensitivity analysis in a novel way to improve the mutations of GA that leads to 5x faster convergence time compared to state of the art GA. To the best of authors' knowledge, this is the first study that exploits SHAP based sensitivity analysis for improving the convergence time of GA.
6) This study thus presents first framework to enable closed loop self-optimization of inter-frequency handover parameters for maximizing all three major KPIs that dictate user experience. Fig. 1 presents the overall schematic of this framework. The sensitivity analysis based training data optimization combined with smart mutation based GA means this solution can be implemented in real networks even with sparse training data and limited computational resources.

Rest of the paper is organized as follows: Section II describes the event A5 and simulation setup along with the problem formulation; the qualitative impact of inter-frequency COPs on KPIs is presented in Section III; in Section IV, we discuss the smart sampling approach to improve the data quality for ML training and the performance of ML models in capturing the COP-KPI relationship; Section V presents the KPI optimization using the data-driven models while Section VI concludes the paper.

II. System Model

This section describes the 3GPP defined measurement event A5 together with the parameters to optimize the mean RSRP, mean SINR and HOSR. We then describe the COP-KPI optimization problem followed by simulation setup.

A. Handover Event A5

Event A5 is triggered when the RSRP to a user u from its serving BS decreases below a threshold, i.e., threshold1,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking

and the RSRP to the same user from a target BS increases above another threshold, i.e., threshold2. These conditions are formally described in the following equations.

$$\begin{aligned} \eta_s^u + A5_{\text{hyst}} &< A5_{\text{th1}} \\ \eta_t^u + O_{s,t} - A5_{\text{hyst}} &> A5_{\text{th2}} \end{aligned} \tag{1}$$

where η_s^u is the RSRP of the user u with serving BS s, η_t^u is the RSRP of the user with target BS t, $O_{s,t}$ is the cell-specific offset also known as CIO from the serving to target BS, $A5_{\text{hyst}}$, $A5_{\text{th1}}$ and $A5_{\text{th2}}$ are the hysteresis, threshold1 and threshold2 for event A5, respectively. HO using A5 is triggered when these conditions remain satisfied for a certain time, called time to trigger, TTT. If multiple base stations satisfy the criteria to trigger event A5, the BS with highest RSRP is chosen as the target BS for handover [38]. Meanwhile, if two or more target BS have same RSRP values, the BS with the lower physical cell ID (PCI) is chosen. This target BS selection logic is based on the implementation of one of the major equipment vendors in the industry. On the other hand, a user will exit event A5 if either of the following conditions are met:

$$\begin{aligned} \eta_s^u - A5_{\text{hyst}} &> A5_{th1} \\ \eta_t^u + O_{s,t} + A5_{\text{hyst}} &< A5_{\text{th2}} \end{aligned} \tag{2}$$

In addition to event A5, 3GPP has also defined measurement events A1, A2, A3, A4 and A6. Cellular network vendors leverage these events for crucial tasks in a cellular network. For instance, event A1 is majorly used to cancel measurement gap (MG), event A2 is mostly used to trigger MG, event A4 is used by most vendors to perform load balancing, and event A6 is majorly used to activate secondary cell for carrier aggregation. Event A3 and A5 are the most popular choices among vendors to perform intra and inter-frequency handovers. However, only event A5 is supported by all the major vendors to trigger inter-frequency handovers as illustrated in Table I. Thus, we utilize event A5 to devise an inter-frequency optimization solution that will work across all major equipment vendors. The parameters of other events are kept constant to observe the variation in KPIs as a result of changing event A5 COPs only.

B. Problem Formulation

RSRP of the user is an important performance metric because it gives an estimate of the link strength between user and the serving BS. The downlink RSRP η_s^u for a user u connected to the serving BS s is given by:

$$\eta_s^u = P_s d_s^u \tag{3}$$

where P_s is the transmit power of serving BS s and d_s^u is the path loss dependent component of the user u with the serving BS s. The pathloss dependent component also contains antenna gains as well as the shadowing for the user, which is modeled as a gaussian random variable. The mean RSRP η of all the users in the network can be described as:

$$\eta = \frac{\sum\limits_{\forall i \in U} \eta_s^i}{|U|} \tag{4}$$

where U is a set of all the users in the network.

Signal to interference and noise ratio (SINR) is also an important KPI, which gives an estimate of the network capacity. SINR $\gamma_{s,j}^u$ on a physical resource block (PRB) j which has been allocated to a user u from BS s can be written as following:

$$\gamma_{s,j}^u = \frac{P_{s,j} d_{s,j}^u}{K + \sum\limits_{\forall i \in B_f} P_{i,j} d_{i,j}^u} \tag{5}$$

where $P_{s,j}$ is the transmit power of serving cell s at PRB j, $d_{s,j}^u$ is the path loss dependent component of user u with the serving cell s at PRB j and K is the thermal noise. $P_{i,j}$ is the transmit power of interferer i at PRB j, $d_{i,j}^u$ is the pathloss dependent component of user u with the interferer i at PRB j and the set B_f contains all the interfering BS using the same frequency band as the user u. The SINR γ_s^u for user u connected to BS s can be obtained by averaging the SINR on all the PRBs allocated to the user. γ_s^u can be written as:

$$\gamma_s^u = \frac{\sum\limits_{\forall j \in R_u} \gamma_{s,j}^u}{|R_u|} \tag{6}$$

where set R_u contains all the PRBs allocated to the user u. The mean SINR γ of all the users can be written as:

$$\gamma = \frac{\sum\limits_{\forall i \in U} \gamma_s^i}{|U|} \tag{7}$$

HOSR is another important KPI that captures the effectiveness of the HO related parameter settings. Poor HOSR can become a key bottleneck for URLLC in 5G and beyond, particularly for applications such as intelligent transport systems and autonomous cars. HOSR ξ can be described as:

$$\xi = \frac{HOS}{HOS + HOF} \times 100\% \tag{8}$$

where HOS and HOF are the number of successful and failed handovers, respectively, in the network.

Mean RSRP, mean SINR and HOSR for the network can be optimized jointly. We formulate a multi-objective optimization problem to minimize the difference of η, γ and ξ with the target values of each KPI using A5 related COPs. The formulation is given in (9). η_t, γ_t and ξ_t are the target values of RSRP, SINR and HOSR. α and β are the operator-defined weights that can be used to adjust the relative importance of RSRP, SINR and HOSR, respectively. The normalization shown in the subscript removes the bias towards large values of KPI and confirms that the importance of each KPI is only defined by their respective weights. $T1$, $T2$ are the ranges of $A5_{\text{th1}}$ and $A5_{\text{th2}}$, respectively, with the subscript showing the minimum and maximum values and T is a set containing all the values of $A5_{\text{TTT}}$. The optimization variables are $A5_{\text{TTT}}$, $A5_{\text{th1}}$ and $A5_{\text{th2}}$. The first three constraints in (9) limit the values of the optimization variables i.e., COPs in the 3GPP defined ranges. The fourth constraint states that the sum of the three weights is equal to one.

The motivation to include mean RSRP and mean SINR of users in eq. (9) is tri-pronged. Firstly, mean RSRP and mean SINR provide a good estimate of the system level quality of

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking

$$\begin{array}{ll} \min\limits_{A5_{\text{TTT}}, A5_{\text{th1}}, A5_{\text{th2}}} & \sqrt{\alpha[(\eta-\eta_t)^2]_{\text{norm}} + \beta[(\gamma-\gamma_t)^2]_{\text{norm}} + (1-\alpha-\beta)[(\xi-\xi_t)^2]_{\text{norm}}}; \\ \text{subject to} & T1_{\text{min}} \leq A5_{\text{th1}} \leq T1_{\text{max}} \\ & T2_{\text{min}} \leq A5_{\text{th2}} \leq T2_{\text{max}} \\ & A5_{\text{TTT}} \in T \\ & \alpha + \beta \leq 1 \end{array} \tag{9}$$

TABLE II
DESCRIPTION OF SIMULATION PARAMETERS

Parameter Description	Value
Simulation area	4km^2
Number of for 1.7GHz macro transmitters	6
Number of 2.1GHz macro transmitters	6
Macro cell height	30m
Small cell height	20m
Macro cell transmit power	30dBm
Small cell transmit power	30dBm
Total bandwidth for 1.7, 2.1 and 3.5 GHz	10, 15 and 20 MHz
Total PRBs for 1.7, 2.1 and 3.5 GHz	52, 78, 106
Pathloss exponent	3
Shadowing standard seviation	4
Active user density λ_u	15 per km^2
Speed vector V	[3, 60, 120, 240] km/h
Transmission time interval (TTI)	1 ms

