Deep-Learning-Enhanced NOMA Transceiver Design for Massive MTC: Challenges, State of the Art, and Future Directions

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Abstract

Non-orthogonal multiple access (NOMA) is a promising evolution path to meet the requirements of massive machine type communications (mMTC) in 5G and beyond. However, the deployment of NOMA is hindered by the non-unified signal processing architectures of various NOMA schemes and the inflexibility resulting from the offline design paradigm. The block-wise optimized transceivers make its performance far from the limit. The recent breakthrough of deep learning and its positive applications to wireless communications have paved the way to tackle these challenges. This article studies the effectiveness and efficiency of deep learning in enhancing NOMA performance. Specifically, we first present the deep neural network (DNN), which is constructed via a uniform signal processing architecture, and use it as the unified multiuser receiver in both data and model-driven approaches. This enables the end-to-end optimization of NOMA transceivers due to the universal function approximation property of DNN. On the other hand, with DNN we can automatically extract the user access behaviors out of the time-series signals and optimize the transceivers to match these cross-layer behaviors. We further analyze the integration of non-orthogonal communication and neural computation to accomplish high-efficiency data transmission at low cost. Finally, we identify some essential future directions of deep-learning-enhanced NOMA from the perspectives of online reconfigurability and adaptability toward the ever changing environment in future mMTC.

Introduction

The Internet of Things (IoT) has been the thriving application to connect hundreds of billions devices worldwide. As the technical enabler of IoT, massive machine type communications (mMTC), which targets machine-centric radio access, is becoming a dominant communication paradigm in 5G. When massive devices encounter scarce radio resources, the commonly deployed orthogonal multiple access (OMA) makes it a bottleneck for mMTC to support ever increasing connectivity for 5G and beyond [1, 2].

In this context, non-orthogonal multiple access (NOMA) has been introduced as the critical enabling technology for mMTC to improve the connection density and spectral efficiency [1–3]. The idea behind NOMA is to overlap multiple signal streams with controllable mutual interference using the elaborately designed multiple access signatures (MASs), and then use a multiuser detection algorithm to distinguish the superimposed signals. The 3rd Generation Partnership Project (3GPP) completed the standardization of downlink NOMA in LTE Release 14, and has considered it a candidate research route for 5G mMTC [1]. More recently, 6G radio access is expected to be intelligent and ubiquitous with 100 times higher connectivity than 5G mMTC. NOMA is thus regarded as a promising research trend in the continuous evolution of mMTC toward 2030 [1].

The deployment of NOMA for future mMTC, however, is hindered by the following challenges:

- **Lack of unified signal processing architecture:** The signal formats of the diverse existing NOMA schemes are significantly different, requiring corresponding signal processing structures at the transceivers. This incompatibility causes difficulty in merging the NOMA schemes toward both standardization and implementation. A unified signal processing architecture is called for in order to avoid secluding each of the various NOMA schemes.
- **Lack of end-to-end optimization:** Existing works on NOMA isolate the design of the transceivers. This block-wise design leads to performance loss due to the simplified and independent models. In contrast, end-to-end optimization can push the performance limit of NOMA because it directly optimizes the ultimate performance metric without block divison or simplifications.
- **Lack of intelligent and fast environmental adaptation:** Current NOMA schemes adopt offline design and prior configuration, and thus cannot deal with unexpected situations such as a nonlinear propagation environment. Hence, it is necessary to arm NOMA with online learning so that it can adapt to the dynamic environment.

Artificial intelligence (AI), especially deep learning technology, has achieved great success in solving very complicated, even intractable, optimization problems in a data-driven fashion [4–6]. With the aim to extract useful distributed repre-

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sentation of multi-level features from the original signals, deep learning has displayed superiority in computer vision and natural language processing. The booming deep learning has also shed new light in enhancing physical-layer technologies including NOMA [7–11]. Specifically, with the universal function approximation property, a deep neural network (DNN) can recast the transceivers of NOMA. Its uniform structure would also enable the unified signal processing architecture for NOMA. Moreover, joint transceiver optimization can be achieved via the DNN-based auto-encoder and the end-to-end reconstruction loss. The automatic learning capability of online deep learning technology can further energize NOMA with environment adaptation ability.

