Machine Learning-assisted Partially Blind Handover Prediction in 5G Network Systems

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***Abstract*—Handover is the process of transferring a cellular call or data session from one base station (BS) to another. This process aims to establish reliable and uninterrupted connection, thereby providing satisfactory Quality of Service (QoS) and Quality of Experience (QoE) for users. 5G networks will use millimetre wave (mmWave) frequencies in addition to sub-6 GHz bands, which will make handover (HO) more challenging. This paper focuses on the problem of partially blind HOs which is a novel HO type. In this sense, we modify an extant algorithm used for the partially blind HOs [1] which the algorithm is based on machine learning (ML). In our modified algorithm, we use the extant algorithm with a powerful boosting method that is Categorical Boosting (CatBoost). We compare our modified algorithm with a baseline algorithm, the originally proposed algorithm, Support Vector Machine integrated original algorithm. Different settings of simulation time and number of users are considered in comparing the algorithms, and our modified algorithm outperforms the rest of the algorithms in majority of the settings with higher HO prediction rates as per obtained results. The obtained results clearly indicate that the integration of ML with partially blind HOs enables accurate predictions whether HO execution will be successful in collocated cells in a network in the real-world case. A noteworthy takeaway from the obtained results is that ML deployment with partially blind HOs will likely contribute to self-organizing networks (SONs) in 5G communication systems.**

***Index Terms*—machine learning, mmWave, 5G, handover, blind handover, self-organizing networks (SONs), Categorical Boosting (CatBoost), eXtreme Gradient Boosting (XGBoost)**

I. Introduction

Millimeter wave (mmWave) frequencies range from 24 GHz to 52.6 GHz [2]. These frequencies are much higher than those used by 4G LTE, and this feature allows mmWave to offer much higher speeds and capacity. However, mmWave signals have a much shorter range and are more susceptible to interference than traditional cellular frequencies. In this sense, this feature limits the use of mmWave in outdoor areas and dense urban areas with good line-of-sight.

Collocated cells are two or more base stations (BSs) located in the same physical location. They are able to use both sub-6 GHz and mmWave frequencies, which can assist in mitigating the disadvantages of mmWave by providing a wider range and better resistance to interference. This feature ensures that a device remains within range and provides an uninterrupted connectivity.

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5G is a wireless communication standard that can operate in both mmWave and sub-6 GHz bands. Both band types have their own advantages and disadvantages. The mmWave offers higher data rates and capacity than sub-6 GHz, but has a shorter range and is more susceptible to interference. Sub-6 GHz offers a longer range and better resistance to interference than mmWave, but offers lower data rates and capacity. As a result, 5G networks can provide a wide range of services and applications, from high-speed data transfer to wide-area coverage.

In this paper, we extend the original algorithm in [1] to predict whether a handover (HO) from LTE to 5G mmWave will be successful without the need for a measurement gap. A measurement gap is a period of time during which data transmission is paused so that a user equipment (UE) can measure the signal strength of target technology. One significant concern associated with measurement gaps is that they may cause a decrease in the perceived end-user throughput.

Our algorithm tries to learn a statistical relationship between the signal strengths of the sub-6 GHz and mmWave frequencies. If the algorithm predicts that the HO will be successful, the UE can skip the measurement gap, and continue data transmission. This can improve the perceived end-user throughput, and reduce the risk of a failed HO.

Ref. [3] presents an FL-based CSI estimation and feedback scheme designed for mmWave massive MIMO systems. This scheme employs a decentralized approach, where each user trains a local model on their own data and subsequently shares model parameters with the central BS. It involves three key components: an CSI estimate module, a compression network, and a CSI recovery network. Numerical results show that the scheme outperforms traditional centralized learning approaches in terms of CSI estimation and feedback performance while also reducing transmission overhead. In certain instances, our methodology obviates the necessity for CSI estimate by delegating the task to the BS, which conducts channel estimation on behalf of the UE utilizing gathered data.

