Deep Learning for Wireless Networking: The Next Frontier

Yu Cheng, Bo Yin, and Shuai Zhang

Abstract

With the growth of mobile technology in the last decade, wireless networks have become an integral part of our everyday lives. To meet the increasingly stringent application requirements, more and more network resources and features are becoming available, which requires innovative system designs such that the configuration and management of the networks can be performed automatically and autonomously. Due to its superior capability of discovering insightful knowledge in a data-driven manner, the emerging deep learning (DL) technology has shown great potential to fulfil this goal. This article systematically reviews recent efforts in leveraging DL for addressing wireless network optimization problems, presenting a fundamental understanding of where and how the supremacy of DL based approaches comes versus the conventional modeling based approaches. The basic research challenges and some promising research directions for fully exploiting the potential of DL in wireless network optimization are also discussed. The effectiveness of DL is illustrated with an innovative case study of integrating DL with multi-hop wireless network flow optimization.

Introduction

Recent years have witnessed the dramatic evolution of wireless networking. At the end of 2018, there were approximately 22 billion connected devices deployed around the world, mostly through wireless networking. Moreover, the recent emergence and integration of the Internet-of-Things and a variety of other computing paradigms (such as cloud computing, edge computing, and software-defined networking) have spawned a wide range of applications and services over wireless networking, imposed new performance requirements on the service providers, and thus suggested a tremendous change in network management. With the proliferation of mobile devices and the adoption of technical innovations, the complexity and diversity of wireless networks skyrocket.

Conventionally, a wireless networking system is divided into several layers and researchers rely on analytical models to design management strategies and control policies for delivering desirable network performance. For example, the scheduling issue at the link layer and the routing problem at the network layer had been intensively studied in the recent two decades, heavily relying on channel models, interference models, and optimization algorithms. These modeling oriented approaches, unfortunately, are becoming ineffective due to the discrepancies between the mathematical tractability and the exponentially increased complexity of wireless networking, and may gradually fail to meet the stringent quality of service (QoS) requirements of emerging applications.

Due to its recent success in various domains [1], deep learning (DL) has been identified as a disruptive enabler for automatic and autonomous network management. Incorporating DL intelligence into wireless networks not only has the potential to replace the manual interventions involved in the current engineering-intensive network management tasks, but also give rise to novel network optimization approaches that deliver superior system performance in real-time. Given the strong capability in big data analytics, DL techniques can be leveraged to distill insightful knowledge (e.g., the intricate correlations between the network configurations and the achievable performances) from the abundant data over modern wireless networks to enable innovative control and optimization methods. In particular, deep reinforcement learning (DRL) techniques, which have demonstrated impressive results in areas such as robotics and video games, provide promising opportunities for developing online control policies in complex and large-scale networking scenarios. Moreover, the emerging DL hardware accelerators significantly speed up the DL-related operations; the network controllers equipped with modern DL technologies are obtaining the capability to promptly adjust and optimize resource allocation efficiently in response to rapidly changing networking conditions.

The great potential of applying DL techniques in wireless network optimization has sparked a growing interest from both academia and industry. However, most of the existing studies in this area are exploratory and conducted in an ad hoc manner. Therefore, we believe it is timely and imperative to review the state of the art with a holistic perspective, probing more insightfully why DL-based approaches have advantages over their traditional counterparts in wireless network optimization. This article systematically reviews recent attempts at leveraging DL for addressing wireless network optimization problems, presenting a fundamental understanding of where and how the supremacy of DL comes regarding the wireless network optimization. In contrast to existing tutorial articles, which focus on the benefits of adopt-

Digital Object Identifier:
10.1109/MWC.001.2100005

The authors are with the Illinois Institute of Technology.

ing DL techniques in specific network layers [2] and/or certain types of wireless networks [3], we instead investigate the power of DL in the context of generic wireless network optimizations that may arise in diverse situations.

The remainder of this article is organized as follows. The conventional approaches for wireless network optimization are discussed first, with a focus on examining the inherent limit in this conventional paradigm. Accordingly, the supremacy of DL based methodologies will then be analyzed from four complementary angles. Then we discuss future research directions and related challenges. An innovative case study of leveraging deep learning in the context of multi-hop wireless network flow optimization is also included.

Conventional Modeling and Optimization

Wireless network optimization tasks usually involve the management or allocation of network resources (e.g., radios, channels and transmit power), intending to deliver good network performance. Most existing approaches to such tasks follow the paradigm of mathematical programming, in which a wireless network utility maximization (WNUM) problem is formulated and solved.

Typically, a WNUM problem consists of an objective function and a set of constraints. The former represents the target network utility one wants to optimize while the latter captures the characteristics of the constrained resource or budget. The problem formulation process involves the establishment of various mathematically describable models. For example, the multipath fading experienced by a wireless channel is commonly modeled by Rayleigh and Rician distributions. Establishing these models requires domain knowledge to properly abstract the physical systems and analytically characterize the effects of different network entities. With more and more advanced features incorporated in real-world wireless networks, it is becoming intractable for the above manual-tuning approach to model the network systems, which may contain unknown characteristics that are difficult to measure and express.

