Multilateration-based Machine Learning for Indoor Localization

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Abstract— **Indoor Positioning Systems (IPS) are becoming increasingly beneficial as they can provide real-time location data to improve various workflows. Their accuracies can be improved by deploying machine learning solutions to serve as the positioning engine. Fingerprinting-based models have been widely proposed as they can utilize the available network devices as reference nodes to build a wireless signal profile of the location. However, this approach requires repetitive manual data collection, which may not be feasible in restricted spaces and is impractical for off-the-shelf consumer solutions. This paper therefore proposes an alternative multilateration-based machine learning model trained on a minimal training set. Experimental results showed that the proposed trilateration-based model outperformed both the traditional multilateration and the fingerprinting-based models.**

Keywords—positioning, localization, machine learning, fingerprinting, multilateration

I. INTRODUCTION

The proliferation of internet-connected devices has prompted a push to data-driven workflows across various industries. As these processes get more automated, Indoor Positioning Systems (IPSs) can offer indoor location data in real time yielding several advantages. For example, the availability of such data can help in keeping accurate inventory, analyzing visitor trends, and optimizing production.

A typical IPS consists of pre-installed reference nodes and mobile tags assigned to assets and personnel. They utilize wireless technologies such as Wi-Fi and Bluetooth Low Energy (BLE) to communicate and gauge how far each tag is from the reference nodes. The positioning engine then uses the collected signal measurements to determine the approximate location of the tag. There is currently a variety of commercial off-the-shelf IPS, but there is still hesitancy in adoption due to issues regarding infrastructure and accuracy. The installation of wireless reference nodes can be a significant investment as there needs to be enough devices installed in strategic locations to provide sufficient wireless coverage. Even with a proper setup, the accuracy achieved during deployment may vary from initial testing. Wireless technologies are inherently prone to interference, electromagnetic noise, and multi-path effects, which can lead to low quality signal measurements. Thus, IPS deployed in settings with substantial clutter and metallic objects may experience diminished performance.

The success of Machine Learning (ML) in other application areas has sparked interest in their utilization towards improving IPS accuracy and mitigating the effects of unfavorable environmental conditions. Most proposed solutions in literature are ML models that replace the traditional positioning engine. They adhere to the fingerprinting approach, which involves collecting data across different points along the site to create a database of signal profiles. This is then used as training data, and the resulting model can predict the target's location via room-based classification [1] or coordinate-based regression [2]. Recent years have seen an increase in such solutions due to their good compatibility with prevalent technologies such as BLE [3] and Wi-Fi [4]. Despite this, fingerprinting-based models retain the vulnerabilities of their traditional counterparts, requiring intensive and regular data collection to remain accurate. Such exercises to update the models can be impractical due to high maintenance costs and restrictions in repeatedly accessing the locations. There is therefore a need to explore alternative ML solutions that can yield acceptable performance given a smaller dataset.

This work proposes a multilateration-based approach that uses the relative distances and locations of the 3 strongest beacons as inputs. To minimize the data collection cost, the model was trained using a single set of data collected while traversing over all the routes at the site. Results showed that the proposed solution was able to outperform both its traditional counterpart and conventional fingerprinting-based ML models.

II. LOCALIZATION ALGORITHMS

Machine learning improves upon the knowledge gained from traditional techniques. Thus, prior to model development, the approaches they are based on must first be studied. This section outlines the two conventional localization algorithms that serve as the basis of the ML models explored in this work.

A. Fingerprinting

Fingerprinting is a positioning technique that determines the target's location by matching signal measurements from reference nodes, termed collectively as a fingerprint, to a known radio map. This fingerprinting database is constructed during the algorithm's offline phase, where measurements are sampled at several points across the site. For the online phase, the positioning engine then refers to the database to match the tags' incoming fingerprints to their likely locations.

