Occupancy-level-aware Indoor Terahertz Channel Prediction: A Robust Deep Learning Approach

Eslam Hasan*[1], Elmahedi Mahalal*[2], Muhammad Ismail*[3], Zi-Yang Wu†[4], Mostafa M. Fouda‡§[5], and Nei Kato¶[6]
*Department of Computer Science, Tennessee Technological University, Cookeville, TN, USA,
†College of Information Science and Engineering, Northeastern University, Shenyang, China,
‡Department of Electrical and Computer Engineering, Idaho State University, Pocatello, ID, USA,
§Center for Advanced Energy Studies (CAES), Idaho Falls, ID, USA,
¶Graduate School of Information Sciences, Tohoku University, Sendai, Japan,
Emails: {[1]ebhasan42, [2]emahalal42, [3]mismail}@tntech.edu, [4]wuziyang@ise.neu.edu.cn,
[5]mfouda@ieee.org, [6]kato@it.is.tohoku.ac.jp

Abstract*—Accurate channel prediction using deep learning (DL) algorithms can address the challenges of terahertz (THz) propagation, such as atmospheric absorption and object scattering, by enabling proactive handover and beamforming. However, indoor environments are inherently dynamic, with factors like occupancy level variations causing the channel characteristics to change over time. This phenomenon, known as concept drift, can severely degrade the DL model performance used in channel prediction. This paper investigates the impact of indoor occupancy level variations on the generalization ability of state-of-the-art DL models for THz channel prediction. We identify three distinct occupancy levels (low, medium, and high) within the THz indoor channel. Our results demonstrate that the state-of-the-art DL models exhibit limited generalization capabilities, with performance deterioration in prediction accuracy ranging from $4-62\%$. We propose a robust two-stage framework to mitigate concept drift in THz channel prediction. The first stage predicts the indoor occupancy level from the THz wireless signal, which is a multi-class classification problem. Due to the reoccurring concept of occupancy levels, the second stage contains a pool of models in a sleeping mode based on a hybrid convolutional neural network (CNN) long-short-term memory (LSTM) architecture. One of these DL expert models is activated for channel prediction based on the occupancy level predicted from the previous stage. Our framework demonstrates superior generalization by limiting the performance deterioration from 62% due to concept drift to $\leq 9\%$. This represents an 85% reduction in performance deterioration compared to the existing state-of-the-art DL models.

***Index Terms*—Channel prediction, Deep learning, Terahertz, Concept drift, Indoor occupancy prediction, domain adaptation.**

I. Introduction

As we transition towards the era of 6G networks, conventional wireless communication technologies are reaching their limits in terms of bandwidth and data rates [1]. Operating in the vast and underutilized terahertz (THz) frequency band ranging from 0.1 to 10 THz [2], THz communication promises terabit-per-second (Tbps) data rates [3]. THz communication is a foundational pillar of 6G networks [4], unlocking a new era of connectivity with applications like immersive virtual reality [5] and holographic communication [6]. However, exploiting this band presents challenges due to its propagation characteristics. THz signals experience severe path loss due to atmospheric absorption and object scattering [7]. The aforementioned factors present significant challenges in achieving reliable and robust communication over the THz band, especially in mobile scenarios. By leveraging deep learning (DL) algorithms, it becomes possible to accurately predict the THz channel gain, allowing for proactive transmission [8], handover [9], and beamforming [10]. By predicting the THz channel gain using DL algorithms, the system can proactively determine the optimal beam direction to maintain signal strength and avoid blockage [10]. Also, the DL algorithms can predict blockage to initiate a handover before the signal quality with the current base station degrades significantly [9]. By predicting THz channel gain, the system can proactively adjust modulation schemes, coding rates, and transmission modes to maintain reliable communication links [8]. However, concept drift can be a significant issue in the context of channel prediction [11].

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In the context of wireless channel prediction, concept drift can occur due to dynamic users' behavior within environments. As the number of users changes over time, the characteristics of the channel, such as channel blockage and path loss, also vary, leading to variations in the wireless channel. This variation introduces concept drift into the wireless channel, making it challenging to predict the wireless channel accurately [11].

