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A survey on machine learning-based routing for VLSI physical design ☆

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ABSTRACT

Routing is one of the most important and time-consuming stages of physical design. As the process node of semiconductors keeps scaling down, the routing process faces increasing challenges, and the traditional solutions are not sufficiently efficient. In recent years, machine learning has aroused much interest in this context, and an increasing number of algorithms have introduced advanced machine learning techniques to help solve the routing problem. In this paper, we survey the recent development of machine learning-based routing algorithms.

1. Introduction

Physical design has a long history and is one of the most important research fields in electronic design automation. According to Moore's law, the number of components on a chip doubles every two years. However, current technologies in physical design are confronting huge difficulties in continuing to follow Moore's Law. Among the several phases in physical design, routing is one of the most complicated and time-consuming stages. With at least thousands of components and millions of transistors being placed on a chip, the routing process has to finish a large number of interconnections under the immensely complicated requirements of design rules, congestion and power. Each of the optimizations from previous stages can contribute to improving the routing results. However, when the routing results fail to meet the design requirements, the routing process is forced to begin the iterative optimization in the routing stage or from the previous stages. In the bad cases, the undesirable routing results obtained will require considerable effort from engineers to satisfy the design functionality. Although many experts have proposed algorithms to solve routing problems through years of development, as the process node of semiconductors keeps getting scaled down, the design requirements are becoming increasingly stringent. As a result, the routing problem faces facing growing challenges. Therefore, more efficient solutions are required to satisfy the application demand.

In recent years, machine learning (ML) has made great breakthroughs. Consequently, ML methods, especially deep learning and reinforcement learning, are now being widely applied in many research fields for classification and detection. In particular, it has also been recently used to solve many physical design problems. Accordingly, in this paper, we focus on routing algorithms that incorporate advanced ML techniques. We survey recent research in this area by grouping it into three subareas, namely, routing violation prediction, routing optimization and intelligent routing.

2. Preliminary

2.1. The routing problem

The routing process of physical design is extremely intricate. There are tens of thousands of standard cells and macros being placed on a chip the size of a fingernail. The cells and macros must be interconnected through millions of wirings. The connection of each net will affect the wiring of other nets, and the routing task has to determine the globally optimal connection of all these nets under constraints involving routing resources and a host of complicated design rules.

Due to such high complexity, experts usually adopt a divide-and-conquer strategy to decompose the whole process into different stages. The most common strategy is to divide the routing process into global routing and detailed routing. Global routing needs to connect all pins in different GCells of one net without considering the detailed routing path within GCells. To date, multiple algorithms have been proposed to solve the global routing problem, such as the negotiation-based rip-up and reroute maze routing method [1–5]. In addition, some recently proposed routers are also attracting interest, such as SPRoute [6], which introduces a two-phase parallel maze routing approach, and [7], which proposes 3D pattern routing and multilevel 3D maze routing. Apart from global routing, detailed routing is required to finish routing the net segments obtained from global routing and achieve design objectives such as meeting design rules and bounds on runtime and power.

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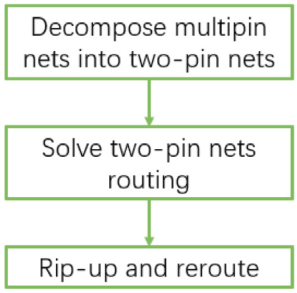

Fig. 1. The standard design flow of global routing.

Conventionally, there are also many detailed routing methods, such as maze routing [8–11] and the multicommodity flow method [12,13]. In addition, some works [14–18] focus on initial detailed routing based on the ISPD2018 initial detailed routing contest [19].

Abstractly, routing is a complex combinatorial optimization problem whose optimal solution is NP-hard to compute. Traditional solutions can be categorized into several kinds, including exhaustive methods that exhaustively explore the search space for a solution, heuristic algorithms and approximation algorithms [20]. In general, heuristic algorithms are commonly used to find the approximate optimal solution to the routing problem within the runtime limit, such as A* search algorithms. However, traditional algorithms are iterative in nature and can only obtain suboptimal solutions based on a changing design rule set. In the case of global routing, some algorithms tend to follow the standard design flow shown in Fig. 1, which may limit the full utilization of parallel resources. Moreover, modeling the characteristics of specific design rules to design optimization functions is commonly used in some traditional methods. As the scale of circuit design and design rules continue to grow, such a solution may face increasing difficulty, and its accuracy is also uncertain. These may lead to a more manual effort to make adjustments and optimizations. In recent years, ML has shown its potential to address NP-hard problems, and many experts are exploring the application of ML in routing instead of being limited to traditional solutions.

