# AI-Assisted RLF Avoidance for Smart EN-DC Activation

Syed Muhammad Asad Zaidi*, Marvin Manalastas*, Adnan Abu-Dayya†, and Ali Imran*
*AI4Networks Research Center, University of Oklahoma-Tulsa, USA
†Department of Electrical Engineering, Qatar University, Doha Qatar
Email: {asad, marvin, ali.imran}@ou.edu, adnan@qu.edu.qa

***Abstract*—In the first phase of 5G network deployment, User Equipment (UE) will camp traditionally on LTE network. Later on, if the UE requests a 5G service, it will be made to camp simultaneously on LTE and 5G. This dual-camping is enabled through a 3GPP-standardized approach known as E-UTRAN New-Radio Dual-Connectivity (EN-DC). Unlike single-network-camping, where poor RF conditions of only one network affect user Quality-of-Experience (QoE), in EN-DC, poor RF condition in either LTE or 5G network can be detrimental to user QoE. Sub-optimal parameter configuration to activate EN-DC can hamper retainability KPI as UE may observe increased radio link failure (RLF). While the need to maximize the EN-DC activation is obvious for 5G network maximum utility, RLF avoidance is equally important to maintain the QoE requirements. We address this problem by first using Tomek Link to counter data imbalance problem and then building an AI model to predict RLF from real network low level measurements. We then propose and evaluate an RLF risk-aware EN-DC activation scheme that draws on insights from the developed RLF prediction model. Simulation using a 3GPP-compliant 5G simulator show that compared to no-conditioning on EN-DC activation, in the evaluated cell cluster, the proposed scheme can help reduce the potential RLF instances by 99%. This RLF reduction happens at the cost of 50% reduction in EN-DC activation. This is first study to present a framework and insights for operators to optimally configure the EN-DC activation parameters to achieve desired trade-off between maximizing 5G sites utility and QoE.**

***Index Terms*—5G, New Radio, EN-DC, Radio Link Failure, Artificial Intelligence**

## I. Introduction

5G with innovative use cases of enhanced Mobile Broadband (eMBB) for large volume transmissions, massive Machine Type Communications (mMTC) for sensors and IoT devices, and Ultra Reliable Low Latency Communications (URLLC) for self-driven comes with unprecedented Quality of Experience (QoE) goals. Studies project that 5G subscriptions will top 2.6 billion by the end of 2025 [1].

While in 5G the capacity crunch will be addressed primarily by ultra-dense base station deployment and mmWave band utilization, ensuring QoE with a conglomeration of new and legacy technologies remains an open challenge of great importance.

As per 3GPP Release 15 specification 37.863 [2], E-UTRAN New Radio Dual Connectivity (EN-DC) allow 5G capable User Equipments (UEs) to simultaneously connect to an LTE eNodeB (eNB) that acts as a master node and a 5G gNodeB (gNB) that acts as a secondary node. This non-standalone 5G network deployment will help mobile operators to reduce the capital expenditure (CAPEX), and will accelerate the penetration of 5G networks even in developing countries with already deployed LTE network. However, the added complexity involves signaling and the decision when to activate/deactivate EN-DC mode.

While the goal is to effectively push UE to dual connectivity with 5G gNB as soon as possible, sub-optimal configuration can lead to excessive amount of ping-pong EN-DC activation/deactivation and repeated Radio Link Failures (RLFs). By accelerating the EN-DC activation in an attempt to increase network efficiency, EN-DC may be triggered at poor RF conditions at either LTE or 5G network. This can result in call disconnect and service interruption. Following the service disruption, repeated re-accessibility attempts not only increases signaling but degrade UE energy efficiency as well. Thus, optimal configuration to activate/deactivate EN-DC is essential to maintain the expected QoE and network efficiency of 5G network.

### A. Related Work

Intra-frequency and inter-frequency dual-connectivity have been studied extensively in literature [3]–[6]. A detailed review of these studies can be found in a recent survey on the topic of mobility management in emerging networks [7]. However, to the best of Author's knowledge no study in existing literature addresses the optimal conditions to activate dual-connectivity between two different mobile technologies viz a viz 4G and 5G. Moreover, RLF instances in context of dual-connectivity have not been studied extensively either.

RLF is the temporary radio link disruption from the serving cell either due to poor signal strength or quality, or because of incorrect handover (HO) configuration. Most of the RLF related literature [8]–[11] addresses intra-frequency HO issues by controlling the system common parameters. For example, in [8], time-to-trigger (TTT) and HO margin are adjusted based on type of RLF observed during HO. Similarly, [9] considers tuning A3-offset to prevent RLF between intra-frequency neighbors. Authors in [10] categorize HO failure into too early, too late and wrong cell HO to adjust TTT and A3-offset accordingly.

