Machine Learning-Based Channel Quality Prediction in 6G Mobile Networks

Zdenek Becvar, David Gesbert, Pavel Mach, and Mehyar Najla

The authors overview state-of-the-art works leveraging the time, frequency, and spatial correlations among already known channel qualities and the channel(s), whose quality should be predicted.

Abstract

Channel quality is an essential information for management of radio resources in mobile networks. To acquire the channel quality information, pilot (or reference) signals are commonly transmitted, measured, and reported to the network. However, the process of channel quality acquisition is both time and energy consuming. Moreover, the radio resources are competitively shared by the pilot signals and users' data. This motivates an employment of prediction-based approaches determining the channel quality at low cost to avoid over-consumption of resources for pilots. Machine learning is seen as an efficient way to deal with the channel quality prediction, since it allows to reveal usually hidden relations among known and unknown channel quality measurements. In this article, we first overview state-of-the-art works leveraging the time, frequency, and spatial correlations among already known channel qualities and the channel(s), whose quality should be predicted. Furthermore, we outline a framework for a network correlation-based channel prediction enabling to determine the quality of unknown channel between any two communicating nodes by knowing only channels of these two nodes to reference nodes. Then, we demonstrate use-cases and application scenarios for all machine learning-based channel quality predictions. We also assess potential reduction in channel quality measurement-related overhead by all approaches to demonstrate their complementarity and capabilities to support low-overhead and energy-friendly massive deployment of devices in 6G mobile networks.

Introduction

With the sixth generation (6G) of mobile networks already taking more tangible shapes, an unprecedented amount of data is expected to be generated in new applications and use-cases by a plethora of devices, spanning from mobile phones, sensors, to vehicles, machines, or Internet of Things (IoT) devices. To cope with this huge amount of data, high data rates should be facilitated while guaranteeing quality of service and quality of experience. This, consequently, promotes the necessity to dynamically optimize key communication-related processes and decisions, such as radio resource, interference, or mobility management [1].

The optimization of communication and corresponding decisions invoke knowledge of the communication channel quality among communicating nodes (note that, in this article, the term ”node” represents any wireless communicating entity including any device or user equipment as well as a base station). In the current standardized view of the mobile networks, the acquisition of channel quality by means of large-scale fading, required for radio resource management and control, is facilitated via pilot (or reference) signals transmitted by communicating nodes and measured by the communicating peer nodes [2]. Unfortunately, the presence of pilot signals reduces the amount of resources available for data communication, as the pilot signals share the radio resources with data communication. Such overhead is manageable if the number of channels to be measured is limited. However, the number of channels inevitably increases with the growing network density and with beyond 5G and 6G use-cases fueled by the various vehicular, IoT, and massive machine-type communication scenarios. Moreover, the dimensionality of the channels grows in the context of massive antenna arrays at the base station and, possibly soon, also at the devices.

Besides, various types of the channels exist depending on the applied communication paradigm, use-cases, and/or infrastructure. For example, device-to-device (D2D) or vehicular communications representing a direct data exchange between two nodes (e.g., devices or vehicles). If such communication is activated, an efficient exploitation of the radio resources requires a measurement of the “direct” channel between two devices or vehicles. However, in a network with an immense density of the devices, the number of direct channels scales quadratically making the acquisition of channel qualities costly. Another example of communication type is the deployment of flying base stations, which replaces the communication between a classical ground base station and the communicating nodes. Such advanced infrastructure necessitates the measurement of both the backhaul channels (i.e., channels between flying base stations and ground base stations) and the access channels (i.e., channels between flying base stations and the devices).