Ref. [4] presents a compressed sensing-based approach for CSI estimation in mmWave MIMO systems. The proposed algorithm simultaneously estimates dynamic angle-of-departure, angle-of-arrival, and channel amplitudes. Simulations demonstrate superior performance compared to Orthogonal Matching Pursuit in terms of computational efficiency and normalized mean squared error (NMSE). The paper found that CSI estimation in mmWave MIMO systems is challenging. The proposed model successfully addressed this challenge by leveraging measurements obtained from the sub-6 GHz system to estimate the received signal power in the mmWave band.

Ref. [5] examines the potential of using out-of-band information for mmWave signal power estimation. While it considers three sources of out-of-band data (spatial information, sub-6 GHz signals, and wireless sensor networks), it neglects statistical learning, temporal reuse of mmWave measurements, and diverse radio protocols, including the HO procedure. Our study aims to address these shortcomings and improve the accuracy of mmWave signal power estimation. Additionally, Ref. [5] does not cover diverse radio protocols associated with the mentioned technologies, including the HO procedure.

This study is based on Ref. [1] in which authors proposed a model to improve HO success rate using the concept of partially blind HOs for collocated LTE sub-6 GHz and mmWave bands, and a machine learning (ML)-based algorithm. Partially blind HOs allow the UE to estimate the mmWave frequencies from the common LTE service cell measurements in the sub-6 GHz band. The measurement of mmWave frequency by the UE prior to HO is not explicitly performed, hence enabling a more precise estimation of the potential success of the HO.

Partially blind HOs have the following advantages over blind HOs and measured HOs:

- They make more accurate predictions than the blind HOs. The blind HOs predict whether a HO will be successful based only on the conditions of the current cell. The partially blind HOs, on the other hand, make more accurate predictions by considering the conditions of both the current and target cells.
- They are more efficient than the measured HOs which measure the conditions of both cells to determine whether the HO will be successful, and this may reduce the UE's data rates. However, the partially blind HOs measure only the conditions of the current cell to spot whether the HO will be successful. Therefore, this helps preserve data rates of the UE.

The concept of partial blind HOs works as follows: (i) the UE performs measurements of the common LTE service cells in the sub-6 GHz band; (ii) these measurements are used by an ML algorithm to estimate the mmWave frequencies; (iii) the estimation is used to determine whether the HO will be successful.

We build our study on the work of Ref. [1] by modifying the originally proposed algorithm for partially blind HOs. The originally proposed algorithm used eXtreme Gradient Boosting (XGBoost) for prediction of HO success or failure, and we replace this ML method with a novel one-that is Categorical Boosting (CatBoost). As a result, we outstrip the originally proposed algorithm with XGBoost. This achievement of CatBoost may stem from its symmetric tree use in model construction leading to get higher performance without using more complex tree structures in modelling, and avoiding overfitting issue. In this sense, the paper brings a novelty for partially blind HO models in the literature by extending the extant algorithm for self-organizing networks (SONs) for 5G communication systems.

II. SYSTEM MODEL

System model comprises of two components as in Ref. [1]; radio network of system and ML model. The network part includes connected users and two co-located cells in an urban-environment. On the other hand, the ML model part includes CatBoost classifier method to orchestrate HO decision by overriding if it is necessary as per the estimation obtained from history of HO decision success for a relevant user in the system.

In the context of the system model, the collection period T is constrained by the *channel coherence time*, which represents a temporal interval during which measurements are gathered. It is important to note that T must not surpass this coherence time. Given that HOs are not required for all users within the system, it is imperative that the quantity of data points collected does not exceed the number of HO attempts. The method is done again by the eNodeB for a specific UE whenever the UE establishes a radio connection or undergoes a HO to a new eNodeB [1].

A. System Radio Network

The radio network used in this study consists of two collocated circular cells in a dense urban environment with a radius of R. The cells employ distinct technologies and frequencies.

In any cellular network, the UE measures the signal strength and quality of signals received from BSs, and then reports them to BSs. In this network, the BSs possess the capability to determine the necessity of implementing a measurement gap in LTE. This determination is made by leveraging the insights generated by an ML algorithm, which forecasts the adequacy of signal strength in the 5G mmWave band for a certain UE. HOs are employed to ensure the uninterrupted provision of services as the UE approaches the boundary of network coverage.