TABLE III
DESCRIPTION OF COPS TO GENERATE THE KPIS

COPs	Values
$A5_{\text{TTT}}$	[64, 128, 256, 320, 512] ms
$A5_{\text{th1}}$	[-90 to -120] dBm
$A5_{\text{th2}}$	[-90 to -120] dBm

service (QoS). Secondly, an analysis of Fig. 2 and 3 in subsection III-A shows that event A5 parameters can considerably impact the RSRP and SINR by as much as 2.5dBm and 2.5dB, respectively. As this paper aims to optimize system level QoS as a function of event A5 parameters, we have incorporated mean RSRP and mean SINR in the optimization eq. (9). Finally, the relatively unexplored nature of mean RSRP and mean SINR as a function of mobility parameters in literature further motivates us to consider them as KPIs. Aside from mean RSRP and mean SINR, we have also included a conventional HO-related KPI in the form of HOSR. While RLF can be a good alternative, it can occur due to several non-mobility related reasons such as RACH abort and when the maximum number of RLC retransmissions are exceeded as defined by 3GPP 36.331 [38]. Meanwhile, repeated handover failure is one of the major reasons for RLFs and hence, optimizing HOSR will reduce the RLF caused by handovers.

Solving this problem using the analytical method is not a viable approach as tractable system level models for RSRP, SINR and particularly HOSR as a function of the three COPs is very difficult, if not impossible to derive. Even if abstract mathematical models are created [12], [13], they cannot capture the dynamics caused by the mobility of the users. Therefore, to enable practical self-optimization solutions, as originally proposed in [2], data-driven modeling is a more viable approach to solve (9).

C. Simulation Setup and Data Generation

Collecting all the needed data from a live network though plausible in theory, is impractical in practice due to sparse and non-representative real data in addition to the privacy and business protection concerns of operators. In this backdrop, to generate the data, we exploit a state of the art 3GPP-compliant system level simulator named SyntheticNET [14]. This is the first simulator to model 5G mobility parameters in detail needed for this study. As shown in [14], this simulator has been calibrated against real network measurements to ensure the authenticity of the data generated through it.

A network with an area of size 2km$\times$2km is used for the data generation. We consider a three-tier heterogeneous network, where each layer operates at different band. Two layers are composed of macro cells and the remaining layer is composed of small cells. Each macro cell has three sectors and each sector operates at two frequency bands, 1.7GHz and 2.1GHz. Small cells have omni-directional antenna operating at a frequency band of 3.5GHz. The initial deployment of the users in the network follows a uniform distribution with user density λ_u. Each user can move in the network with speed v_u chosen from a set V. All elements of the set V are equally probable and the speed value remains constant for a user. The user mobility type is a random way point. The network level simulation parameters are summarized in Table II.

In addition to the optimization parameters of interest, the mobility related parameters of different events also need to be defined to generate realistic data. Event A2 is used to trigger the measurement gap for inter-frequency cell discovery as inter-frequency HOs can only happen when MG is triggered. The values of TTT, threshold, and hysteresis for event A2 are set to 64ms, -90dBm and 1dB, respectively. Table III shows the ranges of event A5 related COPs used to generate the data. A wide range for $A5_{\text{th1}}$ and $A5_{\text{th2}}$ are chosen to cover the effect of hysteresis for making event A5 parameters optimization more robust. A step size of 1dBm is used for both $A5_{\text{th1}}$ and $A5_{\text{th2}}$.

III. IMPACT OF INTER-FREQUENCY HANDOVER PARAMETERS ON KPIS

To date, the effect of changing the values of A5 related COPs on the KPIs such as RSRP and HOSR is not fully understood, even in academic literature [3]. Industry practice, on the other hand, is to use gold standard fixed values recommended by the vendors for A5 parameter settings without any consideration of their optimality. Qualitative and quantitative

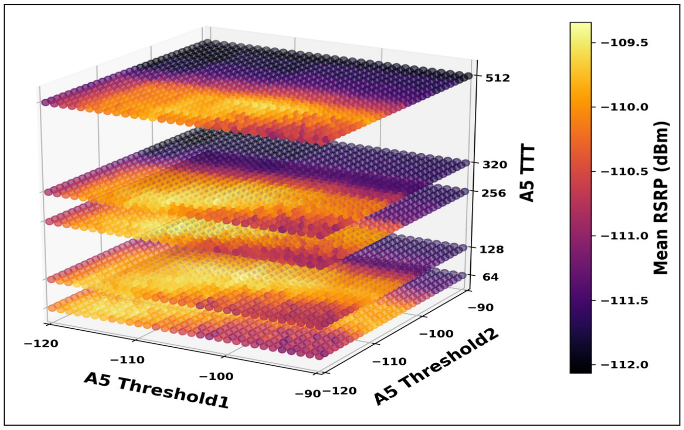


Fig. 2. Impact of A5 thresholds and TTT on mean RSRP.

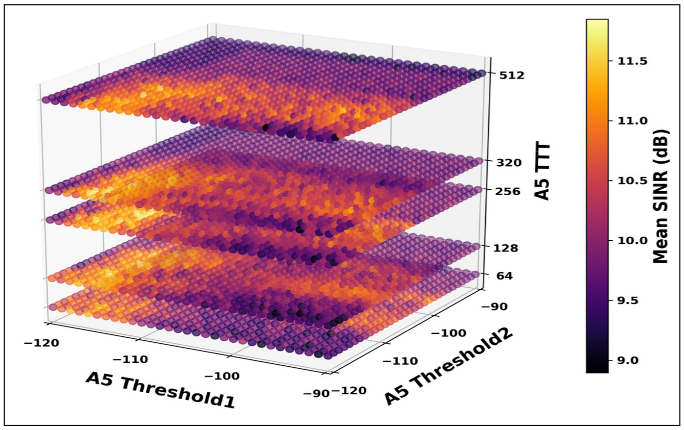


Fig. 3. Impact of A5 thresholds and TTT on mean SINR.

insights into how A5 parameter values affect the KPIs are essential to optimize these parameters. This section presents the analysis to harness these insights. These insights are also used to establish the structure of (9) to see whether or not it is a convex optimization problem so an appropriate solution approach can be adapted.

A. Impact on Mean RSRP and Mean SINR

We begin by analyzing the impact of $A5_{\text{TTT}}$, $A5_{\text{th1}}$, and $A5_{\text{th2}}$ on mean RSRP by changing their values and logging resultant mean RSRP. Result in Fig. 2 shows that the mean RSRP decreases for very high and very low values of $A5_{\text{th2}}$. This happens because very high values of $A5_{\text{th2}}$ trigger late HO as users are unable to transfer to the target BS with better RSRP. This ultimately results in a longer stay of users under the coverage of a BS with poorer RSRP. Similarly, lower values of $A5_{\text{th2}}$ result in the too early HO to BS with bad coverage lowering the overall RSRP. An opposite effect is observed for variations in the values of $A5_{\text{th1}}$. Unlike in $A5_{\text{th2}}$, very low values of $A5_{\text{th1}}$ cause too late HO as event A5 is triggered when the serving RSRP is already very poor. Meanwhile, very high values of $A5_{\text{th1}}$ result in too early HO. In terms of variations in $A5_{\text{TTT}}$, it is observed that different $A5_{\text{TTT}}$ values shift the high RSRP area. As $A5_{\text{TTT}}$ increases, the concentration of higher RSRP goes towards lower $A5_{\text{th2}}$ and higher values of $A5_{\text{th1}}$. This observation provides insight that if larger $A5_{\text{TTT}}$ is used (e.g. in dense urban area where mobility is slow), to maintain good RSRP for the users, a higher value of $A5_{\text{th1}}$ and a lower value of $A5_{\text{th2}}$ should be used.

The impact of A5 thresholds and TTT on SINR is shown in Fig. 3. SINR follows a similar trend as RSRP with poor SINR observed for extreme values of $A5_{\text{th1}}$ and $A5_{\text{th2}}$. This happens because extreme values of thresholds result in too early and too late HO connecting the user to a serving cell with poor signal strength. It also increases the interference from the neighboring cells with better signal conditions and hence poor SINR of the user. Although a similar tend is observed for RSRP and SINR, different COP combinations maximize RSRP and SINR. This observation provides additional rationale to include both RSRP and SINR in the optimization problem.