Bearing in mind plenty of various types of channels, the measurement of the channel quality may cause a drain in the radio resources due to a high number of pilot signals. Consequently, achievable data rates can be impaired, since the

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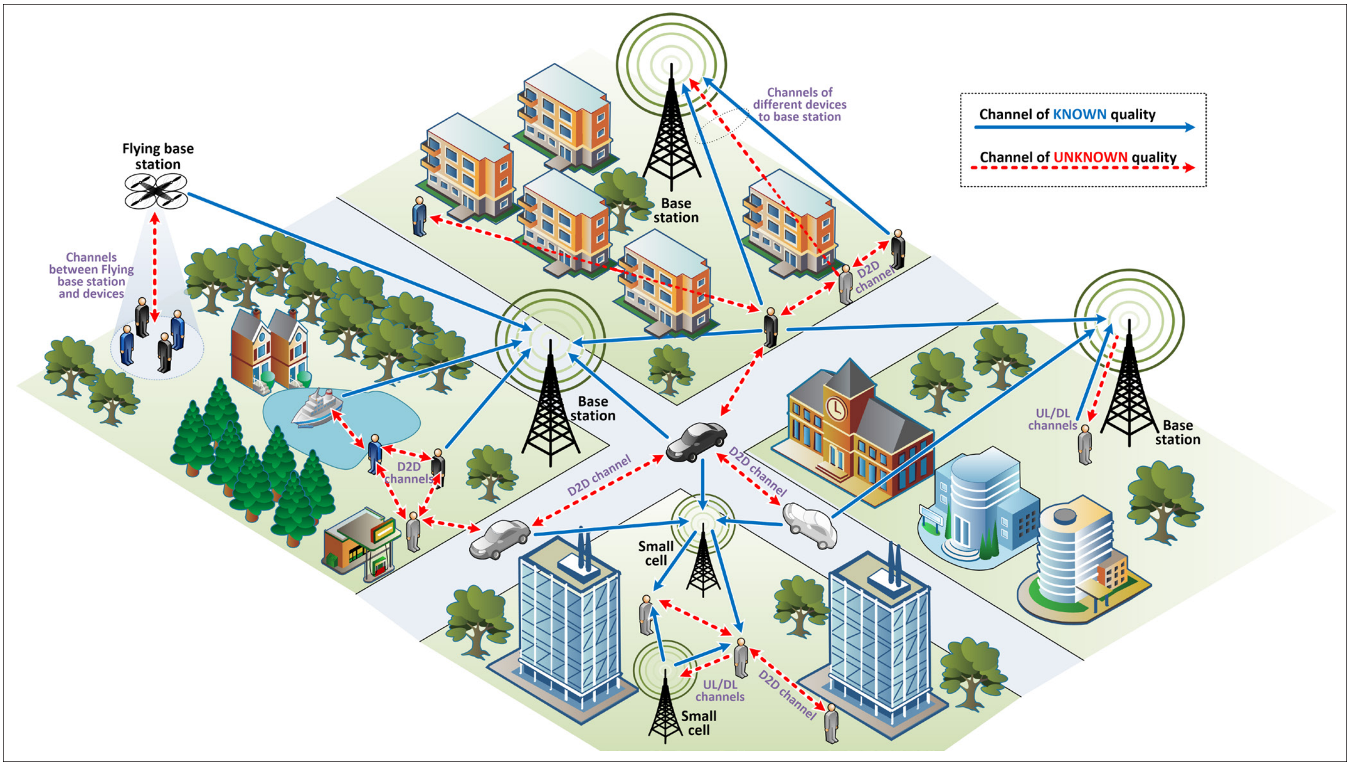

FIGURE 1. Future mobile network with various types of channels, some with quality known to the network via common pilot-based channel quality measurement (blue solid lines) and some with quality not known to the network (red dashed lines).

radio resources are shared for both data as well as for pilot signals. Theoretically, in an extreme case, the channel quality measurement itself could even consume all radio resources and no resources would remain for data transmission. Besides, an undesirable energy consumption and delay in the communication control procedures (such as radio resource or mobility management) can unbearably grow making the pilot-based channel measurement impractical [3]. Therefore, various techniques predicting channel quality based on a channel model and statistics have been developed [4]. These conventional techniques perform well in stationary wireless networks, however, do not reach sufficient accuracy in highly dynamic scenarios [5] envisioned in 6G.