A. Related Works

Authors in [9] developed a long-short-term memory (LSTM) neural network for blockage prediction to enable proactive handover in indoor THz communications. In [10], authors proposed a gated recurrent unit (GRU) based on a recurrent neural network to enable proactive beamforming for THz mobile drone users. Deep reinforcement learning has been adopted in [12] to determine the optimal beam direction for hybrid beamforming in THz communication systems. Authors in [13] proposed a bidirectional LSTM for THz channel gain prediction. Furthermore, computer vision-aided beam management based on a convolutional neural network (CNN) has been proposed in [14] to direct the signal toward the user equipment based on its 3D location identified by the DL object detector. The proposed channel prediction method in [15] introduces a transformer encoder with channel index embedding (TE-CIE) DL model for THz channel prediction. Authors in [6] have adopted generative artificial intelligence for THz channel prediction to enable holographic communications and digital radio twins.

The previous works consider the multi-user scenarios and their mobility. However, they assume the number of users is fixed during the experiment. In real scenarios, the number of users changes over time [16], leading to a concept drift due to the variations in the THz channel. Hence, the deployed DL model cannot accurately predict the THz channel.

This paper focuses on indoor environments since they account for generating 80% of mobile data [17]. The contributions of our paper can be summarized as follows:

- We investigate the concept drift in the THz wireless channel due to the occupancy level variations in real scenarios. To the best of our knowledge, this is the first time to study the concept drift effect on DL models utilized in THz wireless channels. Our results demonstrate that the DL models exhibit limited generalization capabilities due to concept drift. The performance deterioration in THz channel prediction accuracy ranges from $4-62\%$.
- We propose a robust DL-based channel prediction framework for concept drift mitigation in THz communications under occupancy level variations in real scenarios. Our framework demonstrates superior generalization by limiting the performance deterioration in channel prediction accuracy from 62% due to concept drift to $\leq 9\%$. This represents an 85% reduction in performance deterioration compared to the existing state-of-the-art DL models.

The rest of the paper is organized as follows. Section II introduces the system model. Section III presents the statistics of the dynamic THz channel and the performance of the DL THz channel prediction models under occupancy level variations. Section IV proposes the proposed framework for robust THz channel prediction against occupancy level variations. Section V concludes our findings.

II. SYSTEM MODEL

This section introduces the indoor layout, the user mobility model, and the dynamic THz channel data generation.

A. Indoor Setup

We consider a standard office room with dimensions of 5m×5m×3m. This room is furnished with nine desks, with an arrangement detailed in Fig. 1. Wireless communication within the room is facilitated by four THz access points (APs) distributed across the ceiling, as shown in Fig. 1. Mobile users within the environment are modeled as cuboids with dimensions of $1.8\text{m}\times0.2\text{m}\times0.45\text{m}$. These users have a weight of 70 kilograms and a speed of 2.1 m/s.

B. Mobility Model

This study leverages a well-established and validated mobility model introduced in [18] to accurately represent human mobility within the indoor environment. The model operates on two distinct timescales, macro and micro, as follows:

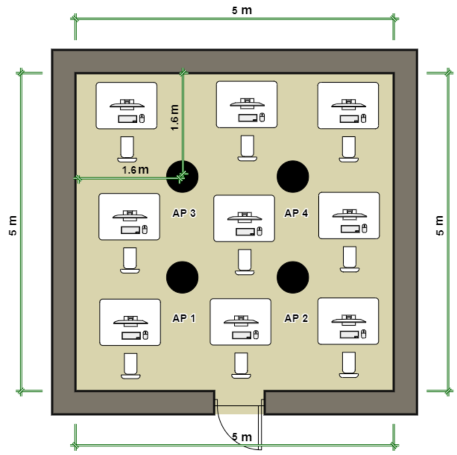

Fig. 1. Illustration of the indoor layout.

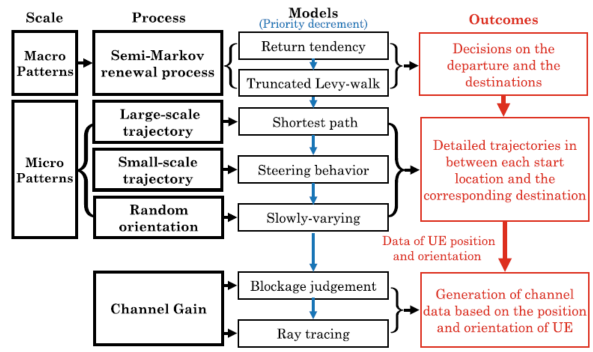

Fig. 2. Framework to generate dynamic THz channel gain.