Apart from optimizing intra-frequency HO parameters, authors in [11] propose transmission power changes to adjust coverage holes. RLF detection approach in [12] uses RF threshold to detect possible RLF situation and accelerates HO to a better cell if available. However, the mechanism of setting appropriate RF threshold, is not defined.

Most of the RLF prevention approaches in literature target intra-frequency HO optimization and do not discuss actual measurement thresholds to detect possible RLF. There is a

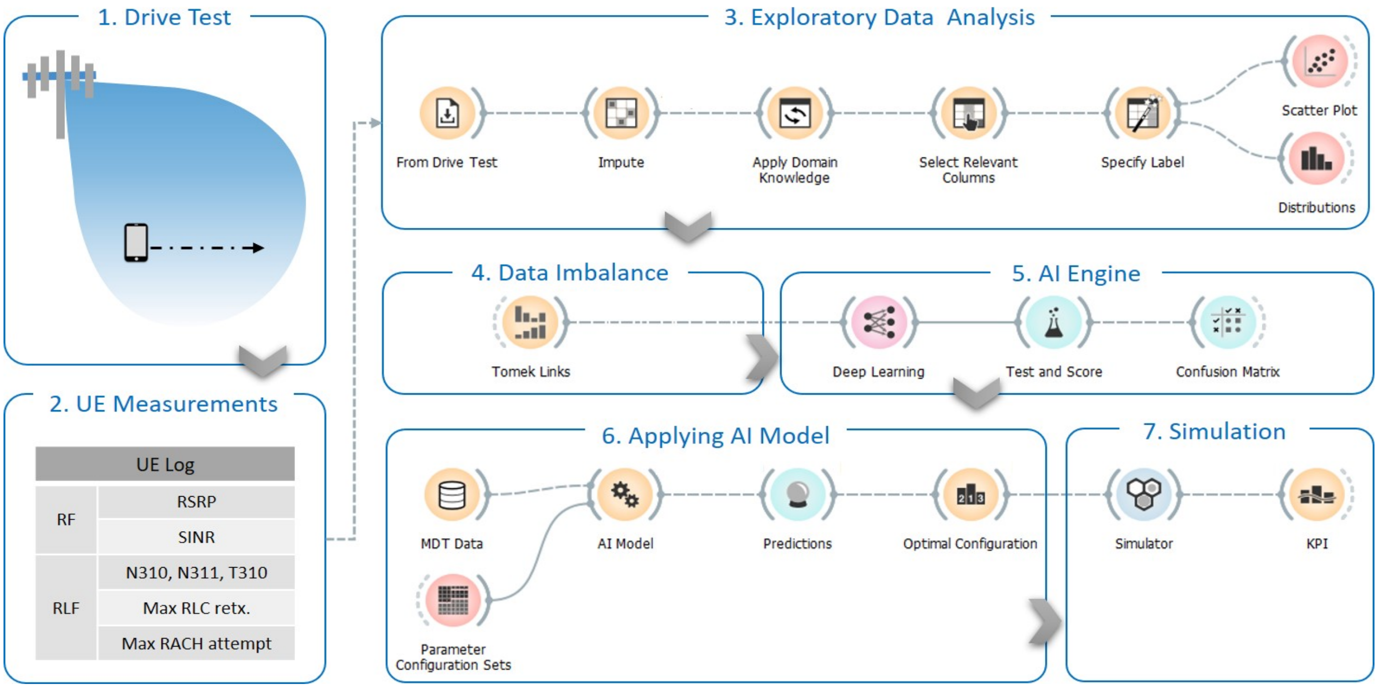


Figure 1: High Level overview of the proposed AI-Enabled EN-DC activation.

need to devise an approach to detect potential RLF threshold (signal strength and quality) and utilize that information to configure optimal inter-RAT parameters for EN-DC activation.

### *B. Contribution*

The importance of minimizing RLF to maintain QoE can not be overemphasized, and several studies have already analyzed the RLF problem as explained earlier. To the best of the authors' knowledge, this is the first study to leverage real network data measurements for devising a model to predict potential RLF. Potential RLF thresholds are obtained by taking into account the 3GPP [13] based low level measurements (N310, T310, maximum RACH attempt, maximum RLC retransmission). We use data labelled as potential RLF instead of focusing only on the actual RLF to minimize the data imbalance problem and to incorporate the problematic instances that lead to actual RLF. Moreover, we use Tomek Links approach to further increase the classification accuracy for the AI model developed to predict the potential RLF cases. A deep learning based model is designed and trained to predict potential RLF and consequently determine a suitable EN-DC activation configuration. The proposed RLF prediction aware activation method for EN-DC mode ensures that the benefits of higher throughput and low latency can be achieved via the optimal use of EN-DC without compromising the UE QoE due to RLF at either LTE or 5G network.