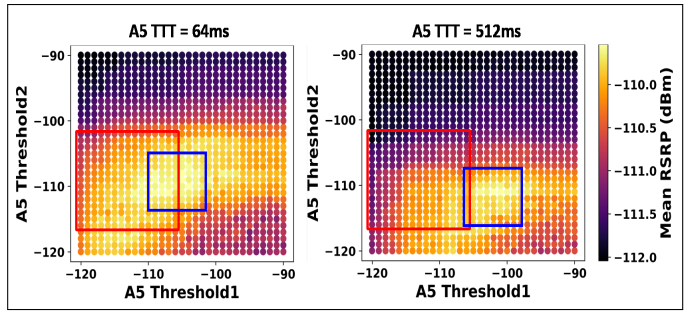


Fig. 4. Comparison of gold standard and simulation results. Red box represents the range of threshold values recommended by the gold standard used in industry. Blue box is the area of high mean RSRP, for analyzed network scenario. This finding can be insightful for the industry.

Fig. 4 shows a 2D plot of mean RSRP versus $A5_{\text{th1}}$ and $A5_{\text{th2}}$ for $A5_{\text{TTT}}$ of 64ms and 512ms. In this figure, we highlight with a red box, the A5 parameter values used as gold standards (GS) by one of the leading operators in the United States. We have also highlighted the blue area where the highest average RSRP has been observed for the analyzed scenario. This comparison shows a significant overlap between the GS and our values of $A5_{\text{th1}}$ and $A5_{\text{th2}}$ for $A5_{\text{TTT}}$ of 64ms. However, the location of the blue box changes when $A5_{\text{TTT}}$ is 512ms i.e., optimal values of A5 thresholds change. Therefore, the current GS based fixed value setting approach is not optimal and hence the need for self-optimization solution as proposed in this study.

B. Impact on HOSR

The impact of different A5 thresholds and TTT setting on HOSR is shown in Fig. 5. At first glance, these results give the impression that 100% HOSR can be achieved using higher values of $A5_{\text{th2}}$ (i.e., greater than -100dBm). However, this does not necessarily mean higher $A5_{\text{th2}}$ is the optimal setting. As HO conditions using higher $A5_{\text{th2}}$ are more challenging to achieve, very few HOs will occur, leading to extremely poor RSRP and SINR, as seen in Fig. 2. In fact, using extreme thresholds and TTT values result in no HO at all. Although these settings result in lower HO failure, the users are forced to stay under inadequate RSRP and SINR conditions for a

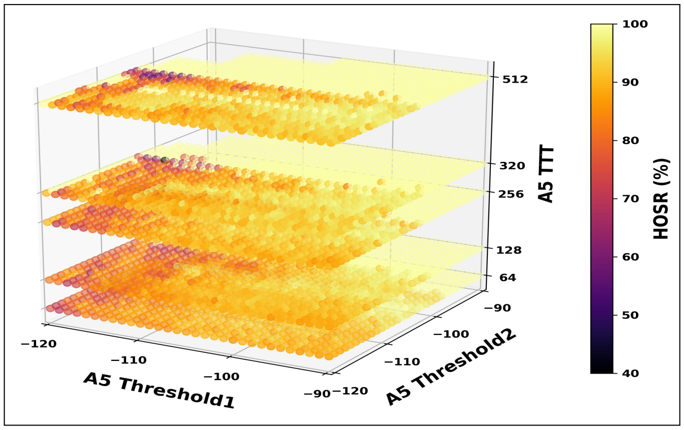


Fig. 5. Impact of A5 thresholds and TTT on HOSR.

long period leading to poor throughput and increased chances of RLF. This can also be validated from Fig. 2 and Fig. 3, showing the worst mean RSRP and SINR in the same area where the HOSR is the highest. Fig. 5 also shows that most HO failures occur when lower $A5_{\text{th1}}$ is used. This result is expected as poor RSRP of the serving BS is one of the main reasons for HO failure.

The conflicting trend of Fig. 5 compared to Fig. 2 and Fig. 3 shows a trade-off between optimizing RSRP and SINR while optimizing HOSR, necessitating the joint optimization of the three KPIs together as proposed in this paper.

IV. Improved Machine Learning Models for COP-KPI Relationship Leveraging SHAP

This section presents the performance of machine learning algorithms modeling the COP-KPI relationship. The goal is to build a model that can predict mean RSRP, mean SINR and HOSR as a function of $A5_{\text{th1}}$, $A5_{\text{th2}}$, and $A5_{\text{TTT}}$. To solve the challenge of rapid and representative data generation, we first present a training data improvement technique using sensitivity analysis on the initial data described in sub-section II-C. The performance of ML models on the initial data and improved data is also discussed.

A. Data Improvement using Sensitivity Analysis

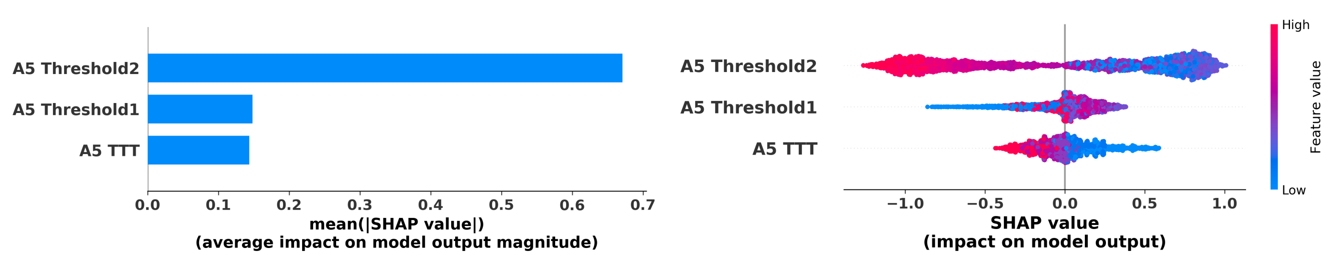
Sensitivity analysis is usually used to explain the black-box nature of data-driven models [39], [40]. In addition, sensitivity analysis can provide the importance of each feature and is also used for feature selection when there are a high number of input features [41]. Different from these conventional use cases of sensitivity analysis, we have used sensitivity analysis to improve our data. We not only use sensitivity analysis to find important COPs but also to identify the range of the COPs, which produces the maximum change in KPI. A lower step size (higher sampling rate) can be used in this important range to enrich the data and ultimately training the machine learning model on a more representative data for each KPI. Hence, the model can learn the rapidly changing behavior of KPI. One of the popular approaches for sensitivity analysis is the Sobol method [42]. Sobol measures the impact of each feature based on the variance of model output and gauges feature relevance on a global scale. This makes Sobol difficult to interpret especially when the input features are inter-dependent. In addition, Sobol leverages a regular conditional expectation and hence it can highlight features that the model does not use but are connected to the features used by the model.

To address the limitations of Sobol, we utilize another sensitivity analysis tool called SHAP [43]. SHAP relies on shapley values [44], a cooperative game theory concept in which the impact of each player is calculated on the output of the collaborative game. SHAP, unlike Sobol, concentrates on local interpretations of each prediction and largely deals with interventional expectations, making it easier to interpret [45]. In addition, each data sample has a separate SHAP value, which is useful to observe the impact on model output for the complete range of features. We leverage this capability of SHAP to find the feature range with the highest impact on the model output. In the following subsection, we leverage the SHAP analysis to study the impact of each COP on the three KPIs and the inter-relation between the COPs. The insights drawn from this analysis pave way for faster generation of a representative data set.