When designing algorithms for WNUM problems, computational overhead and optimality are the two most important concerns. To maximize the network utility, the limited network resources need to be allocated to different network entities in a selective fashion. In a wireless network, due to the broadcast nature of wireless communications, neighboring links that share the same channel may not be activated simultaneously for alleviating the interference. In fact, most WNUM problems fall in the class of combinatorial optimization problems, which are NP-hard in general. Therefore, the major thread of solving these wireless network optimization problems is the development of various approximation algorithms or heuristics, which generate a sub-optimal solution with an acceptable computational cost, referring to [4] and the references therein. In the wake of next-generation wireless networks, technical solutions are expected to deliver improved network performance in real-time, which the existing approaches may not accomplish.

Wireless networks are inherently dynamic and require adaptive control. Regarding a specific network optimization task, it is not uncommon that

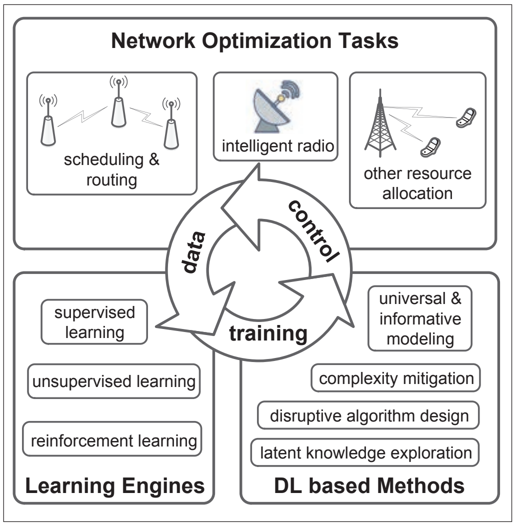

FIGURE 1. The DL4WNET framework.

the network controller has to solve a series of WNUM problems with the same or similar structure to guarantee stable network performance. Traditionally, each problem instance is considered as an isolated input and its solving procedure is started from scratch. Another re-optimization strategy of using the solution to the latest instance as the starting point for the current one is also employed in many studies, which implicitly assumes that a small modification has been made to the previous instance. Those strategies fail to fully exploit the computation experience of solving all the historical problem instances. Intuitively, one can benefit from certain generalizable knowledge if it somehow captures the correlations among different instances [5]. Nevertheless, how to discover this knowledge and leverage it to fuel the re-optimization remains open.

Supremacy of Deep Learning in Wireless Network Optimization

According to the challenges faced by the conventional optimization paradigm, DL technologies can advance the state of the art of wireless network optimization from four aspects: establishing practical and informative formulations of the optimization tasks; alleviating the computational overhead of generating approximated solutions; exploring approaches that are superior to the existing ones; and discovering new latent knowledge that facilitates efficient and effective optimization.These four aspects can be summarized into a deep learning for wireless networking (DL4WNet) framework, as illustrated in Fig. 1.

Universal and Informative Modeling

In light of the ability of a deep neural network (DNN) to fit a wide range of functions, DL technologies provide a universal approach to model the optimization tasks that are intractable to formulate mathematically. The work in [6] employs DNNs to develop an end-to-end wireless communication system in which several key functions, including encoding, decoding, modulation and demodulation, are performed in an integrated fashion. Specifically, the transmitter and receivers are respectively modeled by an auto-encoder

According to the challenges faced by the conventional optimization paradigm, DL technologies can advance the state of the art of wireless network optimization from four aspects: establishing practical and informative formulations of the optimization tasks; alleviating the computational overhead of generating approximated solutions; exploring approaches that are superior to the existing ones; and discovering new latent knowledge that facilitates efficient and effective optimization.

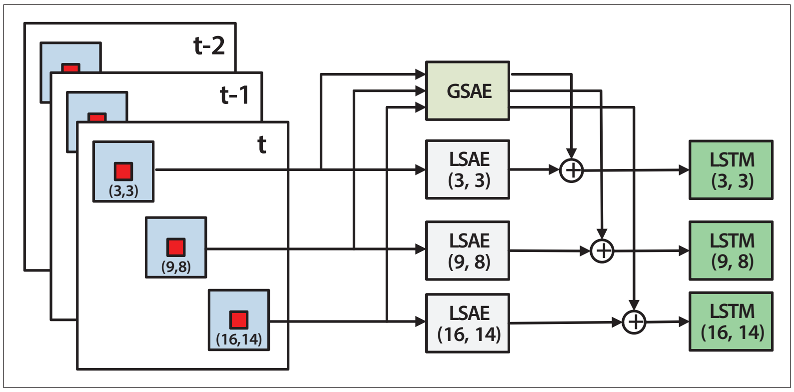

FIGURE 2. Hybrid DL model to perform spatio-temporal modeling and prediction for each cell (m, n), proposed in [7].