The rest of the paper is organized as follows. Section II provides brief description of 3GPP standard based EN-DC mode and RLF trigger. Real LTE network measurement data recording, exploration and development of Artificial Intelligence (AI) model to predict potential RLF is presented in Section III. Since the RLF criteria is same in LTE and 5G NR, the learned AI model is applicable for both LTE and 5G NR. Simulation data in Section IV shows how MDT data can be used to determine suitable EN-DC activation configuration parameters while minimizing chances of RLF by making use of the AI based RLF prediction model developed in Section III. Section V concludes the paper.

## II. Background

### *A. EN-DC in 3GPP Release 15*

A major focus of 3GPP Release 15 [2] is to get a first incarnation of 5G into the field that complements 4G LTE. Primarily due to the higher frequency bands standardized in 5G networks, it is deemed better to enable UEs to connect simultaneously to LTE and 5G New Radio (NR). This is referred to as Dual Connectivity option 3X or E-UTRAN New Radio Dual Connectivity (EN-DC).

UE traditionally camps on LTE eNB, referred to as the Master Node (MN) in EN-DC. Later on, the network may attempt to initiate EN-DC if the UE initiates the services that can be benefited by EN-DC, and if both the UE and network supports EN-DC mode. First, the MN sends the EN-DC configuration with the target 5G frequency and event B1 measurement criteria to the UE.

EN-DC capable UE then starts measuring RF condition of the target EN-DC frequency as configured by the MN. UE sends event B1 to the MN if as per the configuration the Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ) or Signal to Interference and Noise Ratio (SINR) of the 5G cell becomes better than the threshold. Event B1 encapsulates RSRP of the MN, and RSRP and SINR of the target 5G cell. MN can apply further filtration on the RF information inside the received B1 report. MN communicates with the 5G gNB and EN-DC is activated after the admission control check and capability enquiry. 5G gNB upon EN-DC activation is referred to as Secondary Node (SN). UE can now benefit from the services provided by both LTE and 5G network as long as the RF condition of both networks is good otherwise RLF followed by service disruption is observed. Note that signaling is provided to the UE by MN only, hence, LTE RF condition need to be good as well.

### *B. Radio Link Failure in 3GPP*

The event where UE abnormally detaches its connection with the serving cell is known as RLF. RLF procedure in 5G networks is same as in LTE, and is described here.

RLF is observed when either of the following three conditions are met consecutively for a certain period. Each of the RLF condition is controlled by one or more parameters.

- Upon timer T310 expiry after configured consecutive out-of-sync indication represented by N310 counter.
- After the configured number of consecutive unsuccessful RACH attempts have been reached.
- When the configured number of consecutive RLC retransmissions have been reached.

Parameters corresponding to each condition are incremented every time the underlying problem is observed, and RLF is observed upon fulfilment of the threshold condition. A network operator may configure a higher threshold to avoid RLF. However, in that case, UE will be stuck in the poor RF conditions. Though RLF causes poor user experience temporarily, it gives the UE under poor RF condition a chance to reset its current struggling connection and camp on the cell having a better coverage. Optimization of these RLF related parameters to minimize the RLF are beyond the scope of this paper and can be the subject of a future study. Here we are interested in developing a model that can predict the RLF failure and thus can be used for smart EN-DC activation decision.

## III. AI MODEL FOR RLF PREDICTION TO ENABLE SMART EN-DC ACTIVATION

This section describes how actual measurement data from a real LTE network is collected to develop a deep learning based AI-model to help identify the set of RSRP and SINR conditions that correspond to potential RLF. This model is then used to help activate EN-DC mode after the MN receives the RSRP and SINR of the MN and SN in the B1 report from the EN-DC capable UE. Since the RLF criteria is same in LTE and 5G NR, the proposed RLF prediction AI model is applicable for both LTE and 5G NR. Fig. 1 illustrates the high level overview of the proposed AI powered EN-DC activation method.