This article is devoted to elaborating on how deep learning helps to tackle the above challenges of NOMA. We first deploy deep learning to enhance the multiuser receiver (Rx) from both data-driven and model-driven viewpoints. We then illustrate deep learning as the enabler of end-to-end NOMA transceiver optimization, under the guidance of domain knowledge or practical transmitter (Tx) constraints. The integration of computation and communication in NOMA via end-to-end learning is also treated. We study the ability of deep learning in the excavation and exploitation of upper-layer data for transceiver design. Finally, we discuss promising future directions of deep-learning-enhanced NOMA for future mMTC. The organization of this article is shown along with the typical NOMA system model in Fig. 1.

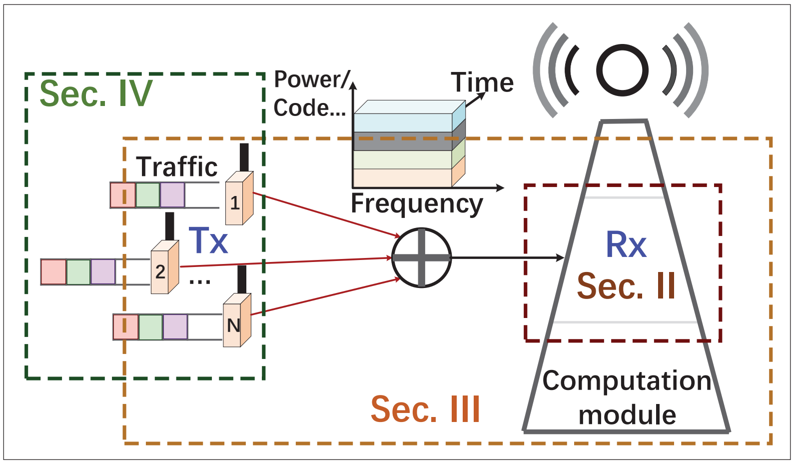


FIGURE 1. NOMA system model and the organization of this article.

Rx: Multiuser Detection Design

In NOMA, the signals of different users are sent non-orthogonally. In order to eliminate inter-user interference (IUI), multiuser detectors (MUDs) are applied at the receiver to distinguish the superimposed signal streams. Advanced MUDs, such as successive interference cancellation (SIC), parallel interference cancellation (PIC), and message passing algorithm (MPA), have been developed for different NOMA schemes. However, a unified signal processing architecture for multiuser detection is still lacking. Enhancing MUD via DNN can bring unified architecture, along with better detection accuracy and reduced processing delay. In general, DNN-based designs can be largely categorized into data-driven and model-driven approaches. A data-driven approach deploys vanilla DNNs, which lead to less design effort but increased training data requirement. On the contrary, a model-driven approach exploits expert knowledge of NOMA to relieve the data requirement and promote learning efficiency. In the following, we discuss both data-driven and model-driven designs of DNN-based MUDs.

Data-Driven Design

NOMA detection aims to jointly recover the source messages of multiple users in a limited search space, which is equivalent to the classification problem in machine learning. Therefore, we can apply the standard neural network, fully connected DNN (FC-DNN), as shown in Fig. 2a, and train it using a synthetic dataset in such a way that the symbol error rate is minimized [7]. The dataset consists of labeled data pairs, each including the received superimposed signal and the source messages. After the convergence of offline training, the trained DNN is deployed online where detection can be done in a single shot and thus holds much less computational delay than the conventional iterative-based detector (e.g., MPA).

With the universal function approximation property, data-driven DNN is compatible with any NOMA scheme once the network parameters are updated according to the specific NOMA transmitters, without any change of the network structure. The multiple hidden layers also prompt the approximation of the complicated NOMA signals, which ensure better detection accuracy than the conventional shallow learning methods. While the data-driven approaches can normally achieve better performance with less complexity, their performance heavily depends on a huge amount of labeled data, as the network cannot gain much insight if the training set is small. Also, data-driven methods do not utilize the structure of NOMA signals and thus lead to low training efficiency. Meanwhile, the classification types increase exponentially as the increase of user number, which requires large width of hidden layers in DNN and brings high complexity. Moreover, the lack of a theoretical understanding about the relationship between neural network structure and performance leaves its structure unexplained and unpredictable.

Superimposed Signal Model-Driven Design

In contrast to the pure data-driven deep learning, model-driven design constructs the DNN structures based on known algorithms and domain knowledge, which can balance the efforts in exploration and exploitation [4, 5]. The idea of model-driven design has been incorporated in multiuser detection for NOMA, which aims to take advantage of the signal processing structure of the existing MUDs while still retaining the strong learning capability of DNN. The unique insight is about the exploitation of the superimposed signal model or existing NOMA detection algorithm models in the design of DNN structures. Compared to its data-driven counterpart, a model-driven MUD can realize multiuser detection with lower computational complexity. The following parts analyze typical model-driven design ideas for MUDs: deep unfolding and deep parameterization.