The UEs inside the network are spatially dispersed in accordance with a homogeneous Poisson point process (PPP) [6]. The PPP has an intensity parameter λ, which represents expected number of UEs per unit area. The number of UEs in the network service area W is a Poisson random variable with mean $\lambda W \triangleq \lambda \pi R^2$.

Position of each UE is independently and identically *(i.i.d.)* sampled from a continuous uniform distribution in the plane R^2 using polar coordinates (r_i, θ_i), where $0 \leq r_i \leq r$ and $0 \leq \theta_i \leq 2\pi$. Figure 1 shows a simulated network layout at time *t=0*. In the figure, blue dots represent the users in the system while red triangle in the origin represents the BS. Poisson point process resampling is performed while the users move throughout $1 < t \leq T_{sim}$. The radio parameters of this network are presented in Table III.

B. Machine Learning Model

In this part of the system model, we utilize CatBoost classifier method, which was proposed by Yandex research team [7], to predict HO success or failure to make decision of overriding action based on historical HO success for the user. CatBoost

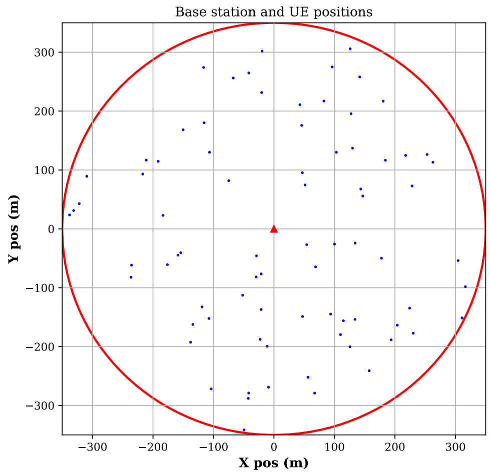

Fig. 1. The simulated network layout at time *t=0* [1].

TABLE I
FEATURES FOR MACHINE LEARNING METHOD

	Parameter	Type	Description of the parameter
x_1	(x,y)	float	UE coordinates
x_2	Distance	float	Euclidian distance between the UE and BS
x_3	RSRP_x	float	RSRP in x=LTE,mmWave bands
x_4	Gap_closed	boolean	Was event A1 based on UE's RSRP measurement reported?
x_5	Gap_open	boolean	Was event A2 based on UE's RSRP measurement reported?

method replaces previously utilized ML method in the original algorithm [1], XGBoost, to outstrip it in the prediction of HO success or failure to guide a 5G SON system. This method is one of the boosting methods similar to XGBoost. It is scale invariant, robust to overfitting problem, and adept in better capturing relationship between inputs and output, and learning higher order relationships as well [8]. The method tries to minimize convex loss function by differentiation to get an optimum solution. Input set used in the paper is an $m \times n$ matrix that is $\mathbf{X}$. The input set $\mathbf{X}$ contains features showcased in Table I as is the same in Ref. [1].

We use supervisory label vector y correspondingly to the input matrix $\mathbf{X}$. These y values are boolean which represent whether HO execution is done or not. In this sense, y value with integer 1 represents HO execution while it is with integer 0 represents HO non-execution. The features x_3, x_4, and x_5 in Table I are directly results of UE measurements. On the other hand, the remaining x_1 and x_2 are modified values according to standards to make UEs report their coordinates through Radio Resource Control (RRC) messaging. The generation of coordinates can be facilitated using positioning technologies [1], such as *global navigation systems* (GNSS) or *observed time difference of arrival* (OTDOA), as proposed by LTE positioning protocol (Ref. [9]).

III. HANDOVER ALGORITHMS

A. Baseline Algorithm (Inter-RAT Handover Algorithm)

The baseline Inter-RAT HO algorithm ensures seamless HOs between sub-6 GHz LTE and mmWave frequency bands as specified by 3GPP standards [10]. This subsection explains the basic principles and steps of the baseline algorithm's operation.