### *A. Data Collection, Cleansing and Pre-Processing*

Drive test is conducted for 13 hours and RSRP, SINR measurement are recorded at an interval of 100ms. Moreover, the low level RLF related parameters mentioned in Section II-B are also registered. Out of the 0.45 million data samples recorded, only 543 actual RLF ($\sim$7 RLF every 10 minutes) are observed. This data if used as it is to train a model can lead to a poorly performing model due to the class imbalance in the training data. For that reason, and to incorporate all the chances of possible RLF, using domain knowledge we mark those rows of the data as potential RLF where even though actual RLF is not observed but the underlying RLF parameters showed abnormality.

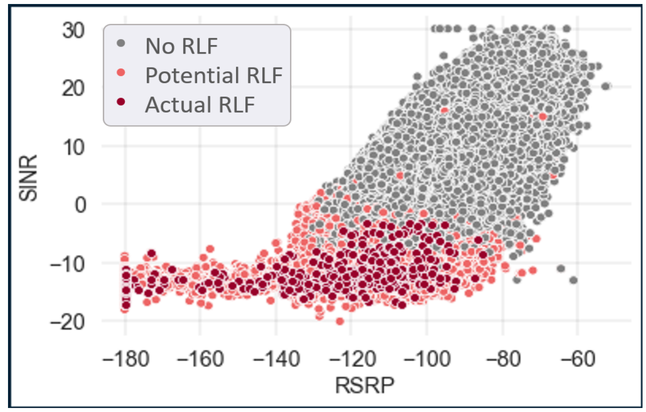


Figure 2: Potential RLF occurrences versus the UE RSRP and SINR measurements.

Next, some of the RLF parameters were not received in sync with the RSRP and SINR information, so empty cells were filled in with the relevant RF information. Empty cells were filled while keeping in view the correct serving cell during the HO procedure. Fig. 2 shows the potential RLF occurrences versus the UE RSRP and SINR measurements recorded during the drive test. The tail of the scatter plot in the bottom left area are poor RSRP samples due to late HO instances, where UE is unable to perform HO to best cell due to poor SINR. Ultimately, RLF occurs and UE camps on cell with the best signal strength.

### *B. Ways to Address Data Imbalance Problem*

We have used several approaches to address the problem of accuracy paradox, where the high accuracy of machine learning model is driven by the majority class, and the minority class shows poor performance. In our case, minority class is the more significant potential RLF class, and hence, data imbalance problem should be addressed. Now, we will briefly discuss some approaches to address data imbalance problem.

- Random over-sampling randomly duplicates observations from the minority class to reinforce its signal.
- Synthetic Minority Oversampling Technique (Smote) synthesises new minority instances.
- Random under-sampling randomly removes observations from the majority class.
- Near Miss is the synthetic under-sampling of the minority class. Near Miss selects examples from the majority class that have the smallest average distance to the three closest examples from the minority class.
- A pair of data instances (a and b) belonging to different classes is called a Tomek link (a,b) if there is no instance c such that the distance $d(a,c) < d(a,b)$ or $d(b,c) < d(a,b)$. Instances participating in Tomek links are either borderline or noise so both are removed.
- Edited Nearest Neighbor Rule (ENN) removes any instance whose class label is different from the class of at least two of its three nearest neighbors.
- Neighborhood Cleaning Rule (NCL) checks three nearest neighbors of each instance belonging to majority or

Table I: Accuracy and F-1 score of the minority class (potential RLF class) for various data-imbalance resolution techniques.

| Classification Algorithm | Metric | Raw Data | Random over sampling | Smote | Random under sampling | Near Miss | Tomek Links | ENN | NCL |
|---|---|---|---|---|---|---|---|---|---|
| Regression | Accuracy | 97.3% | 88.1% | 88.8% | 87.9% | 95.3% | 97.3% | 97.1% | 97.1% |
| KNN | Accuracy | 97.6% | 97.6% | 95.3% | 97.6% | 87.6% | 97.5% | 87.6% | 97.2% |
| SVM | Accuracy | 97.4% | 88.9% | 88.3% | 88.6% | 92.2% | 96.6% | 92.2% | 97.1% |
| Naive Bayes | Accuracy | 96.6% | 88.1% | 89.6% | 96.6% | 95.2% | 96.6% | 95.2% | 96.3% |
| XGBoost | Accuracy | 97.6% | 93.1% | 91.3% | 91.3% | 78.4% | 97.6% | 97.3% | 97.3% |
| Decision Trees | Accuracy | 96.9% | 98.3% | 89.5% | 89.5% | 47.6% | 96.9% | 96.2% | 97.2% |
| Random Forest | Accuracy | 97.6% | 98.4% | 92.6% | 92.6% | 57.5% | 97.6% | 97.1% | 97.2% |
| Deep Learning | Accuracy | 97.4% | 88.9% | 88.1% | 88.8% | 91.2% | 98.4% | 96.9% | 97.9% |
| Regression | F1 | 0.75 | 0.88 | 0.94 | 0.88 | 0.68 | 0.74 | 0.74 | 0.74 |
| KNN | F1 | 0.78 | 0.78 | 0.68 | 0.78 | 0.44 | 0.78 | 0.44 | 0.77 |
| SVM | F1 | 0.78 | 0.78 | 0.68 | 0.78 | 0.44 | 0.78 | 0.44 | 0.74 |
| Naive Bayes | F1 | 0.7 | 0.88 | 0.5 | 0.7 | 0.66 | 0.7 | 0.66 | 0.69 |
| XGBoost | F1 | 0.78 | 0.93 | 0.91 | 0.91 | 0.31 | 0.78 | 0.78 | 0.78 |
| Decision Trees | F1 | 0.75 | 0.94 | 0.9 | 0.9 | 0.16 | 0.81 | 0.73 | 0.74 |
| Random Forest | F1 | 0.79 | 0.95 | 0.92 | 0.92 | 0.2 | 0.88 | 0.78 | 0.79 |
| Deep Learning | F1 | 0.74 | 0.88 | 0.88 | 0.88 | 0.32 | 0.95 | 0.8 | 0.81 |