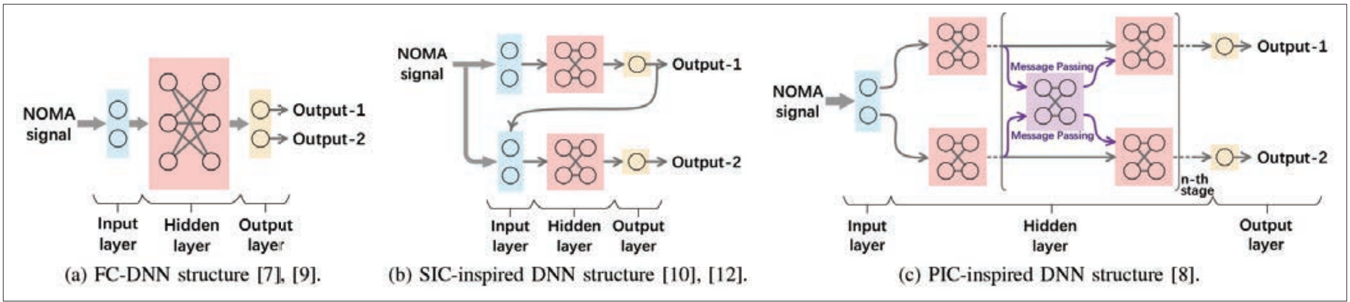


FIGURE 2. Deep-learning-enhanced multiuser detectors.

Deep Unfolding: The NOMA system can be described as a bipartite Tanner graph. The graph consists of variable nodes (VNs) and function nodes (FNs), where the former and the latter correspond to NOMA transmit codeword and orthogonal radio resources, respectively. Belief propagation-based algorithms, such as MPA and expectation propagation algorithms (EPAs), are commonly deployed on the Tanner graph to approach near-optimal multiuser detection.

Given any iterative signal processing method, it is straightforward to unfold the iterations into a nested structure that is similar to the layered structure of DNN [6]. To unfold the iterative multiuser detection algorithm, we regard the VNs and FNs in each iteration as a pair of neuron layers and cascade the layers along with iterations. The neurons are then connected with edges according to the construction of the Tanner graph. The edges between the neurons are assigned with the weights that allow the network to exactly resemble the iterative algorithm. Then the weights are regarded as trainable parameters and are tuned with synthetic dataset using gradient descent-based optimization methods to achieve better detection accuracy.

Since the initialization of a deep-unfolding-based method can perfectly mimic the conventional multiuser detection algorithms, the system performance can be guaranteed. Moreover, the algorithms are first put on the unfolded DNN structure, which can shrink the hypothesis space and thus reduce the training overhead. Nevertheless, the strict prior placement on DNN introduced by unfolding eventually results in unalterable structure, which may hinder the self-learning ability of deep learning.

Deep Parameterization: As an alternative approach, the deep parameterization methods consider a general signal processing architecture inspired by the existing MUDs and introduce DNN to parameterize the major parts within the architecture [8, 10, 12]. This design paradigm can exploit the joint benefits of the domain knowledge of NOMA and the universal function approximation ability of DNN, which is a trade-off between exploitation and exploration.

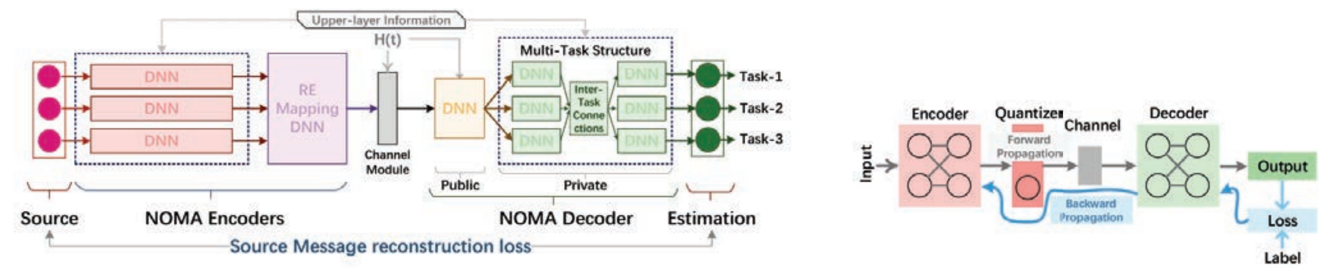
Recall that the concept of NOMA originates from multi-user information theory, where superposition transmission and interference cancellation (IC) are developed in an information-theoretic perspective to approach the outer bound of the multiple access channel capacity pentagon. The IC technique has also been incorporated in the state-of-the-art MUDs to lessen the IUI and reduce the complexity. Based on the concept of IC, model-driven deep learning has been utilized to enhance the performance of MUDs.