Motivated by the above, it is essential to devise new and practical methods that can acquire the knowledge about various channels while reducing the number of pilot transmissions and measurements. Due to complex and dynamic scenarios with many communicating nodes, obstacles, and moving objects envisioned in 6G, machine learning is seen as an efficient way to predict the channel quality from other channel-related information available in the network. A successful prediction with a high accuracy relies on any, possibly hidden, correlations and similarities that may exist between the available and missing channel qualities. In existing solutions, the similarity between different channels or channel-related information typically results from time [5, 6], frequency [7–9], or spatial [10–12] correlations among the channels.

In this article, we first survey state-of-the-art channel quality prediction techniques exploiting machine learning. Then, we complement existing works with the network correlation-based approach predicting the channel quality between any two communicating nodes solely based on information commonly available in the network, i.e., channel qualities to reference nodes. Since the relation between known and unknown channel qualities is complex and hidden due to unknown and changeable environment and network topology, it cannot be predicted via traditional techniques. Hence, the network correlation-based prediction is facilitated by deep neural network (DNN). We show the proposed network correlation-based prediction supplements portfolio of use-cases, where a channel prediction can be applied to significantly reduce the overhead in the channel quality measurement. Such reduction paves the way to an efficient radio resource management in scenarios with a massive amount of communicating nodes directly exchanging information with each other, for example, as in vehicular communications. We also investigate the impact of disclosing additional user-related information represented by known location of some communicating nodes on the prediction accuracy.

Overview of Conventional Machine Learning-Based Channel Quality Predictions

This section overviews state-of-the-art ways to predict the quality of one channel from the known quality of another channel(s) based on a sort of similarity between the predicted and known channels. For presentation purposes, we classify the similarity according to a changing variable (time, frequency, space) in the prediction of channel quality, as illustrated in Fig. 2 and we discuss these, respectively, in the following subsections. In practice, of course, two or even all correlations may overlap and coexist.

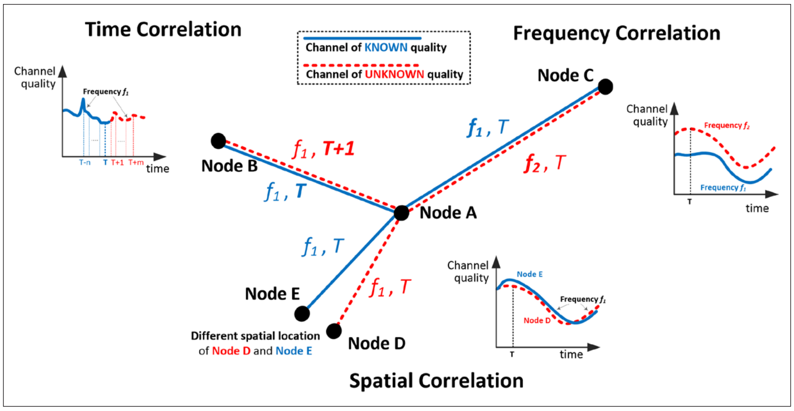

FIGURE 2. Principle of channel quality prediction based on: *time correlation* between previous (historical) and future channel qualities between Nodes A and B (left side of figure), *frequency correlation* of channels between Nodes A and C at frequencies f_1 and f_2 (right side), and *spatial correlation* of channel between Nodes A and D with channel between Nodes A and E (bottom).

Time Correlation-Based Channel Quality Prediction

The time correlation represents a relation, which maps previous (historical) channel quality between two communicating nodes to the future channel quality between the same two nodes. Such correlation exists, since the channel between the two communicating nodes changes following a certain pattern depending on the environment and propagation medium. Therefore, the changes in the channel quality *over time* can be predicted knowing the quality of the same channel in the past, as demonstrated in [5, 6]. This, however, can be done over only a relatively short period of time (order of milliseconds) within which the pathloss between the two nodes is quite similar and the prediction aims mainly to mimic the fast fading behavior over this short period [4].

The principle of time correlation-based channel quality prediction is illustrated in Fig. 2 on an example of the channel between Node A and Node B. The channel quality between these two nodes in the interval from $T - n$ till the current time T at frequency f_1 are exploited to predict the channel quality between the same two nodes and at the same frequency f_1, but in the future time $T + 1$. Similarly, the channel quality from the time $T - n + 1$ till the time $T + 1$ allows to predict the quality of the same channel at the time $T + 2$ and so on so forth.