minority class, and removes them if the neighboring data instances are mis-classified, then those nearest neighbors are removed.

Now, we will talk about the training, testing and validation of the machine learning algorithms evaluated after applying the data imbalance resolution approaches discussed above.

### *C. Model Building and Validation*

The prepared data was scaled and later used to train and test several AI techniques for creating a best performing model for RLF prediction as function of observed RSRP and SINR. The gathered data is periodically split into a 30:70 ratio of training and test dataset. The classification based machine learning models using KNN, decision trees, regression, deep learning etc. are developed and evaluated. Table I shows the accuracy and F1 score of minority class (potential RLF class) for various machine learning models trained on the same data to predict RLF. F1 score observed for majority class for all the machine learning algorithms is higher than 0.9 and has been not included in Table I. Deep learning with data imbalance problem addressed by Tomek links shows the best results in terms of both accuracy and F1 score. Tomek Links work on the class boundary to help slightly improve the isolation between the overlapped classes by removing majority samples at the border area.

Deep Neural Network algorithm belongs to a special class of machine learning, called deep learning and creates a multi-layer perceptron to find the input-output associations. Its basic structure consists of an input layer, output layer and one or more hidden layers between them, each containing several neurons (or nodes). Neurons in the input layer equals the number of input features, whereas output layer consists of one neuron which holds the prediction output. Number of hidden layers and its neurons are variable, and depends on the complexity of model it is trying to learn. Deep learning model with a variety of hyper-parameters to prevent under- or over-fitting were tried as shown in table II. Best result is obtained using deep learning model with fully connected three hidden layers having 16, 16 and 8 neurons respectively as shown in the Fig. 3. The model was learned using epoch size of 50 and batch size of 1.

Table II: Deep Learning Hyperparameters

| Hyperparameter Name | Search Range/Value |
|---|---|
| DNN depth d | {1,2,3,5} |
| DNN width w | {5,8,10,16} |
| Activation Function (Hidden Layers) | Relu |
| Activation Function (Output Layers) | Sigmoid |
| Optimizer | Adam (Gradient Descent) |
| Loss Metric | Binary Cross Entropy |

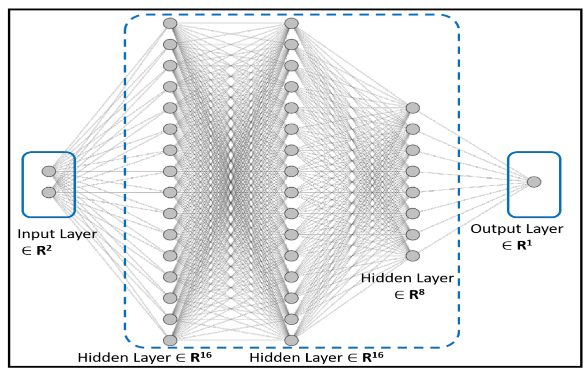


Figure 3: Structure of the deep learning model used for the training, testing and validating of the processed data.

### *D. Suitable EN-DC parameters*

This subsection explains how we can use MDT data from a real network to devise a smart EN-DC activation scheme. The goal is to maximize the chances of EN-DC trigger, but at the same time avoid chances of RLF for both LTE and NR. The input MDT data from 4G LTE and 5G NR can be fed into the AI model to predict the potential RLF instances for both LTE and NR. We then apply several combinations of RSRP and SINR parameters to evaluate the configured parameters in terms of potential RLF.

