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A Deep Learning Method for Predictive Channel Assignment in Beyond 5G Networks

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***Abstract*—In Beyond Fifth Generation (B5G) networks, Internet of Things (IoT) and massive Machine Type Communication (mMTC) traffic are anticipated to be offloaded by multi-hop, Device-to-Device (D2D)-enabled relay networks. The relays offer an energy and spectral-efficient solution to the rising problem of spectrum scarcity and overloading of cellular base stations. Moving beyond the conventional paradigm of the relay nodes employing channels on a specific band at a time, in this article, we aim to investigate how to simultaneously leverage multiple bands at a relay node to improve spectral efficiency. We address the challenge associated with dynamic channel conditions in the multi-band relay networks, and envision a deep learning-based predictive channel selection method to solve the problem. A 1-D (one-dimensional) Convolutional Neural Network (CNN) model is employed to predict the suitable channels across multiple bands with the best Signal-to-Interference-plus-Noise Ratio (SINR). The packets received from the source or previous relay node are scheduled to be transmitted to subsequent relay node/destination based on the best modulation and coding rates to transmit over the predicted band. Our envisioned approach, based on shallow and deep-CNN models, proposes two proactive channel assignment strategies, namely controlled and smart prediction. Our proposal is evaluated with several, comparable machine/deep learning methods. Experimental results, based on datasets, demonstrate encouraging performance of our proposed light-weight deep learning-based proactive channel selection in multi-band relay systems.**

***Index Terms*—Internet of Things (IoT), Device-to-Device (D2D), Beyond 5G (B5G) network, deep learning, Convolutional Neural Network (CNN).**

I. Introduction

With the proliferation of Internet of Things (IoT) and massive Machine Type Communication (mMTC), relay-based wireless transmission technologies (e.g., Device-to-Device (D2D) communications) are emerging as a promising technique in Beyond Fifth Generation (B5G) networks [1]. Since legacy cellular networks were originally designed for human-driven services, they are unable to cope with the surging IoT/mMTC traffic. To complement the cellular base stations, as depicted in Fig. 1, mobile devices (e.g., user-smartphones, hovering Unmanned Aerial Vehicles (UAVs), and so forth) can act as D2D nodes or relays without increasing the transmission power, and extend the coverage area for deployed IoT devices over remote communities and natural resource ranges (e.g., forest, oil-rigs, energy supply lines, and so forth). To improve spectral efficiency and throughput of such a system, it is crucial to maintain the quality of the communication channel with minimal delay and packet drops. In the traditional Decode and Forward (DF) technique, encoded data are passed to a relay node, where decoding and demodulation are performed, and then the data are transmitted to the subsequent relay/destination node after re-encoding [2]. However, this sequence of reception, decoding, encoding, and forwarding contributes to a significantly high delay and packet drops at the relay. In an earlier work [3], a Truncated Decode and Forward (TDF) technique was implemented to conceptualize simultaneous reception and transmission over multiple bands in a wireless system. Using this technique, while receiving data from source to relay over one frequency band, the data can be transferred to the subsequent node using another band. In this article, we argue that the prediction of channel quality using deep learning-based light-weight models followed by the proactive selection of the best band and channel for data transmission at a relay node, ahead of time, can significantly improve the throughput in multi-hop relay systems offloading massive IoT traffic.

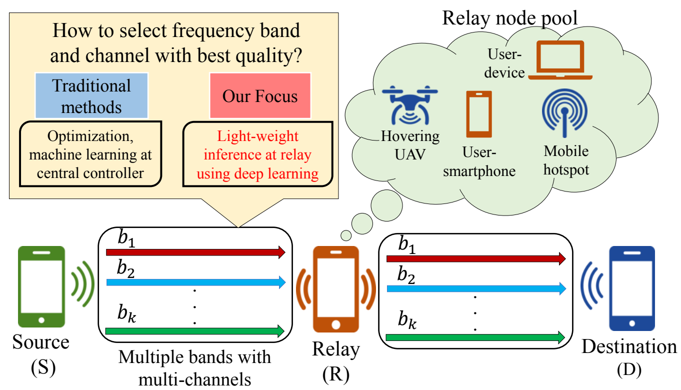

Fig. 1. Our research focus compared to the traditional focus for selecting the most suitable channel in multi-band relay networks.