Such process represents prediction of a future sequence (channel qualities from $T + 1$ till $T + m$) from the past sequence (channel qualities from $T - n$ till T). Such prediction of sequences is typically solved via recurrent neural networks (RNNs), since the RNN includes feed-back connections in its structure allowing to understand the sequence [5].

Frequency Correlation-Based Channel Quality Prediction

Another option for the channel quality prediction is to capitalize on the relation among the channels at *different frequencies* between two nodes at the same time and at the same position. Figure 2 shows an example, where the channel between Node A and Node C at the frequency f_1 is correlated with the channel between the same nodes at the same time, but at different frequency f_2; $f_1 \neq f_2$. This concept is usually exploited to predict the downlink channels from the uplink channels as considered, e.g., in [7]. In this case, the neural network is trained to extract the function that maps the uplink channel state information of one communicating node to the downlink channel state information of the same communicating node [7].

The frequency correlation can be used to directly predict the communication related decisions for the high frequency bands (e.g., mmWaves) based on the channel information from a lower frequency band as demonstrated in [8, 9]. In this case, the channel prediction is inexplicit as the channel information at the mmWave frequencies are not directly predicted from the channel information in the low frequency band. Instead, the decisions related to the communication via mmWaves are predicted from the channel quality in the low frequency bands. To perform this prediction, DNNs are adopted in [8, 9].

Spatial Correlation-Based Channel Quality Prediction

In addition to the time and frequency correlations, also the spatial correlation exploring the location-related commonality among the communicating nodes is adopted in literature. The concept of the spatial correlation is based on the fact that, theoretically, channels from two *spatially close* nodes to another node at the same frequency and at the same time are influenced by a similar signal propagation. This basic principle is shown in Fig. 2, where Node E and Node D are close to each other. Consequently, the channel quality between Node A and Node D can be extracted from the quality of the channel between Node A and Node E (or vice versa).

The spatial correlation for the prediction of the channel quality is adopted in [10]. The authors suggest measuring the channel quality between the communicating and reference nodes via pilot signals only when the reference node is active. The measured pilot channel qualities are stored with their corresponding locations of the communicating nodes. Then, the stored information is used for the channel estimation when the reference nodes (e.g., BSs) are in an energy saving mode and the pilot signals are not transmitted [10]. Missing channel qualities at the locations, where no measurement has been done can be predicted from the stored channels exploiting the spatial correlation and implemented via K-nearest neighbor (KNN) supervised machine learning [10]. The KNN gives a rough channel quality that can be further improved via a convolutional neural network (CNN) [10]. The CNN is suitable since the cell can be interpreted as pixel-like set of discrete locations, where every location (or "pixel") includes a number representing the channel quality from this location to the reference node. The area with the discrete pixel-like locations can be seen as an image and CNN is known to perform well in image-related prediction problems.

The spatial correlation is also used in [11], where the goal is to build a radio map composed of the pairs of location and channel quality (represented by path loss) to the reference node (represented by the BS) similarly as the pixels in [10]. In [11], the channel quality to the reference node is known for some locations and the rest of the unknown path losses to the reference node from the remaining locations are predicted via DNN. This way, the radio map is filled and the path losses to the reference node for all locations in the map are determined.

The spatial correlation can also be used for prediction of channel state information including complex channel matrix and signaling overhead reduction in the networks with Multiple-Input-Multiple-Output (MIMO) [12]. In this case, instead of using the pilot signals to estimate the channel matrices between all the antennas at the reference and communicating nodes, only the channels from a subset of antennas to the communicating node are estimated conventionally via the pilots. Then, the pilot estimated channel matrices are exploited to predict the rest of the channel matrices from the remaining antennas to the communicating node via linear regression and support vector regression models [12].

Network Correlation-Based Channel Prediction

In previous section, the predicted channel is assumed to be tightly coupled in time, frequency, or space to the known channel(s). Such approach, however, does not allow to predict channels seemingly disconnected from the known channels. Hence, in this section, we focus on the problem of the channel quality prediction between any two nodes based on a complex relation among various information available in the network. This approach targets prediction of a large scale fading for radio resource management purposes.