One typical design is the SIC-inspired DNN-based MUD [10, 12], as shown in Fig. 2b. The SIC-inspired methods are based on the conventional SIC detection structures, where each detection layer in SIC is replaced by DNN before operating data-driven optimization. As shown in the two-user example in Fig. 2b, reconstruction of the output signal of the first branch is cancelled in the second branch so that the IUI can be mitigated. Since each branch only targets estimating the signal of a single user, SIC-inspired structure can deploy a significantly reduced number of neurons within each branch compared to FC-DNN.

The drawbacks of the above SIC-inspired structure involves the increased successive processing latency and inflexibility caused by the predetermined detection order where the latter may introduce unexpected error propagation. A straightforward solution is to deploy parallel detection branches and introduce inter-branch IC. We illustrate the design example, which is inspired by the PIC and message passing (MP) detector to take advantage of the parallel processing ability of DNN, as displayed in Fig. 2c. Here, the inter-branch connections are designed to pass the messages such that each branch can use the side information to derive better estimations. The hidden layers are further divided into multiple stages. For each stage, we roughly estimate the signals and use the estimated results to cancel the interference. By doing so, the superimposed NOMA signal is split into some less-interfered signals, which can be detected with low complexity. To mitigate the error propagation introduced by IC, the IC mechanism is also allowed to be learned [8]. Recent research has shown the superiority of model-driven deep learning with respect to representational power, multiuser detection accuracy, and processing delay [8, 10, 12].

Tx-Rx: End-to-End Design

Existing research adopts the block-wise optimization paradigm, which isolates the design of NOMA transceivers. However, this divide-and-conquer philosophy has introduced simplified operations in the transmitter design and cannot simultaneously optimize the overall performance. Thus, it is difficult to approach the performance limit of the complicated multiuser system for mMTC. In this section, we reconstruct NOMA transceivers with DNNs to realize end-to-end optimization. By involving more tunable vari-



(a) End-to-end optimziation framework for NOMA using multi-task DNN [8]. (b) Finite-alphabet transmitter based on QNN [10].

FIGURE 3. Deep-learning-enhanced joint transmitter and receiver optimizations.

ables, the end-to-end design normally achieves better performance than solely optimizing the receiver.

Then we study the use of deep learning to satisfy realistic constraints on the mMTC transmitter (e.g., geometric constellation shape or finite-alphabet constraints). The end-to-end deep learning framework of NOMA can also facilitate the integration of communication and computation where non-orthogonal transmission inherently performs over-the-air computation.

End-to-End Framework: DeepNOMA

DeepNOMA is a unified framework for NOMA [8]. To resemble the end-to-end NOMA system, DeepNOMA adopts an auto-encoding structure, shown in Fig. 3a, which comprises a multiple access signature mapping module, namely a NOMA encoder, a channel module, and a multiuser detection module (NOMA decoder). The source messages are encoded by NOMA encoders into multi-dimensional complex symbol vectors, which are then superimposed on orthogonal resource elements (REs). Subsequently, the NOMA decoder recovers the source messages for all users.

In the DeepNOMA framework, DNN acts as an underlying universal function approximator providing strong learning ability to learn near-optimal transceivers. Offline training and online deployment are adopted for DeepNOMA. We can first train DeepNOMA in offline mode to derive good transceivers by minimizing the overall cross-entropy or ℓ_2 reconstruction loss over the synthetic dataset. Then the trained encoders and decoder are deployed at the transmitters and receiver, respectively, for online NOMA transmissions.

While FC-DNN is certainly applicable to DeepNOMA [7], a model-driven approach should be exploited to design the structures of DeepNOMA to improve the training speed. The major insight is that we can regard the superimposed NOMA transmissions as multiple distinctive but correlated tasks. This indicates that the design of DeepNOMA should be different from that of OMA, which only occupies a single task [4]. This concept motivates the incorporation of deep multi-task learning in DeepNOMA to realize inductive migration among multiple NOMA transmission tasks. Deep multi-task learning deploys the public hidden layers to provide inductive bias from one task to the other, which prompts the DNN to reach better generalization. With the shared feature extracted out of the public DNN, multiple private DNNs are then placed to generate outputs for NOMA users. Specifically, inter-task connections are introduced to propagate instant information among tasks for better demultiplexing. We see that the above multi-task structure actually matches the PIC-inspired DNN proposed Fig. 2c, where the interactions among tasks are specified as IC modules.