DNN and auto-decoder DNN while the channel effects are represented by a conditional generative adversarial net (GAN). In this way, the prior information of the channel is not required and the whole system can be trained in a supervised manner. Such an end-to-end framework provides a universal solution for different channels. In particular, encouraging results on additive white Gaussian noise (AWGN) channels, Rayleigh fading channels, and frequency-selective channels are reported in [6] that the neural-based approach can achieve similar or better performance than those of traditional approaches with expert knowledge and channel models.

Additionally, the advancements in DL technologies motivate researchers to incorporate extra information into the optimization models. Thanks to the convenience brought by the DL models for making predictions, proactive resource allocation algorithms have recently received a great deal of attention. By leveraging the near-term predictions of some system parameters (e.g., traffic loads, content requests, and user trajectory), those approaches can serve the demands proactively to improve the performance, which also demonstrate good adaptability to the dynamic environments. As the prerequisites, the prediction methods play a critical role in the development of proactive serving algorithms. Taking traffic prediction as an example, a hybrid DL model is proposed in [7] to capture the spatial-temporal correlations of traffic loads in cellular networks. As shown in Fig. 2, an autoencoder-based model, which consists of a global stacked autoencoder (GSAE) and multiple local SAEs (LSAEs), is used to characterize the spatial correlations, while the temporal characteristics are represented through a long short-term memory (LSTM) architecture. In terms of prediction accuracy, the advantages of the proposed model over two commonly used baseline models, support vector regression (SVR) and autoregressive integrated moving average (ARIMA), are validated by extensive experiments with a real-world dataset.

Complexity Mitigation

In addition to the benefits in the aspect of modeling, exploiting the expressive power of DNNs brings huge potential to reduce the computational overhead of solving optimization problems. A natural way to achieve this goal is to replace some computation-intensive tasks with properly designed DNNs as the output of a DNN can be efficiently evaluated. With the help of modern DL platforms, a DL model can be built generically without expert knowledge about the approximated procedure. For example, the channel state information (CSI) is normally required for appropriate resource allocation over wireless networks, whereas the CSI estimation is expensive in dense networks. Recognizing that the CSI is basically determined by the geographic location information (GLI) of the transmitters and receivers, the authors in [8] propose to construct a DNN, which takes the GLI as input and bypasses the CSI estimation, to learn the optimal link scheduling in D2D networks. Experimental results show that the ML-based scheduling can converge to a near-optimal solution within a small number of iterations in online operation.

Another interesting application of DL methodology for the purpose of speeding up the problem-solving process is based on the idea of dimensionality reduction. Roughly speaking, a DL model is utilized to figure out the key factors that have a great impact on the network performance. In this way, the complexity of designing a reasonable control policy can be alleviated. Consider the novel features and emerging protocols that are incorporated into the 5G networks, it is becoming difficult, if not impossible, to enumerate the relationships between the network parameters and the quality of experience (QoE) relevant key performance indicators (KPIs) explicitly. In the work of [9], a deep learning-based QoE prediction approach is proposed to evaluate users' experiences in mobile video transmission. To enable such a data-driven approach, a large-scale QoE dataset, which consists of more than 80000 pieces of data about four kinds of subjective scores and 89 network parameters, is first established. Observing that a specific QoE score may be influenced by a small portion of network parameters, the feature selection and boxplot methods are applied to reduce the redundancy among the network parameters and clean the raw data, respectively. With the preprocessed data, it is shown in [9] that a DNN-based model results in more accurate QoE assessments than that achieved by some classic methods, such as support vector machines (SVM) and decision tree.

Disruptive Algorithm Design

Beyond increasing the efficiency of tackling wireless network optimization tasks, researchers also adopt DL techniques, particularly DRL techniques, to develop innovative neural-based approaches that can yield better utility, as shown in Fig. 3. The end-to-end optimization framework aims to train a DL model that can output a solution to the optimization problem directly. A general procedure to achieve this is to recast the optimization problem in the form of the Markov decision process (MDP) and train a learning agent that explores the solution space and derives the optimal control policy from its experience. In the setting of DRL, the control policy is commonly parameterized through DNNs. Such an experience-driven framework offers a flexible way to deal with highly dynamic systems with complicated state space (e.g., many factors are jointly considered) in an end-to-end fashion. In other words, learning out of experience can circumvent the necessity of developing an extra scheme to coordinate a set of algorithms or protocols that are studied separately for different sub-systems. Therefore, the potential performance degradation caused by the coordination can be avoided. In this context, the work in [10] studies the resource allocation problem in an LTE-WiFi coexistence environment, where multiple small base stations (SBSs) proactively perform dynamic channel selection, carrier aggregation, and fractional spectrum access. With a game-theoretic model, an RL-LSTM framework is proposed to predict the spectrum availability and plan the channel usage autonomously. It is shown that the control policy learned by each SBS can drive the whole system to a mixed-strategy Nash equilibrium (NE), which witnesses the great performance boost for the SBSs while preventing WiFi performance degradation.