1) Activation Mechanisms for Inter-RAT Measurements: The algorithm's initiation is contingent upon specific events detected by the UE within the cellular network. These events trigger the commencement and conclusion of Inter-RAT measurements which are essential for informed decision-making during HOs.

a) Event A2 (Measurement Initiation): The UE continuously monitors the serving cell's reference signal received power (RSRP). If the RSRP falls below a predefined threshold, it initiates Inter-RAT measurements during scheduled measurement gaps. These measurements evaluate neighboring cells' RSRP values, enabling the UE to identify potential handover opportunities and maintain uninterrupted connectivity.

b) Event A1 (Measurement Termination): Upon obtaining an RSRP measurement surpassing a predefined threshold, the UE concludes the Inter-RAT measurements triggered by Event A2. This indicates that the UE has acquired sufficient information for potential HO decision-making.

2) Initiating Handover to mmWave: The HO procedure to the mmWave frequency band involves distinct sequential stages:

a) Threshold-Based Activation (Event B2): The UE continuously monitors the mmWave signal's power level. Once the mmWave power surpasses a designated threshold, the UE initiates an RRC event termed B2. This event serves as an indicator that favorable conditions for mmWave communication may be attainable.

b) Random Access and Handover Execution: Following the B2 event, the UE proceeds with a random access procedure targeting the mmWave carrier. Successful execution of this procedure denotes readiness for HO to the mmWave frequency band. The culmination of this process results in a successful HO, thereby maintaining uninterrupted communication via mmWave.

B. Visualizing the Baseline Procedure

Figure 2 provides an illustrative representation of the sequential stages comprising the baseline procedure leading to and executing the HO. Noteworthy trigger points are delineated for enhanced clarity:

- **Trigger Point A**: At this juncture, the HO attempt is activated, prompted by the UE's measurements and associated events.
- **Trigger Point B**: The HO execution counter advances when the eNodeB (BS) authorizes the HO. This denotes the transition from preparatory stages to the tangible execution of the HO process.

The baseline Inter-RAT HO algorithm employs these trigger mechanisms, events, and decision points to facilitate seamless transitions between sub-6 GHz LTE and mmWave frequency bands. While fundamental, the algorithm's reliance on immediate local metrics and threshold-based triggers motivates the exploration of more sophisticated approaches to elevate HO success rates.

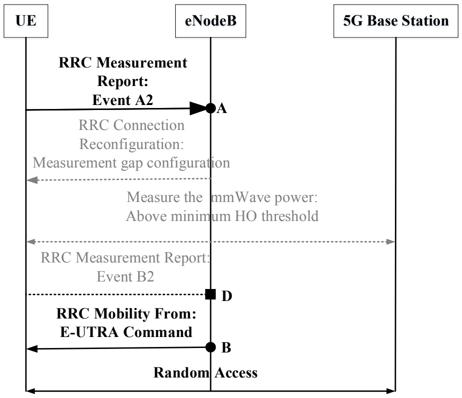

Fig. 2. This figure shows the HO signaling procedure adapted from [2]. The dashed gray lines represent the signals that are impacted by the proposed algorithm. The diagram additionally displays the HO decision point (D) as well as the metric trigger points (A and B). (eNodeB is the LTE BS, EUTRA is the evolved universal terrestrial radio access, HO is abbreviated as HO) [1].

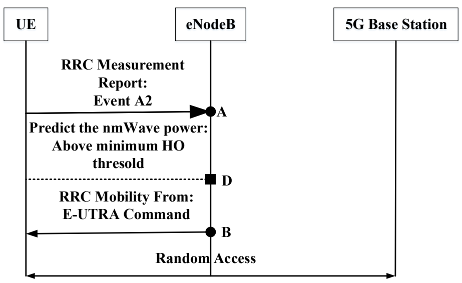

Fig. 3. The presented diagram illustrates the suggested HO signaling protocol, wherein the HO decision point (D) is shifted to an earlier stage in the process. This adjustment enables the eNodeB to anticipate the mmWave band measurement [1].