- Macro-scale mobility: This timescale governs the decision-making process behind the user's movement, including the timing and destination of their next move. It achieves this through a semi-Markov renewal process, which incorporates both regular return patterns (e.g., returning to a desk) and bounded Levy-walk behavior (accounting for unpredictable elements in human movement).
- Micro-scale mobility: This timescale focuses on the details of user movement within the environment. Specifically, it considers factors such as the user's shortest path to the destination point, the user's steering behavior (e.g., avoiding obstacles), and the user equipment's (UE) orientation.

A detailed illustration of the adopted mobility model can be found in Fig. 2. After generating the mobility traces, the position of each user and the position of its serving THz AP are used to decide channel blockage. Hence, the THz channel gain is calculated based on the multi-ray THz channel propagation model presented in the following subsection.

C. Multi-ray Channel Propagation Model in the THz Band

In this subsection, we summarize the multi-ray channel model used to simulate the electromagnetic wave propagation in the THz band, employing ray tracing techniques. The multi-ray channel model is expressed as a superposition of individual paths, where the THz channel model is represented according to [19] as follows

$$h(\tau) = \sum_{i=1}^{I} \alpha_i \cdot \delta(\tau - \tau_i), \quad (1)$$

where I is number of paths, α_i is the attenuation of i^{th} path, τ is the propagation delay, and τ_i is the delay of i^{th} path. The multi-ray channel model consists of line-of-sight (LoS), reflected, scattered, and diffracted paths. However, diffracted paths can be neglected in indoor THz environments as this propagation phenomenon is only pivotal at lower microwave frequencies [20]. Also, scattered paths can be neglected due to the very high losses that occur after scattering [20], so we only consider the LoS and the reflection paths. Hence, the multi-ray channel model can be represented as follows

$$h(\tau) = \alpha_{\text{LoS}} \cdot \delta(\tau - \tau_{\text{LoS}}) \cdot \mathbb{1}_{LoS} + \sum_{p=1}^{N_{\text{Ref}}} \alpha_{\text{Ref}}^{p} \cdot \delta(\tau - \tau_{\text{Ref}}^{p}), \quad (2)$$

where α_{LoS} represents the LoS attenuation, τ_{LoS} represents the LoS delay, $\mathbb{1}_{LoS}$ is one if there is a LoS path or zero otherwise, α_{Ref}^{p} is the attenuation for p^{th} reflected path, and τ_{Ref}^{p} is the p^{th} reflected path delay. The transfer function of the LoS, $H_{\text{LoS}}(f)$, can be described in terms of spreading loss function, $H_{\text{Spr}}(f)$, and molecular absorption loss function, $H_{\text{Abs}}(f)$, as follows

$$H_{\text{LoS}}(f) = H_{\text{Spr}}(f) H_{\text{Abs}}(f) e^{-j2\pi f \tau_{\text{LoS}}}, \quad (3)$$

where the spreading loss function can be represented in terms of the speed of light c and the distance r between the transmitter and the receiver as $H_{\text{Spr}}(f) = \frac{c}{4\pi \cdot f \cdot r}$, the molecular absorption loss function can be represented in terms of medium absorption coefficient k that depends on the utilized frequency as $H_{\text{Abs}}(f) = e^{-\frac{1}{2}k(f) \cdot r}$, and the LoS arrival time, τ_{LoS}, equals $\frac{r}{c}$. The transfer function of the reflected path, $H_{\text{Ref}}(f)$, can be described as follows

$$H_{\text{Ref}}(f) = \frac{c}{4\pi f \cdot (r_1 + r_2)} \cdot e^{-j2\pi f \tau_{\text{Ref}}} \cdot e^{-\frac{1}{2}k(f)(r_1+r_2)} \cdot R(f), \quad (4)$$

where r_1 is the distance between the transmitter and the reflector, r_2 is the distance between the reflector and the receiver, R is the reflection coefficient, and the reflected path time of arrival equals $\tau_{\text{Ref}} = \tau_{\text{LoS}} + \frac{r_1+r_2-r}{c}$. By applying Kirchhoff scattering theory, the reflection coefficient for a rough surface is calculated by multiplying the Rayleigh roughness factor, ρ, with the smooth surface reflection coefficient for transverse electric (TE) derived from the Fresnel equations, γ_{TE}, as follows