2.2. Machine learning techniques

In recent years, machine learning has attracted increasing interest from various research fields. The breakthroughs in deep learning and reinforcement learning have promoted the applications of ML even more. In particular, they are now commonly used for solving routing problems. In the following, we will introduce several such popular ML techniques.

2.2.1. Neural networks

Research on artificial neural networks (ANNs) is the origin of deep learning. The core components of ANN are artificial neurons. An ANN constructs a hierarchical network structure composed of multiple neurons, and each neuron is trained to model a certain function through a backpropagation algorithm [21]. ANN uses an input layer to receive input features. Then, the results are connected to one or more hidden layers. These hidden layers communicate the results to an output layer when all the processing is completed [22]. With multiple layers connected, an ANN can be trained to model different nonlinear functions.

Different from ANN, convolutional neural network (CNN) is a neural network that contains a convolution computation. The typical structure of a CNN is consists of convolutional layers, pooling layers and fully-connected layers. Convolutional layers usually perform feature extraction. Pooling layers compress the input feature map. Fully connected layers connect all the features and produce output. CNNs have achieved great success in many research fields, such as image processing and natural language processing. In routing problems, CNNs have also resulted in great breakthroughs in recent years.

2.2.2. Reinforcement learning

Based on Markov's decision processes, reinforcement learning (RL) is mainly concerned with the interaction between an agent and its environment. Agents make decisions based on observations gained from the environment, and the environment gives a reward for the decision. Then, agents judge the quality of decisions through rewards and perform optimization. There are four key elements, namely, the environment, reward, action and state. Through the collaboration of these elements, RL can be trained to determine an optimal policy to solve a certain problem. However, in most situations, the observation and action space will be too large to learn an optimal policy. This motivates deep reinforcement learning (DRL) which combines deep learning and reinforcement learning. It applies the powerful representation ability of the neural networks to compute the optimal policy. Reinforcement learning has been used in recent years to solve the routing problem.

Overall, it can be observed that the performance of ML techniques has several characteristics. First, it has a strong learning ability and can learn from historical experiences. Given enough training data, deep learning methods can help train a model that automatically realizes specific objectives, such as recognizing human faces or classifying different images. Reinforcement learning can even train the computers to play games with humans. Compared with these technologies, traditional methods used to solve routing problems will rely greatly on the analysis of experts. Additionally, ML methods are more accurate. The learning of ML is based on the given training data. With enough data, a very high accuracy of the learning model can be achieved. This has led to its wide application. Moreover, ML methods are more efficient. Some well-trained models can feed back results within a few seconds, which in some cases can greatly shorten the runtime compared with traditional algorithms.

3. Machine learning-based routing algorithms

As technology advances, many traditional routing algorithms have been proposed that perform well. However, there are still some issues that need to be addressed for long-term development. An essential issue is the difficulty of problem analysis. Conventionally, many traditional routing methods tend to analyze and simulate some specific characteristics in routing when constructing their algorithms, such as modeling several design rules or modeling the use of vias. With the rapid development of semiconductor technology, circuit design has become increasingly complicated. A large number of cells need to be integrated into a circuit layout, and the number of nets is increasing, while the area and power available to the chip keep shrinking, and the number of design rules are increasing rapidly. In light of this fact, it may be no longer feasible to continue to analyze the characteristics through human effort before formulating the routing solution. In addition, conventional heuristic algorithms used to solve the routing problem face difficulty in providing results that are close to optimal solutions within limited runtime due to the growing scale of circuit designs and the increasingly stringent design requirements. Some routing algorithms based on advanced ML methods have recently been proposed to solve the above issue. In the next part, we will present our survey on some research works by categorizing them into three types.

