Machine Learning-Based Handover Failure Prediction Model for Handover Success Rate Improvement in 5G

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***Abstract*—This paper presents and evaluates a simple but effective approach for substantially reducing inter-frequency handover (HO) failure rate. We build a machine learning model to forecast inter-frequency HO failures. For improved accuracy compared to the state-of-the-art models, we use domain knowledge to identify and leverage the model input features. These features include reference signal received power (RSRP) of the source and target base stations as well as the RSRP of the interferers for both the source and the target layers. Six machine learning classifiers are tested with the highest accuracy of 93% observed for the XGBoost classifier. The novel idea to include the RSRP of the interferes improved the accuracy of XGBoost by 10%.**

***Index Terms*—Inter-Frequency Handover, Handover Failure Prediction, Machine Learning Classifiers**

I. Introduction

In a cellular network, handover failures (HOF) happen when the signal condition between the user equipment (UE) and base station (BS), both the source and target, is not good enough. Aside from that, sub-optimally tuned handover parameters might also lead to HOF. One way to minimize HOF is to tune HO related parameters, i.e., offset, hysteresis, cell individual offset (CIO) and, time-to-trigger (TTT) [1], [2]. Additionally, tuning of hard parameters such as tilt, azimuth and transmit power helps alleviate HOF issues by improving the coverage and reducing interference. Parameter tuning mostly involves deep domain knowledge but sometimes end up with a hit and trial approach. This approach to mitigate HOF is also time-consuming and requires a lot of human interventions making it prone to errors. Some self-organizing network (SON) solutions such as mobility robustness optimization (MRO) can automate the process to some extent by automatically adjusting the CIO values based on HO performance to execute HO earlier or later. However, this approach is not proactive and most of the time conflicts with other SON solution, such as mobility load balancing (MLB). In addition, most commercially available MRO SON solution essentially rely on automated hit and trial or, at best, some heuristic to determine the CIO values, yielding mixed results. Recently, machine learning (ML) techniques have also been utilized to mitigate HOF occurrence. With ML, the process of minimizing HOF can be proactive, less dependent on hit and trial, less time consuming, and less prone to human errors [3].

We present a novel approach for advanced HOF prediction by using the reported RSRP of the source and target BS. We leverage the fact that the UEs report the RSRP of not just the target and serving BS but also the RSRP of the five strongest interferers of source and target layers. The intelligent use of the RSRP of serving and target interferers as input features to the ML model along with the RSRP of the serving and target BS helps to improve the accuracy of the prediction model compared to studies that rely on prediction of RSRP of serving cell alone to predict and optimize HOSR [4]–[6]. To overcome the class imbalance between the successful HO and failed HO data points in the training data, we use Synthetic Minority Oversampling Technique (SMOTE).

II. Machine Learning Models for HO Failure Prediction

We have modeled HOF prediction as a binary class classification problem. With classification, labels of the data points are predicted by mapping input features (X) to discrete labels (y). In our study, input features (X) include the measurements that a UE sends to the BS which trigger handover. These include the RSRP values of the serving and target BS as well as up to 5 strongest interferers for both serving and target layer. UE can report these RSRP values when the event is triggered. The RSRP values are saved at the start of the TTT when the entering condition of the event becomes true for the first time. Each of the RSRP combinations (X) are labeled as either HO success (HOS) or HOF. This HOS and HOF represents the discrete classes (y). Six classification techniques are evaluated namely Support Vector Machine (SVM), Naive Bayes Classifier (NBC), Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and k-Nearest Neighbors (KNN). These models are selected based from their effectiveness as binary classifiers, their performance with small data set and the ease of implementation.