$$R(f) = \rho(f) \cdot \gamma_{TE}(f). \quad (5)$$

The Fresnel reflection coefficient for TE polarized waves on a smooth surface can be approximated as follows

$$\gamma_{TE}(f) \approx -e^{-\frac{-2cos(\theta_i)}{\sqrt{n_t^2-1}}}, \quad (6)$$

where θ_i is the incident wave angle and n_t is the refractive index. The roughness effect can be calculated based on the rough surface height standard deviation, σ, as follows

$$\rho(f) = \exp\left(-\frac{8\pi^2 \cdot f^2 \cdot \sigma^2 \cdot \cos^2(\theta_i)}{c^2}\right). \quad (7)$$

Hence, the THz channel gain can be calculated as follows

$$\begin{aligned} h(\tau) = & \left| \frac{c}{4\pi \cdot f \cdot r} e^{-\frac{1}{2}k(f)r} \right| \cdot \delta(\tau - \tau_{\text{LoS}}) \cdot \mathbb{1}_{\text{LoS}} \\ & + \sum_{p=1}^{N_{\text{Ref}}} \Bigg| \left(\frac{c}{4\pi f \cdot (r_1+r_2)}\right) e^{-\frac{1}{2}k(f)(r_1+r_2)} \cdot \left(-e^{\frac{-2\cos(\theta_i)}{\sqrt{n_t^2-1}}}\right) \\ & e^{-\frac{8\pi^2 \cdot f^2 \cdot \sigma^2 \cdot \cos^2(\theta_i)}{c^2}} \Bigg|_p \cdot \delta(\tau - \tau_{\text{Ref}}^{p}). \end{aligned} \quad (8)$$

III. DL THz Channel Prediction Models Performance Under Occupancy Level Variations

In this section, we present the statistics of the dynamic THz channel, formulate the THz channel gain prediction problem, and introduce the baseline and benchmark prediction models.

A. Dynamic THz Channel Statistics

Using the framework presented in Fig. 2, we simulated the THz channel gain over 1000 mobility traces for low, medium, and high occupancy levels given the indoor layout in Fig. 1. Fig. 3 demonstrates the probability density function (PDF) of THz average channel gain for these occupancy levels. The low occupancy level has only one user, whereas the medium and high occupancy levels have up to 4 and 8 users, respectively.

As shown in Fig. 3, the statistics of the THz channel gain vary according to the occupancy level. We observe that the average channel gain distribution shifts as the occupancy level increases. Since the occupancy level changes throughout the time [21], the channel gain could belong to any of these different distributions. Hence, we investigate the impact of this non-stationarity on the performance of THz channel prediction.

B. Problem Formulation

We consider a wireless THz network in a dynamic environment with mobile users in an indoor room layout. Given a fixed window of n historical wireless THz channel gain values calculated using equation eight, denoted as $\{h(t_1), h(t_2), ..., h(t_n)\}$ collected at discrete time instances $t_1, t_2, ..., t_n$, the task is to design a predictive model to predict the THz channel gain $h(t_{n+1})$ based on the past observations while minimizing the prediction error.

C. Data Preprocessing

In this study, we employed data preprocessing to ensure the robustness and reliability of our DL models. We utilized a sliding window approach to segment the THz channel gain time series data into overlapping windows. This technique enhances the DL model's ability to capture temporal dependencies and patterns within the data. Each window is treated as an individual

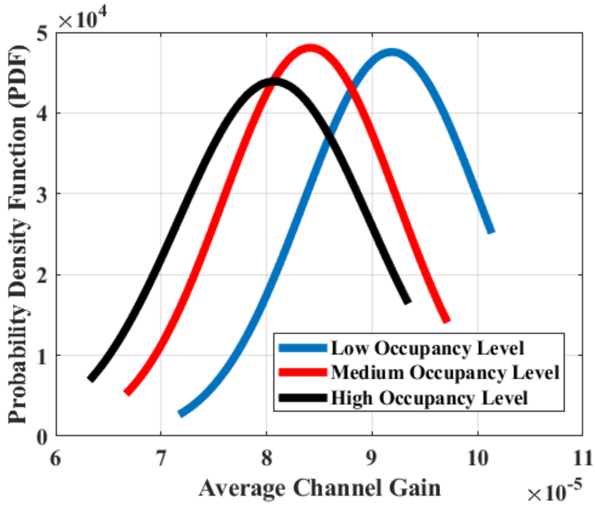

Fig. 3. The PDF vs. THz wireless channel gain under different occupancy levels.

sample for subsequent processing. For the prediction task, each sample was normalized to have a fixed range between zero and one. This normalization processes ensure that all features contribute equally to the model's learning process and help accelerate convergence during training. Each dataset is split into training, validation, and testing. The splitting ratio is 60%, 20%, and 20% for training, validation, and testing, respectively.