C. Partially Blind Handover Algorithm

In this algorithm, the decision of whether to accept or override the UE measurement is made based on the receiver operating characteristic (ROC) area under the curve (AUC). This curve is an outcome of a ML technique to predict whether a HO execution will be successful. If the ROC-AUC value indicates that the predictions are accurate, the algorithm utilizes this information to determine whether a HO should be attempted. On the other hand, if the ROC-AUC value is low or indicates uncertainty, the algorithm may follow a more cautious approach by sticking to a predetermined procedure.

In the traditional approach (baseline algorithm), each step of the HO procedure is followed regardless of the specific circumstances. However, in the proposed algorithm, the ML model predicts whether a HO is likely to succeed or fail based on various factors, including signal strengths and historical data. This prediction hence allows the algorithm to skip unnecessary steps when a HO is predicted to be unsuccessful.

If the power of the signal from the LTE network is lower than a certain threshold (A2 threshold) defined in the baseline algorithm, and the *predicted* mmWave received power is higher than another threshold (B2 threshold), or if the ROC AUC prediction is adequate, then the algorithm follows the same steps as is the baseline algorithm. However, if *predicted* mmWave received power is lower than a certain threshold, it means the mmWave connection might not be good. In this case, the eNodeB preempts the UE from attempting to switch its connection to the mmWave frequency band. This action prevents the UE from going through a HO that is likely to fail.

D. CatBoost-assisted Algorithm for Handover

This paper utilizes the same proposed algorithm in Ref. [1] for Inter-RAT HO which makes decision of whether accepting the UE measurement or skip it according to ROC-AUC value that is a landmark measurement of classification tasks. In the originally proposed algorithm, one of the aforementioned three conditions are monitored to maintain performing the baseline algorithm. On the other hand, a different condition is monitored to execute HO for a UE to avoid failure for the executed HO. Details of the executions of the algorithm is given in Ref. [1], and the proposed algorithm with our modification is given in Algorithm 1. In this paper, we replace used ML method in Ref. [1], XGBoost, with a novel ML method-CatBoost, proposed by Yandex researchers [7], to extend the performance of the previous work. In addition, we utilize Support Vector Machine (SVM) with the originally proposed algorithm to see the clear performance difference between the methods used as well. Fig. 3 shows the reduction in the proposed procedure by ML deployment [1].

Algorithm 1 Partially blind HO success estimation

Input: CatBoost classifier and radio environment parameters presented in the tables, ϵ the acceptance threshold, and the simulation time T_{sim}.
Output: Time sequence of decisions whether the HO to 5G must be overridden or not according to estimated mmWave received signal level.

Compute N the total number of UEs in the cell per Section (Mismar)
for $i \in 1 \ldots N$ **do**
  Obtain the generated simulation data for UE i for all times $t = 1, \ldots, T_{sim}$ for the features given.
  Compute the HO success of the relevant UE by using the values measurement gap opened AND mmWave power exceeding the threshold that is label.y value of the relevant UE. ***i.e.*** y_i is the label of UE i.
  Split i^{th} UE's dataset into training and test parts. Training data is collected over a period $1, \ldots, T$, where $T \triangleq min(T_{coherence}, \lceil t_{\text{training}} \times T_{sim} \rceil)$.
  Train CatBoost method on training data by using K-fold cross validation by using grid search to tune the hyperparameters of the methods.
  Obtain the proposed HO decision $\hat{y}$ through the trained ML model.
  Obtain the model's ROC-AUC value.
  if (ROC-AUC value $\geq \epsilon$) **then**
    Use $\hat{y}$ as a valid estimation of HO execution decision (Follow Fig. 3)
  else
    Use the reported UE measurements (the baseline algorithm).
  end if
end for