3.1. Routing violation prediction

Usually, physical design consists of five parts: floor planning, global placement, detailed placement, global routing and detailed routing. The final routing stage is particularly complicated and time-consuming. During the routing process, the router must not only finish routing all net segments but also satisfy the requirements of the design rules. If the router cannot continue routing or the design rule violations are too many, it may iteratively rip up and reroute or return to the earlier stage to further optimize. Both of these processes will cost much time and

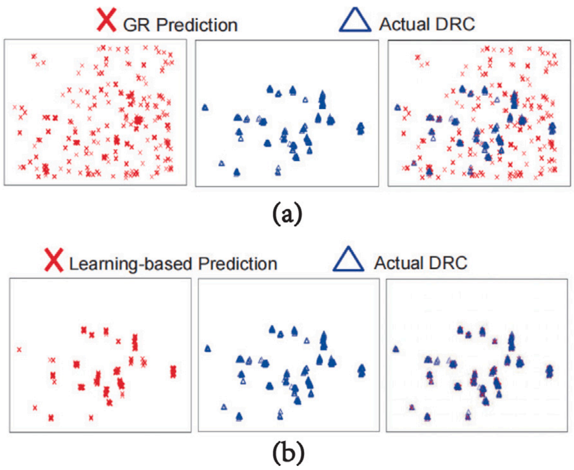

Fig. 2. (a) is the comparison between routing violation hotspots predicted by global routing and actual routing violation hotspots, and (b) is the comparison between routing violation hotspots predicted by machine learning methods and actual routing violation hotspots [23].

effort. To better address this issue, one commonly used strategy is to predict routability early.

Routing violation prediction has been a historical research area. In some early works, experts formulated the prediction models by modeling design rules or congestion. Such conventional methods may require considerable manual effort and reduce efficiency. In addition, the performance of the model may be limited due to the analysis being totally manual. In [24], a congestion model is proposed to cooperate with their 3D global router. [24] discovers two major design rules that affect local congestion and proposes a congestion model based on these two rules to practically model detailed routing resource consumption. Although it achieved satisfactory performance at that time, with the rapid increase in design rules, it may not be possible to model all related rules or determine the several essential rules by analyzing a large number of rules by manual effort. Recently, ML has been used to solve the above problem.

ML, especially deep learning is well-known for accurate prediction. Based on a set of training data, deep learning methods construct a model that learns to identify unseen routing violations. Different from traditional algorithms such as [24], deep learning-based methods will not rely on manual analysis to obtain all possible situations for designing predictors. The excellent learning ability of deep learning methods enables them to conduct in-depth explorations of the training data and find useful information to optimize their predictors. With the rapid development of deep learning, many deep learning-based routing information prediction algorithms have been proposed recently, and they are showing more accurate, more efficient, more specific and more diverse performance.