The current popularity of fingerprinting solutions can be attributed to their suitability for use with existing wireless connectivity infrastructure. It is common for many buildings to have Wi-Fi Access Points to provide internet connection, thereby removing the need for additional hardware for localization. However, the accuracy of this approach depends heavily on the quality of the collated radio map. The offline data collection process can become manpower heavy as enough unique locations need to be sampled to obtain acceptable accuracy. Furthermore, fingerprinting is commonly used with Wi-Fi and BLE technologies, which use

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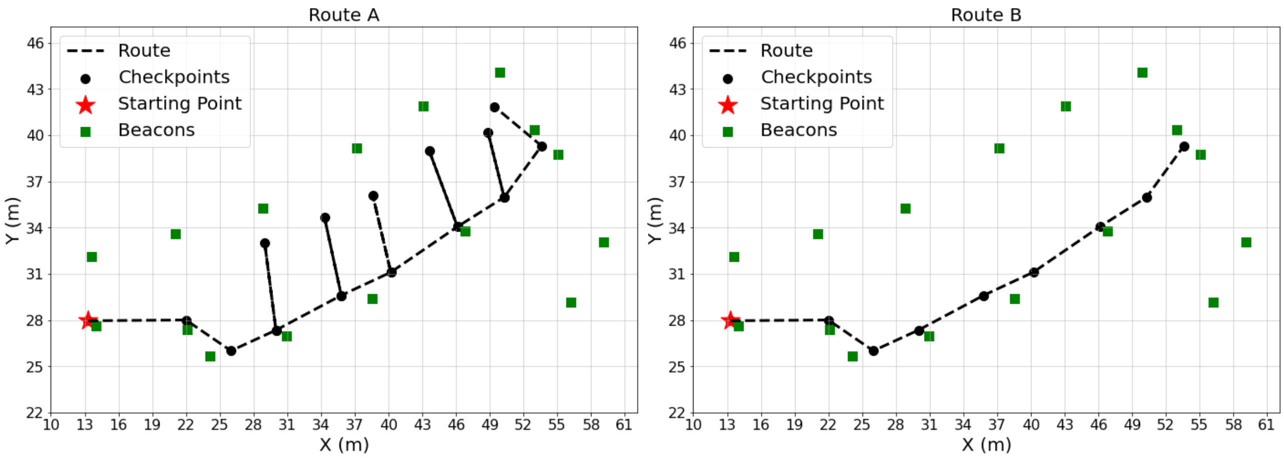

Fig. 1. Test Site Plots of Routes used in Data Collection

Received Signal Strength Indicator (RSSI) values. RSSI is known to have high uncertainty and is especially sensitive, which can lead to inconsistent measurements. The resulting radio map would tend to vary considerably over time as it is affected by even minute environmental changes. Thus, the fingerprinting approach requires periodic data resampling as a maintenance step, which further compounds data collection costs.

B. *Multilateration*

Multilateration is a localization technique that determines the position of a tag with respect to known reference nodes. At each timestep, a tag communicates with available devices and approximates its distance to each node. Thus, the problem of position estimation can be viewed as solving for the intersection between several circles centered at the known device positions.

This positioning technique can be used by most technologies provided that the system employs distance estimation schemes such as Time of Arrival, Angle of Arrival, or Two-Way Ranging. As RSSI values can also be converted into distance, multilateration is compatible with Wi-Fi and BLE. Much like fingerprinting, it can make use of the already existing network infrastructure and reduce installation costs. However, unlike fingerprinting, multilateration relies on mathematical techniques to calculate the position estimate and therefore does not need intensive data collection. These advantages therefore make multilateration more feasible to use in certain cases as most of its requirements, such as determining the locations of the reference nodes, can be completed during the IPS setup.

III. Machine Learning Methodology

In the context of indoor positioning, trained ML models employ real-time wireless signal measurements from reference nodes as inputs. The resulting predictions vary in terms of granularity, as it depends on the setting and requirements of the positioning application. Predictions can typically range from determining the current room of the target to approximating their exact position at sub-meter level accuracy. It is also possible for multiple models to work in tandem, such as a trained classifier determining the current floor while a regressor determines the target's exact location.