IV. SIMULATION RESULTS AND DISCUSSIONS

We used our modified algorithm, and compared the obtained results of the methods used in this paper. Table II and Table III present parameters of CatBoost method found by cross-validation and radio environment parameters in order. Graphical outputs of an arbitrarily selected UE are produced as well. For signals in the frequencies of both mmWave and sub-6 GHz, the RSRP values for the same UE throughout the simulation time with the RRC events' thresholds are depicted in Fig. 4. In Fig. 5 both algorithms' corresponding HO executions in relation to simulation time, which the identical

TABLE II
HYPERPARAMETERS FOR CATBOOST MODEL

Parameter	Value
Training data split ratio	0.7
Cross-validation fold K	5
depth	[4,5,7,8,10]
learning rate	[0.01, 0.02, 0.03, 0.04]
# of iterations	[50, 90, 150, 200]

TABLE III
RADIO ENVIRONMENT PARAMETERS [1]

Parameter	Value
LTE Bandwidth	20 MHz
LTE center frequency	2.1 GHz
LTE cyclic prefix	normal
5G mmWave bandwidth	100 MHz
5G mmWave center frequency	28 GHz
LTE Propagation model	COST 231 (LOS; no shadowing)
5G mmWave propagation model	[11]
PPP intensity parameter λ	2 x 10^{-5}, 10^{-4}
Simulation time T_{sim}	40, 400, 800 ms
Cell radius r	350 m
LTE BS power	46 dBm
5G BS power	46 dBm
Antenna pattern	omnidirectional
Antenna height	20 m
Antenna sub-6 GHz gain	17dBi
Antenna mmWave gain	24 dBi
RRC event A1 trigger	-125 dBm
RRC event A2 trigger	-130 dBm
RRC event B2 trigger	-95 dBm

HO decision are made for a determined period-that is 28 ms, (=0.7 x 40 ms) are visualized. It is followed by ML method prediction to spot whether upcoming HO will probably succeed or fail, thereby producing different HO decisions with respect to the baseline algorithm. Lastly, performance of the proposed algorithm where its ROC-AUC performance is below a certain threshold (thr=0.7) is visualized in Fig. 6. Through ROC-AUC curve which covers an area and shows the trade-off between true positive rate and false positive rate for the utilized algorithm, prediction capability of the algorithm for an IRAT HO success is spotted. The threshold is generally in-between 0.5 and 1, and it is denoted by epsilon in the algorithm. We use the same threshold used in Ref. [1] that is above 0.5 which corresponds to random guess without using any model for the prediction.

The simulations were made for different time spans which represent short and long durations, and the coherence time of the channel does not go beyond the range. Different time spans and different number of UEs in the cell provide robustness of the utilized algorithm as well [1]. In Table II, obtained paremeter results from the simulations with respect to previous work are presented. The best results of each simulation results are given in **boldface** in Table IV as well.

As per the results given in Table IV, number of failures with both the originally proposed algorithm and the baseline one are the same with the least number of users. However, CatBoost integrated-proposed algorithm outperforms the rest of the other ones with the least number of failures. SVM method produces the worst results in the whole comparison, and the baseline algorithm results spot the upper bound for the number of failures for us as well as previously mentioned in Ref. [1].

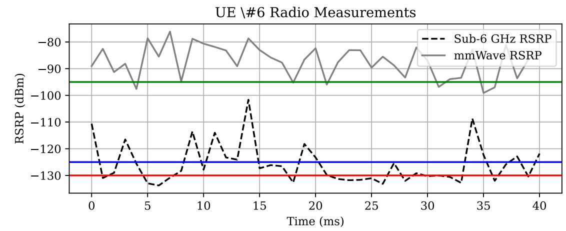

Fig. 4. Simulated received power for 6th UE. Thresholds of A1, A2, and B2 events are represented by the blue, red, and green lines respectively.