Numerous Artificial Intelligence (AI) models and machine/deep learning techniques emerged in the literature to predict network traffic flows and Channel State Information (CSI) [4]. However, to the best of our knowledge,

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such techniques have not been considered to predict optimal band/channel in a multi-band relay system as depicted in Fig. 1 whereby each relay node utilizes heterogeneous bands (e.g., 920MHz, 2.4GHz, 5GHz, and so on). Moreover, due to their resource-constrained nature, the relay nodes are unable to locally train complex deep learning models. Therefore, in this article, we aim to investigate several pre-trained AI models for the multi-band, multi-channel prediction task with minuscule error. Linear Regression (LR), shallow Artificial Neural Network (shallow-ANN), deep Artificial Neural Network (deep-ANN), and Convolutional Neural Network (CNN) with shallow and deep layers are considered as candidate models to be adopted locally for channel quality inference at the relay node. The shallow-CNN model is adopted as the most viable candidate, for deployment at the resource-constrained relay node, to predict the most suitable channels for data transmission. After our uniquely constructed deep learning model predicts the quality of the channels at the relay node, the modulation, coding rate, and sending rate are determined from the Modulation and Coding Scheme (MCS) table. These are then used to calculate the link rates. The header of the data frame is passed from the source to relay node, where the need for a relay node is determined and data are accordingly passed. The data are then forwarded from the relay to destination node over another band. This process minimizes the delay significantly; because unlike the conventional DF method, data transmission and reception take place simultaneously instead of waiting for the entire data frame to arrive prior to transmission. The effectiveness and accuracy of our proposed model are evaluated using extensive computer-based simulations and real datasets.

The remainder of the article is organized as follows. Section II surveys the relevant research work. The considered system model is discussed in Section III. Next, in Section IV, the problem of proactively predicting and assigning the suitable band and channel in a multi-band relay network is formally presented. Our proposed deep learning model for selecting the channel with the best quality is presented in Section V. The prediction performance and the efficiency of our proposal are evaluated in Section VI, and compared with the performances of several machine/deep learning algorithms. Finally, Section VII concludes the article.

II. Related Work

In this section, we survey the relevant research work from the perspective of two domains, namely, the application of machine/deep learning to predict channel quality and the design of a suitable algorithm for increasing the spectral efficiency of the overall process.

A. AI-based Wireless Network Condition Prediction

AI-based models have been extensively leveraged to predict the link quality of wireless sensor networks, model and predict cellular network conditions, and forecast failure-prone links [5]. A survey conducted by Mao et al. [6] identified the importance and scope of deep learning in a plethora of wireless network scenarios. An encoder-decoder based sequence-to-sequence deep learning model named DeepChannel was designed employing Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) to predict later wireless signal strength variations based on the preceding signal strength data [7]. A machine learning-based predictor employing a time-division duplex scheme was designed by Yuan et al. [8] to reduce channel estimation overhead. The work by Herath et al. [9] employed Recurrent Neural Networks (RNNs) such as LSTM and GRU models on a series of past signal strength data to predict the signal strength of subsequent time-slots in various wireless networks. The adopted models in [9] outperformed baseline algorithms like Linear Regression and Auto Regression. However, the work considered base stations with adequate computational resources to be able to make such predictions. As a consequence, there still remains a pressing need to improve upon the prediction using deep learning models, which can be transferred to resource-constrained relay nodes for light-weight real-time predictive channel assignment.

B. Multi-Band Packet Transmission Over Relay Networks

An earlier work [3] aimed to increase spectral efficiency of a multi-band relay transmission system while minimizing the end-to-end communication delay. Instead of using a traditional Decode and Forward (DF) method, a Truncated Decode and Forward (TDF) technique was incorporated at the relay node to perform demodulation, de-interleaving, de-puncturing, and Viterbi decoding. The Signal-to-Noise Ratio (SNR) was considered for each channel and the transmission duration was calculated using the MCS table. The channel with the lowest transmission time was selected for data transfer. An extension to the work in [10] considered SINR instead of SNR and the finite buffer size at the relay node while selecting the channel. Furthermore, the importance of an efficient multi-band system to select the optimal interface subject to the physical proximity and channel conditions of the base stations was stated in [11].