This work considers a prototype IPS that consists of BLE beacons as reference nodes and personnel smartphones as tags. The smartphones run an app that scans for nearby BLE devices in the background and sends the scan results to a central server. The positioning engine, which can either utilize traditional localization techniques or machine learning, should use the scan results to approximate the exact location of the phone on the site. This scenario depicts a regression problem, and so the models in this section will be trained to predict the x- and y-coordinates of the target.

A. *Data Collection Exercise*

Fig. 1 depicts the 40 m x 15 m test site where the prototype IPS is installed. The location is an office environment consisting of cubicles and IT equipment with personnel freely walking around. The green squares mark the locations of the 16 BLE beacons mounted on the ceiling at a height of 2.65 m.

Data was collected for the two routes. Route A (Fig. 1, left) is a multi-turn route that covers most of the test site. As it is ideal for training, two sets of mobile data and two sets of stationary data were collected, with each second set reserved for testing. Meanwhile Route B (Fig. 1, right) is a commonly used route that runs across the location. One set of mobile data and one set of stationary data were taken as test sets to gauge model accuracy under a different route. Lastly, additional mobile and stationary test data were collected using Route B at a separate date to study the effects of subtle environmental changes on model performance.

The data collection exercises were performed while adhering to practical constraints to ensure that the reported results would resemble what can be achieved under real-life conditions. At the start of each round, the target started the app and placed the smartphone (Samsung A30) in the pants pocket. For mobile sets, they walked along the stipulated route in Fig. 1 from the designated starting point to each of the marked checkpoints before returning. Similarly, for stationary sets, the target walked along the route and stopped at each checkpoint to collect 10 seconds worth of data before resuming motion. To determine the ground truth, a stopwatch was used to denote the times when the target passes the checkpoints for the mobile case, or when the target stops and starts moving for the stationary case. By utilizing these timestamps and step data from the app, the ground truth can be determined in post-processing. For the stationary sets, the mobile datapoints were removed so that only the stationary datapoints remained.

B. Fingerprinting-based Model

The BLE scan results contain a list of MAC Addresses of detected BLE devices and their respective RSSI values. Based on traditional fingerprinting, the ML models trained under this approach compile the RSSI values of the 16 known reference nodes and use them as features.

To mitigate inherent RSSI instability, the latest RSSI values for each beacon are stored in moving average windows. The obtained values are in decibel-milliwatts (dBm), so they are first converted to milliwatts (mW). The converted value is stored in its respective moving average window and the resulting mean is converted back into dBm.

The training set for the Fingerprinting-based ML model (FPML) is created by first processing the training data sequentially, obtaining the mean RSSI value for each of the beacons at each timestep, and then shuffling the rows. Two versions of FPML were trained for the experimental trials. FPML-S was trained using the Route B stationary set as it is customary to use stationary data for fingerprinting. The other, named FPML-M, was trained with the mobile set. To more closely evaluate the difference in the two approaches, the FPML models were trained in the same manner as the multilateration-based model in the next section, adopting the same regression algorithm with optimized parameters.

C. Multilateration-based Model

The proposed multilateration-based model filters out and averages the received RSSI as described in the previous section. Instead of the retaining values from all 16 nodes, the three strongest beacons were determined at each timestep. As the traditional approach uses distance, the mean RSSI values were converted from dBm to meters. The distance $d_{i,t}$ of the phone from beacon i at time t can therefore be calculated via:

$$d_{i,t} = 10^{\frac{\overline{RSSI\_dBm_{i,t}} - PL_0}{10\alpha}} \tag{1}$$

where $\overline{RSSI\_dBm_{i,t}}$ is the mean RSSI value in dBm, PL_0 is the path loss coefficient, and α is the path loss exponent. The inputs of the Trilateration-based model (TLML) therefore consist of nine features: the distance measurements of the three closest beacons, and their respective x- and y-coordinates.

