A Deep Autoencoder and RNN Model for Indoor Localization with Variable Propagation Loss

Allan Espindola, Eduardo K. Viegas, Andre Traleski, Marcelo E. Pellenz, Altair O. Santin
Graduate Program in Computer Science — Pontifical Catholic University of Parana, Brazil
{allan.espindola, eduardo.viegas, andre.traleski, marcelo, santin}@ppgia.pucpr.br

***Abstract*—Current machine learning techniques for indoor localization of wireless devices assume a single wireless propagation loss setting, making them unfeasible for reliable production deployment. This paper proposes a new indoor localization technique designed for variable propagation loss environments based on deep autoencoder and recurrent neural network (RNN), implemented threefold. This paper proposes a new indoor localization technique designed for variable loss propagation environments based on deep autoencoder and recurrent neural network (RNN), implemented in three stages. First, we extract statistical feature values from collected RSSI. Second, a deep autoencoder is used to remove wireless propagation noises introduced by variable fading settings. Third, an RNN performs the localization task taking into account previous sensor measurements. Experiments performed in 3 simulated testbeds with distinct propagation loss settings have shown that current approaches decrease localization accuracy by up to 30% when a different propagation loss is faced. In addition, our proposed model improved localization accuracy by up to 25.8% regardless of the current environment propagation loss.**

***Index Terms*—WiFi-based indoor localization, Deep AutoEncoder, Recurrent Neural Network**

I. Introduction

Recently, a plethora of works have proposed accurate localization techniques for wireless sensor networks (WSN) [1]. In general, to achieve such a goal, due to their low cost, wireless localization is made through radio frequency (RF) approaches that make use of WiFi, Bluetooth, and even Radio Frequency Identification (RFID) devices [2]. Among these, WiFi is typically used due to its convenient deployment that does not require additional infrastructure and its pervasive penetration [3].

In such a context, WiFi localization is often made through the analysis of the Received Signal Strength Indicator (RSSI), which measures the received signal power [1]. Thus, geographically distributed reference points (*Access Points* - APs) are used to measure the RSSI from a given device. The collected data can then be analyzed to establish the device's relative location to the deployed APs [1] in a multilateration-based approach. Several techniques have been used to fulfill such a task, wherein machine-learning (ML) approaches have provided the most accurate results [4].

In a nutshell, a behavioral model is built through a computationally expensive process of model training that evaluates the behavior in a training dataset [5]. The dataset is expected to provide the production environment behavior that the built model will experience when deployed in real-world (production) settings. In such a way, the production environment behavior is assumed to not change over time. Otherwise, a new training dataset must be assembled and model retraining executed [6].

In practice, the measured RSSI values are subject to a variable propagation loss that affects the attenuation of the received signal strength over time, typically due to the channel fading, user geographical location, or even radiofrequency interference [7]. As the RSSI values may significantly vary, proposed localization techniques must assume a predefined propagation loss setting (fading properties) during the building of the training dataset [1]. Although the training data set may provide realistic RSSI attenuation as time passes, the ML models built will only perform their task when used in production if they are subject to the same propagation loss adjustments used during the training phase. Surprisingly, current ML-based localization techniques are designed according to the expected RSSI fading in a production environment, making them infeasible for a wider range of applications, taking into account the challenges related to model updates [8], [9].

Designing an ML-based localization technique that can operate regardless of the environment's current RSSI fading characteristics is challenging. The main reason is that the RSSI fading identification can only be achieved after the evaluation of several device measurements [2]. In contrast, current techniques perform the localization task through the evaluation of the current received RSSI values from all deployed APs, thus, discarding previous measurements that may be useful for the identification of the environment RSSI fading characteristics [1].