A. Dealing with the Class Imbalance Problem

Majority of the samples are HOS with few HOF in the dataset. This phenomenon wherein the number of samples of one class dominate the other is called class imbalance. Training models directly using unbalanced data is not recommended as it might lead to model poorly learning the decision boundary. Therefore, to address the imbalance issue, we have

Table I: Performance Metrics for Different Machine Learning Classifiers

Performance Metrics	Support Vector Machine	Decision Tree	Random Forest	XGBoost	KNN	Naïve Bayes
Precision	79%	79%	85%	90%	79%	67%
Sensitivity	93%	88%	94%	95%	100%	79%
Specificity	77%	79%	84%	90%	76%	64%
F1-Score	85%	83%	89%	93%	88%	72%
Accuracy	85%	82%	89%	93%	88%	71%

used a technique known as Synthetic Minority Oversampling Technique (SMOTE). SMOTE is a type of data augmentation wherein the minority class is over sampled to match the length of the majority class. However, instead of merely duplicating examples of the minority class, which does not add any new information to the model, SMOTE produces synthetic examples of the minority class. In our examined scenario, a total of 1,567 data points are gathered via simulation, of which 1,366 are HOS and 201 are HOF. SMOTE is applied to address this class imbalance.

B. Input Features for Handover Failure Prediction

The approach to predict HOF builds on the fact that HOF occurs mostly due to poor signal condition of the serving or target BS and strong interference from the neighboring BS. With this in mind, we have selected input parameters which are reported by the UE to the BS before the start of a handover process. These parameters include the RSRP of the serving and the target BS.

Aside from the signal condition of the source and target BS, another metric that we have considered as input to the model is the G-Factor. G-Factor can be used as a metric to measure the degree of interference by taking the ratio between the serving BS, or the strongest target BS and the summation of the interfering BS. G-Factor can be calculated using expression 1. A low G-Factor means a high degree of interference from the neighboring cells.

$$G = \frac{RSRP_x}{\sum\limits_{\forall i \in U_x} RSRP_i} \quad (1)$$

where G is the G-Factor, x is either serving or target BS while the set U_x contains 5 strongest interferers for the BS x.

C. Handover Failure Prediction Performance

A 80%-20% split is used for training and test data. To evaluate the models, we used performance metrics of accuracy, sensitivity/recall, specificity, precision and F1-score on the test set. The performance metrics of the six ML classifiers are shown in Table I. Results demonstrate that the selected ML classifiers are able to predict HOF occurrences with an accuracy ranging from 71% to 93%. Overall, XGBoost performance is the best considering all the metrics used. Unlike other models which struggle to classify successful handovers (i.e. poor specificity), XGBoost displays high specificity of 90% compared to others. This means that aside from correctly classifying failures, with XGBoost, chances of misclassifying HOS as HOF are also small.

The effect of adding interferers as input features to the model performance is shown in Figure 1. Accuracy of the models with only the source and target RSRP as input features ranges from 70% - 83%. However, with five strongest

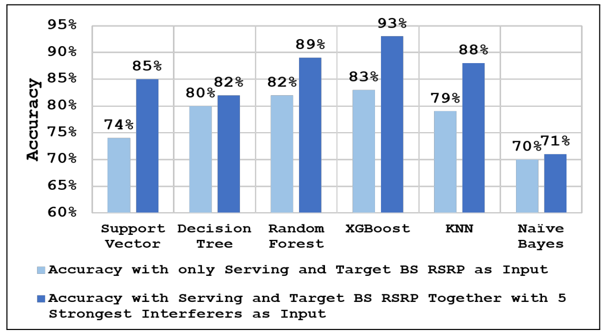

Figure 1: Effect of adding top interferers as input feature to the accuracy of the ML classifiers.

interferers for both source and target layers included as input, the accuracy for each model increases. A big leap of 10% in accuracy of XGBoost is observed.

III. Conclusion

This paper presents an ML based method for handover failure prediction. We have determined novel input features which include; serving and target layer RSRP together with the top interferers. XGBoost classifier outperformed other classification techniques in predicting the HO performance with an accuracy of 93%.

Acknowledgment

This work is supported by the National Science Foundation under Grant Numbers 1730650 and 1923669. The statements made herein are solely the responsibility of the authors. For more details about these projects please visit: http://www.ai4networks.com

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