To reduce data collection overheads, the proposed TLML model was trained using Route B's mobile dataset. The training set was further divided into a 75%/25% training/validation split to determine the appropriate regression algorithm and model parameters. Based on preliminary trials, the Random Forest algorithm was chosen and further optimized using k-fold cross-validation. All machine learning models were trained using scikit-learn [5].

IV. Results and Discussion

The experiment proper simulates a scenario portraying an office with restricted access using the BLE-based IPS described in the previous section. Hence only a single session is allotted for data collection with no repeated sessions for updating the model over time.

Three positioning schemes were proposed for the positioning engine: traditional multilateration based on Weighted Path Loss (WPL) [6], the fingerprinting-based ML model (FPML-M), and the trilateration-based ML model (TLML). In addition, FPML-S was included in the evaluation to study the effectiveness of using stationary training data as opposed to FPML-M's mobile training data. All methods undergo the same pre-processing and post-processing steps. For the former, they utilize the RSSI averaging method described in Section III-B. After localization, the location estimates were again averaged using another moving window to further stabilize trajectory.

A. Evaluation Criteria

A total of three test sets were collected for the experiment proper, each consisting of a mobile and stationary test. For each test, the candidate positioning schemes were evaluated using both ML-based and localization-based metrics. Positioning systems are primarily evaluated using error statistics, which were derived by calculating the Euclidean distance between the position estimates and the ground truth positions. The error $Err_{t,TLML}$ at time t for a prediction from TLML can therefore be expressed as:

$$Err_{t,TLML} = \sqrt{\left(x_{t,GT} - x_{t,TLML}\right)^2 + \left(y_{t,GT} - y_{t,TLML}\right)^2} \tag{2}$$

where $x_{t,GT}$ and $y_{t,GT}$ are the ground truth coordinates at time t, and $x_{t,TLML}$ and $y_{t,TLML}$ are the predicted x- and y-coordinates from TLML at time t. The mean and maximum errors are subsequently determined using (2).

The Coefficient of Determination (R^2) is a metric commonly used to assess the fit of regression-based machine learning models. Its value ranges from 0 to 1.0, where 1.0 implies that the trained regressor is perfectly effective. The R^2 of TLML R^2_{TLML} is given by:

$$R^2_{TLML} = 1 - \frac{\sum_{i=1}^{N}\left(p_{i,GT} - p_{i,TLML}\right)^2}{\sum_{i=1}^{N}\left(p_{i,GT} - \overline{p_{GT}}\right)^2} \tag{3}$$

where $p_{i,GT}$ is the ground truth position at index i, $p_{i,TLML}$ is the position estimate predicted by TLML at index i, N is the total number of data points in the test set, and $\overline{p_{GT}}$ is the mean of the ground truth positions.

Lastly, this work considered the error distribution of the proposed methods. Aside from plotting the error distribution curve, the ACC_M metric from [7] was included to provide additional granularity to the error distribution. The ACC_M for TLML is defined as the percentage of predicted position estimates with errors below M m:

$$ACC_{M,TLML} = \frac{\sum_{i=1}^{N}\left[\left(p_{i,GT} - p_{i,TLML}\right) \leq M\right]}{N} \times 100\% \tag{4}$$

where $\sum_{i=1}^{N}\left[\left(p_{i,GT} - p_{i,TLML}\right) \leq M\right]$ is the number of predicted TLML estimates below M m error. $ACC_{1.0}$, $ACC_{5.0}$, and $ACC_{10.0}$ were calculated for each method to compare the percentage of estimates whose errors fall below 1 m, 5 m, and 10 m, respectively.

B. Route A Test Results

The Route A test set consists of mobile and stationary data that were collected on the same route and date as the training dataset. This makes this test set highly similar to the training set, and it can therefore be used to evaluate ML models performance on unseen but similar data. Table I reports the results of all proposed methods while Fig. 2 depicts the error distribution curves.