This paper proposes a new WSN localization technique for environments subject to variable propagation loss settings that use deep autoencoder and recurrent neural networks (RNN), implemented in three stages. First, to properly identify the RSSI loss propagation settings of the environment, our proposed scheme extracts univariate statistical values for each deployed AP. The extracted values help to establish the fading characteristics of the environment. Second, to decrease collected RSSI noises introduced by wireless fading, our proposed scheme uses a deep autoencoder. As a result, noises caused by wireless fading, regardless of the propagation loss environment, can be decreased as the deep autoencoder will remove irrelevant relations in its input. Third, to evaluate historical device measurements, applicable due to a variable channel fading, our scheme performs the device localization through an RNN. Thus, previous device measurements are used by our model localization scheme, further increasing its localization accuracy. The main contributions of this paper are:

- An evaluation of a (current) ML-based localization technique regarding its accuracy in a variable propagation loss environment. Our experiments indicate that a current ML-based approach is unable to operate regardless of the propagation loss used during model training, increasing its localization error by up to 30%;
- A new model based on deep autoencoder and RNN for localization of wireless devices regardless of the environment propagation loss characteristics. The proposed scheme can provide higher localization accuracies when compared to traditional approaches.

II. Preliminaries

A. RSSI-based Wireless Localization

The wireless communication channel is subject to slow and fast fading, which affects the deployed AP measured RSSI values [4]. Fading can be caused due to a variety of reasons, including geographical position, device and environment's mobility, objects along the path, and even atmospheric conditions [7]. As a result, wireless localization techniques must cope with a variety of propagation loss properties, taking into account that when such scheme is used in production, the environment wireless fading will vary as time passes, e.g., due to objects passing between devices. However, current techniques proposed in the literature often overlook variable fading properties, making use of a single fading setting during model building and evaluation [2]. As a result, proposed schemes cannot be reliably used in production, considering that as time passes, the environment behavior may change the wireless fading properties, making deployed schemes unreliable for localization tasks.

B. Machine Learning for Localization

Indoor localization approaches through ML techniques have yielded promising results [1]. The authors generally perform the localization task using ML model input a feature vector with the current device RSSI values from all deployed APs. The proposed approaches builds the *training*, *validation*, and *testing* datasets with an expected wireless propagation loss characteristic [2]. As a result, proposed schemes are only able to achieve the measured accuracies during *testing* phase if the deployed environment presents the same wireless propagation loss characteristics used during the training phase. That happens because the underlying ML model is trained according to a specific wireless propagation loss characteristic [10]. In practice, if a different fading is observed, a model retraining must be executed [11], making proposed schemes unfeasible for production. Reliable ML-based indoor localization approaches must operate regardless of the current wireless propagation loss, considering it may change drastically according to each environment settings.

In this work, we focus on two main deep-learning strategies, namely Deep autoencoder [12], and Recurrent Neural Network (RNN) [13]. Deep autoencoders have been typically used for dimensionality reduction and image denoising through a two-step process, namely *encoder* and *decoder*. The *encoder* goal is to perform the compression of the deep neural network input by learning a set of useful input feature relations. In contrast, the *decoder* goal is to perform the decompression of the *encoder* output. The deep autoencoder output is a learned representation of the most valuable relations between its input features. On the other hand, RNN architectures are composed of loops that enable pattern recognition, taking into account the information from previous inputs. The RNN stores its input values according to a given interval. Thus, it is typically used to classify temporal series or scenarios that are affected by previous inputs.