1) Sensitivity Analysis for RSRP: Fig. 6 shows the mean SHAP values and their distribution for RSRP. It is evident from Fig. 6(a) that $A5_{\text{th2}}$ has the highest impact on RSRP while $A5_{\text{th1}}$ and $A5_{\text{TTT}}$ have lesser and almost the same impact on RSRP. Fig. 6(b) gives more detailed insights with color indicating the COP (feature) value. The horizontal axis specifies the SHAP value for each data point and the vertical thickness indicates the data point density. The vertical thickness at the extremes for $A5_{\text{th2}}$ implies that a large fraction of $A5_{\text{th2}}$ value range (data points) has an extremely positive or negative impact on RSRP. On the other hand, the thickness around zero for $A5_{\text{th1}}$ and $A5_{\text{TTT}}$ shows that most of values for these two parameters have minimal impact on RSRP. It can also be seen that purple color, which corresponds to the mid values of thresholds has the highest positive impact on RSRP for both $A5_{\text{th2}}$ and $A5_{\text{th1}}$. This gives the insight that RSRP maximizes when $A5_{\text{th2}}$ and $A5_{\text{th1}}$ are not set to extremely high or low values. In addition, extremely high values of $A5_{\text{th2}}$ (red color) while extremely low values of $A5_{\text{th1}}$ (blue color) have the most negative impact on RSRP and hence should be avoided when tuning the COPs for optimizing the RSRP. In addition, it is also evident that lower values of $A5_{\text{TTT}}$ (blue color) have the most positive impact on RSRP as shorter values of $A5_{\text{TTT}}$ ensures faster HO to a BS with better RSRP.

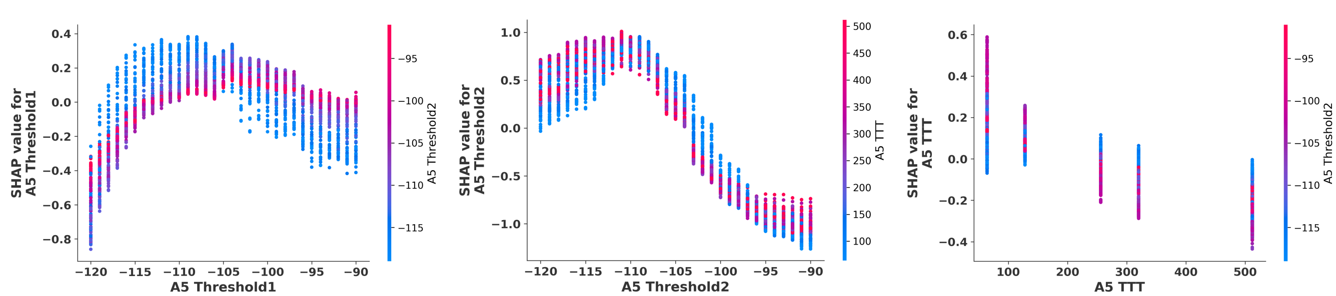
The inter-dependency of the three COPs is shown in Fig. 7 using the SHAP dependency plots. The horizontal axis shows the variation in one COP and the vertical axis indicates the impact on the output. The color bar shows another COP which produces the highest change in the SHAP value of the first COP under consideration. Each colored point represents a data point with corresponding two COPs and the SHAP value.

Fig. 7(a) shows that, starting from -120dBm, increasing the values of $A5_{\text{th1}}$ impacts RSRP positively until it reaches around -105dBm and then the impact starts to decrease. It can be seen that the rate of change in RSRP is highest when $A5_{\text{th1}}$ is in the range of -120dBm to -114dBm. The rate of change in RSRP is lower outside this range of $A5_{\text{th1}}$. In addition, $A5_{\text{th1}}$



(a) Mean SHAP value (b) SHAP value distribution

Fig. 6. Impact of each input parameter on RSRP



(a) (b) (c)

Fig. 7. Impact of each parameter on RSRP and their inter-dependence

TABLE IV
RANGES OF COPS WITH THE MAXIMUM RATE OF CHANGE IN THE KPIS

KPI	$A5_{\text{th1}}$ (dBm)	$A5_{\text{th2}}$ (dBm)
RSRP	[-120 to -114]	[-108 to -98]
SINR	[-120 to -110]	[-118 to -97]
HOSR	[-120 to -110]	[-106 to -97]
Total Range	[-120 to -110]	[-118 to -97]

interacts the most with $A5_{\text{th2}}$. The trend of SHAP values for $A5_{\text{th2}}$ follows a similar trend as that of $A5_{\text{th1}}$ as shown in Fig. 7(b). The impact increases with increasing values of $A5_{\text{th2}}$ increases up to the maximum SHAP value and then starts to decrease. However, it can be seen that the rate of change of RSRP is maximum when $A5_{\text{th2}}$ is in the range of -108dBm to -98 dBm. Using these insights from SHAP analysis, we have devised a smart data improvement approach. Since we know that the rate of change of RSRP is higher from -120dBm to -114dBm and -108dBm to -98dBm for $A5_{\text{th1}}$ and $A5_{\text{th2}}$, respectively, we have sampled more values of both COPs in this important range to capture the rapidly changing behavior of RSRP. Fig. 7(c) shows that the impact on RSRP becomes negative with increasing $A5_{\text{TTT}}$ and $A5_{\text{th2}}$ interacts the most with $A5_{\text{TTT}}$.

A similar sensitivity analysis for SINR and HOSR reveals a range of COPs which produces a higher rate of change in the KPIs. This range of $A5_{\text{th1}}$ and $A5_{\text{th2}}$ for all the three KPIs is shown in Table IV. A lower step size of 0.5dBm is used in this range for the two COPs. This intelligent variation in step size based on the relative rate of change of the three KPIs improves the training data. This improved data contains more information where the KPIs are rapidly varying and hence the machine learning algorithms trained on this data are expected to better predict the KPI behavior. We have not over sampled $A5_{\text{TTT}}$ because there are fixed 3GPP defined values of $A5_{\text{TTT}}$ and hence a data sample outside these values cannot be implemented in a practical cellular system. In addition, $A5_{\text{TTT}}$ has the least impact on all the three KPIs, which indicates that more samples of $A5_{\text{TTT}}$ may not improve the data-driven models significantly.

B. Performance Comparison of Machine Learning Models

The performance of different machine learning algorithms with uniform and variable COP sampling is presented in this sub-section. A 80%-20% train-test data split is used and the performance of six different regression techniques is evaluated. Table V shows the performance of linear, polynomial, support vector, decision tree, random forest and XGBoost regression algorithm in terms of both training and testing normalized RMSE. Due to the complex non-linear relationship between COPs and KPIs, linear regression is not able to capture the relationship leading to a high testing and training RMSE of all the three KPIs with fixed sampling size. Similarly, the fourth order polynomial and support vector regression techniques also failed to capture the COP-KPI relationship displaying higher RMSE compared to other algorithms. Results also show that tree-based algorithms exhibit promising results in predicting the KPIs. Top 3 algorithms with lowest test RMSE for RSRP, SINR and HOSR are all tree-based with XGBoost being the best showing test RMSE of only 2.63%, 6.40% and 5.2% for mean RSRP, mean SINR and HOSR, respectively with a fixed sampling size. Another important insight is very low training

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking

TABLE V
NORMALIZED RMSE COMPARISON OF DIFFERENT MACHINE LEARNING ALGORITHMS FOR RSRP, SINR AND HOSR PREDICTION WITH FIXED AND VARIABLE SAMPLING SIZE.

KPI	Data Type	Linear		Polynomial		Support Vector		Decision Tree		Random Forest		XGBoost	
		Fixed	Variable	Fixed	Variable	Fixed	Variable	Fixed	Variable	Fixed	Variable	Fixed	Variable
RSRP (%)	**Train**	16.52	15.84	6.51	6.27	4.20	3.90	0.0007	0.0007	1.12	0.097	1.41	1.64
SINR (%)		13.56	13.97	8.50	8.71	7.69	7.62	0.0003	0.0003	2.87	2.74	6.21	6.11
HOSR (%)		9.33	11.58	8.03	9.95	8.15	9.73	0.0035	0.0038	2.16	2.41	2.22	3.55
RSRP (%)	**Test**	16.80	15.95	6.63	6.29	4.27	3.97	3.37	2.96	2.78	2.32	2.63	2.29
SINR (%)		13.59	13.59	8.34	8.42	7.55	7.39	8.74	8.41	6.51	6.66	6.40	6.28
HOSR (%)		9.82	10.97	8.62	9.43	8.85	9.1	7.45	6.65	5.53	5.08	5.2	4.98

TABLE VI
TUNED HYPERPARAMETERS FOR XGBOOST

KPI	gamma	learning_rate	max_depth	n_estimators
RSRP	0	0.63001	4	402
SINR	0.30331	0.27910	6	541
HOSR	0.00038	0.24219	9	146

RMSE of decision tree compared to the test RMSE indicating an overfitting due to inherent absence of regularization.