D. DL Baseline Models for THz Channel Prediction

To investigate the impact of occupancy level variations on indoor THz channel prediction, we developed all-occupancy-levels and occupancy-specific DL models. These baseline models are based on the hybrid CNN-LSTM architecture.

The occupancy-specific DL models are trained using a dataset corresponding to a specific indoor occupancy level, allowing it to specialize in capturing the patterns within that occupancy level. These occupancy-specific DL models are low, medium, and high occupancy models. The low occupancy model is trained on a low occupancy level scenario dataset, where the features of the training dataset are the time series of the THz channel gain, and the ground truth is the THz channel gain value of the next time step. Similarly, for the medium and high occupancy models, the features of the training dataset are the time series of the THz channel gain for their respective occupancy levels, with the ground truth being the next value of the THz channel gain for that occupancy level scenario.

Adam optimizer is used during the training process of the low, medium, and high DL occupancy models with a learning rate of 0.001. Also, dropout is used to prevent overfitting during the training phase. The hyperparameters of the low occupancy DL model are optimized using random search. The low occupancy DL model consists of a one-dimension convolutional layer of 153 filters with a kernel size of three, followed by a one-dimension max pooling layer, followed by two LSTM layers where each LSTM layer has 153 neurons. Finally, a dense layer with one neuron follows the LSTM layers to provide the prediction of the THz channel gain in the low occupancy scenario. Also, the hyperparameters of the medium occupancy DL model are optimized using random search. The medium occupancy DL model consists of a one-dimension convolutional layer of 138 filters with a kernel size of three, followed by a one-dimension max pooling layer, followed by seven LSTM layers where each LSTM layer has 138 neurons. Finally, a dense layer with one neuron follows the LSTM layers to provide the prediction of the THz channel gain in the medium occupancy scenario. Furthermore, the hyperparameters of the high occupancy DL model are optimized using random search. The high occupancy DL model consists of a one-dimension convolutional layer of 53 filters with a kernel size of three, followed by a one-dimension max pooling layer, followed by eight LSTM layers where each LSTM layer has 53 neurons. Finally, a dense layer with one neuron follows the LSTM layers to provide the prediction of the THz channel gain in the high occupancy scenario.

On the other hand, the all-occupancy-levels DL model is trained using the entire range of occupancy scenarios. Hence, the input is the THz channel gain time series data from low, medium, and high occupancy scenarios, whereas the ground truth is the next time step of the THz channel gain in each occupancy scenario. Adam optimizer is used during the training process of the all-occupancy-levels DL model with a learning rate of 0.001. Also, dropout is used to prevent overfitting during the training phase. The hyperparameters of the all-occupancy-levels DL model are optimized using random search. The all-occupancy-levels occupancy DL model consists of a one-dimension convolutional layer of 201 filters with a kernel size of three, followed by a one-dimension max pooling layer, followed by two LSTM layers where each LSTM layer has 201 neurons. Finally, a dense layer with one neuron follows the LSTM layers to provide the THz channel gain prediction.

E. Benchmark Prediction Model

To evaluate the performance of the proposed CNN-LSTM models for THz channel gain prediction, we developed three benchmark deep neural network (DNN) models corresponding to low, medium, and high occupancy levels and trained on their corresponding datasets. The first benchmark model, developed for the low occupancy level, consists of five dense layers with 992, 384, 32, 224, and 992 neurons, respectively. These layers are followed by one dense layer with one neuron to predict the THz channel gain in the low occupancy level scenario. The second benchmark, developed for the medium occupancy level, consists of a single dense layer containing 672 neurons, followed by a dense layer with one neuron for THz channel gain prediction in the medium occupancy level scenario. Finally, the third benchmark model for high occupancy level comprises eight dense layers with 228, 192, 800, 608, 544, 160, 736, and 32 neurons, respectively, followed by a dense layer with one neuron to output the predicted THz channel gain in the high occupancy level scenario. Adam optimizer is used during the training process of the DNN benchmark models with a learning rate of 0.001.