In contrast to the approaches presented in the previous section, the network correlation does not rely on proximity between communication nodes, historical channel quality, or the communication frequency. Hence, the network correlation is of a different nature and the channel quality in terms of the large-scale fading is predicted from network-related information, represented by channels of the communicating nodes to the reference nodes, that share topology- and environment-based commonalities with the predicted channels. This commonality leverages the fact that the channel between two communicating nodes is correlated with the channels from these two nodes to reference nodes. An example of the reference nodes is a set of base stations surrounding the communicating nodes between which the channel quality should be predicted. We illustrate the principle of network correlation-based channel prediction and, then, we discuss a possibility to enhance performance by exploiting partially disclosed information on the users' location.

To understand the network correlation, let us first imagine a simple scenario in an open field without obstacles, where the channel quality from any two communicating nodes (e.g., devices) to the neighboring reference nodes (e.g., BSs) is estimated via pilot signals. The locations of these two communicating nodes are unique in terms of a representation via the quality of channels from each communicating node to the reference nodes similar to triangulation principle adopted in navigation and positioning systems. The unique locations of the two communicating nodes correspond to a specific quality of the channel between these two nodes. Therefore, it is expected that the channels from these two communicating nodes to three reference nodes are enough to predict the quality of the channel between the two communicating nodes. However, this simple principle does not apply for a generic environment with obstacles,

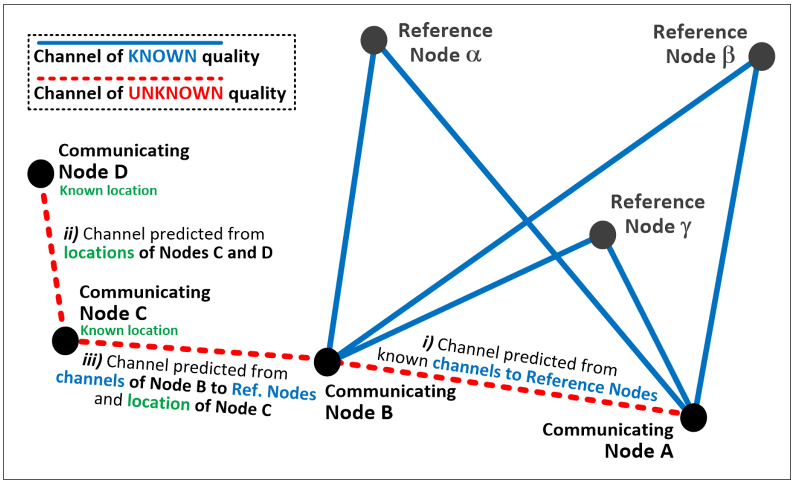

FIGURE 3. Network correlation-based channel quality prediction.

where the relation between the channels from two communicating nodes to the reference nodes and the channel between the two communicating nodes is unknown and cannot be assumed linear. This motivates the use of DNN to extract the network correlation and to predict the channel quality between the communicating nodes [13–15].

For the network correlation-based channel quality prediction, we design the fully connected DNN. The input information for DNN includes one of the following:

1. Set of actual channel qualities between the communicating nodes and R reference nodes (communicating nodes A and B in Fig. 3)
2. Location information in a form of 3D coordinates of both communicating nodes if such information is disclosed by these nodes as, e.g., in case of vehicular communications for autonomous driving (communicating nodes C and D in Fig. 3)
3. Combination of the location information of one communicating node and the channel qualities between the second communicating node and R reference nodes (communicating nodes B and C in Fig. 3).

The locations of communicating nodes can substitute the channel quality to reference nodes in the input information for DNN, since even the channel qualities to reference nodes represent a sort of information on the communicating nodes' locations. However, while the channel quality to reference nodes is known to the network, the location may not be always available due to privacy choices of users or due to absence or inaccuracy of localization systems. We compare performance of all three cases later.