Since Minimization of Drive Test (MDT) data is currently unavailable in the existing networks, particularly due to huge data and processing requirements, we evaluate our proposed model using a state of the art 3GPP compliant cellular network simulator called SyntheticNET [14].

## IV. Simulation Results

This section first discusses the network deployment specifications used in the SyntheticNET simulator [14], followed

Table III: Simulation Details

| Technology | 4G LTE | 5G NR |
|---|---|---|
| Frequency | 2.1GHz | 3.5GHz |
| Cell Type | Macro Cell | Small Cell |
| Antenna Type | Directional | Omni (for hotspots) |
| Number of Cells | 27 | 16 |
| Transmit Power | 40dBm | 30dBm |
| Base Station Height | 30m | 20m |

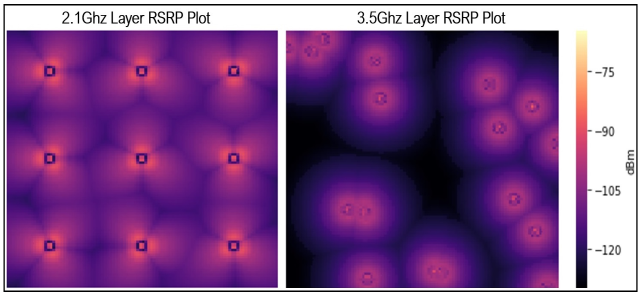


Figure 4: RSRP plot of deployed 4G and 5G network.

by EN-DC activation criteria. The measurements from the simulator are fed into the AI model to reveal potential RLF scenarios. Finally, we elucidate the proposed scheme to determine the smart EN-DC activation criteria.

A multi-RAT (Random Access Technology) network with nine macro LTE eNBs each having three sectors, and sixteen higher frequency omni directional 5G gNBs are deployed in a square of 25km$^2$ area. LTE eNBs are laid out uniformly in a grid form, while 5G small cells are deployed randomly representing hotspot locations. A total of 300 mobile UEs traverse the area following random way point mobility model. RSRP plot of the deployed network is shown in the Fig. 4. Speed of the users is set to 120km/h and the simulation run for 12,000ms. More detail about the network configuration can be found in Table III.

UEs are configured to measure RF condition of 5G gNB every 0.5s, and B1 measurement report is sent to the MN if the B1 criteria is met. B1 configuration can be varied to increase the number of B1 reports. This leads to an increase in EN-DC activation rate. However, the number of RLF at either LTE or 5G side increase as well. This relationship between number of B1 reports and potential RLF occurrences has been shown in Fig. 5. Fig. 5 signifies the need for a smart EN-DC activation scheme i.e.,the importance of optimally assigning B1 threshold. An incorrect B1 threshold may deteriorate retainability Key Performance Indicator (KPI) through large number of RLF instances at either LTE or 5G side.

For demonstration purposes, we set B1 configuration as -120dBm for RSRP, which ensures that the UE will send B1 report to the MN if 5G gNB RSRP is more than -120dBm. B1 threshold of -120dBm generates 7206 B1 reports as shown in Fig. 5. RLF occurrences is minimized by having another check at MN before initiating EN-DC activation process. Event B1 report encapsulates RSRP of MN, along with RSRP and SINR of 5G gNB. Note that SINR reporting is supported by 5G NR and not by 4G LTE.

Next, the MN also applies another condition on RF measurement reported by UE in the B1 report. This is an optional condition not defined by 3GPP, but vendors can implement it to ensure that both RSRP and SINR of both technologies are above certain thresholds. In this way, QoE can be guaranteed by minimizing RLFs.

Now we explain the procedure to define the LTE RSRP, 5G RSRP and 5G SINR threshold by taking into account the potential RLF predicted by the AI model. Note that its not necessary to implement all three thresholds, and only one or two thresholds can be implemented at MN for triggering EN-DC mode.

Fig. 6, 7 and 8 shows the statistics of successful SN addition (EN-DC activation) by varying 5G SINR, 5G RSRP and LTE RSRP thresholds described earlier. Upon receiving B1 report from EN-DC capable UE, MN checks for the configured threshold(s). MN communicates with with SN for EN-DC activation only if the RF condition as reported in the B1 report is higher than the configured threshold(s). For example, if configured thresholds are -100dBm and -90dBm for LTE RSRP and 5G RSRP respectively, MN will attempt to add SN only if the RSRP values for LTE and 5G is higher than -100dBm and -90dBm irrespective of 5G SINR.