- **More accurate**. Many experts are searching for more suitable learning models and more effective features to perform prediction. In some previous algorithms, global routing (GR) congestion is often used as essential information for prediction. In 2017, [23] pointed out that some design rules used in detailed routing are not visible in GR; therefore, GR-based congestion maps may not have a close correlation with the final design rule check (DRC) violation maps, as shown in Fig. 2(a). To achieve better prediction, [23] introduces ML techniques to predict DRC violations after GR. They evaluate several mathematical models of ML and determine the most suitable one. For the extracted features, instead of using GR-based congestion information, they obtain some GR parameters from a global routing invocation and cooperate with other information, including density parameters, connectivity parameters and pin proximity. Compared with GR-based prediction, their machine learning-based predictor achieves nearly 50% of improvement. The comparison result in Fig. 2 clearly shows this. [26] also discovers the miscorrelation between GR-based congestion and DRC violations. The effects of local nets are ignored in global routing, while these local nets greatly influence the quality of the final routing. In addition, using GR information to predict violations is time-consuming and not sufficiently effective. Therefore, [26] decides to totally remove GR information when predicting and proposes a short violation predictor based on a neural network. The experimental results in [26] show that their predictor can detect 90% of the short violations with only 7% false alarms based on placement results.
- **More efficient**. As discussed above, some early works rely on the global router or modeling the design rules to predict the violation maps but they may not satisfy current efficiency requirements. In recent years, many efficient ML-based predictors have been proposed, and they show improvements in training efficiency and runtime. Instead of modeling design rules or defining related features and constraints completely by manual efforts, ML-based algorithms extract features from the given data and learn the deeper associations. [25,26] predict short violations after placement using deep learning, which are more efficient. As shown in Fig. 3, [25] uses a pin pattern as the main feature and proposes a CNN model to extract features and predict violations. Once the features are fed into the CNN model, the different neural network layers begin to extract useful information, and all the information is concatenated and fed to the classifier for prediction. Experimental results demonstrate an average of over 90% accuracy in prediction with low false alarm rates. In 2020, [27] considered that some pin features may vary greatly among different cell libraries and predictors that rely on specific pin features [25] may not be able to provide an accurate prediction of features from other cell libraries. Accordingly, the first work on cell library-based pin accessibility prediction is proposed in [27]. Its results will be next to impossible to achieve by conventional methods. Moreover, to obtain further efficiency, [27] introduced active learning incorporating cell libraries to alleviate the pressure of generating a large amount of labeled data before training the model. In addition to violation prediction, DRC hotspot prediction is also a popular research area. Different from violation prediction, DRC hotspot prediction predicts areas with multiple violations, which is more complicated. Traditionally, many DRC hotspot prediction algorithms can only predict DRC hotspots after performing global routing. With the help of ML techniques, [28] achieves for the first time, prediction after placement with high accuracy. This greatly improves the efficiency of DRC hotspot prediction. Pin accessibility is emphasized in [28], and a customized convolutional network architecture, J-Net, is proposed. To further improve the training efficiency, they also introduce data augmentation techniques to address the limited data issue. Their total runtime of a circuit design with approximately 108K nets is shorter than 1 min.
- **More specific and more diverse**. In addition to prediction performance, we observe that with ML techniques, the prediction of routing information is becoming more specific and more diverse. [26] identifies the location of detailed routing short violations from placement results based on a neural network. [29] proposes a CNN-based framework to check whether a GCell contains any violations. [25] predicts short violations caused by the pin accessibility problem between adjacent cells. To better detect such violations, they apply pin pattern as the main input features and introduce a CNN to predict whether a pin pattern will cause short violations. Moreover, a deep learning-based routability-driven macro placement is proposed in [30]. This is the first

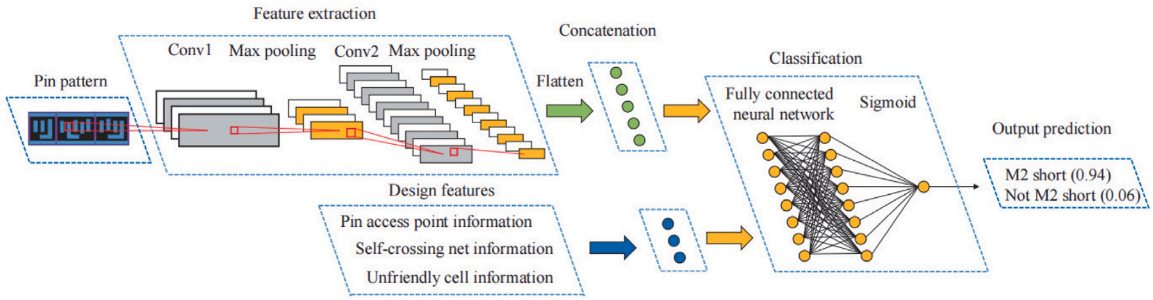

Fig. 3. The feature extraction flow based on the proposed CNN model in [25].

work to predict the number of DRC violations based on macro placement. In [30], deep learning technique is used to search for the optimal macro placement with the least violations.

Although ML has brought multiple advantages, it also faces limitations and challenges.