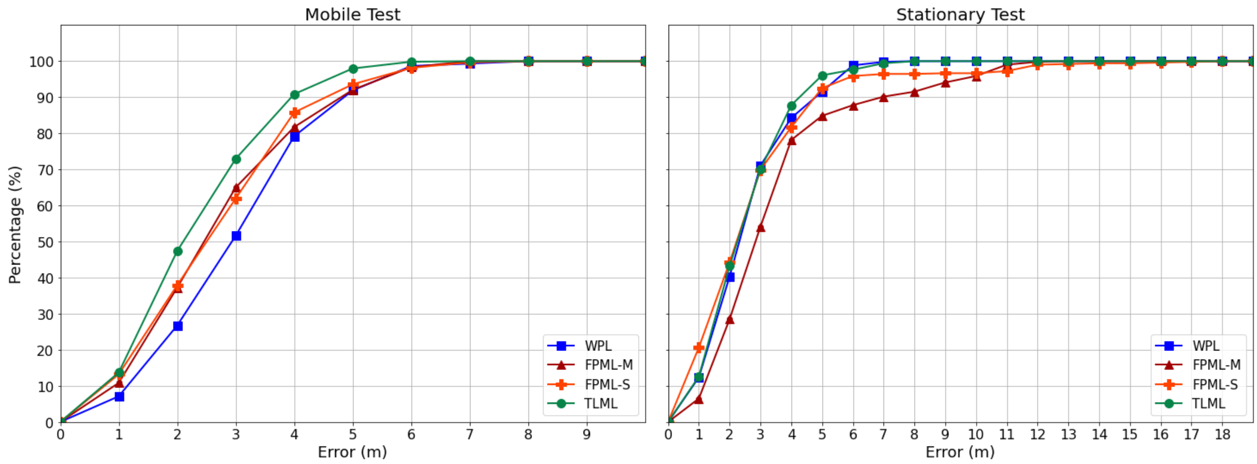

Fig. 2. Error Distribution Curves for Route A Mobile and Stationary Tests

TABLE I. TEST STATISTICS FOR ROUTE A MOBILE AND STATIONARY TESTS

Criteria	Mobile Test				Stationary Test			
	WPL	*FPML-M*	*FPML-S*	*TLML*	*WPL*	*FPML-M*	*FPML-S*	*TLML*
Mean Error (m)	2.94	2.63	2.60	2.26	2.51	3.40	2.63	2.41
Max. Error (m)	7.85	6.95	7.30	6.17	7.18	12.42	17.82	7.47
R^2	0.80	0.89	0.87	0.91	0.89	0.86	0.88	0.92
$ACC_{1.0}$ (%)	7.11	10.83	13.20	13.71	12.40	6.50	20.67	12.60
$ACC_{5.0}$ (%)	91.88	92.05	93.57	97.97	91.54	84.84	92.52	96.06
$ACC_{10.0}$ (%)	100.00	100.00	100.00	100.00	100.00	95.87	96.65	100.00

WPL was included in the experiment proper to provide a benchmark of what can be realistically achieved by conventional methods. For the Route A tests, WPL yielded approximately 2.5 - 3 m mean error, with maximum errors of over 7 m. This can be attributed to the pocket placement of the phone, where occlusion by the human body can prevent certain beacons' signals from reaching the smartphone. This makes it possible for the nearest beacons to not appear in the BLE scans and cause the position estimate to erratically jump to a location farther away than the ground truth. Despite this phenomenon, approximately 91% of WPL position estimates yielded errors of less than 5 m for both tests, which is reasonable for an office-like environment with little metal and clutter.