F. Performance Metrics

To evaluate the effectiveness of the THz channel gain prediction models, we employed the mean squared error (MSE) as our evaluation metric. MSE is widely used in prediction tasks and provides a robust measure of the average of the squares of the errors. Since MSE squares the errors before averaging, it places greater emphasis on larger errors. This sensitivity is particularly beneficial in THz communications, where large prediction errors can significantly impact the performance of the communication system. The MSE is calculated as follows

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2, \tag{9}$$

where N is the total number of THz channel gain samples, y_i represents the ground truth of the THz channel gain, and $\hat{y}_i$ denotes the predicted THz channel gain.

G. Performance Evaluations

We evaluate the prediction performance of the proposed CNN-LSTM and the DNN benchmark models for THz channel prediction under varying indoor occupancy levels. Table I demonstrates the MSE of the baseline CNN-LSTM and benchmark DNN models when tested on their corresponding occupancy level scenario. From Table I, we can see that the DNN models have significantly higher MSE in predicting the THz channel gain than the CNN-LSTM models. Hence, the CNN-LSTM baseline models outperform the DNN models in accurately predicting the THz channel gain as the CNN component extracts spatial features from the input data, while the LSTM captures the temporal dependencies within the data.

TABLE I. The MSE of the baseline CNN-LSTM and benchmark DNN models for THz channel prediction.

Model	Scenario	MSE
CNN-LSTM	Low	1×10^{-8}
	Medium	2×10^{-8}
	High	1×10^{-8}
DNN	Low	2×10^{-6}
	Medium	2×10^{-6}
	High	1×10^{-6}

Fig. 4 shows the percentage of the performance deterioration in THz channel prediction accuracy using the CNN-LSTM baseline models when tested against different occupancy level scenarios. In Fig. 4, the y-axis shows the percentage of deterioration in terms of prediction accuracy when THz channel gain data from an occupancy level scenario is used on a given model. The x-axis shows the three distinct occupancy level scenarios. In each scenario, its THz channel gain dataset is applied to four models, namely, low, medium, high, and all-occupancy-levels DL models. For instance, in each occupancy level scenario, when its channel gain data is applied through its corresponding occupancy level model, a zero deterioration is achieved since the input data has the same distribution as the one used to develop the model. However, when a different occupancy level data than the model was trained on is applied through it, a deterioration between $4-62\%$ is observed.

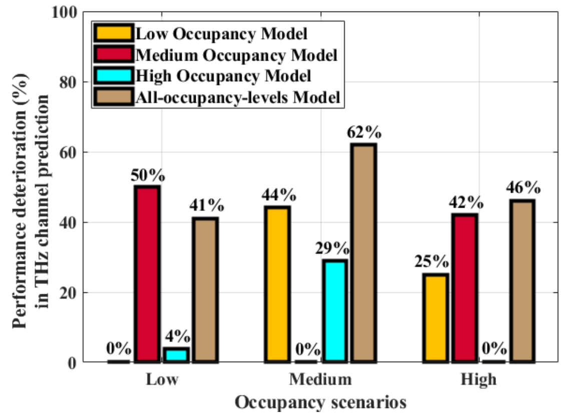

Fig. 4. Percentage of performance deterioration in THz channel prediction accuracy using CNN-LSTM under occupancy level variations.

The prediction performance of the high occupancy DL model deteriorates only by 4% when tested against the low occupancy level scenario. This is because the high occupancy scenario that the high occupancy level model is trained on has an occupancy range of up to 8 users. Hence, the high occupancy level scenario implicitly contains a mixture of low and medium occupancy level scenarios. Therefore, this exposure to diverse scenarios enables the model to capture a simple occupancy level scenario, such as the low occupancy level scenario. However, The high occupancy DL model cannot generalize across all the occupancy level scenarios as its prediction performance deteriorates by 29% when tested on the medium occupancy level scenario.

The prediction performance of the all-occupancy-levels DL model deteriorates between $41-62\%$ when tested against different occupancy level scenarios; however, it was trained based on a dataset that contains all of these scenarios. This is because developing a DL model using diverse occupancy level scenarios confuses the DL model in capturing the underlying data distributions, as each occupancy level scenario has its own data distribution.