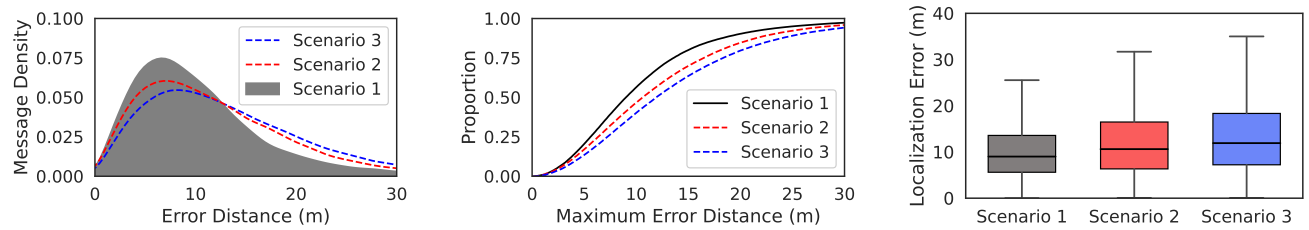
III. Related Works

In the literature, in general, the authors attempt to mitigate channel fading effects increasing localization accuracy. For instance, Y. Sun *et al.* [4] proposes an underwater wireless localization approach through support vector regression. Their approach localizes sensors in noisy environments with high accuracy. However, the authors have not addressed different channel fading properties. W. Xue *et al.* [10] proposes a filter-based approach to decrease RSSI noises. The proposed approach was able to remove noisy collected values and increase localization accuracy. They considered a single channel fading model for the environment in order to evaluate the scenario.

Localization approaches through ML-based techniques have also been widely explored in the literature [1]. For instance, V. Annepu *et al.* [14] perform wireless localization through a multilayer perceptron (MLP) model. The proposed scheme was able to provide high localization accuracies without pre-processing noisy collected data. However, a single channel fading model was also assumed. Another MLP-based approach was proposed by Z. Munadhil *et al.* [15] wherein devices were located in a real testbed through a 2-layered MLP. The proposed model provided high accuracy in a real setting. However, it demands retraining for each deployed environment, making it unfeasible for production usage. Much recent research made efforts on deep-based ML techniques due to their high reported accuracy in several fields. For instance, M. T. Hoang *et al.* [16] performs the localization task through recurrent neural networks (RNN). The proposed scheme was able to provide high localization accuracies without performing additional cleaning on collected RSSI values. However, a single wireless propagation fading setting is assumed. Another deep-based technique was proposed by A. Poulose *et al.* [17] wherein an RNN receives as input an RSSI heatmap, as an attempt to decrease noisy data. In such a case, a single wireless propagation fading was also assumed.

IV. Problem Statement

This section further investigates how a current ML-based technique performs when used for indoor localization purposes at a different wireless propagation setting. More specifically,



(a) Kernel density estimate (KDE) of localization errors

(b) Cumulative distribution function (CDF) of localization errors

(c) Boxplot of localization errors

Fig. 1: Localization performance of a MLP trained in *Scenario* 1, according to the environment settings (Table II).

we first introduce our testbed, then we evaluate an MLP model performance on it.

A. Testbed Environment

Localization techniques deployed in production environments will be subject to a variety of wireless propagation fading properties. Thus, they must be able to operate regardless of the environment they were built. We set up a controlled environment to evaluate how proposed schemes perform when different wireless fading properties are evidenced. The testbed was implemented in network simulator 3 (*ns3*) v.3.33, where 3 channel fading settings were evaluated. The wireless network simulation parameters are summarized in Table I. Each scenario is executed 30 times, being each execution deploys 20 sensors in pseudorandom locations. Each sensor sends periodic probe requests ($\approx$ 200 messages per execution round) through the wireless channel. The sensors are devices that localization techniques can reach. To measure the sensor's RSSI, we deploy 30 APs through the ns3 *GridPositionAllocator*. The fading model is Nakagami-m, and the parameters for each scenario are shown in Table II, where d is the distance between sensor and AP. The received network traffic from each AP is logged in a PCAP file, then used for further analysis.

B. A Realistic Evaluation

Our evaluation aims at answering two main research questions (RQ): (***RQ1***) *How does current ML-based approaches perform when facing the same wireless fading properties used at the training phase?* (***RQ2***) *What is the impact of variable wireless fading propagation on ML-based localization techniques?*

To achieve such a goal, we build a MLP model at *Scenario* 1 and evaluate its performance on other *Scenarios* (Scenarios 1 to 3, Table II). The models are built using a 30-valued feature vector as input according to the measured RSSI values from each deployed AP. If a given AP did not receive a sensor message due to channel fading, it is not able to provide a corresponding RSSI value. Therefore a default value of -100 is assumed. The rationale of such a technique is to perform the traditional ML-based localization technique, which only considers the current measured RSSI values from APs.