The performance of each technique is also shown for improved data after variable sampling of $A5_{\text{th1}}$ and $A5_{\text{th2}}$ as described in sub-section IV-A. It can be seen that the test RMSE of XGBoost improved by 0.34%, 0.12% and 0.22% for mean RSRP, mean SINR and HOSR, respectively. This corresponds to an improvement of almost 12.9%, 1.9% and 4.2% for mean RSRP, mean SINR and HOSR, respectively with variable data sampling as compared to the fixed one. A small improvement of 1.9% for SINR shows that it is a difficult KPI to predict even with more data. This happens due to high variation in SINR because of randomness in interference at each PRB. On the other hand, the train RMSE of XGBoost decreased with variable sampling compared to the fixed sampling for both mean RSRP and HOSR. With variable sampling, an increase in the test RMSE along with the decrease in the train RMSE of XGBoost for mean RSRP and SINR indicate that the model with variable sampling can better address the overfitting problem. The RMSE might not improve for some of the regression models with variable sampling because the SHAP analysis was done for the best performing ML model, which is XGBoost. SHAP analysis for XGBoost model highlighted the important range of $A5_{\text{th1}}$ and $A5_{\text{th2}}$, but the important range of the two COPs will vary from one ML model to another. The reason is the different underlying learning behavior of each ML technique. The RMSE is decreased for RSRP in all the ML techniques indicating similar important range of the two COPs. The RMSE of polynomial regression and random forest increased for SINR while it decreased for all other techniques. This shows that the important range of the two COPs is different for polynomial regression and random forest as compared to XGBoost for predicting SINR. The RMSE of linear regression, polynomial regression and support vector machine increased for HOSR with variable sampling highlighting a different important range of the two COPs.

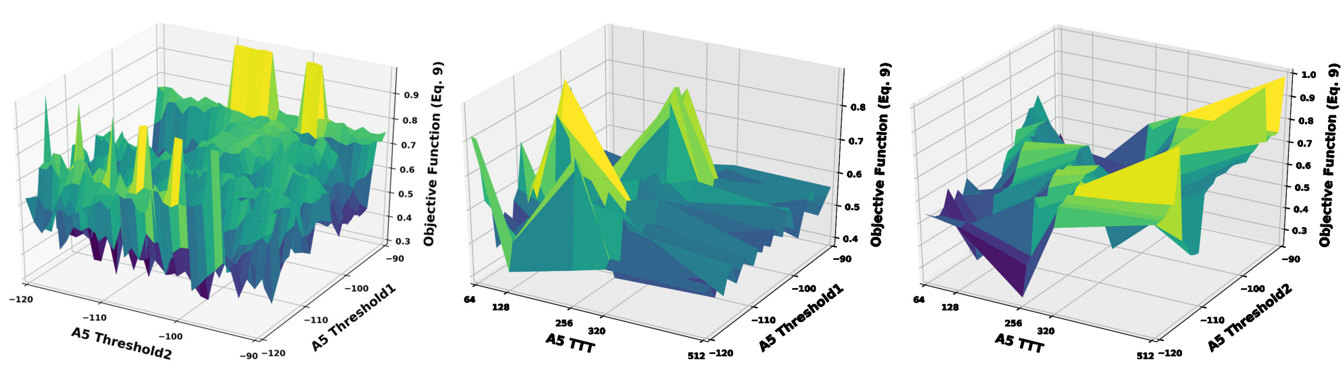
We have performed Bayesian hyperparameter optimization of the XGBoost models for all three KPIs. The choice of Bayesian optimization is based on the ability to find better hyperparameters in less time compared to grid-based or random search methods. The superiority of Bayesian optimization lies on the ability to evaluate best set of hyper-parameters based on the information of the past trials. Table VI shows the tuned hyperparameters for XGBoost model to predict mean RSRP, mean SINR and HOSR. The XGBoost models to compute train and test RMSE reported in Table V are trained using the respective tuned hyperparameters of Table VI. The improved XGBoost model has learned the COP-KPI relationships with lower errors and can be used for KPI optimization in the absence of a tractable analytical model.

V. OBJECTIVE FUNCTION OPTIMIZATION

The data-driven model developed in the previous section can be used to find the optimal value of the objective function defined in eq. (9). The COP combination producing the optimal value of objective function can be used by network operators. The solution thus can replace the current manual and hit and trail based COP tuning with a self-optimization system.

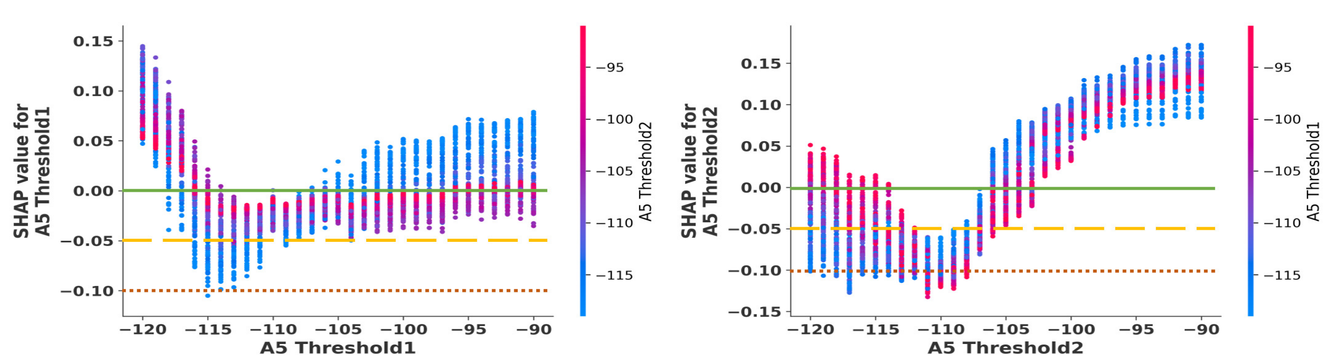
Fig. 8 shows the plot of the objective function defined in eq. (9) with 0.33 value of both α and β (equal importance for all three KPIs). Fig. 8(a), 8(b) and 8(c) shows how the objective function varies with fixed $A5_{\text{TTT}}$, fixed $A5_{\text{th1}}$ and fixed $A5_{\text{th2}}$, respectively. As shown in the plots, the objective function has several minima for all the different COP combination, making eq. (9) a non-convex optimization problem. Moreover, eq. (9) is a discrete optimization problem and has a finite search space. Hence, eq. (9) is neither convex nor NP hard. As the problem is not NP hard, it can be solved using a brute force approach. However, the higher convergence time of brute force is not suitable for the rapidly changing network conditions and the time sensitive nature of handovers. To reduce the convergence time, we leverage well-defined heuristic optimization tools such as GA and propose IMGA to further accelerate the convergence compared to off-the-shelf GA. We compare the performance of the brute force method for optimization with well-defined heuristic approach, genetic algorithm. The choice of genetic algorithm as a heuristic tool is based on its effectiveness in solving complex optimization problems of cellular networks [46], [47]. We also compare the performance with current industrial practice of using gold standards. The objective function value reported for GS is very optimistic because we have considered all the 225 combinations from GS. However, gathering data even for 225 different combinations from live network is a long shot for most network operators.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking



(a) $A5_{\text{TTT}}$=64ms (b) $A5_{\text{th2}}$=-110dBm (c) $A5_{\text{th1}}$=-110dBm

Fig. 8. Objective function defined in eq. (9) with $\alpha = 0.33$, $\beta = 0.33$



(a) (b)

Fig. 9. Dependence plot of $A5_{\text{th1}}$ and $A5_{\text{th2}}$ for the utility function with $\alpha = 0.33$ and $\beta = 0.33$