Both fingerprinting-based ML models outperformed WPL for the mobile test. FPML-M has a mean error of 2.63 m, a maximum error of 6.95 m, and an R^2 of 0.89. Meanwhile, FPML-S reported a mean error of 2.60 m, a maximum error of 7.30 m, and an R^2 of 0.87. FPML-M's slightly better performance may be because it was trained with mobile data. This is supported by its diminished performance in the stationary test, where FPML-M's mean and maximum errors increased to 3.40 m and 12.42 m, respectively. Meanwhile, FPML-S was able to obtain a similar mean error, but also reported a significant increase in maximum error to 17.82 m. With approximately 4-5% of position estimates attaining more than 10 m error, the FPML models report lower R^2 scores than WPL. This may be an indication that they need more training data in order to generalize. Unlike the mobile test data, the stationary test data contains several rows of BLE scans at the designated checkpoints. It is possible that some of these checkpoints are in blind spots with high RSSI uncertainty. Combined with bodily occlusions, this can bring about lower quality fingerprints that can confuse the models into thinking they belong to another location.

TLML attained the best performance for both mobile and stationary tests, being the only positioning method reporting R^2 scores above 0.9. When compared to WPL, it was able to decrease mean and maximum errors to 2.26 m and 6.17 m in the mobile test. Its distribution curve also depicts a significant reduction in errors, which is further supported by the ACC metrics. The stationary test results seem to follow the same trend, as TLML reduces the mean error to 2.41 m despite a slight increase in maximum error. This suggests that TLML was able to generalize well and is less affected by the jumping phenomena, unlike the FPML models.

C. Route B Test Results

The Route B Test was taken the same day as the training set but utilized a different route (Fig. 1). In practice, personnel would not traverse the entirety of a site. They would typically walk along a subset of the overall route. This section studies the performance of the models under such conditions, with the test statistics reported in Table II, and the error distribution curves plotted in Fig. 3.

As a traditional positioning technique, WPL should give results similar to the previous section. This is true of the mobile test, where it reported a mean error of 2.33 m, a maximum error of 7.54 m and an overall R^2 of 0.88. WPL's performance slightly degrades in the stationary test, with its mean error increasing to 3.21 m and maximum error increasing to 9.55 m.

FPML-M and FPML-S reported comparable results to WPL. Both have slightly higher mean errors at 2.54 m (FPML-M) and 2.68 m (FPML-S). Despite FPML-S reporting a lower maximum error of 6.96 m, Fig. 3 shows that the error