Recent research attempts at embedding DL models in the traditional algorithmic frameworks for combinatorial optimization also reveal promising results in advancing the state of the art methodologies [11, 12], which shed light on a hybrid optimization framework for algorithm design. The former work focuses on a greedy heuristic framework in which the criterion for selecting the next step option is learned using DRL methods. The latter work investigates the local search framework, where the search direction is guided by the outputs of DNNs. Given the pervasiveness of heuristics in the wireless networking domain, we envision that the idea of leveraging DL to promote existing algorithms can be leveraged to address wireless network optimization tasks in a broader sense. Note that many conventional optimization algorithms, especially for multi-hop wireless networks, cannot be fully replaced by machine learning based solutions yet [5]. The hybrid model enables gradual progress toward the ultimate goal.

Latent Knowledge Exploration

Traditional approaches with the paradigm of mathematical programming typically aim to develop mathematical expressions that can relate user Traffic, network Resource, and the Quality of service metrics, which can be termed as TRQ functions. Nevertheless, the DL-based approaches enable people to exploit latent knowledge embedded in the historical data from new angles, beyond the traditional TRQ relationship. The seminal work in [5] proposes the idea of leveraging DL to identify insightful patterns from the conventional solutions of previous wireless network flow optimization instances. The knowledge extracted with DL is leveraged to tailor the new optimization instances to reduce the problem size, which can then be solved by the conventional algorithm with significantly less computation time but solution quality maintained. The view in [5] in fact brings a complementary angle to integrate DL with conventional optimization algorithms, enabled by ML's capability of revealing latent knowledge beyond human expertise. Specifically, the work in [5] addresses the demand constrained energy minimization problem in generic multi-commodity flow networks. A deep belief net

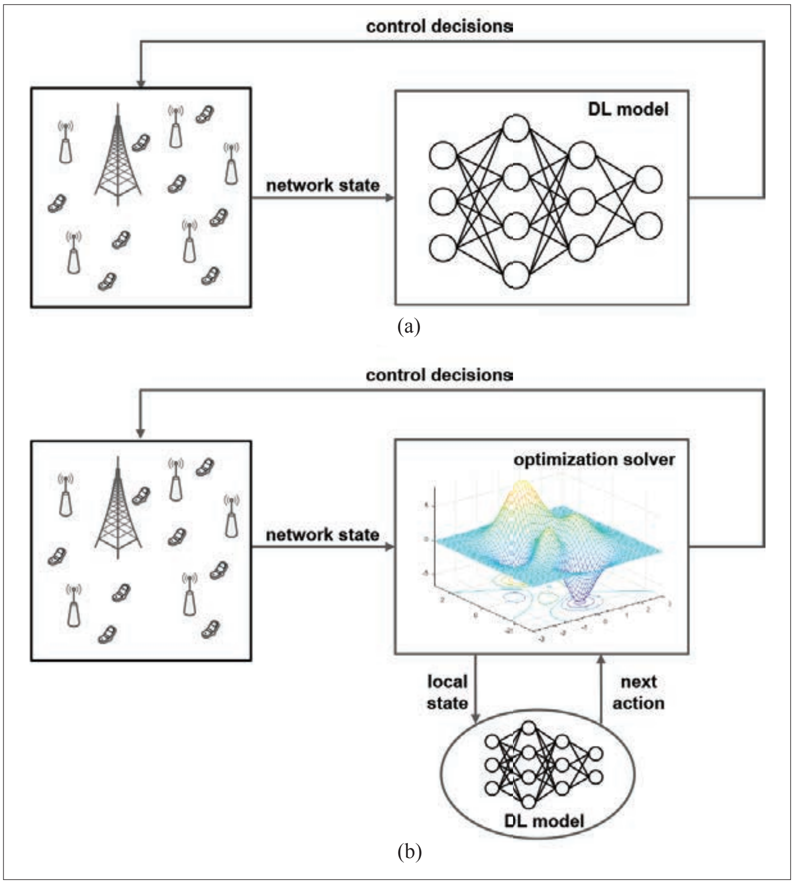

FIGURE 3. DL based network control: a) end-to-end optimization framework; b) hybrid optimization framework.

(DBN) based DNN is developed to capture the latent relationship between flow information and link usage. Based on the flow demands, the DL model can estimate the usefulness of each link in the network, that is, the probability that a specific link will be scheduled. In this way, those links that are unlikely to be used will be pruned before applying the existing optimization algorithms. Despite the extra prediction overhead, this method can greatly improve the efficiency of solving network optimization problems. It is reported in [5] that solutions with minor quality degradation can be produced by dealing with the reduced-size problems while the computational costs decrease by up to 50 percent.

Challenges and Discussions

Despite the advantages of incorporating DL models in wireless network optimization, some fundamental research challenges have yet to be addressed to fully unleash the potential of DL technologies in simplifying network management and enhancing network performance. In this section, we discuss such challenges and illustrate some of the research topics that deserve further considerations.