TABLE VII
COMPARISON BETWEEN GOLD STANDARD, GENETIC ALGORITHM AND BRUTE FORCE

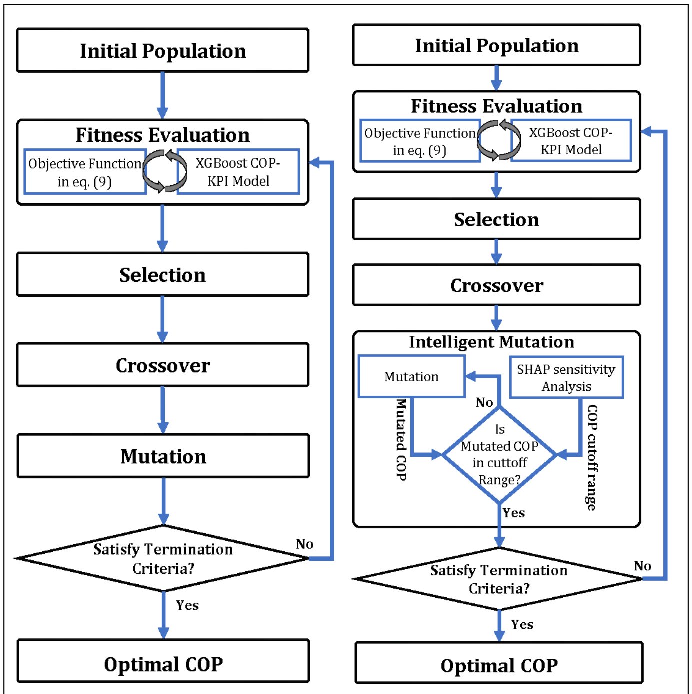
α	β	Optimization Solution	Objective Function	Optimal COP Values $[A5_{\text{TTT}}, A5_{\text{th1}}, A5_{\text{th2}}]$
0.33	0.33	Gold Standard	0.4138	[512, -109, -112]
		GA + XGBoost	0.3136	[256, -113, -117]
		Brute Force	0.3136	[256, -113, -117]
0.5	0.25	Gold Standard	0.4197	[512, -104, -111]
		GA + XGBoost	0.3575	[128, -115, -120]
		Brute Force	0.3447	[256, -113, -117]
0.25	0.5	Gold Standard	0.4060	[512, -112, -112]
		GA + XGBoost	0.3022	[256, -113, -118]
		Brute Force	0.2940	[128, -115, -113]
0.25	0.25	Gold Standard	0.3629	[512, -109, -112]
		GA + XGBoost	0.2965	[256, -113, -117]
		Brute Force	0.2965	[256, -113, -117]

Table VII shows the optimal objective function and the corresponding value of COPs for different weights of the three KPIs, mean RSRP, mean SINR and HOSR. It can be seen that the presented solution, GA combined with XGBoost, offers significant improvement in objective function values compared to GS. Table VII shows that both the objective function and optimal COPs returned by GA+XGBoost are either similar or much closer to the brute force compared to GS and this trend is observed for all the values of α and β. This highlights the superiority of the proposed solution over GS in finding the optimal COPs. On the other hand, brute force returns the optimal ground truth value of the objective function and COPs. It is observed that GA+XGBoost returns the same objective function and optimal COPs as brute force for $\alpha = 0.33$, $\beta = 0.33$ and $\alpha = 0.25$, $\beta = 0.25$. In addition, GA+XGBoost returns a value of objective function very close to the brute force for $\alpha = 0.5$, $\beta = 0.25$ and $\alpha = 0.25$, $\beta = 0.5$, indicating convergence to the near-optimal COPs. Although GA+XGBoost returns nearoptimal values in some cases, GA+XGBoost has significantly lower convergence time compared to brute force. For instance, the brute force needs to look at all the 4805 COP combinations to converge while the off-the-self GA takes 1200 iterations on average to converge as shown in Fig. 11. In addition, the convergence time of the proposed solution can be further reduced with SHAP sensitivity analysis inspired novel IMGA presented in the following subsection. This faster convergence is particularly useful for handovers and rapidly changing network conditions.

A. Intelligent Mutations in Genetic Algorithm

It has been observed in Section IV that $A5_{\text{th1}}$ and $A5_{\text{th2}}$ have the highest impact on all the three KPIs. The dependence SHAP analysis of the utility function for the two COPs is shown in Fig. 9 and can give insightful information that can be exploited to improve convergence time of the GA. As the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking



(a) Off-the-shelf-GA (b) IMGA

Fig. 10. Comparison between the structures of off-the-shelf GA and the proposed IMGA.

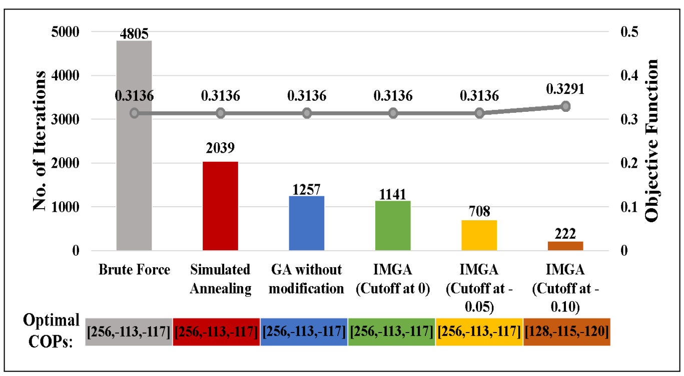


Fig. 11. Convergence time and objective function comparison between brute force, GA and intelligently mutated GA with different SHAP value cutoff.

optimization problem in (9) aims at minimizing the utility function, the values of the two COPs producing the negative impact on the utility should be chosen. Horizontal lines with green, yellow and brown color in Fig. 9 highlight cutoffs on SHAP values of 0, -0.05 and -0.10, respectively. All the values of $A5_{\text{th1}}$ and $A5_{\text{th2}}$ below the green have a negative impact on the utility and hence, should produce the minimum utility function. Similarly, the points below the yellow and brown lines have more negative values narrowing down the two COPs. We leverage this information for intelligent mutations in $A5_{\text{th1}}$ and $A5_{\text{th2}}$. The mutations of the two COPs are restricted to the values below each line to expedite the finding of the fittest offspring. The comparison of the mutation process of off-the-shelf GA and the proposed SHAP-based intelligent mutation process of IMGA is illustrated in Fig. 10(a) and 10(b), respectively. GA leverages the XGBoost COP-KPI model developed in Section IV along with eq. (9) for fitness evaluation. The faster convergence of IMGA stems from the intelligent mutation block, which restricts the mutations of $A5_{\text{th1}}$ and $A5_{\text{th2}}$ within the SHAP cutoff range. A COP mutation is only accepted if it is lies below the SHAP cutoff value.

The convergence time along with the corresponding objective function value and optimal COPs for brute force, simulated annealing, GA without modification and GA with intelligent mutations of $A5_{\text{th1}}$ and $A5_{\text{th2}}$ is shown in Fig. 11. A comparison of simulated annealing and GA without modification shows that even off-the-shelf GA converges quicker for the handover optimization problem compared to the simulated annealing. The newly designed SHAP enabled IMGA further accelerates the convergence widening the convergence time gap between simulated annealing and IMGA. These results show that IMGA is the best candidate solution for the optimization problem in eq. (9). It can be seen that lowering the cutoff of SHAP values for restricted mutations improves the convergence time of IMGA. The convergence time of IMGA for SHAP cutoff at 0, -0.05 and -0.10 improves by 4.2, 6.8 and 21.6 times, respectively, compared to brute force while GA without intelligent mutation is only 4 times faster. The faster convergence of IMGA comes without any degradation in the objective function compared to that returned by the GA without intelligent mutations when the cutoff is 0 and -0.05. However, a slight degradation of 0.0155 in the objective function is observed when the cutoff is -0.10. The fast convergence time can make the solution agile especially for fast changing network conditions. Compared to gold standard such self-optimization can improve the KPIs like RSRP, SINR and HOSR substantially.

VI. Conclusion

In the wake of densification and multi-band operation envisioned for emerging and future cellular networks, inter-frequency handovers can become a major bottleneck in user experience. This paper presents the first solution to systematically analyze and optimize three key mobility management COPs that dictate inter-frequency handover: $A5_{\text{th1}}$, $A5_{\text{th2}}$ and $A5_{\text{TTT}}$. The proposed optimization solution jointly optimizes three KPIs that contribute to user experience: RSRP, SINR and HOSR. As analytical modeling is not viable for such system level problem, we leverage data-driven approach. The insights from SHAP sensitivity analysis are used to address the training data scarcity problem and improve the training data through selective over-sampling in important range and under-sampling in less important range. SHAP sensitivity analysis shows that $A5_{\text{th2}}$ has the highest impact on RSRP, SINR and HOSR followed by $A5_{\text{th1}}$ and $A5_{\text{TTT}}$. State of the art machine learning techniques are used to develop a COP-KPI model. Results show XGBoost performs the best with RMSE of 0.0635dBm, 0.1995dB and 2.99% in predicting mean RSRP, mean SINR and HOSR, respectively. After showing that the joint RSRP, SINR and HOSR optimization problem is non-convex, we solve it with GA that converges 4 times faster than the brute force. We propose and utilize SHAP analysis based intelligent mutation scheme in GA. Results show that proposed scheme can lead to 21 times faster convergence in GA compared to brute force search at the cost of slightly sub-optimal objective function.