The aforementioned research works demonstrate that there remains a significant gap between the wireless network channel prediction and channel assignment. In other words, the existing researches have overlooked the exploitation of the multi-band prediction for proactive assignment, particularly in the relay networks.

III. Considered System Model

For the packet transmission, we consider the TDF model [3], which utilizes different channels to receive and forward data to the destination node D from source node S simultaneously using $(N-2)$ number of relay nodes, denoted as R. The data block is divided and the header of the block is forwarded to the consecutive node in order to realize relay transmission. If no error is detected, the remaining data are also forwarded to the relay node. Here, the link between source and relay is considered to be L_{S-R} and that between relay to destination is denoted by L_{R-D}. The link rate L_r of these links can be calculated as the product of s, m, and r_c, which denote

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the symbol rate, symbol density, and coding rate, respectively. We calculate s by dividing the roll rate W by the bandwidth B. Assuming that M is the number of waveforms on which the binary digits are mapped, m is computed to be $\log_2 M$. Additionally, based on the data size, S_d, the transmission time of header T_h, data transmission time from source to relay T_{S-R}, and data transmission time for relay to destination T_{R-D} for each channel is calculated.

IV. Problem Statement

The channel selection problem in multi-band systems can be regarded as a Mixed Integer Non-Linear Programming (MINLP) optimization problem similar to the communication architecture considered in [12]. However, the communication model presented by Li et al. in [12] considered multi-radio, base stations with adequate computational resources to solve this problem by relaxing the NP-hard problem into Master Problems (MPs) and employing a column generation-based technique to solve the MPs. Solving such optimization problems, thus, requires extensive processing power and memory of a centralized server or a powerful Software Defined Network (SDN) controller. However, the relay nodes, considered in our system model (Section III), are usually resource-constrained and unable to locally solve the optimization problem with the dynamic variation in network conditions. Therefore, this problem needs to be locally solved by designing a light-weight model and deploying at the resource-constrained relay node.

The formal problem statement, in this article, is to predict channel quality at a particular time, t for the next few time-steps δ_{pred}, which can be represented as $Y_t = \{y\}_{t+1}^{t+\delta_{pred}}$ based on the SINR or other measures such as SNR, CSI, or Received Signal Strength Indicator (RSSI) by employing a sequence of past data for δ_{past} duration, i.e., $X_t = \{x\}_{t-\delta_{past}+1}^{t}$. Here, t refers to the specific time instance at which training and inference take place. The vector X_t corresponds to the historical data employed for the training while the vector Y_t denotes the future channel conditions predicted by the model at t. The efficiency of the proposed model in predicting Y_t is based on the past data X_t as the model utilizes historical data denoted by X_t from $(t-\delta_{past}+1)$ to t time instances to predict the channel quality Y_t for $(t+1)$ to $(t+\delta_{pred})$ time instances.

The resource-constrained relay node needs to solve this problem by incorporating inference capability for predictive channel assignment in a light-weight manner. Solving this problem is critical to significantly reduce the channel assignment time while improving the communication throughput by avoiding potential packet loss at the relay node. In the following section, we explore a viable solution to the aforementioned problem.

V. Proposed Deep Learning-Based Approach for Proactive Channel Assignment at Relay Nodes

In order to solve the problem formulated in Section IV, in this section, we first train a deep learning model in a centralized network based on existing traffic datasets containing channel conditions and other network parameters. The model is trained to accurately assess the suitable channel conditions (q_C) across heterogeneous bands ahead of time. Then, the pre-trained channel inference model is transferred to each relay node.

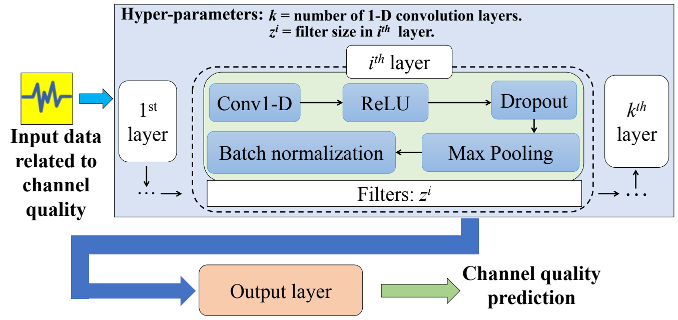

Fig. 2. Proposed CNN-based training and inference model.