Overall, the CNN-LSTM DL models cannot generalize over the different occupancy level scenarios. Hence, the results emphasize that the dynamic indoor occupancy levels negatively impact the generalization ability of the DL models for THz channel prediction. The following section introduces a proposed framework to obtain generalization against different occupancy level scenarios.

IV. Proposed Framework for Robust THz Channel Prediction Against Different Occupancy Levels

This section introduces the proposed framework for robust THz channel prediction, the benchmark classifier, and the performance evaluations of the proposed framework.

A. Proposed Framework

The proposed framework is a two-stage approach where the first stage is a multi-class classifier that classifies the occupancy

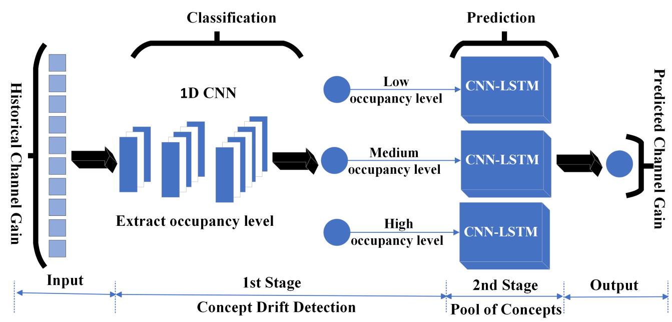

Fig. 5. The proposed framework architecture for robust THz channel prediction against different occupancy level scenarios.

level into low, medium, or high. Based on the classified occupancy level, the second stage predicts the THz channel gain by activating the corresponding CNN-LSTM baseline prediction model introduced in the previous section, as shown in Fig. 5.

Extracting real-time occupancy level information from the THz wireless signal builds an awareness of the indoor environment to mitigate the concept drift. In the first stage of our proposed framework, a CNN classifier is utilized to predict the occupancy level from the THz wireless signal. This classifier is trained on a balanced labeled dataset containing the three distinct occupancy levels to learn the patterns/wireless-signature for each occupancy level.

To elaborate more, the features of the classification dataset are the time series THz channel gain data of the low, medium, and high occupancy scenarios, while the label is the distinct class for each occupancy level, which is low, medium, or high. We utilized a sliding window approach to segment the THz channel gain time series data into overlapping windows. Each sample was standardized to have a mean of zero and a standard deviation of one. Also, the dataset is split into training, validation, and testing. The splitting ratio is 60%, 20%, and 20% for training, validation, and testing, respectively. Adam optimizer is used during the training process of the DNN classifier with a learning rate of 0.001. Also, batch normalization after each layer is used to prevent overfitting during the training phase. The hyperparameters of the CNN classifier are optimized using random search. The CNN classifier consists of three convolutional layers with 512 filters and a kernel size of three in each layer. Then, a dense layer with three neurons using a softmax activation function is used to predict the occupancy level class.

The second stage predicts the THz channel gain. There is a pool of three distinct occupancy-specific DL models in a sleeping mode. This stage activates the corresponding expert model, i.e., the occupancy-specific DL model, based on the predicted occupancy level provided from the first stage. These experts are the CNN-LSTM baselines introduced in the previous section. Hence, the proposed framework enables informed decisions about activating the right occupancy-specific DL model. This signifies that the framework adapts its model selection based on the occupancy level.

B. Benchmark Classification Model

We developed a benchmark DL model based on a DNN to compare the proposed CNN classifier performance in detecting occupancy level scenarios. The DNN benchmark classifier was trained on the same dataset that the proposed CNN classifier was trained on. Adam optimizer is used during the training process of the DNN classifier with a learning rate of 0.001. Also, batch normalization after each layer is used to prevent overfitting during the training phase. The hyperparameters of the DNN classifier are optimized using random search. The DNN classifier consists of three dense layers with 256, 512, and 1024 neurons in the first, second, and third layers, respectively. Then, a dense layer with three neurons using a softmax activation function is used to predict the occupancy level class.

C. Performance Evaluations

Fig. 6 shows the relative accuracy between the CNN and DNN classifiers in detecting the occupancy level scenarios. From Fig. 6, we can see that there is a small gap in the accuracy between the DNN and the CNN classifiers in the high occupancy scenario. However, this gap increases when the DNN is used to classify the low and medium occupancy level scenarios. This indicates that the CNN classifier outperforms the DNN classifier due to its capabilities of extracting the hidden signatures in the data.