Informative Training Data Generation

Training a sensible DL model usually requires a large amount of data. Moreover, the quality of the dataset is critical to the generalization performance of the learning-based algorithm. Unfortunately, the lack of high-quality large-scale datasets

The design of traditional approximation algorithms crucially relies on the worst-case analysis to certify the quality of the proposed algorithms. In contrast, the development of the DL-based algorithms is mainly experiment-oriented. In this way, the DL-based algorithms can hardly give any guarantee in terms of optimality.

is not uncommon for many network optimization tasks, which will stifle the adoption of DL techniques in the network control domain. A natural strategy to mitigate this issue is data augmentation, which generates modified versions of samples in the existing dataset. This process needs to perform carefully such that the distribution of the problem instances does not change significantly. In this context, generative models such as GAN may provide powerful tools for data augmentation. Another candidate solution that has received increasing attention recently is transfer learning. That is, first training the DL model by leveraging the data of relevant tasks and then fine-tuning the model with the data associated with the specific task.

The information involved in the network control domain typically has a different structure from that of the data in perceptual domains, such as computer vision and natural language processing. How to find a generic paradigm for organizing and representing the information remains an open issue. Considering that many network resource allocation problems are modeled over graphs, the emerging family of graph neural networks (GNNs) could be a viable architecture to handle the data.

Effective Training Objective Design

In the context of learning-based wireless network control, the methodologies for training the DL models can be broadly categorized into either *imitation learning* or *reinforcement learning*. In the imitation learning setting, a DL model is often used to approximate the solutions produced by a teacher algorithm. Intuitively, the DNN is trained for minimizing the distance between its outputs and the expected solutions. The distance metric has significant impacts on the final objective values of the network optimization problems. Given a near-optimal solution to the D2D link scheduling problem, a solution that looks "close" to the given one (e.g., activating one extra link) may result in substantial performance degradation. Therefore, the distance metric is supposed to reflect the optimization objective, whereas designing a desirable metric is usually non-trivial. In the case of reinforcement learning, the agent improves the control policy for accumulating the rewards through trial and error. To facilitate sufficient exploration for discovering a reasonable policy, it is sometimes necessary to introduce surrogate reward signals that direct the agent to accomplish several subgoals. Matching these subgoals with the objective of the optimization problem can be very challenging. An inappropriate reward function may lead to an agent getting stuck at a tricky situation in which rewards can be collected without making any progress toward the ultimate goal (e.g., achieving some subgoals repeatedly).

It is worth mentioning that some recent studies [8] streamline the procedure of the teacher algorithms and the backpropagation process in DNN training. In this way, the DL models can be trained in an unsupervised fashion, which can bypass the difficulty of metric design. However, those approaches are limited to optimization problems for which the teacher algorithms are gradient-based such that the intermediate results of gradient descent steps can be used directly for backpropagation. The application of this idea to approximation algorithms of other types is yet to be explored.

Performance Guarantees

A fundamental challenge that arises in developing neural-based algorithms for wireless network optimization tasks is the feasibility issue of the learned solutions. By its nature, a DNN is trained in a stochastic sense, minimizing the empirical loss. Therefore, the DL model offers no guarantee on whether its output can respect the constraints of the optimization problem. To produce feasible solutions, dedicated modules are expected to be incorporated in the neural architecture, which can drive the outputs in the right direction. Deciding how to project an arbitrary result onto the feasible region is not an easy task. Note that the projection mapping needs to be differentiable to support the backpropagation.

The design of traditional approximation algorithms crucially relies on the worst-case analysis to certify the quality of the proposed algorithms. In contrast, the development of the DL-based algorithms is mainly experiment-oriented. In this way, the DL-based algorithms can hardly give any guarantee in terms of optimality. In particular, DL models have been reported to perform poorly over adversarial examples (e.g., normal examples with small perturbations) [13]. Although several countermeasures have been proposed to mitigate the adversarial attacks, a generic methodology that can evaluate the robustness of a DL model is still missing. This methodology is of critical importance since it not only determines to what extent people can safely deploy the learned algorithms in production systems, but also provides insights into algorithm comparisons. In light of the difference in the design philosophy between traditional algorithms and DL-based algorithms, the analytical framework used to evaluate the robustness of the learned algorithms might be fairly different from the methodologies which are currently used for designing approximation algorithms.

Scalability

When developing learning-based algorithms for wireless network optimization tasks, the challenge in terms of scalability contains many aspects. On one hand, as the network size keeps increasing, a well-trained DL model may have to handle problem instances with an unprecedented scale. Studying how to preserve its performance or avoid significant performance degradation on larger problems remains a demanding job. One possible research direction to tackle this issue is to use the DL techniques to discover locally "stationary" patterns of optimization solutions. In this way, the same DL model can be applied to different areas of network coverage. One may construct a reasonable global solution by leveraging the local information. On the other hand, the growth of the network scale indicates the rise of heterogeneity. It is very challenging for a centralized controller to manage the resources from a large number of network entities with diverse capabilities. Therefore, training and deploying the DL models distributedly becomes an interesting research topic. The advances in the areas of federated learning and multi-agent reinforcement learning are particularly attractive. The former enables multiple devices to collaboratively learn a shared DL model without exchanging their training samples, while the latter addresses tasks in which multiple agents learn their individual control policy via interactions with others.