Fig. 2 depicts our proposed deep CNN-based architecture. Here, k refers to the number of hidden layers of the proposed model used to extract relevant features from the model automatically. In each layer, a 1-D (one-dimensional) CNN is considered with z^i number of filters and Rectified Linear Unit (ReLU) as activation function, Ω [6]. A batch normalization layer is used to normalize the output, followed by the max-pooling layer, which reduces the feature size and decreases computational complexity. In the output layer, we employed a Linear activation function, which produces the quality of the channels as a prediction.

In order to carry out the experiment of channel prediction, a sliding window of size δ_{past} is employed to predict the channel quality of the next δ_{pred} steps. The window is then moved to the next δ_{pred} steps to predict further steps into the future. The model employs two forecasting strategies: (i) *controlled prediction*, and (ii) *smart prediction*. To exhibit the *controlled prediction* strategy, the original signal strength values are passed to the deep learning model instead of the predicted values. This leads to a speedier convergence. However, during the prediction on the test dataset, the model encounters poor generalization due to lack of access to the previous data. On the other hand, the *smart prediction* strategy employs the newly predicted data to make predictions of the future steps. Thus, the model exploits online learning to reduce the prediction error.

The steps of the proposed process are demonstrated in Fig. 3. For each band, the signal strength features of each channel in the training window δ_{past} (e.g., measured SINR) or other band-specific channel quality measurements such as RSSI and CSI along with other features (e.g., energy information, packet loss, throughput, and delay) are passed to the deep learning-based model. The channel quality (q_C) for each of the available channels over the prediction window, δ_{pred}, is predicted and appended to a vector of all channels' quality Q_C for each band. Then, Q_C vector are sorted to determine the best channel. Based on this, the corresponding coding rate, r_c, is looked up from the MCS table [3]. The link rate of each channel is then calculated followed by the estimation of transmission

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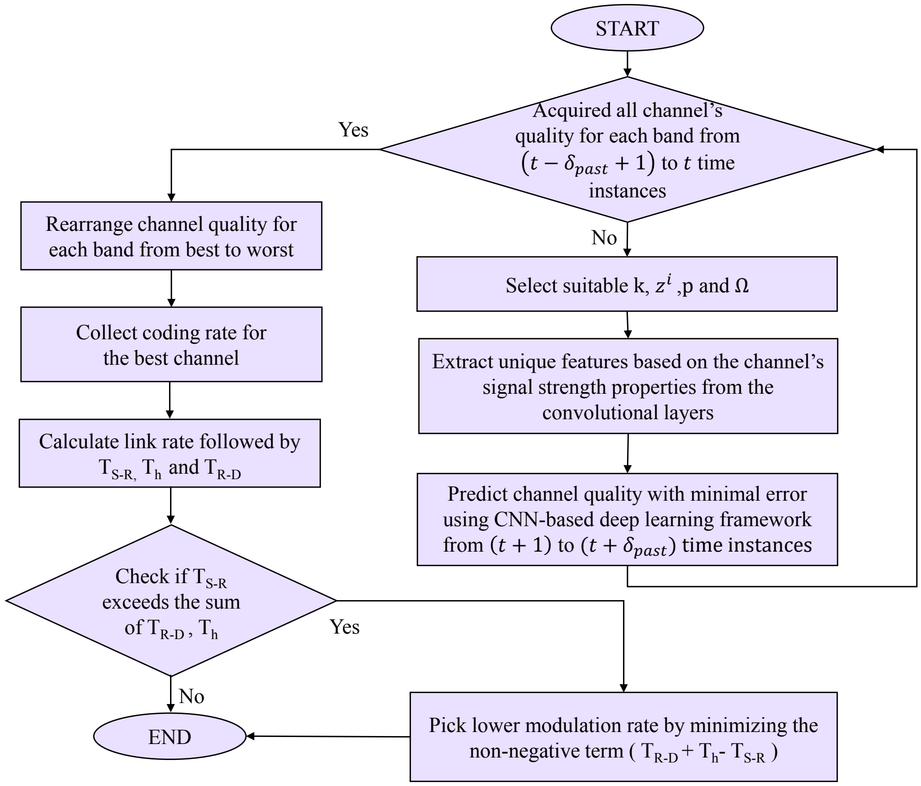


Fig. 3. Proposed deep learning-based predictive channel assignment approach at the relay nodes for simultaneous transmission and reception of source node frames using multiple frequency band.

times. The channel where the sum of T_{R-D} and T_h is smaller than T_{S-R} is selected ahead of time. Otherwise, the proposed model chooses a channel the subsequent with lower modulation method satisfying the stated condition.