DeepNOMA can also deal with fading channel effects by feeding the fading channel coefficients into the NOMA decoder. In this case, the joint optimization of the NOMA encoder and decoder is carried out using a synthetic dataset generated in fading channels. It is shown that the multi-task structure improves the efficiency of DeepNOMA in fading channels.

To ensure fairness among NOMA transmission tasks during gradient-based training, the multi-task balancing technique is developed by introducing the fairness penalty, which aims to weaken or reinforce the back-propagated gradients of the tasks whose performance is beyond or below average. Using fairness penalty can be regarded as a generalization of min-max optimization that guarantees fairness among users and avoids local optima [8]. Figure 4a illustrates the uncoded bit error rate (BER) performance of deep-learning-enhanced NOMA and conventional NOMA in fading channels with typical overloading of 150 percent, where six users overlap on four orthogonal resources. The result shows that model-driven design remarkably improves BER performance more than either conventional schemes or the pure data-driven scheme. Furthermore, we observe that the end-to-end optimization can provide additional BER gain compared to solely optimizing the DNN receiver.

Tx Constraint in End-to-End Design

NOMA encoders are the key components of the end-to-end design framework. As mMTC services involve a large number of power-constrained and low-cost devices, the demand for an easy-to-implement transmitter arises, which puts additional constraints on NOMA encoders.

If we parameterize the NOMA encoder in Fig. 3a with FC-DNN, the derived multiple access signatures for NOMA can be in arbitrary forms (i.e., the transmit signal alphabet is not in a regular shape such as lattice constellation). The irregular alphabet may worsen the peak-to-average ratio performance and cause additional hardware complexity. One possible solution to this problem is to introduce regulations on a NOMA encoder by constraining the output of

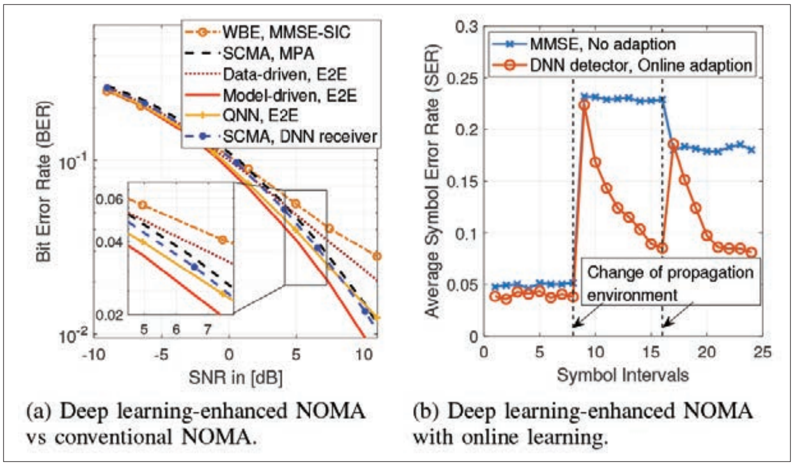


FIGURE 4. Performance evaluations of deep-learning-enhanced NOMA schemes with typical overloading of 150 percent.

a NOMA encoder to be in a certain geometric shape. To achieve this, the desired geometrical shape of the transmit alphabet should be embedded in the encoder DNN, and only the parameters related to the shape are optimized during training. This design also reduces the number of trainable parameters and enhances the learning efficiency.

For low-cost mMTC devices, finite-alphabet signature is required at NOMA transmitter to be compatible with a finite-resolution digital-to-analog converter (DAC). To satisfy this constraint, the existing method adopts a divide-and-conquer design approach. First, the signatures are optimized in a real number field. Then the conventional NOMA signatures are quantized during online implementation. As an example, NOMA spreading signatures, such as Welch-bound equality (WBE) sequences, can be projected onto the QAM constellations during implementation [1]. However, the quantization can cause unexpectable cross-correlation among signatures, which results in unpredictable degradation of the transmission accuracy.