The MLP was implemented on top of *scikit-learn* API v.0.24.2. The model relies on 1000 hidden neurons while performing 1000 epochs at the training phase. The $relu$ activation function is used, with $adam$ optimizer with a 0.001 learning rate using *RMSE* objective. The *Scenario* 1 testbed environment (Table II) was split into *train*, *validation*, and *test* datasets, each with 40%, 30% and 30% respectively of the testbed deployed sensors (600 sensors at total for each testbed, 20 sensors $vs.$ 30 execution rounds). The *train* dataset is used for model building, the *validation* dataset is used for model fine-tuning, the *test* dataset is used to report the model accuracies. Our first experiment aims at answering $RQ1$ and evaluates the localization performance of the built MLP on the same testbed it was built (Table II, *Scenario* 1). Therefore, it uses the same approach as commonly made in related works that do not consider different channel propagation loss characteristics. Figure 1 shows the localization accuracy distribution of the built MLP when deployed on the same testbed configuration that was used during model building, as measured on the *test* dataset. In such a case, the average localization error achieved was 10.6 meters. It is possible to note that the localization performance of the evaluated model was significantly high, wherein 75% of sensors were able

TABLE I: Wireless Network Simulation Parameters

Parameter	**Description**
Channel Model	Free Space Path Loss + Nakagami-m Fading
Number of APs	30
AP Distribution	Grid
Number of Sensors	20 randomly deployed at each exec. round
Execution Rounds	30
Sensor Positioning	Random (Uniformly Distributed)
Coverage Area	100m x 100m
Traffic Model	Periodic Probes ($\approx$ 200 messages per sensor)
Physical Layer	IEEE 802.11n
Operating Frequency	2.4GHz
Transmission Power	0 dBm (1mW)
Antenna Type	Omnidirectional
Antenna Gain	G_t = G_r = 1 dBi

TABLE II: Fading Scenarios for the Testbed.

Scenario	**Nakagami-m Fading Setting**				
	d_0	d_1	$0 \leq d \leq d_0$ m	$d_0 < d \leq d_1$ m	$d > d_1$ m
1	20	50	4	2	1
2	80	200	1.5	0.75	0.75
3	50	100	1	1	1

to be localized within 0 to 13.1 meters range in *Scenario* 1 (Figure 1b, *Scenario* 1 at 0.75 proportion). Therefore, current techniques can provide significantly high localization accuracy when a single wireless propagation loss condition is assumed.

Our second experiment aims at answering $RQ2$ and evaluates the localization performance of the trained MLP when a different wireless propagation loss configuration is faced. In such a case, the model localization accuracy for *Scenarios* 2 and 3 is significantly degraded, providing an average localization error of 12.4 and 13.8 meters, respectively, thus, increasing localization error by up to 17% and 30%. More specifically, the MLP trained in *Scenario* 1 that was able to localize 75% of messages with up to only 13.1 meters of error, significantly degraded its performance, increasing the error range to 16.1, and 18.2 meters in *Scenarios* 2 and 3 respectively (Figure 1b). As a result, proposed ML-based localization schemes cannot cope with a variable wireless fading propagation loss. However, the propagation loss of production environments is highly variable. Hence, proposed schemes must be able to operate regardless of the current environment behavior.

V. A Deep Autoencoder and RNN Model for Localization with Variable Propagation Loss

To address the non-stationary propagation loss nature of wireless channels over time, we propose a localization model based on deep autoencoder and recurrent neural network (RNN). The proposal insight is that a deep autoencoder can remove RSSI noises introduced by variable propagation fading over time. In addition, higher localization accuracies can be achieved by extracting univariate statistic values on collected RSSI values, while the localization task is performed through RNNs, thus, following a time-series rationale. The proposal overview is shown in Figure 2.