A Case Study

We initiated the study of integrating DL with multi-hop wireless network flow optimization in [5], which was however limited to the situation with a static topology. In this section, we present some of our current studies that extend the methodology to a more generic scenario with dynamic topologies. To maintain the tutorial nature, we here focus on the methodologies and illustrating numerical results; technical details can be found in [14].

Specifically, we consider the multi-commodity network flow optimization problem in a multi-hop single-radio single-channel wireless network. Given the network topology, the task is to calculate a time-sharing link schedule and associated link flow allocation to maximize the system throughput for nodes with traffic demands (specifically, to maximize the minimum of the commodity flows for a reasonable consideration of fairness). The scheduling is constrained by a *protocol interference model* [4] where an active transmission link should be free of interference within the receiver's interference range. The conflict relationship among all the links can be characterized by a conflict graph, where a node represents a link in the original network and two nodes are connected if they conflict with each other. An independent set (IS) over the conflict graph corresponds to a set of links that can be scheduled for transmission simultaneously without interfering each other. With such modeling, the scheduling can be mapped to a problem of searching for the optimal time sharing among an optimal collection of ISs. While this computation problem is still NP-hard (due to the exponentially many possible ISs), it can be formulated as a linear programming problem and solved iteratively by the delayed column generation (DCG) method, with guaranteed performance bound [4].

In order to facilitate computing the optimization problem as described above, we propose a topology-aware deep learning (TADL) framework as illustrated in Fig. 4. The TADL follows the basic principle that we initiated in [5], but incorporates new elements to extend the applicability of the trained machine to different topologies. Specifically, we compute a large number of problem instances, with different network topologies and commodity flow deployments, and their solutions, which are used to train a DL model that predicts the importance of a link based on whether it is used in the DCG scheduling decisions. Therefore, given a new problem instance, the trained model can predict the importance level of each link and prune off the unimportant ones, so the network scheduler only needs to solve a smaller-sized problem.

As shown in Fig. 4, the TADL framework consists of a graph embedding unit and a topology reduction network. The embedding unit is the key element that enables the topology-aware capability of TADL. A straightforward idea to incorporate topology into learning is feeding the topology information, in the form of the adjacency matrix, directly to the machine. However, the topology

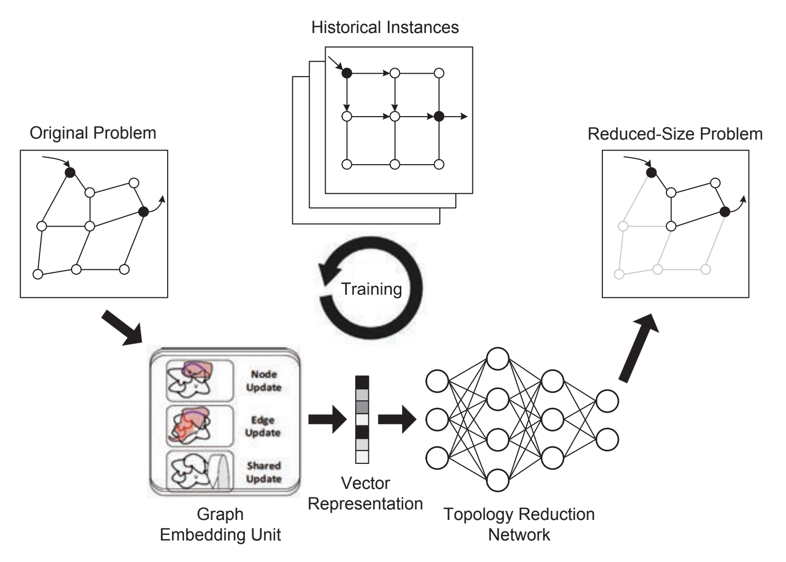

FIGURE 4. An illustration of the topology-aware deep learning (TADL) framework.

representation based on the adjacency matrix will be dependent on the specific node indexes: one topology may lead to different adjacency matrix representations based on different node index assignments, which may be interpreted by the machine as different networks. To address such an index-dependent issue, the embedding unit will attach each node and link with an embedding vector that encodes appropriate index-independent topological information: it can be interpreted as a summary, obtained through training, of the locations of the transmitters and receivers within a neighborhood, their interference relationships, and the impact of such information on scheduling. The implementation details about embedding are available in [14]. Those embedding vectors are then leveraged by the topology reduction network, in which attention mechanism is used to identify network links that are likely to be used in an optimized way.