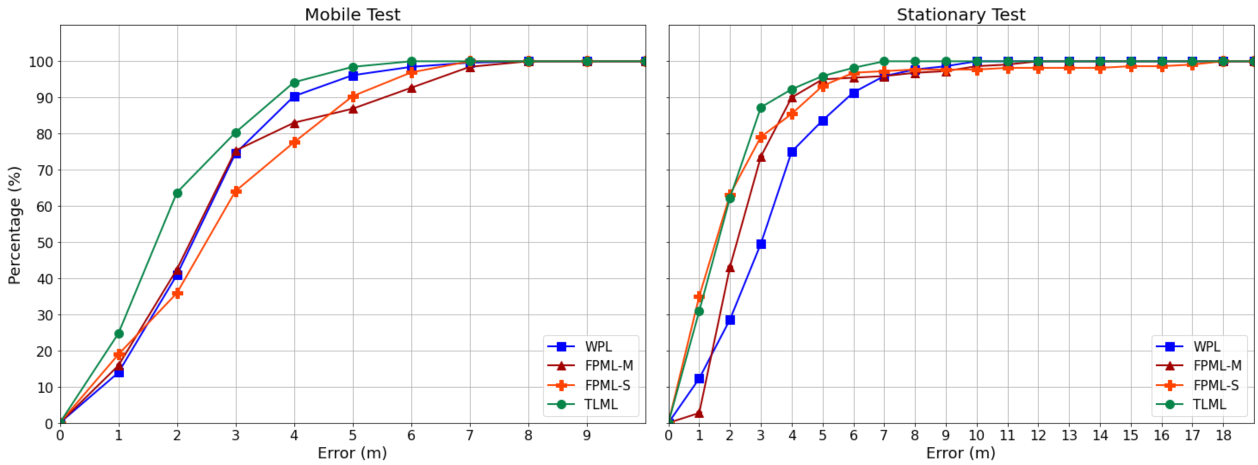

Fig. 3. Error Distribution Curves for Route B Mobile and Stationary Tests

TABLE II. TEST STATISTICS FOR ROUTE B MOBILE AND STATIONARY TESTS

Criteria	**Mobile Test**				**Stationary Test**			
	WPL	***FPML-M***	***FPML-S***	***TLML***	***WPL***	***FPML-M***	***FPML-S***	***TLML***
Mean Error (m)	2.33	2.54	2.68	1.86	3.21	2.66	2.15	1.84
Max. Error (m)	7.54	7.88	6.96	5.97	9.55	11.76	17.63	6.94
R^2	0.88	0.91	0.91	0.95	0.78	0.88	0.89	0.93
$ACC_{1.0}$ (%)	13.90	15.83	18.92	24.71	12.27	2.73	35.00	30.91
$ACC_{5.0}$ (%)	96.14	86.87	90.35	98.46	83.64	95.00	93.18	95.91
$ACC_{10.0}$ (%)	100.00	100.00	100.00	100.00	100.00	98.64	97.73	100.00

distribution curves for both FPML models were slightly lower than that of WPL. For the stationary test, FPML-S performs better than WPL and FPML-M, with a mean error of 2.15 m and having 35% of predicted positions below 1 m error. However, both fingerprinting-based models have markedly higher maximum errors at 11.76 m (FPML-M) and 17.63 (FPML-S), which is similar to the Route A tests. Thus, both the mobile and stationary tests seem to suggest that the models may need more training data in order to generalize.

TLML outperforms traditional WPL and the FPML models, being the only positioning method that reported mean errors of 1.8 m and reduced approximately 60% of positioning estimates to below 2 m error for both tests. These results corroborate with those in the Route A test and show that TLML's multilateration-based approach can perform better despite using only mobile training data.

D. Resampled Route B Test Results

Lastly, a second test set of Route B data was taken at a different date to explore the effects of minor environmental changes to ML model performance. The results are reported in Table III and the respective error curves are shown in Fig. 4. As a multilateration scheme, WPL seemed to remain stable to such changes, as proven by its statistics for both tests, which resemble the previously recorded Route B tests.

As expected, the results for the conventional fingerprinting-based models were markedly different from those reported in the previous section. FPML-M appeared to be more affected, experiencing a notable decrease in its performance in the mobile test when it had previously performed better for mobile cases. While FPML-S did not experience such drastic changes in performance, it still yielded worse results than WPL. These results suggest that the FPML models remain susceptible to a known vulnerability of conventional fingerprinting. Over time, there can be several minor changes to the wireless signal profile of a location. While this approach can account for minute changes in the fingerprint due to RSSI fluctuations, its accuracy can decrease significantly when there are several such changes that the updated fingerprints no longer closely match the initially collected set. Thus, for the FPML models to improve, resampling and retraining would be needed, which may not be possible in some cases.

On the other hand, TLML attained the lowest mean errors, maximum errors, and the only R^2 scores greater than 0.9. While the performance this round was not as good as the results in the previous Route B test, it managed to outperform both traditional WPL and the FPML models. This suggests that it remains robust to such slight changes in the test environment. This can be attributed to TLML's design. Because it is based on multilateration, only the 3 strongest beacons are used for each prediction, and these are more likely to remain the same across several positions despite the minute environmental changes in the dataset that can cause the reported RSSI values to vary by small amounts.