The proposal starts with a to-be-localized sensor message propagated in the wireless channel. A subset of deployed APs receives the sent message, and the corresponding RSSI values are collected. According to the collected RSSI values, a set of univariate statistic values are extracted through a sliding window mechanism, e.g., the average AP RSSI values from the last 10 received sensor messages. The extraction of univariate statistic values aims at helping our proposed mechanism to operate regardless of the current environment propagation fading settings. Therefore, the distribution of the previous RSSI values can improve localization accuracy in dynamic propagation fading environments. The extracted values are input by a deep autoencoder, which removes noises introduced by a variable fading in the wireless channel. Finally, an RNN is applied, aiming the sensor localization according to previous neural network inputs.

The following subsections further describe our proposed model, including the components that implement it.

A. Univariate Statistics

In general, traditional localization techniques rely on the current measured RSSI values for the localization task. There-

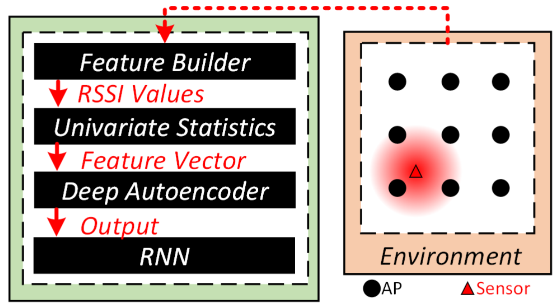


Fig. 2: Proposed localization model for variable propagation loss environments.

fore, the variation of the RSSI values that can be used to assess the current environment propagation loss settings can not be evaluated. Our proposal extracts an additional set of features for each deployed AP, recalling that our proposal relies on fixed APs to measure the sensors' RSSI values. The rationale of such an approach is that the computation of the variation of the previous RSSI values can be used to improve localization accuracy under highly variable propagation loss environments.

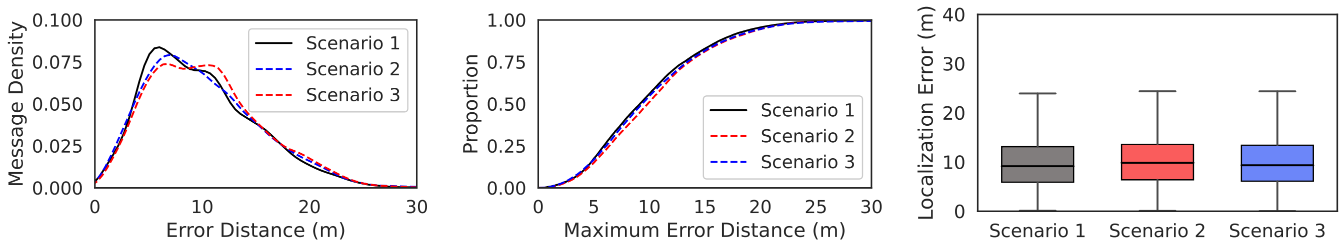
Our proposal makes use of a *Univariate Statistics* module, as shown in Figure 2. The procedure starts with the collection of the received RSSI values from all deployed APs when a given sensor sends a message through the wireless channel. The collected values are standardized by a *Feature Builder* module, which outputs the RSSI collected values in a vector format, including from those APs that did not receive the sensor message. The *Univariate Statistics* extracts additional univariate feature values for each deployed AP, according to a predefined message window (w). For instance, the module may extract the median, average, and standard deviation values of the last w received messages from the analyzed sensor for each deployed AP. Finally, the extracted values, including the current RSSI values, are used to compound a feature vector, which is then fed as input to a deep autoencoder module.