We define two performance metrics to evaluate the performance of TADL. One is the approximation ratio (AR), defined as the ratio of the optimum value achieved from the pruned instance to that achieved from the original instance; the other is the time reduction (TR), defined as the ratio of the amount of computation time reduction to the original instance's computation time. A normalized performance index (PI), combining both AR and TR, can be further defined as PI = 0.5 × (AR + TR). For all three metrics, a larger value indicates a better performance.

In Table 1, we list the measures achieved by TADL in comparison to the topology-blind (BLIND) approach: each link is independently pruned with a probability that is equal to the pruning ratio in the counterpart TADL scenario, while certain processing [14] is conducted to maintain the feasibility in optimization over the reduced topology. Note that with TADL, the machine is trained in the setting of 50 nodes, where the node positions are randomly placed to generate different topologies. More than 1 million instances (with different topologies and commodity settings) are solved to generate the training data. The trained machine is then applied,

Commodities	10 nodes			30 nodes			50 nodes		
	1	3	5	1	3	5	1	3	5
TADL-AR	0.96	0.94	0.93	0.95	0.91	0.92	0.92	0.91	0.88
TADL-TR	0.78	0.72	0.69	0.67	0.64	0.58	0.66	0.62	0.60
BLIND-AR	0.67	0.72	0.72	0.68	0.64	0.66	0.56	0.51	0.43
BLIND-TR	0.42	0.40	0.37	0.48	0.35	0.35	0.37	0.33	0.04
TADL-PI	0.87	0.83	0.81	0.81	0.78	0.75	0.79	0.77	0.74
BLIND-PI	0.55	0.56	0.55	0.58	0.50	0.51	0.47	0.42	0.24
Tested instances	726	3450	4902	3620	4686	12990	19660	39160	39480

TABLE 1. The performance of TADL versus the BLIND approach, in different topology sizes (10, 30, or 50 nodes) with different number of commodity flows(1, 3, or 5 flows), respectively. The machine is trained in the scenario with 50 nodes using more than 1 million instances, and then applied to all the cases in this table without retraining.

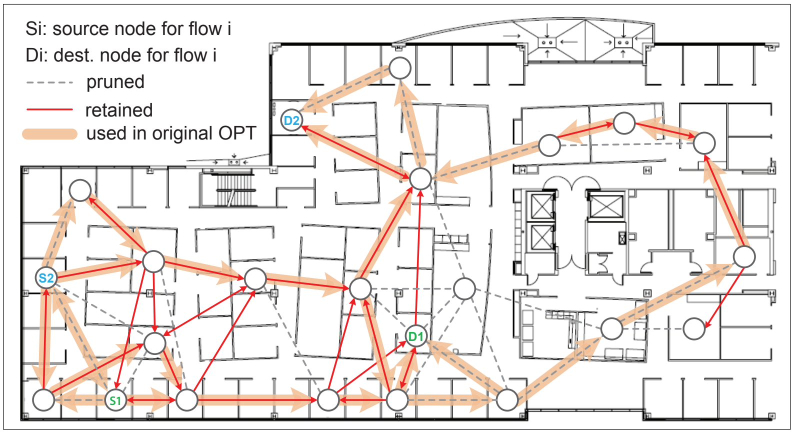

FIGURE 5. A wireless mesh topology in an office setting constructed in [15]. TADL link prediction and the optimal link set are shown. The links in red color are the ones maintained by the DL model.

without any retraining, to all the cases reported in Table I to evaluate the topology-aware capability of TADL. The number of tested cases to generate the average performance measures in each scenario is also reported in Table I. It can be seen that the TADL approach significantly outperforms the BLIND counterpart in all cases, credited to the intelligence of DL. The robustness of TADL over dynamic topologies is explicitly demonstrated through the steady high PIs over different network scales, with the same number of commodity flows. For example, when we observe the cases of five commodity flows under the setting of 10, 30, and 50 nodes respectively, the TADL-PI values are 0.81, 0.75, and 0.74 accordingly. The 50-node (largest scale for training) scenario defines the capacity boundary of the TADL; when it then applies to easier tasks over smaller scale networks, we indeed see better performance as indicated by the PI value. In [14], the advantage of TADL is further demonstrated with comparison to the situations that the network topology is input to TADL in the form of adjacency matrix (which is order-dependent) instead of using a proper graph embedding technique.

While Table 1 presents performance evaluation averaged over many random topologies, Fig. 5 illustrates the operation of TADL over a specific wireless mesh topology with 23 nodes and two commodity flows, in a practical office setting such as is studied in [15]. In the topology, each edge represents a bi-directional link, thus giving 96 unidirectional links in total. TADL leads to a reduced problem of 29 links, which results in a TR of 76 percent and an AR of 97 percent (i.e., only with 3 percent performance degradation). Figure 5 also indicates the exact set of links that are activated in the optimal solution from the original problem to benchmark the prediction accuracy. We can tell that TADL only incorrectly prunes a few links and includes a small set of redundant links.