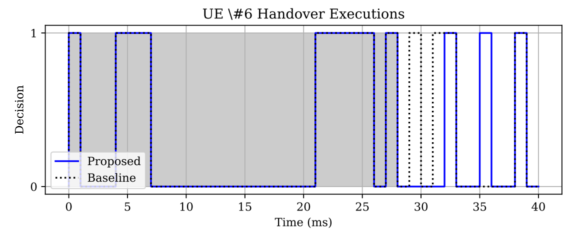

Fig. 5. HO executions throughout the simulation time for 6th UE. The baseline algorithm and our algorithm decisions are depicted by the dotted black line and solid blue line respectively. The collection period T is depicted by shaded region where the HO executions are identical and not included results. Non-shaded region in the figure is the area where HO executions differ.

Obtained results are showcased in Table IV in a compact form where compared methods denoted by baseline, originally proposed one in Ref. [1], proposed with SVM (PwSVM), and proposed with CatBoost Classifier (PwCBC) in the figures, respectively.

As per seen from Table IV, PwCBC outstrips baseline algorithm, originally proposed algorithm, and PwSVM in majority of the HO prediction results. While simulation time is equal to 40 ms, our method (PwCBC) has improved the results of originally proposed algorithm by 0.67% and 0.76% for $N = 78$ and $N = 8$, respectively. The method is only able to outstrip the originally proposed one by 0.98% improvement with the settings which the simulation time is equal to 400 ms and $N = 78$. PwCBC algorithm only falls behind the originally proposed algorithm with a slight difference with the settings $N = 8$ and the simulation time is equal to 400 ms. This may be because of the least number of the

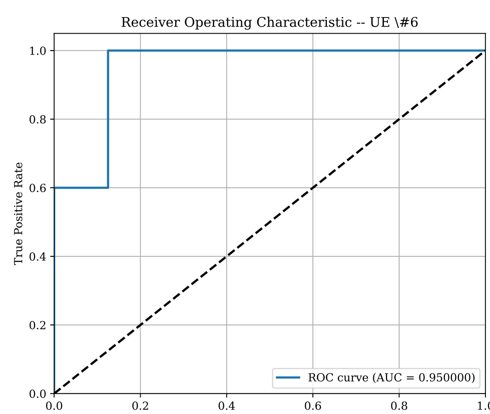

Fig. 6. ROC curve for 6th UE with settings T_{sim}=*800 ms* and $\lambda = 2 \times 10^{-4}$.

TABLE IV
RESULTS

Sim. time	Rate	Algorithm	Attempts	Failures	Success Rate
$T = 40$ ms	$\lambda = 2 \times 10^{-4}$ (N=78)	Baseline	1259	58	95,39%
		Proposed	1259	55	95,63%
		Pr. with SVM	1259	224	82,2%
		Pr. with CBC	1259	**47**	**96,27%**
	$\lambda = 2 \times 10^{-5}$ (N=8)	Baseline	1259	6	95,56%
		Proposed	135	6	95,56%
		Pr. with SVM	135	11	91,85%
		Pr. with CBC	135	**5**	**96,29%**
$T = 400$ ms	$\lambda = 2 \times 10^{-4}$ (N=78)	Baseline	12,601	695	94,48%
		Proposed	12,601	450	96,43%
		Pr. with SVM	12,601	3,997	68,28%
		Pr. with CBC	12,601	**332**	**97,37%**
	$\lambda = 2 \times 10^{-5}$ (N=8)	Baseline	1254	70	94,42%
		Proposed	1254	**13**	**98,96%**
		Pr. with SVM	1254	264	78,95%
		Pr. with CBC	1254	25	98,01%
$T = 800$ ms	$\lambda = 2 \times 10^{-4}$ (N=78)	Baseline	25,070	1,378	94.50%
		Proposed	25,070	757	96.98%
		Pr. with SVM	25,070	11,726	53.23%
		Pr. with CBC	25,070	**543**	**97.83%**
	$\lambda = 2 \times 10^{-5}$ (N=8)	Baseline	2,535	132	94.79%
		Proposed	2,535	19	99.25%
		Pr. with SVM	2,535	270	89.35%
		Pr. with CBC	2,535	**0**	**100%**