B. Noise Removal

Current localization schemes attempt to remove noises in collected RSSI caused due to a variable propagation loss through filter-based approaches. As a result, proposed techniques cannot portray meaningful relations on collected RSSI values, especially on highly variable wireless fading settings. Our proposal makes use of a deep autoencoder model. The assumption is that a deep autoencoder will remove noises introduced by a variable fading setting on the wireless channel, considering that such noises are not meaningful relations in production environments. A deep autoencoder model is applied on the extracted feature vector output by the *Univariate Statistics* module. The deep autoencoder output that removes noises on collected data is fed as input to the subsequent module.

C. Sensor Localization

Variable wireless fading can only be detected through the analysis of several sensor RSSI values. Therefore, localization



(a) Kernel density estimate (KDE) of localization errors

(b) Cumulative distribution function (CDF) of localization errors

(c) Boxplot of localization errors

Fig. 3: Localization performance of our proposed model according to the environment settings (Table II).

TABLE III: Extracted features for each deployed AP.

#	Feature	Description
1	RSSI	Current measured AP received RSSI
2	Mo	Mode of RSSI values from last w received msg.
3	$\tilde{x}$	Avg. RSSI of values from last w received msg.
4	σ	Std. Dev. of RSSI values from last w received msg.
5	σ^2	Variance of RSSI values from last w received msg.
6	Q_1	25^{th} Quartile of RSSI values from last w received msg.
7	Q_2	Mean of RSSI values from last w received msg.
8	Q_3	75^{th} Quartile of RSSI values from last w received msg.

schemes must also take into account the historical behavior of previous input samples. To perform the regression task while also evaluating previous input samples, our proposed model uses an RNN. Therefore, our model applies an RNN model on the output of the deep autoencoder, hence, with noise-free data. It is important to note, to improve localization accuracy, in addition to the current RSSI values, we also leverage univariate statistical feature values from each deployed AP (Section V-A).

VI. Evaluation

Our evaluation aims at answering the following research questions: (***RQ3***) *How does our proposed scheme performs on variable fading settings?* (***RQ4***) *How does our proposed model perform when compared to traditional techniques?*

A. Model Building

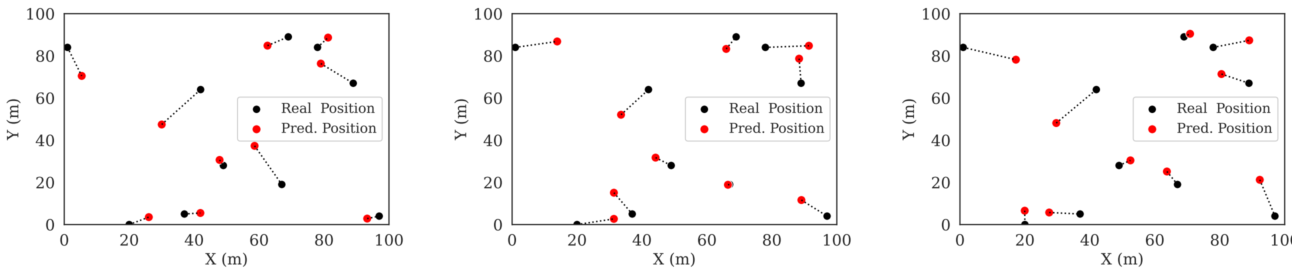
The proposed model (Figure 2) was evaluated on top of our used testbed (Section IV). Our proposed *Univariate Statistics* module was implemented through Pandas API v.1.2.4, which evaluates the network packets read from a PCAP file format as interpreted by Scapy API v.2.4.3. In total, 8 features are extracted for each deployed AP, as listed in Table III.