The input information is fed to the input layer of DNN. The output of the input layer is processed via H hidden layers with V_h neurons in the h-th hidden layer. Experimentally, we have determined five hidden layers with 20, 18, 15, 12, and 8 neurons in respective hidden layers, as the setting leading to the highest prediction accuracy. The output of the last hidden layer is processed by the output layer with one neuron. This single neuron implements a linear activation function and returns the channel gain between the two communicating nodes.

In Table 1, we summarize key aspects of machine learning inputs and outputs of individual

	Learning tool	Learning Inputs	Learning Output	Typical use-case
Time Correlation	RNN	Previous quality of channels between two nodes	Future quality of channel between the two nodes	Prediction of future channel quality
Frequency Correlation	DNN	Quality of channel between two nodes at a specific frequency	Quality of channel between two nodes at another frequency	Prediction of UL channel quality from DL channel quality (or vice versa) of one communicating node, prediction of channel quality in high frequency bands (e.g., mmWave) from channel in low frequency bands
Spatial Correlation	KNN+CNN, DNN	Quality of channel between two nodesLocations and proximity of one of the nodes and a third node	Quality of channel between two nodes	Prediction of channel quality for multi-antenna systems
Network Correlation	DNN	Quality of channels from the communicating nodes to the reference nodes or location of the communicating nodes	Quality of channel between the two nodes	Prediction of channel quality between two communicating nodes from already known channels to other nodes, e.g., communication among vehicles

TABLE 1. Summary of machine learning-based channel prediction approaches and related use-cases.

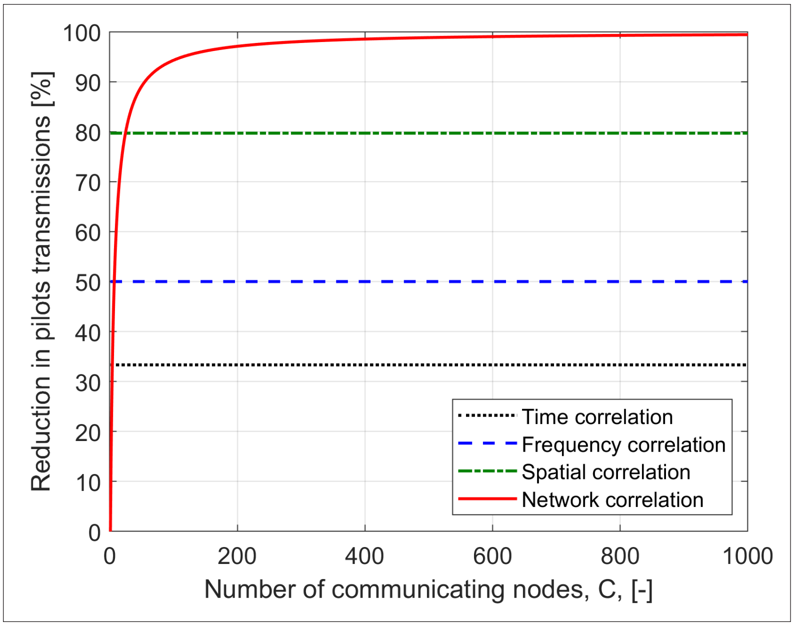

FIGURE 4. Reduction in the number of transmitted and measured pilots to determine channel quality by various approaches.

state-of-the-art channel quality prediction including the network correlation-based one and we also provide typical use-cases for each prediction to demonstrate their complementarity.

Signaling Overhead for Channel Quality Acquisition

The objective of the channel quality prediction is to reduce overhead related to channel quality measurement via pilot signals while predicted channel quality is as close to the real one as possible. We analyze and demonstrate the reduction in the number of transmitted and measured pilots achieved by individual presented prediction principles exploiting various correlations with respect to conventional case where all channels are pilot-based measurement in Fig. 4.

First, let us look at the time correlation, which predicts the channel quality between two nodes in the future. According to experiments carried out in [5], the highest prediction accuracy is reacheed if the channel quality in future 10 time instances is predicted from the channel quality in the past 20 measured time instances. Consequently, the signaling overhead reduction is $10/(10 + 20) \approx 33\%$.