VI. Performance Evaluation

In this section, we manifest the experimental results to assess the performance of our proposed deep learning-based proactive channel assignment approach at the multi-band relay nodes. A brief description of the datasets used to feed our proposed deep learning model is presented, followed by experimental results and discussion.

A. Data Preparation

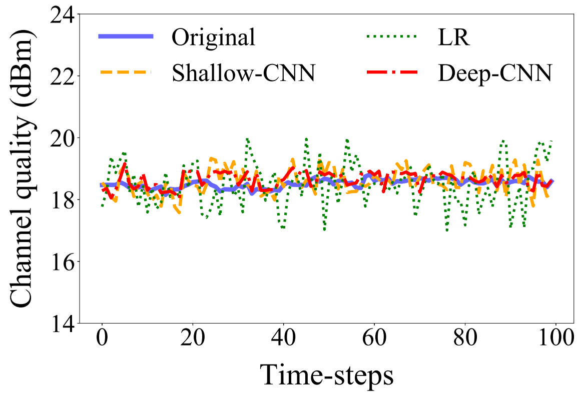
We employed two relevant datasets, denoted by DS1 and DS2, respectively, for performing the channel quality prediction. Brief details of the datasets are given below.

1) DS1: This dataset consists of RSSI data obtained with a mobile robot in two environments: indoor and outdoor [13]. RSSI data of five wireless receivers in indoor condition are collected using a youBot mobile robot. For the outdoor environment, data for signal strength and location are obtained from a mobile robot in a semi-outdoor environment.
2) DS2: This dataset contains signal strength measurement of a Zigbee-based wireless network [14]. It contains around 8000 data samples between a transmitting and receiving/relay pair is placed over a distance of 10 to 35 meters, and it consists of information of energy, throughput, delay, and loss of data transfer from source to destination nodes.

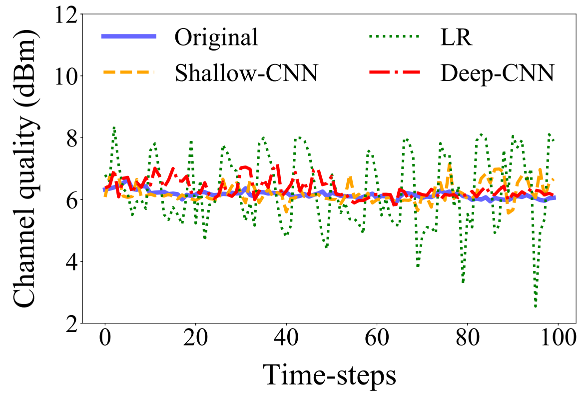
B. Results and Discussion

We applied Linear Regression (LR), a shallow Artificial Neural Network (shallow-ANN), and a deep Artificial Neural Network (deep-ANN) [15] to compare the performance of our proposed CNN-based controlled and smart channel prediction methods. The hyper-parameters of ANN and CNN algorithms are tuned as follows: δ_{past} = 200, δ_{pred} = 50% of the sliding window size (i.e. 100), and k in the range of one to four. Note that these hyper-parameters are manually tuned without resorting to grid search. For validation, training and test data splitting was manually performed.

Table I lists the performances of shallow-ANN, deep-ANN, and CNN-based methods compared to that of the LR technique for both outdoor and indoor conditions using the DS1. The prediction performance of the model for each band is determined using Root Mean Square Error (RMSE) between the predicted value (V_p) and the actual value (V_a). The results are represented in terms of the average RMSE across all the channels. We evaluated the performance of the deep learning model in both controlled and smart prediction scenarios by employing a shallow (i.e., a single layer of 1-D CNN) and deep architecture (more than one layer of 1-D CNN). In



(a) Distance of 10 meters between the sending and receiving node.



(b) Distance of 30 meters between the sending and receiving node.

Fig. 4. LR and CNN-based prediction methods compared to the original channel quality (for DS2).