Fig. 6 shows that without any threshold configured at MN, there will be 7206 EN-DC activations (same as B1 reports send by UE). However, 2403 out of the 7206 EN-DC activations may be followed by RLF. As we configure SINR condition at MN, the number of potential RLF occurrences decrease. This trend becomes more prominent as SINR threshold is increased. However, the number of SN

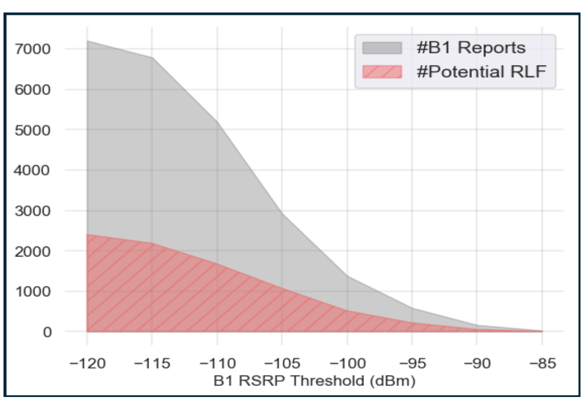


Figure 5: Number of UE generated B1 reports (EN-DC activation requests) against RSRP threshold.

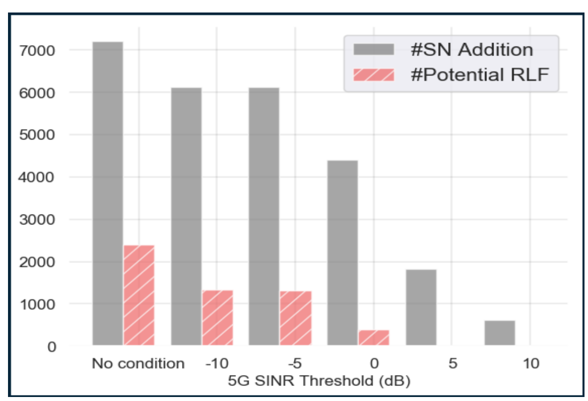


Figure 6: Effect of 5G SINR threshold on successful EN-DC activations (constant 5G and LTE RSRP thresholds of -120dBm).

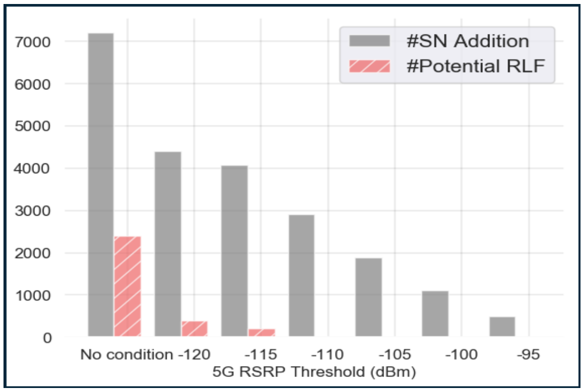


Figure 7: Effect of 5G RSRP threshold on successful EN-DC activations (with constant 5G SINR and LTE RSRP thresholds of 0dB and -120dBm respectively).

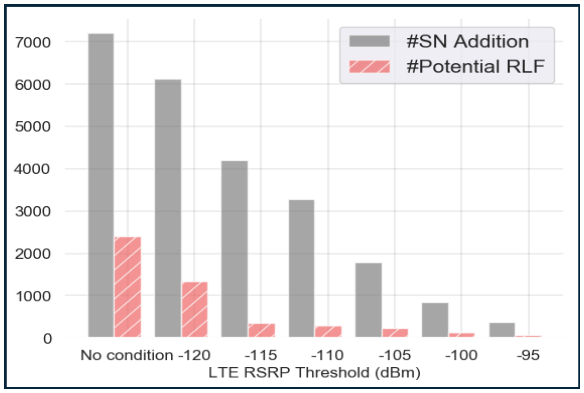


Figure 8: Effect of LTE RSRP threshold on successful EN-DC activations (with constant 5G SINR and RSRP thresholds of 0dB and -120dBm respectively).

addition attempts decreases as well. SINR threshold should be configured while keeping this trade-off in mind. For the particular scenario analyzed in this study, we can use SINR threshold of 0dB since the number of SN attempt is large and potential RLF occurrences are few.