ACKNOWLEDGMENT

This work is supported by the National Science Foundation under Grant Numbers 1718956 and Qatar National Research Fund (QNRF) under Grant No. NPRP12-S 0311-190302. The statements made herein are solely the responsibility of the authors. For more details about these projects please visit: http://www.ai4networks.com

REFERENCES

[1] B. Romanous, N. Bitar, A. Imran, and H. Refai, "Network densification: Challenges and opportunities in enabling 5G," in *2015 IEEE 20th International Workshop on Computer Aided Modelling and Design of Communication Links and Networks (CAMAD)*, pp. 129–134, IEEE, 2015.

[2] A. Imran, A. Zoha, and A. Abu-Dayya, "Challenges in 5G: how to empower SON with big data for enabling 5G," *IEEE Network*, vol. 28, pp. 27–33, Nov 2014.

[3] S. M. A. Zaidi, M. Manalastas, H. Farooq, and A. Imran, "Mobility management in emerging ultra-dense cellular networks: A survey, outlook, and future research directions," *IEEE Access*, vol. 8, pp. 183505–183533, 2020.

[4] H. Ji, S. Park, J. Yeo, Y. Kim, J. Lee, and B. Shim, "Ultra-reliable and low-latency communications in 5G downlink: Physical layer aspects," *IEEE Wireless Communications*, vol. 25, no. 3, pp. 124–130, 2018.

[5] A. Lobinger, S. Stefanski, T. Jansen, and I. Balan, "Coordinating handover parameter optimization and load balancing in LTE self-optimizing networks," in *2011 IEEE 73rd Vehicular Technology Conference (VTC Spring)*, pp. 1–5, 2011.

[6] A. Asghar, H. Farooq, and A. Imran, "Concurrent optimization of coverage, capacity, and load balance in HetNets through soft and hard cell association parameters," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 9, pp. 8781–8795, 2018.

[7] H. Farooq, A. Asghar, and A. Imran, "Mobility prediction based proactive dynamic network orchestration for load balancing with QoS constraint (OPERA)," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3370–3383, 2020.

[8] H. Farooq, A. Asghar, and A. Imran, "Mobility prediction-based autonomous proactive energy saving (AURORA) framework for emerging ultra-dense networks," *IEEE Transactions on Green Communications and Networking*, vol. 2, no. 4, pp. 958–971, 2018.

[9] E. Balevi and J. G. Andrews, "Online antenna tuning in heterogeneous cellular networks with deep reinforcement learning," *IEEE Transactions on Cognitive Communications and Networking*, vol. 5, no. 4, pp. 1113–1124, 2019.

[10] 3GPP, "LTE; evolved universal terrestrial radio access network (E-UTRAN); self-configuring and self-optimizing network (SON) use cases and solutions (Release 9)," Technical Report (TR) 36.902, 3rd Generation Partnership Project (3GPP), 2011. Version 9.3.1.

[11] S. Manzoor, S. Mazhar, A. Asghar, A. Noor Mian, A. Imran, and J. Crowcroft, "Leveraging mobility and content caching for proactive load balancing in heterogeneous cellular networks," *Transactions on Emerging Telecommunications Technologies*, vol. 31, no. 2, 2020.

[12] K. Vasudeva, M. Simsek, D. López-Pérez, and I. Güvenç, "Analysis of handover failures in heterogeneous networks with fading," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 7, pp. 6060–6074, 2016.

[13] X. Xu, Z. Sun, X. Dai, T. Svensson, and X. Tao, "Modeling and analyzing the cross-tier handover in heterogeneous networks," *IEEE Transactions on Wireless Communications*, vol. 16, no. 12, pp. 7859–7869, 2017.

[14] S. M. A. Zaidi, M. Manalastas, H. Farooq, and A. Imran, "Syntheticnet: A 3GPP compliant simulator for AI enabled 5G and beyond," *IEEE Access*, vol. 8, pp. 82938–82950, 2020.

[15] 3GPP, "Technical Specification Group Radio Access Network; NR; Radio Resource Control (RRC) Protocol Specification (Release 16)," Technical Specification (TS) 38.331, 3rd Generation Partnership Project (3GPP), 03 2020. Version 16.0.0.

[16] P. Legg, G. Hui, and J. Johansson, "A simulation study of LTE intra-frequency handover performance," in *2010 IEEE 72nd Vehicular Technology Conference-Fall*, pp. 1–5, IEEE, 2010.

[17] T. Jansen, I. Balan, S. Stefanski, I. Moerman, and T. Kurner, "Weighted performance based handover parameter optimization in LTE," in *2011 IEEE 73rd vehicular technology conference (VTC Spring)*, pp. 1–5, IEEE, 2011.

[18] I. M. Bălan, B. Sas, T. Jansen, I. Moerman, K. Spaey, and P. Demeester, "An enhanced weighted performance-based handover parameter optimization algorithm for LTE networks," *EURASIP Journal on Wireless Communications and Networking*, vol. 2011, no. 1, p. 98, 2011.

[19] P. Muñoz, R. Barco, and I. de la Bandera, "On the potential of handover parameter optimization for self-organizing networks," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 5, pp. 1895–1905, 2013.

[20] R. D. Hegazy and O. A. Nasr, "A user behavior based handover optimization algorithm for LTE networks," in *2015 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1255–1260, IEEE, 2015.

[21] D. Castro-Hernandez and R. Paranjape, "Optimization of handover parameters for LTE/LTE-A in-building systems," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 6, pp. 5260–5273, 2017.

[22] K. D. C. Silva, Z. Becvar, and C. R. L. Frances, "Adaptive hysteresis margin based on fuzzy logic for handover in mobile networks with dense small cells," *IEEE Access*, vol. 6, pp. 17178–17189, 2018.

[23] B. Zhang, W. Qi, and J. Zhang, "An energy efficiency and ping-pong handover ratio optimization in two-tier heterogeneous networks," in *2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 532–536, IEEE, 2018.

[24] F. B. Tesema, A. Awada, I. Viering, M. Simsek, and G. Fettweis, "Evaluation of context-aware mobility robustness optimization and multi-connectivity in intra-frequency 5G ultra dense networks," *IEEE Wireless Communications Letters*, vol. 5, no. 6, pp. 608–611, 2016.

[25] S. S. Mwanje, L. C. Schmelz, and A. Mitschele-Thiel, "Cognitive cellular networks: A Q-learning framework for self-organizing networks," *IEEE Transactions on Network and Service Management*, vol. 13, no. 1, pp. 85–98, 2016.

[26] M. T. Nguyen, S. Kwon, and H. Kim, "Mobility robustness optimization for handover failure reduction in LTE small-cell networks," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 5, pp. 4672–4676, 2017.

[27] A. Alhammadi, M. Roslee, M. Y. Alias, I. Shayea, S. Alraih, and K. S. Mohamed, "Auto tuning self-optimization algorithm for mobility management in LTE-A and 5G HetNets," *IEEE Access*, vol. 8, pp. 294–304, 2019.

[28] J. Joseph, F. Ahmed, T. Jokela, O. Tirkkonen, J. Poutanen, and J. Niemela, "Big data enabled mobility robustness optimization for commercial LTE networks," in *2020 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–6, IEEE, 2020.

[29] M.-T. Nguyen and S. Kwon, "Geometry-based analysis of optimal handover parameters for self-organizing networks," *IEEE Transactions on Wireless Communications*, vol. 19, no. 4, pp. 2670–2683, 2020.

[30] T. Goyal and S. Kaushal, "Handover optimization scheme for LTE-Advance networks based on AHP-TOPSIS and Q-learning," *Computer Communications*, vol. 133, pp. 67–76, 2019.

[31] S. Chaudhuri, I. Baig, and D. Das, "Self organizing method for handover performance optimization in LTE-advanced network," *Computer Communications*, vol. 110, pp. 151–163, 2017.