V. CONCLUSION

Indoor positioning can provide real-time locations of assets and personnel, which can vastly improve data-driven production across various industries. Their accuracy can be further improved with the use of machine learning solutions. However, current fingerprinting-based approaches require periodic data collection to remain accurate, which is an additional overhead and may not even be possible in many cases. This paper proposes an alternative ML approach that is based on multilateration. To reduce data collection costs, it

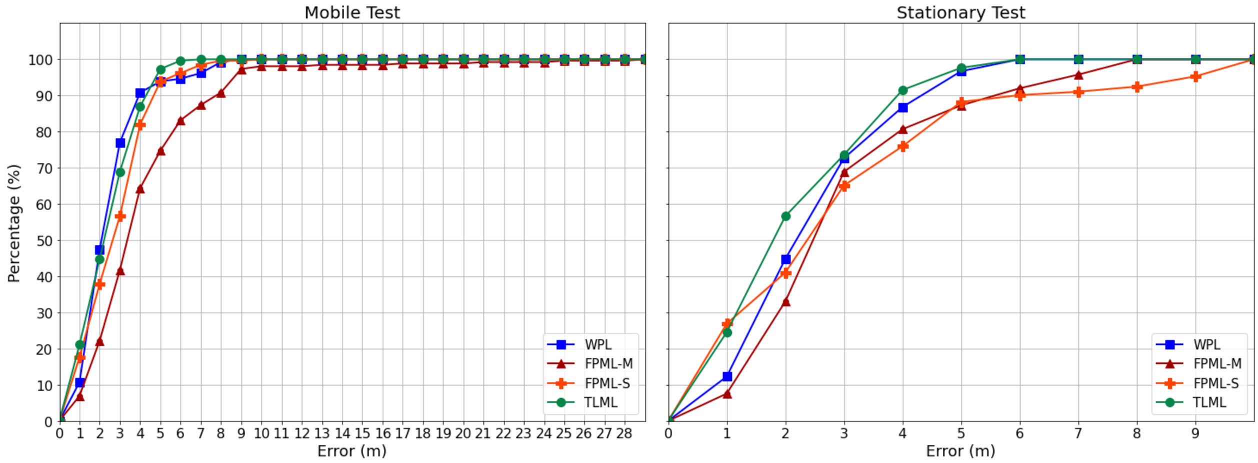

Fig. 4. Error Distribution Curves for Resampled Route B Tests

TABLE III. TEST STATISTICS FOR RESAMPLED ROUTE B MOBILE AND STATIONARY TESTS

Criteria	**Mobile Test**				**Stationary Test**			
	WPL	***FPML-M***	***FPML-S***	***TLML***	***WPL***	***FPML-M***	***FPML-S***	***TLML***
Mean Error (m)	2.36	4.03	2.66	2.31	2.34	2.85	2.82	2.04
Max. Error (m)	8.58	28.19	9.47	6.26	5.68	7.28	9.39	6.00
R^2	0.84	0.83	0.86	0.94	0.88	0.90	0.89	0.92
$ACC_{1.0}$ (%)	10.73	6.90	17.62	21.07	12.26	7.55	26.89	24.53
$ACC_{5.0}$ (%)	93.87	74.71	93.87	97.32	96.70	87.26	88.21	97.64
$ACC_{10.0}$ (%)	100.00	98.08	100.00	100.00	100.00	100.00	100.00	100.00

uses mobile data for training. The trained model is compared against traditional multilateration and fingerprinting-based ML models.

The results show that it is possible to train an accurate model using a mobile dataset using the proposed approach. TLML outperformed WPL and both FMPL models for all tests. While this solution still requires data collection, the manpower needed for the training dataset is much lower as it only needs a single round of mobile data. This contrasts with the performance of the conventional fingerprinting-based models, whose performances diminished when evaluated with the resampled test set.

This work shows the potential of multilateration-based ML models, which have not been widely explored in literature. There are multiple avenues of work that can be investigated, such as deploying the approach under harsher environments, using simulated training data to further reduce the data collection requirement, and exploring a generic model that is both location independent and technology agnostic.

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