With the recent development of quantized neural network (QNN), we are able to realize the joint optimization of signature optimization and quantization. A QNN-based NOMA encoder with quantization module is proposed in Fig. 3b to design the finite alphabet spreading sequences [10]. However, using quantization causes indifferentiable DNN mapping function, which cannot be trained by a conventional optimizer. Therefore, the straight-through optimizer is developed, which uses the quantized version of signal in forward propagation while only training the full-precision weights of the encoder. Specifically, as illustrated by the gray arrow in Fig. 3b, forward propagation passes the input through a DNN encoder as well as a quantizer to generate the NOMA codeword. The NOMA codeword is then recovered by the NOMA decoder to output the estimated source signal. Then the loss function is calculated by comparing the output and the training label. During backward propagation, as illustrated by the black arrow, the quantizer is bypassed, and only the weights of the encoder are adjusted according to the loss until convergence. As observed in Fig. 4a, introducing quantization in DNN does not cause significant performance loss, especially in medium-to-low SNR regions.

End-to-End Design for Integrated Communication and Computation

Massive devices will be connected in future IoT to collect a large amount of data. The collected data is transmitted to the center processing unit (CPU), which processes the data locally to generate the computation results. Conventionally, the communication tasks and computation tasks involved in the above process are conducted separately. This isolated design results in excessive resource consumption due to the fact that redundancy retained among the devices makes it unnecessary to losslessly transmit all the collected data for obtaining the intended results.

As one promising evolution direction, the integration of communication and computation over NOMA can break this bottleneck. Due to its superposition nature, NOMA inherently accomplishes analog computation while transmitting. With the help of NOMA, computation over multiple access channels (CoMAC) is enabled by computing a designated function while transmitting. Communication-theoretic tools have been exploited to achieve simple computation tasks, such as distributed addition, using hand-crafted design of the transmitter and receiver. To further accomplish complicated computation tasks while resisting the additional noise introduced by wireless channels, joint optimization of the non-orthogonal communication and the distributed neural transceivers shall be accomplished by deep learning toward better end-to-end computation accuracy.

One such example is the wireless backhaul design for cell-free multiple-input multiple-output (CF-MIMO) system [14]. First, NOMA is deployed at backhaul for the access points (APs) to reduce the bandwidth. Then the end-to-end design of the transceivers at the APs and the CPU is conducted using deep auto-encoder where NOMA-based backhaul is integrated as a neural computing layer, as illustrated in Fig. 5. Using deep learning in this case significantly outperforms the conventional CoMAC schemes with respect to computation accuracy [14]. In the future, much more complicated human-level tasks that involve massive mMTC devices are expected to be accommodated by integrating the communication and computation via deep-learning-enhanced NOMA.

Excavation and Exploitation of User Activity Information for Transceiver Design

The modeling of mMTC differs from conventional human-centric communications in a way that mMTC serves massive autonomous devices with small and sporadic traffic [3]. As such, grant-free access has been investigated in mMTC to reduce the scheduling overhead, while NOMA technology is simultaneously exploited to resolve collisions introduced by statistical multiplexing. The scheduling-based NOMA schemes can be directly deployed for grant-free NOMA. However, these schemes ignore the sparse and non-uniform traffic patterns of the mMTC devices, which results in overestimated IUI and thus cannot fully exploit the degree of freedom (DoF) of the system [10].

Deep learning provides an intelligent approach to exploit the traffic patterns of different mMTC services. With the strong data mining capability, DNN can excavate the user activation profiles, such as the activation profiles, out of the data streams. The extracted activation probabilities of the devices can be further incorporated in the DNN-based NOMA encoder and decoder for joint transceiver optimization.

Sparse Activation Profile Prediction

The transmit data streams of the mMTC devices are generated according to their activation patterns. Reversely, the diversified activation profiles of the devices can also be anticipated from the historical received data. Conventionally, the statistical analysis methods for time series, such as autoregressive, moving average, and autoregressive integrated moving average model schemes, have been developed to predict the upcoming data based on history. However, sophisticated feature extraction methods should first be designed to convert the physical-layer waveforms to the upper-layer user behaviors, after which the above prediction schemes can be employed. Information loss is likely to happen in this procedure. Moreover, the non-stationary property of the activation profiles further requires efficient adaptation between long-term and short-term dependencies. Therefore, intelligent methods should be developed to extract activation profile prediction out of raw data directly.

DNN with recurrent structures (i.e., recurrent neural network, RNN) can deal with time series data to automatically extract high-level representations. The fact that RNN has internal memory comes from the recurrent architecture, which takes the previously generated hidden states as the input along with newly received data. As a powerful variant of RNN, long short-term memory (LSTM) designs mechanisms to learn how and what to remember over a long time period. This is especially effective in predicting the activation profiles in long and unknown time periods [13], which can be exploited for grant-free NOMA transceiver optimization.