TABLE I
COMPARISON OF AVERAGE RMSE VALUES ACROSS ALL TIME-STEPS FOR LR, ANN, AND CNN-BASED METHODS (FOR BOTH DS1-INDOOR AND DS1-OUTDOOR ENVIRONMENTS).

Environment	Method	Controlled prediction	Smart prediction
DS1-indoor environment	LR	12.73	6.092
	Shallow-ANN	11.39	3.526
	Deep-ANN	7.544	3.220
	Shallow-CNN	9.947	2.697
	Deep-CNN	5.967	**1.985**
DS1-outdoor environment	LR	8.133	26.19
	Shallow-ANN	4.777	13.24
	Deep-ANN	3.225	8.022
	Shallow-CNN	3.602	6.602
	Deep-CNN	3.150	**2.042**

all the cases, the deep learning-based prediction performance exhibits better performance in contrast with that of LR. Between controlled and smart prediction schemes, the smart prediction demonstrated better estimation performance than its controlled prediction counterpart. This implies that the deep learning-based techniques were able to explore the search space more robustly in contrast with the LR method, and therefore, were able to generalize the diverse channel conditions. In the case of the outdoor environment, the proposed CNN-based method outperformed the baseline LR by a significant margin. This massive performance gap between CNN and LR models demonstrates that in noisy outdoor environments, the traditional methods are unable to predict channel conditions accurately compared to deep learning-based techniques. Furthermore, the performance comparison between shallow-ANN, deep-ANN, and CNN reveals the superiority of the CNN in terms of consistency and stability. Hence, we have not considered shallow-ANN/deep-ANN for further experiments, and elected one and four-layer architectures of CNN, referred to as shallow and deep-CNN, respectively, for further analysis.

Fig. 4 presents a fragment of two example cases of the actual and predicted q_C values for a particular situation (DS2, distances 10, and 30 meters) using smart predictive strategy. The experimental results demonstrate that the performance of the proposed CNN model is significantly better than that of LR. In case of LR, the overall gap of an estimated q_C compared to an actual value gradually increases over time. On the other hand, in the CNN model, accuracy increases significantly with time. Figs. 4(a) and 4(b) depict that the proposed CNN model's predictive efficiency remains consistent for the diverse situations when the distance between the sender and receiver is varied. On the other hand, the basic LR method's prediction error increases with both distance and time. Thus, it may be concluded that LR, although performs well in a single-hop, single-radio wireless network for predicting channel conditions [9], is not appropriate for real-time channel prediction in multi-band relay networks.

Next, as a part of choosing the best prediction window-size, we tuned the prediction window-size, δ_{pred}, by taking different ratios with respect to the training window δ_{past}. The RMSE values for different distances from dataset DS2 were computed for δ_{pred} duration varied among 25%, 50%, and 75% of δ_{past}, respectively. In all these cases, the basic LR method was significantly outperformed by the proposed CNN-based approach. As the distance between the sender and the receiver nodes was increased from 10 to 30 meters, the estimation error (i.e., RMSE) of LR showed a dramatically increasing trend. This means that the LR method was not able to interpret channel quality in diverse situations with growing distances. However, the CNN-based approach is able to perform with much less error compared to that incurred in LR. Among these three ratios, both the shallow and deep-CNN models exhibit their best of the average RMSE values of 0.537 and 0.396, respectively, when 50% of the training window δ_{past} is taken into consideration for the prediction window-size. The LR method suffered drastically for all the considered distances, with the average RMSE value of 17.779 for the same length of δ_{past} = 50% of δ_{pred}. Therefore, we set δ_{pred} to this value for accurately predicting the best bands and channels in order to transmit data at a higher throughput in multi-hop relay system.