[32] Y. Sun, G. Feng, S. Qin, Y.-C. Liang, and T.-S. P. Yum, "The smart handoff policy for millimeter wave heterogeneous cellular networks," *IEEE Transactions on Mobile Computing*, vol. 17, no. 6, pp. 1456–1468, 2017.

[33] Y. Sun, W. Jiang, G. Feng, P. V. Klaine, L. Zhang, M. A. Imran, and Y.-C. Liang, "Efficient handover mechanism for radio access network slicing by exploiting distributed learning," *IEEE Transactions on Network and Service Management*, vol. 17, no. 4, pp. 2620–2633, 2020.

[34] Y. Koda, K. Nakashima, K. Yamamoto, T. Nishio, and M. Morikura, "Handover management for mmwave networks with proactive performance prediction using camera images and deep reinforcement learning," *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 2, pp. 802–816, 2019.

[35] S. Khosravi, H. Shokri-Ghadikolaei, and M. Petrova, "Learning-based handover in mobile millimeter-wave networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 7, no. 2, pp. 663–674, 2020.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCCN.2022.3152510, IEEE Transactions on Cognitive Communications and Networking

[36] M. Manalastas, "Realistic modeling of handover events in a multi-carrier 5G network: A preliminary step towards COP-KPI relationship realization," *OU-Theses*, 2020.

[37] M. U. Bin Farooq, M. Manalastas, W. Raza, A. Ijaz, S. M. A. Zaidi, A. Abu-Dayya, and A. Imran, "Data driven optimization of inter-frequency mobility parameters for emerging multi-band networks," in *IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, 2020.

[38] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA); Radio Resource Control (RRC); Protocol specification," Technical Specification (TS) 36.331, 3rd Generation Partnership Project (3GPP), 09 2021. Version 16.0.0.

[39] A. Adadi and M. Berrada, "Peeking inside the black-box: A survey on explainable artificial intelligence (XAI)," *IEEE Access*, vol. 6, pp. 52138–52160, 2018.

[40] A. Ghasemi, "Predictive modeling of LTE user throughput via crowd-sourced mobile spectrum data," in *2018 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN)*, pp. 1–5, IEEE, 2018.

[41] C. C. F. Chu and D. P. K. Chan, "Feature selection using approximated high-order interaction components of the shapley value for boosted tree classifier," *IEEE Access*, vol. 8, pp. 112742–112750, 2020.

[42] S. IM, "Sensitivity estimates for nonlinear mathematical models," *Math. Model. Comput. Exp*, vol. 1, no. 4, pp. 407–414, 1993.

[43] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Advances in neural information processing systems*, pp. 4765–4774, 2017.

[44] L. S. Shapley, "A value for n-person games," *Contributions to the Theory of Games*, vol. 2, no. 28, pp. 307–317, 1953.

[45] A. B. Owen, "Sobol'indices and shapley value," *SIAM/ASA Journal on Uncertainty Quantification*, vol. 2, no. 1, pp. 245–251, 2014.

[46] J. Chen, Y. Deng, J. Jia, M. Dohler, and A. Nallanathan, "Cross-layer QoE optimization for D2D communication in CR-enabled heterogeneous cellular networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 4, no. 4, pp. 719–734, 2018.

[47] T. Yang, C. Han, M. Qin, and C. Huang, "Learning-aided intelligent cooperative collision avoidance mechanism in dynamic vessel networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 1, pp. 74–82, 2019.

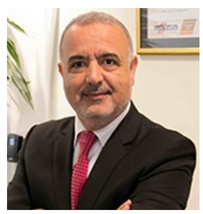
Muhammad Umar Bin Farooq received the BS degree in electrical engineering from Lahore University of Management Sciences in 2015 and MS degree in computer science from Information Technology University, Pakistan in 2018. He received another MS degree in electrical and computer engineering from University of Oklahoma in 2021. He is currently pursuing a Ph.D. degree in electrical and computer engineering at University of Oklahoma, where he is a part of AI4Networks research center. He has done multiple internships in AT&T Labs and Interdigital. His research interests include machine learning based zero-touch optimization for 5G and beyond networks.

Marvin Manalastas received a B.S. degree in electronics and communication engineering from the Polytechnic University of the Philippines in 2011, and an M.S. degree in electrical and computer engineering from The University of Oklahoma in 2020. He is currently pursuing a Ph.D. degree in electrical engineering with The University of Oklahoma, working AI4Networks Research Center. He has more than seven years of industry experience in the field of cellular network optimization in the Philippines and Japan. He did multiple internships in the USA and worked as an RF Optimization intern in Mobilecomm Professionals, TX, as an AI/ML intern for Synopsys, VA, and as a research fellow at US FDA, MA. His research interests include machine learning applied in the optimization of 5G and beyond networks.

Waseem Raza received the B.Sc. and M.Sc. degrees in Telecommunication Engineering from the University of Engineering and Technology, Taxila, in 2014 and 2016, respectively. He is currently pursuing his Ph.D. in Electrical and Computer Engineering from the University of Oklahoma, USA. His research interests include AI and ML techniques for 5G and beyond wireless networks.

Syed Muhammad Asad Zaidi received the B.Sc. degree in information and communication engineering from the National University of Science and Technology (NUST), Pakistan, in 2008, MS from Ajou University, South Korea in 2013, and PhD Electrical engineering from University of Oklahoma in 2021. With almost 13 years' experience in telecom industry, he has worked in Mobilink, Pakistan, Korea Electronics and Technology Institute (KETI), South Korea, MOTiV Research, Japan, AT&T, USA, Sprint, USA and T-Mobile, USA. Currently, he is leading 5G radio-frequency optimization team in T-Mobile networks. His research domain is mobility robustness and optimization of futuristic ultra-dense base station deployment.

Ali Rizwan received the bachelor's degree in applied and theoretical math in 2006, the MBA-IT degree in 2008, from Bahauddin Zakariya University, Pakistan and the M.Sc. degree in big data science from the Queen Mary University of London, London, U.K., in 2016, Ph.D. degree from the University of Glasgow, Glasgow, U.K, 2021. He is currently working as AI Research Scientist at Qatar Mobility Innovations Center (QMIC), Qatar University. He is active in the research in artificial intelligence for self-organizing wireless networks.



Adnan Abu-Dayya (Senior Member, IEEE) received the Ph.D. degree in digital mobile communications (electrical engineering) from Queen's University, Kingston, ON, Canada, in 1992. He worked with AT&T Wireless, Seattle, USA, for ten years, where he served in a number of senior management positions covering product innovations, emerging technologies, systems engineering, product realization, and intellectual property management. He is the Executive Director of Qatar Mobility Innovations Center, Doha, Qatar. He led the establishment of the Qatar Mobility Innovations Center in 2009. It is one of the first independent innovations institution in the Middle East focused on translating Research and Development and technology innovations into scalable digital platforms and solutions in the field of intelligent mobility and smart cities. He worked as a Senior Manager with the Advanced Technology Group, Nortel Networks, Canada, and as a Senior Consultant with the Communications Research Centre, Ottawa, ON, Canada. He has ten issued patents, and about hundred refereed publications. Dr. Abu-Dayya serves as the Chairman of the Advisory Board of the Electrical and Computer Engineering Department, Texas A&M University at Qatar, where he is a member of the Steering Committee of the Smart Grid Research Center.

Ali Imran (Senior Member, IEEE) is a Presidential Associate Professor and Willams Professor in ECE and founding director of the Artificial Intelligence (AI) for Networks (AI4Networks) Research Center and TurboRAN Testbed for 5G and Beyond at the University of Oklahoma. His research interests include AI and its applications in wireless networks and healthcare. His work on these topics has resulted in several patents and over 100 peer-reviewed articles including some of the highly influential papers in the domain of wireless network automation. On these topics he has led numerous multinational projects, given invited talks/keynotes and tutorials at international forums and advised major public and private stakeholders and co-founded multiple start-ups. He holds a B.Sc. degree in electrical engineering from the University of Engineering and Technology Lahore, Pakistan, in 2005, and the M.Sc. degree (Hons.) in mobile and satellite communications and the Ph.D. degree from the University of Surrey, Guildford, U.K., in 2007 and 2011, respectively. He is an Associate Fellow of the Higher Education Academy, U.K. He is also a member of the Advisory Board to the Special Technical Community on Big Data, the IEEE Computer Society.