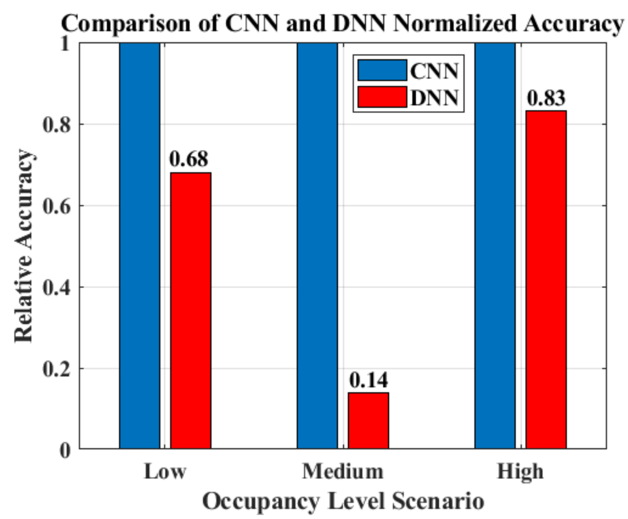

Fig. 6. The relative accuracy between the CNN and DNN classifiers in detecting different occupancy level scenarios.

In Figure 7, the x-axis represents different occupancy levels, and the y-axis represents the accuracy deterioration in the THz channel gain prediction using the proposed CNN and the benchmark DNN classifiers. Both classifiers show minimal deterioration in the high occupancy scenario. In the low occupancy scenario, the DNN benchmark classifier deteriorates more than the proposed CNN classifier by 30%. However, in the medium occupancy scenario, the DNN classifier shows a significant deterioration of almost 70% compared to the proposed CNN classifier. Hence, Figure 7 shows the robustness

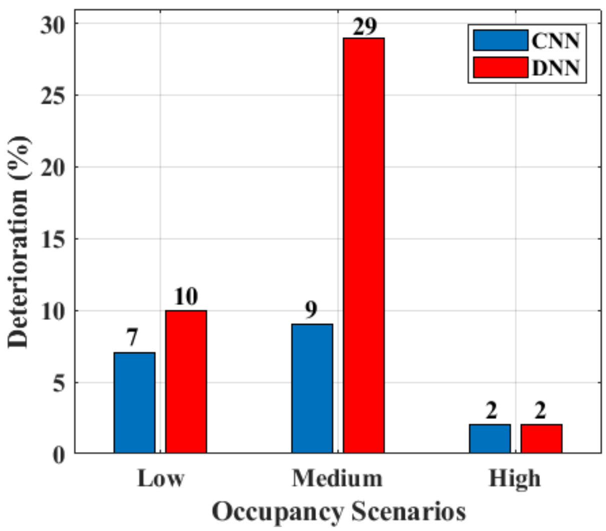

Fig. 7. Percentage of performance deterioration in THz channel prediction accuracy using the proposed framework.

of the CNN classifier, which can maintain the deterioration under 9% in different occupancy level scenarios due to its robust accuracy compared to the DNN classifier as shown in Fig. 6.

The results demonstrate that the proposed two-stage THz channel prediction framework effectively mitigates the concept drift due to occupancy level variations for robust THz channel prediction. Performance deterioration remains $\leq 9\%$ compared to the baselines' MSE in Table I across all occupancy levels (low, medium, high) rather than 62% when using the baseline models. This robustness is attributed to the framework's first stage, which establishes indoor occupancy level awareness, leading to an 85% reduction in performance deterioration compared to the baseline models.

V. Conclusion

This paper investigates the concept drift within indoor THz channels resulting from variations in indoor occupancy levels. To mitigate the concept drift issue, we developed a two-stage framework. The first stage employs THz signals to predict the indoor occupancy level. Based on the predicted occupancy level from the first stage, the second stage activates the corresponding occupancy-specific model to predict the THz channel gain. Our results demonstrate the superior generalization of the proposed THz channel prediction framework, limiting performance deterioration from 62% due to concept drift to $\leq 9\%$. This represents an 85% reduction in performance deterioration compared to the existing state-of-the-art DL models.

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