Conclusion

This article provides a survey, with a holistic perspective, of the recent efforts in leveraging DL for wireless network optimization, probing insightfully where and how the supremacy of DL based approaches comes versus the conventional modeling based approaches. We have also discussed the challenges of applying the state of the art from the machine learning community to general wireless network optimization problems and pointed out several promising research directions. In addition, to demonstrate the potential of DL techniques, we have presented a case study in which DL based approaches are used to mitigate the computation complexity in the canonical yet challenging wireless network flow optimization problem.

Acknowledgment

This work was supported in part by the NSF under grants CNS-1816908 and CNS-2008092.

References

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, 2015, pp. 436–44.
[2] Z. Qin *et al.*, "Deep Learning in Physical Layer Communications," *IEEE Wireless Commun.*, vol. 26, no. 2, 2019, pp. 93–99.
[3] H. Huang *et al.*, "Deep Learning for Physical-Layer 5G Wireless Techniques: Opportunities, Challenges and Solutions," *IEEE Wireless Commun.*, vol. 27, no. 1, 2019, pp. 214–22.
[4] Y. Cheng *et al.*, "A Systematic Study of the Delayed Column Generation Method for Optimizing Wireless Networks," *Proc. ACM MobiHoc*, 2014, pp. 23–32.
[5] L. Liu *et al.*, "Deep Learning Meets Wireless Network Optimization: Identify Critical Links," *IEEE Trans. Network Science and Engineering*, vol. 7, no. 1, 2020, pp. 167–80.
[6] H. Ye *et al.*, "Deep Learning-Based End-to-End Wireless Communication Systems with Conditional GANs as Unknown Channels," *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, 2020, pp. 3133–43.

[7] J. Wang *et al*., "Spatiotemporal Modeling and Prediction in Cellular Networks: A Big Data Enabled Deep Learning Approach," *Proc. IEEE INFOCOM*, 2017, pp. 1–9.
[8] W. Cui, K. Shen, and W. Yu, "Spatial Deep Learning for Wireless Scheduling," *IEEE JSAC*, vol. 37, no. 6, 2019, pp. 1248–61.
[9] X. Tao *et al.*, "Learning QoE of Mobile Video Transmission with Deep Neural Network: A Data-Driven Approach," *IEEE JSAC*, vol. 37, no. 6, 2019, pp. 1337–48.
[10] U. Challita, L. Dong, and W. Saad, "Proactive Resource Management for LTE in Unlicensed Spectrum: A Deep Learning Perspective," *IEEE Trans. Wireless Communications*, vol. 17, no. 7, 2018, pp. 4674–89.
[11] E. Khalil *et al*., "Learning Combinatorial Optimization Algorithms over Graphs," *Advances in Neural Information Processing Systems*, 2017, pp. 6348–58.
[12] X. Chen and Y. Tian, "Learning to Perform Local Rewriting for Combinatorial Optimization," *Advances in Neural Information Processing Systems*, 2019, pp. 6278–89.
[13] X. Yuan *et al*., "Adversarial Examples: Attacks and Defenses for Deep Learning," *IEEE Trans. Neural Networks and Learning Systems*, vol. 30, no. 9, 2019, pp. 2805–24.
[14] S. Zhang, B. Yin, and Y. Cheng, "Topology Aware Deep Learning for Wireless Network Optimization," arXiv preprint arXiv:1912.08336v2, 2020.
[15] R. Draves *et al*., "Routing in Multi-Radio, Multi-Hop Wireless Mesh Networks," *Proc. ACM MobiCom*, 2004, pp. 114–28.

Biographies

Yu Cheng [S'01, M'04, SM'09] received B.E. and M.E. degrees in electronic engineering from Tsinghua University in 1995 and 1998, respectively, and a Ph.D. degree in electrical and computer engineering from the University of Waterloo in 2003. He is now a full professor in the Department of Electrical and Computer Engineering, Illinois Institute of Technology. His research interests include wireless network performance analysis, network security, big data, cloud computing, and machine learning. He received the National Science Foundation (NSF) CAREER Award in 2011. He was an IEEE ComSoc distinguished lecturer in 2016-2017. He is an associate editor for *IEEE Transactions on Vehicular Technology*, *IEEE Internet of Things Journal*, and *IEEE Wireless Communications*. He is an IEEE senior member.

Bo Yin [S'14] received his B.E. degree in electronic information engineering and M.E. degree in electronic science and technology from Beihang University in 2010 and 2013, respectively. He received his Ph.D. degree in electrical and computer engineering from Illinois Institute of Technology in 2020. His research interests include network security, network resource allocation, information freshness, and machine learning based network optimization.

Shuai Zhang [S'15] received the B.Eng. and M.S. degrees from Zhejiang University and the University of California, Los Angeles in 2013 and 2015, respectively. He is pursuing his Ph.D. degree at Illinois Institute of Technology. His research interests include next generation wireless networks, wireless network optimization, and machine learning.