The frequency correlation is typically exploited to predict the downlink channel quality from the uplink channel quality. Hence, the signaling overhead is typically reduced by 50% (i.e., for every predicted downlink channel, one pilot-estimated uplink channel is required).

The spatial correlation predicts the channel between the communicating node and subset A_1 of all antennas at the reference node (e.g., BS) from the pilot-estimated channels between that same communicating node and the subset A_2 of remaining antennas as in [12]. According to [12] the number of antennas $|A_1|$ to which the channel is pilot-estimated is a function of the number of propagation paths in a multi-path channel model environment. For a common scenario with 128 antennas at the reference node ($|A_1| + |A_2| = 128$), the authors exploit known quality of channels from a single communicating node to $|A_1| = 26$ antennas to predict the channels from that same communicating node to the remaining $|A_2| = 102$ antennas. Consequently, the pilot transmission reduction for the channel prediction exploiting the spatial correlation in [12] is $102/128 \approx 80\%$.

Unlike for the spatial, time, and frequency correlation-based predictions of channel quality, the reduction in the number of transmitted and measured pilots by the network correlation depends also on number of communicating nodes. Hence, lets consider $N = C + R$ nodes in the network consisting of C communicating nodes (e.g., devices communicating with each other) and R reference nodes (e.g., BSs in the area). The channels between C communicating nodes to the R reference nodes are enough to predict all $C(C - 1)/2$ channels among all C communicating nodes. Hence, $C \times R$ channels should be pilot-estimated to predict all channels among all communicating nodes. Then, the network correlation-based prediction reduces the number of pilot transmissions and measurements by

$$(C(C - 1)/2)/(C(C - 1)/2 + C \times R). \qquad (1)$$

As demonstrated in [13], the number of required reference nodes is very low, typically three. For an example with 100 communicating nodes ($C = 100$) and three reference nodes ($R = 3$), the reduction is $4950/(4950 + 300) \approx 94\%$. The overhead savings are even more significant if one considers thousands or even millions of communicating nodes per km^2, as expected in 6G [1].

As shown in Fig. 4, the network correlation-based channel quality prediction is very efficient in scenarios with a high density of communicating nodes, such as in vehicular or IoT communication scenarios including, e.g., smart factories or cities. Moreover, as indicated in the previous section, the network correlation can also exploit partial knowledge on location of some nodes and substitute pilot-estimated channel quality between the communicating node and all reference nodes with the location. Hence, we further investigate also an impact of the known location(s) on the accuracy of channel quality prediction in the next section.

Impact of Location Information Availability on Performance of Network Correlation-Based Channel Prediction

To investigate the impact of known locations on channel quality prediction accuracy, we simulate an urban area of 250 × 250 *m* with up to 1000 devices served by five BSs positioned on rooftop of the buildings with a height randomly generated between 20 and 30 meters and deployed regularly in the area (see [13]). The path loss is generated in line with 3GPP TR 36.843 and we assume that the communication channel intercepted by one or more building walls is exposed to an additional loss of 10 dB per wall [13].

To indicate the prediction accuracy of the network correlation, represented by a similarity between the true and the predicted channel quality, we use Pearson correlation coefficient (PCC). Note that PCC is widely adopted by various machine learning-based approaches to indicate their prediction accuracy.

Following three cases of the network correlation-based channel quality prediction (illustrated in Fig. 3) are considered:

1. *Reference – Reference*, where the locations of communicating nodes are *not* known and, therefore, the pilot-estimated channels between the communicating nodes and surrounding reference nodes are used as inputs to DNN.
2. *Location-Location*, where the locations of all communicating nodes are known and are inputs to DNN.
3. *Reference-Location*, where the location of only a half of the communicating nodes (one node in each communicating pair) is known and inserted to DNN while, for the rest of the nodes, the pilot-estimated channels between these communicating nodes and the reference nodes are inputs to DNN.