Sparsity-Aware Transceiver Optimization

Multiuser Detection Based on Prior Information: At the receiver of grant-free NOMA, both the device activity and the data symbol should be estimated by the MUD. The multi-task structure of DeepNOMA is inherently compatible with grant-free NOMA, where the device activity detection can be regarded as an additional task [8]. Since the inactive device can be equivalently regarded as transmitting a zero symbol, the hidden layers trained for the symbol detection task can be reused in the activity detection task. The activity estimation is a binary decision;, thus, cross-entropy loss can be used. The prior information about the activation profiles of the devices incorporates a confidence penalty in the cross-entropy loss, which urges the statistical output distributions to exactly follow the prior distributions [9]. To jointly optimize these tasks, an additional activity estimation loss should be added on the symbol recovery loss with a weight coefficient. As a result, the DNN-based scheme demonstrates excellent performance with respect to the area under curve receiver operating characteristic (AUC-ROC) curve of activity detection.

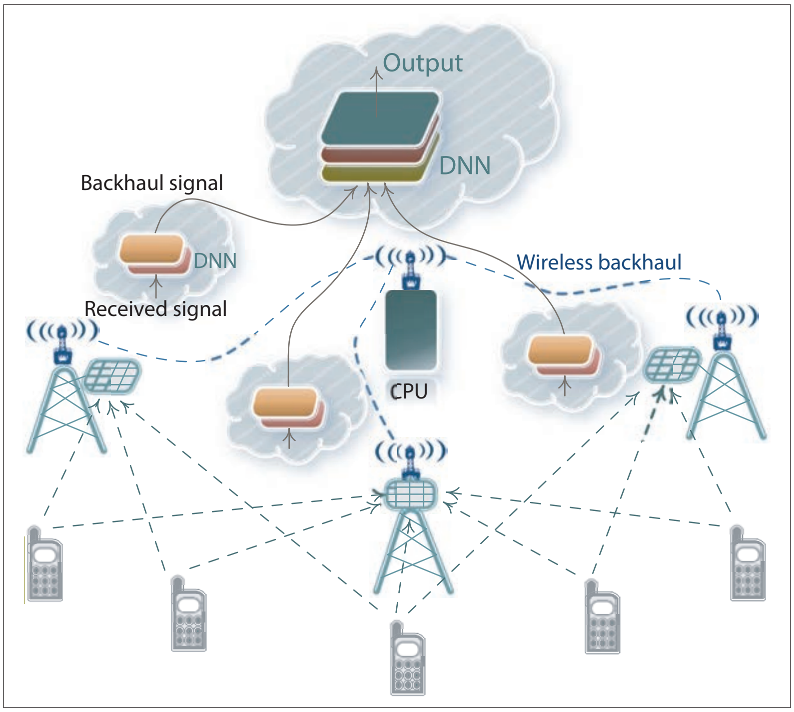


FIGURE 5. Integration of communication and computation in non-orthogonal wireless backhaul via deep learning [14].

It is worthwhile to mention that, in addition to the DNN-based MUDs, the conventional counterparts can also benefit from the sparse activation profiles. A modified orthogonal matching pursuit (OMP) algorithm is proposed in [13] to exploit the activation prediction results for joint activity and symbol detection. The resulting symbol error rate can be reduced by one order of magnitude compared to the conventional OMP methods.

Encoder Design Based on Activation Probabilities: As initial research, [10] examines the case where NOMA transmitters hold different activation probability. It is observed that the NOMA signatures derived by the end-to-end training can perfectly leverage the heterogeneous activation profiles of the users; that is, the signatures corresponding to the devices with high activation probability are more likely to have low cross-correlations. This design achieves significant performance gain compared to the conventional grant-free NOMA methods when the users hold non-identical activation profiles. This result indicates that deep learning can properly exploit the heterogeneous activation profiles of devices to design NOMA encoders [10].