The deep autoencoder (Figure 2), used the *RMSE* formula as $loss$ using $adam$ optimizer, and was implemented with the following architecture: ***(i) Input***. The extracted 240 features (8 features vs 30 deployed APs) are fed as input to the deep autoencoder. ***(ii) Encoder***. Three $dense$ layers implemented with a $relu$ activation function, with 512, 256, and 128 units respectively. ***(iii) Encoder Output***. A *encoder* output layer implemented with a $linear$ activation function, and 48 units. ***(iv) Decoder***. Three decoder layers with a $relu$ activation function, with 128, 256, and 512 units respectively. ***(v) Decoder Output***. A decoder output layer with 240 units, and a $sigmoid$ activation function. As RNN architecture (Figure 2) our proposal make use of the Long-Short Term Memory (LSTM), and was implemented with the following architecture: ***(i) Input***. The 240 features output by the deep autoencoder are fed as input to the LSTM; ***(ii) LSTM***. A LSTM layer with 256 units. ***(iii) Output***. Two $dense$ layers implemented with a $linear$ activation function, with 512, and 2 units respectively.

The implemented LSTM architecture used the $RMSE$ as $loss$ using $adam$ optimizer. For the model building procedure, 1000 epochs are executed with a batch size of 512 for both deep autoencoder and LSTM. It is important to note that the used set of parameters, from both deep autoencoder and LSTM, were set similarly to related works, and no significant differences were found while varying them. The architectures were implemented through $keras$ API $v.2.4.0$, and $tensorflow$ API $v.2.4.1$.

B. Variable Fading Environments

Our first experiment aims to answer $RQ3$ and evaluate the performance of our proposed model when facing variable fading settings. The proposed scheme was trained with the train dataset from *Scenario* 1 (Table II), using a window (w) size of 10 events in the *Univariate Statistics* module (Table III). Figure 3 shows the localization accuracy of our method in all evaluated scenarios. It is possible to note that our proposed scheme improved the localization accuracy compared to traditional techniques significantly. More specifically, 75% of the testbed sensor messages are successfully localized with at most 12.5, 12.6 and 12.6 meter range in *Scenarios* 1, 2, and 3 respectively (Figure 3b). Our proposed scheme was also able to provide higher average localization accuracies for all scenarios, reaching 9.9, 10.5, and 10.2 of average localization error for *Scenarios* 1, 2 and 3 respectively. Thus, varying the average localization accuracy by up to 0.6 meters, the proposal has significantly shown improvements when compared to the traditional approach (Figure 1). Figure 4 shows the localization performance of our model for 10 sample sensors according to each scenario, showing that it can provide significantly high localization accuracies regardless of the deployed testbed.



(a) Scenario 1 (b) Scenario 2 (c) Scenario 2

Fig. 4: Localization error of our proposed model for 10 sample devices according to the deployed scenario (Table II).

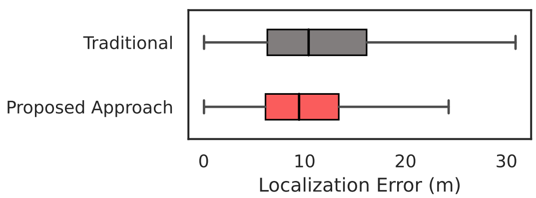


Fig. 5: Localization error distribution of evaluated techniques.

Finally, to answer question $RQ4$ we further investigate the localization accuracy of our model when compared to the traditional approach (MLP evaluated on Section IV). Figure 5 shows the boxplot of the localization error of our model and the traditional approach when deployed on all 3 evaluated scenarios. In such a case, our model's 75% of messages are localized with at most 12.6 meters of error, while the traditional approach localizes with up to 17 meters of error, a 25.8% of localization accuracy improvement. Consequently, our proposed model was able to provide higher localization accuracies regardless of the deployed environment.

VII. Conclusion

As said before, the ML-based techniques for wireless localization, in the literature, assumes a static wireless propagation fading setting. As a result, those proposed schemes can provide high localization accuracies but perform poorly when used in production due to high variability in the fading settings in real-world environments. In this paper, we have proposed a new technique aiming the reliable operation in variable wireless fading environments. Our proposed scheme that uses deep autoencoders and recurrent neural networks improved localization accuracy compared to the current localization approach from literature. As future works, we aim the localization of moving sensors while making use of fewer APs.

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