users in mobility in the network as it is equal to 8. Lastly, with the setting that the simulation time is equal to 800 ms, PwCBC method has also improved the results of originally proposed algorithm by 0.88% and 0.76% for $N = 78$ and $N = 8$, respectively. As per the results in Table IV, the performance of PwCBC increases when the number of the users and/or the simulation time increase. Ref. [1] proposed the original algorithm with a powerful ML method, XGBoost, and exceeded a baseline algorithm. In general, it is apparent from the obtained results that the improved algorithm with CatBoost (PwCBC) makes better prediction of HO success or failure rate with respect to the compared ones including the originally proposed algorithm as it has decreased number of failures in the HO predictions seen in the table. Since ML employment further improves the results with respect to the originally proposed algorithm, it may be seen as a clear indication of efficiency of ML in mobility management and HO prediction issue in 5G networks. A noteworthy takeaway from the results is that prediction performance of our method usually increases when the simulation time is increased. Another noteworthy takeaway of the results from ML perspective is that SVM method performs worse than the baseline algorithm, and boosting methods improve the results. This may be due to the fact that SVM method is not capable of capturing the relationship between feature space and corresponding output value well. Boosting methods' superior performance may be due to the fact that they are adept in dealing with tabular data, and the used data set is in this kind of tabular data form. Hence, they have exhibited good performance with respect to the baseline algorithm and the proposed method with SVM.

V. CONCLUDING REMARKS

This paper improves the previously proposed algorithm for predicting HO success rate. The originally proposed algorithm incorporated ML in order to make BSs predict HO success rate by utilizing both prior measurements of mmWave and sub-6 GHz. The proposed algorithm efficiently overrides the UE measurements by utilizing data acquired in the range of coherence time. We replace XGBoost algorithm in the proposed scheme with CatBoost, and have improved inter-RAT HO success rate found by the originally proposed algorithm with this replacement. Hence, CatBoost integrated-proposed algorithm has outperformed the originally proposed one. The results clearly show the contribution of ML in next generation network systems' performance which HO is one of their inherited characteristics.

REFERENCES

[1] F. Mismar, and B. Evans, "Partially blind handovers for mmWave new radio aided by sub-6 GHz LTE signaling," *IEEE ICC Workshops*, 2018, pp. 1-5.

[2] X. Lin, *et al.*, "5G new radio: Unveiling the essentials of the next generation wireless access technology", *IEEE Commun. Mag.*, vol. 3, no. 3, pp. 30-37, 2019.

[3] L. Zhao, *et al.*, "Joint Channel Estimation and Feedback for mm-Wave System Using Federated Learning", *IEEE Commun. Lett.*, vol. 26, no. 8, pp. 1819-1823, 2022.

[4] N. Purohit, and N. Gupta, "Channel Estimation for Sparse mm-Wave MIMO System," *Wireless Personal Communications*, vol. 129, no. 3, pp. 2123-2140, 2023.

[5] N. Gonzales-Prelcic *et al.*, "Millimeter-wave communication with out-of-band information", *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 140-146, 2017.

[6] F. Baccelli *et al.*, "Stochastic Geometry and Wireless Networks", vol. 3, no. No 3-4 of Foundations and Trends in Networking, 2009.

[7] L. Prokhorenkova *et al.*, "CatBoost: unbiased boosting with categorical features", *Advances in neural information processing systems*, vol. 31, 2018.

[8] E. Gures, *et al.*, "A comparative study of machine learning-based load balancing in high-speed", *Alexandria Engineering Journal*, vol. 72, pp. 635-647, 2023.

[9] LTE, Evolved Universal Terrestrial Radio Access, "LTE Positioning Protocol (LPP) (3GPP TS 36.355 version 9.2. 1 Release 9)," *ETSI TS*, vol. 136, no. 355, pp. V9.

[10] Evolved Universal Terrestrial Radio Access, "RRC; Protocol Specification (Release 10)"; 3GGP Standard; 3GGP TS 36.331," *RAN WG2*, no. 10, 2011.

[11] S. Sun *et al.*, "Millimeter-wave distance-dependent large-scale propagation measurements and path loss models for outdoor and indoor 5G systems,", *10th EuCAP*, 2016, pp. 1-5.