Potential RLF occurrences can further be decreased by having configured the 5G RSRP and or LTE RSRP threshold at MN. Fig. 7 and 8 illustrate the impact of changing 5G RSRP threshold and LTE RSRP threshold respectively. 5G RSRP can be set as -110dBm to achieve 2922 SN additions with just 14 potential RLF occurrences (Fig. 7). This gives a 99% reduction in RLF occurrences. Conversely, we can set 5G RSRP threshold as -120dBm (same as B1 threshold) and can assign LTE RSRP threshold as -110dBm to have 3283 SN addition attempts. However, with this case, 292 RLF are observed.

## V. Conclusion

EN-DC mode addresses strict QoE requirements of the UE by enabling multi-connectivity to 4G and 5G cells. However, multi-connectivity can be beneficial only if the RF condition of participating 4G and 5G cells are above a certain threshold. Currently, there does not exist EN-DC mode selection scheme in literature that takes into account the risk of RLFs. This paper proposes a smart EN-DC triggering scheme by which RLF due to poor RF conditions can be minimized. The scheme works by selecting the best B1 thresholds based on insights from a Deep learning based AI model to predict RLF. The core RLF prediction model is developed, trained and validated using real networks measurements of RSRP, SINR and underlying 3GPP based RLF related parameters. The value of these low level parameters are used to identify potential RLF against RSRP, SINR values. We use Tomek Links approach to enhance the classification accuracy. Simulation results based on a state of the art 3GPP compliant network simulator show that for the presented network deployment, compared to no smart conditioning on EN-DC i.e. without using proposed scheme, RLF can be reduced from 2403 cases to just 14 potential RLF cases when using 5G SINR and RSRP threshold of 0dB and -110dBm respectively as per proposed scheme.

## Acknowledgment

This work is supported by the National Science Foundation under Grant Numbers 1718956 and 1730650 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] Ericsson, “Ericsson Mobility Report: 5G subscriptions to top 2.6 billion by end of 2025,” Tech. Rep., 2019.

[2] 3GPP, “37.863 - E-UTRA (Evolved Universal Terrestrial Radio Access) - NR Dual Connectivity (EN-DC) of LTE 1 Down Link (DL) / 1 Up Link (UL) and 1 NR band,” Tech. Rep., 2019.

[3] F. B. Tesema, A. Awada, I. Viering, M. Simsek, and G. P. Fettweis, “Mobility modeling and performance evaluation of multi-connectivity in 5g intra-frequency networks,” in *2015 IEEE Globecom Workshops (GC Wkshps)*, 2015, pp. 1–6.

[4] D. Öhmann, A. Awada, I. Viering, M. Simsek, and G. P. Fettweis, “Achieving high availability in wireless networks by inter-frequency multi-connectivity,” in *2016 IEEE International Conference on Communications (ICC)*, 2016, pp. 1–7.

[5] M. Boujelben, S. Ben Rejeb, and S. Tabbane, “A novel mobility-based comp handover algorithm for lte-a / 5g hetnets,” in *2015 23rd International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, 2015, pp. 143–147.

[6] D. S. Wickramasuriya, C. A. Perumalla, K. Davaslioglu, and R. D. Gitlin, “Base station prediction and proactive mobility management in virtual cells using recurrent neural networks,” in *2017 IEEE 18th Wireless and Microwave Technology Conference (WAMICON)*, 2017, pp. 1–6.

[7] Syed Muhammad Asad Zaidi, Marvin Manalastas, Hasan Farooq, and A. Imran, “Mobility Management in 5G and Beyond: A Survey and Outlook (Submitted),” *IEEE ACCESS*, 2020.

[8] A. Alhammadi, M. Roslee, M. Y. Alias, I. Shayea, and S. Alraih, “Dynamic handover control parameters for lte-a/5g mobile communications,” in *2018 Advances in Wireless and Optical Communications (RTUWO)*, 2018, pp. 39–44.

[9] Y. Mal, J. Chen, and H. Lin, “Mobility robustness optimization based on radio link failure prediction,” in *2018 Tenth International Conference on Ubiquitous and Future Networks (ICUFN)*, 2018, pp. 454–457.

[10] 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, 2018.

[11] M.-h. Song, S.-H. Moon, and S.-J. Han, “Self-optimization of handover parameters for dynamic small-cell networks,” *Wireless Communications and Mobile Computing*, vol. 15, no. 11, pp. 1497–1517, 2015. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/wcm.2439

[12] J. Puttonen, J. Kurjenniemi, and O. Alanen, “Radio problem detection assisted rescue handover for lte,” in *21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, 2010, pp. 1752–1757.

[13] 3GPP, “Evolved Universal Terrestrial Radio Access (E-UTRA); Radio Resource Control (RRC) Protocol Specification,” Tech. Rep., 2016.

[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*, pp. 1–1, 2020.