We also study different numbers of learning samples for the DNN training to show the effect of the training on the different use cases of the channel quality prediction exploiting the network correlation. Furthermore, we consider a possible error in the learning inputs representing inaccuracies in the pilot-estimation or localization systems. To this end, we define signal to noise ratio (SNR) representing the ratio between true value of the input and an error in this input so that

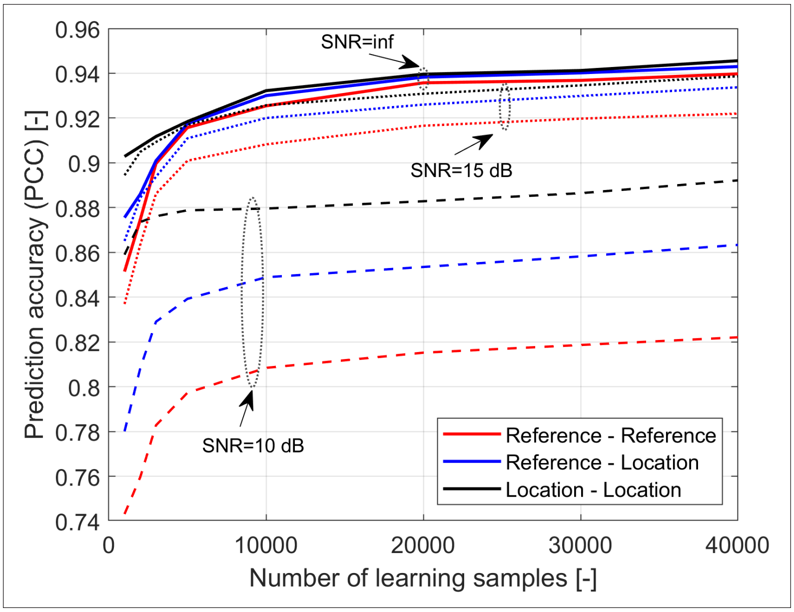

FIGURE 5. Channel quality prediction accuracy (measured by PCC) versus different numbers of learning samples for three different cases of channel prediction exploiting network correlation. SNR represents the error in channel quality measurement.

$$SNR = 10 \log_{10}(TrueValue/e)\ [dB], \qquad (2)$$

for the error $\mathcal{N}(0, e)$. When SNR is equal to infinite (*SNR* = inf), the inputs (pilot-based measured channel quality or locations) are with no error.

In Fig. 5, we observe that PCC increases promptly with the number of learning samples until about 10.000 samples, when the increase slows down and becomes marginal. We also see that the reached PCC is high for the different simulated cases even if the learning inputs are impacted heavily with a high error (e.g., for SNR of 10 dB). Moreover, with higher error, the Location-Location prediction outperforms the Reference-Location as well as the Reference-Reference. This is explained by the nature of the network correlation itself. In fact, when the channels between the communicating node and surrounding reference nodes are available, the prediction relies on the hidden relation between these gains and the locations of this communicating node and, consequently, the quality of the direct channel to the other communicating nodes. However, if the location information is available, the relation between the location and the channel quality is straightforward and easier to learn.

Furthermore, in Fig. 5, we also observe that the lower the error in the learning inputs, the lower difference among PCC of the three investigated cases. This allows us to state that the higher the accuracy of the pilot-estimated channels between the communicating and reference nodes during the learning and inference phases, the higher the effectiveness of the network-correlation based prediction in terms of prediction accuracy.

Conclusion

In this article, we have surveyed the different channel quality prediction approaches based on machine learning to reduce number of transmitted and measured pilots for the channel quality acquisition in future mobile networks with many communicating nodes. Furthermore, we have outlined the concept of machine learning-based channel prediction exploiting the advanced network correlation. We have demonstrated complementarity of this approach to the frequency, time, and spatial correlation-based predictions. Besides, we have shown a high accuracy of the network correlation-based channel quality prediction in generalized scenario even if communicating nodes' private information on location is not disclosed by the users. We have also quantified the reduction in the transmission and measurement of pilots for the different types of channel quality prediction underpinning their benefits and limits. The machine learning-based channel prediction exploiting network correlation cuts down more than 90% of the overhead generated by conventional pilot-based approach for scenario with a high number of communicating nodes. This makes the channel prediction exploiting network correlation a suitable approach for 6G mobile networks with a massive amount of nodes communicating with each other.

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