Conclusions and Future Directions

Deep learning has provided the unified signal processing architecture for end-to-end transceiver optimization for NOMA in mMTC scenarios. In offline training, sophisticated data and model-driven designs of deep-learning-enhanced NOMA have been developed. Complicated optimizations, such as the exploitation of user activation profiles and the integration of communication and computation, have also been achieved via DNN. Deep-learning-enhanced NOMA normally outperforms conventional methods with respect

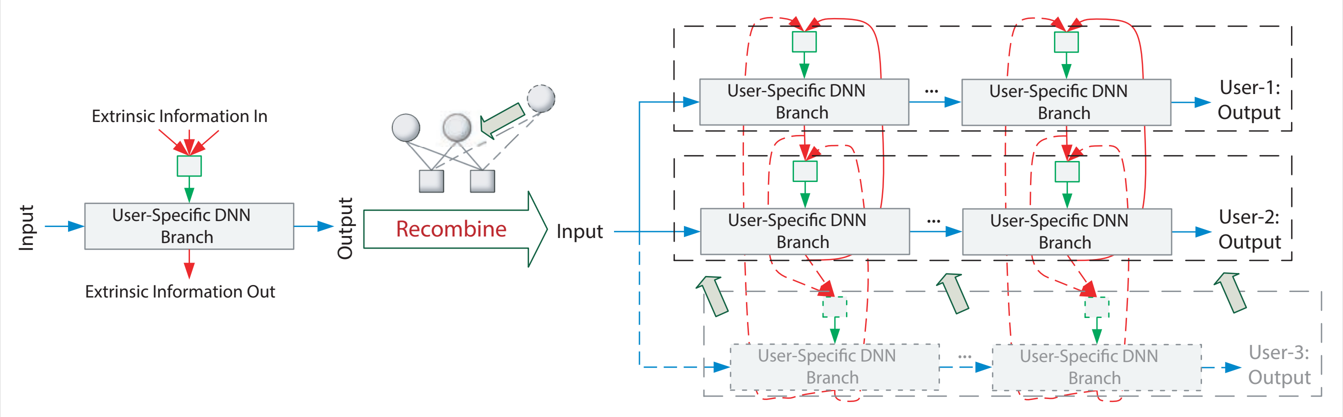


FIGURE 5. Graph-model inspired reconfigurable multiuser detector.

to both transmission accuracy and computational complexity.

Nonetheless, with the diversified connectivity in future mMTC, NOMA technology still faces the major challenges of heterogeneous quality of service (QoS) requirements, dynamic system configurations, nonlinear propagation environments, and so on. Research efforts shall be made in the future to bring more intelligence, flexibility, and adaptability to NOMA technology. In the following, we identify some promising future directions and initial thoughts of deep-learning-enhanced NOMA, including cross-layer optimization, reconfigurable design, and online adaption.

QoS-Aware Cross-Layer Optimization for NOMA

Due to the limited transmission resources in future mMTC scenarios, meeting different QoS requirements, including energy efficiency, is challenging. The layered optimization methods limit the further enhancement of NOMA performances. Therefore, it is necessary to design proper cross-layer technologies to guarantee diversified QoS of NOMA users. However, facing the complex relationship between different protocol layers and the highly dynamic environment of a NOMA system, the cross-layer optimization problem is usually nontrivial to solve. The end-to-end processing ability of DNN should be further studied to enable personalized QoS via effective cross-layer optimization.}

Reconfigurable DNN Structure for NOMA

In an on-site NOMA system, configurations such as the number of users may dynamically change. However, a vanilla DNN-based MUD only has fixed output dimensions, and any number of users larger than offline training cannot be supported online. The major challenge is to design DNN with a plug-and-play structure to match the system configurations. Observing the factor graph representation of NOMA, we can regard the NOMA system as multiple mutually interfered single-user transmissions and design the DNN structure accordingly. Figure 6 illustrates an initial design of the reconfigurable deep learning framework. This framework is a combination of several single-user detection branches, which are mutually connected via specific modules to transfer extrinsic messages. This structure allows the dynamic recombination of the branches during online deployment.

Meta-Learning-Aided NOMA Online Adaptation

mMTC devices with low-cost power amplifiers may introduce unexpected distortion, which leads to nonlinear propagation during online deployment. This mismatch greatly degrades the performance of deep-learning-enhanced physical-layer technologies. Meta-learning, also known as learning to learn, aims at acquiring an inductive bias that is suitable for the entire class of the system configurations of interest [15]. However, the online adaptation can be very challenging for NOMA due to the overlapped multiple signal streams. Based on the above reconfigurable DNN structure, one initial thought is to first decouple the system into multiple single-user subsystems, update each subsystem with meta-learning, and finally re-organize these subsystems as a whole. We show the performance of the proposed design in Fig. 4b. Compared to the conventional minimum mean square error detector without adaption, a DNN detector with online learning can quickly adapt to the changing transmission environment.

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