As the prediction performance of the proposed CNN-based approach demonstrated encouraging results, in Fig. 5, we

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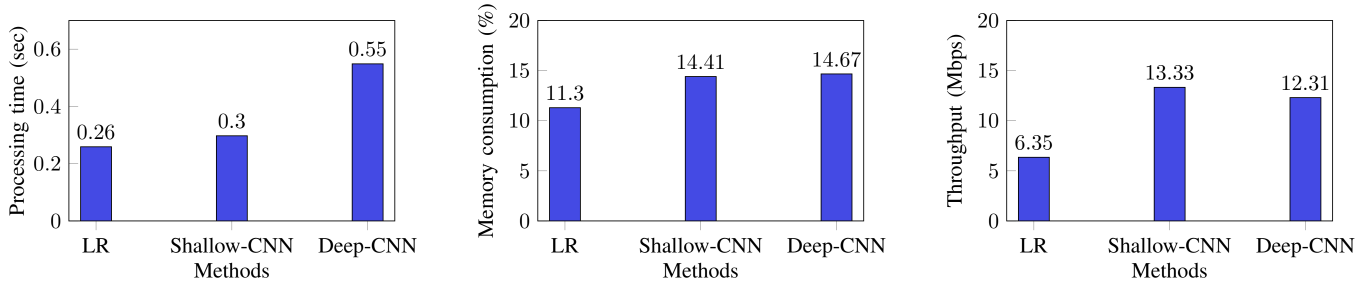

(a) Processing time of different methods. (b) Memory consumption of different methods. (c) Throughput of different methods.

Fig. 5. Comparison of processing time, memory consumption, and average throughput achieved by the proposed deep learning-based predictive channel assignment method exploiting both shallow and deep CNN architectures compared to conventional LR method.

conducted a numerical analysis of the model in terms of the average memory consumption, processing delay, and throughput per time-step. The latency is calculated based on the difference of error for poor channel selection (in percentage) between CNN and LR. Fig. 5(a) demonstrates the processing delay for the model, while Fig. 5(b) illustrates the memory consumption by the model with respect to the machine's overall capacity at each time-step. The trade-off, in this case, can be explained as follows. Although the predictive performance of the proposed CNN-based method is significantly better than that of LR, it requires slightly more time and memory. However, the additional processing delay can be considered negligible by considering the prediction efficiency of the proposed CNN model. Indeed, the model will predict all the channels' conditions over many time-steps, ahead of time. This substantially decreases the overall communication delay. Thus, the obtained experimental results clearly elucidate that the proposed deep learning-based CNN model is appropriate for efficient channel prediction and proactive channel assignment in a multi-band relay network.

Fig. 5(c) represents the throughput for sending data over the heterogeneous band network. For the numerical approximation of throughput, we assumed an average data generation rate of 1MB/s from IoT devices, and assumed latency of 1s due to poor channel selection for LR. The throughput is calculated by considering the processing delay and possible delay for choosing a poor quality channel. Although the processing time of LR is less than that of the deep learning-based CNN model, the throughput is approximated to be considerably lower. So, it demonstrates that traditional LR cannot be as efficient as the proposed CNN, and possible packet loss may occur for specific relay nodes where the resources are limited.

Therefore, the experimental results clearly exhibit that the pre-trained shallow-CNN model emerges as the most viable light-weight, predictive channel inference model for the resource-constrained relay node for enhanced spectral efficiency and throughput for offloading IoT traffic.

VII. Conclusion

In this article, we addressed the challenge of assigning the best channels on different bands over resource-constrained relays, which are gaining popularity for offloading massive IoT traffic in the next-generation networks. The use of different bands for downlink and uplink at the relay node requires decoding the header of the received packets on one band, processing, and then transmitting the packets on another band. In this article, we stressed designing a light-weight technique for intelligently predicting the channel conditions of the relay node's downlink and uplink to assign the best bands with the best possible channels proactively. Time-variant channel condition data from real datasets, in existing wireless networks, were used to train a 1-D Convolutional Neural Network (CNN) model to make controlled and smart channel prediction on several bands. A scheduling technique was then adopted based on the predicted band and channel to select the best modulation and coding rates for transmission to the subsequent relay/destination node. The proposed method was compared with several relevant techniques, such as LR, shallow-ANN, and deep-ANN. Experimental results demonstrated that the proposed CNN-based channel prediction and assignment method outperform the other comparable methods in terms of throughput, memory consumption, and processing delay at the relay node. Furthermore, the pre-trained shallow-CNN architecture exhibits comparable efficiency with its deep-CNN counterpart, while incurring low processing delay and memory at the relay node and enhancing communication throughput. Thus, the proposed shallow-CNN model emerges as the most viable candidate as a light-weight predictive channel inference technique for the resource-constrained relay node.

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BIOGRAPHIES

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