- ML is skilled in solving the problems in computer vision, and therefore, most of the ML-based routing information prediction research give priority to transform the prediction problems into image processing problems. This will need the effort to preform the problem transformation and introduce some limitations.
- Many works use supervised learning to solve their problem; however, to obtain a well-trained model, a large amount of labeled data must be prepared before training. Therefore, in physical design where design data are scarce, many algorithms will generate multiple design results, such as placement results and violation results, based on a layout to construct the training dataset. This will require considerable effort.
- Since the violation areas may only occupy a small part of the whole layout, some algorithms may also suffer from imbalanced dataset problems.
- ML-based models rely heavily on input data. As a result, if the input data contain some specific features that related to a certain cell library, the model will not perform well on test data from other cell libraries. This means that it is necessary to train a new model whenever the cell library changes.
- The performance of the model may be easily affected by model parameters.
- Most of the algorithms are not sufficiently practical. Many algorithms are difficult to apply to industrial designs and to incorporate into commercial design tools.

The above mentioned issues still remain to be further studied.

3.2. Routing optimization

Routing information prediction is usually used before the routing stage to help perform early prevention. This can help improve the final routing result. In addition to early prevention, we observe that some studies have introduced ML techniques to cooperate with traditional methods to solve routing problems or help optimize routing results. This helps enhance the efficiency and routing performance. Alpha-PD-Router, which can detect and correct short violations, is proposed in [31]. Based on reinforcement learning, the routing problem is converted into a two-player collaborative game in which one players is trained to detect violations and the other player trained to perform routing. In 2020, [32] focused on the timing problem in global routing and introduced an ML technique to help accelerate the proposed reconnection approaches. Motivated by the difficulty of applying an efficient routability optimizer in a commercial EDA tool, [33] proposes a plug-in named PROS with negligible runtime for optimizing routability, which can be conveniently integrated into commercial EDA tools. Before

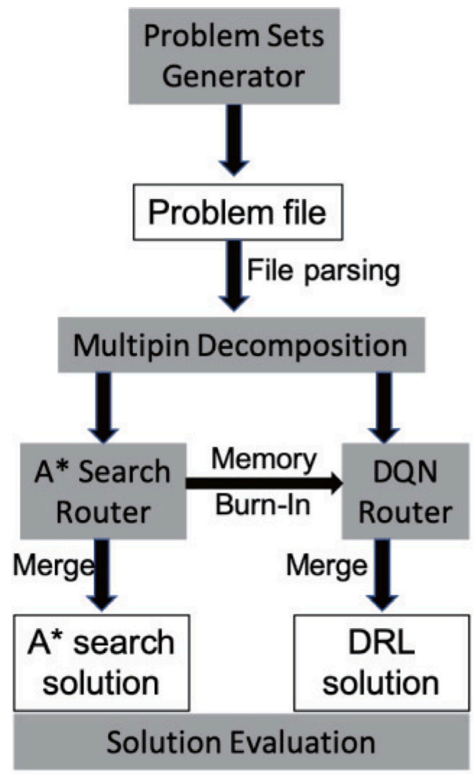

Fig. 4. The flow of the deep reinforcement learning-based global routing algorithm proposed in [34].

optimization, PROS applies a fully convolutional network to predict global routing congestion after placement and help optimize the global routing cost parameters of the global routing tool.

3.3. Intelligent routing

Although ML techniques have achieved improvements in helping to predict routing information and optimize routing, they still cannot solve the fundamental problems of traditional routing algorithms. As a long standing NP-hard problem, routing is facing increasing difficulty with using conventional solutions. In particular, satisfying the design requirements is becoming harder while formulating and solving the routing problem through expert analysis is becoming intricate. Furthermore, heuristic methods still require large manual efforts to optimize the results. Finally, the solution space of the routing algorithm is becoming extremely large due to the increasingly dense routing nets and the large and changing design rule set. These aspects magnify the difficulty of solving routing problems with conventional methods. To address these issues, many experts have begun to apply new techniques, among which ML techniques are attracting much attention. One reason that ML techniques are of interest is the discovery that they have great potential to address combinatorial optimization problems [35]. With ML techniques, the model can automatically extract various features from massive data and be trained to search for a satisfactory solution. Moreover, the powerful computing and search ability of ML can be fully utilized to improve the efficiency of problem solving. An example in which ML techniques have greatly improved the efficiency of solving combinatorial optimization problems in physical design is presented in [36]. In 2020, Google proposed a deep reinforcement learning-based placement algorithm [36], which can greatly shorten the runtime with comparable results compared with traditional methods. This breakthrough further supports the feasibility and necessity of promoting automation and intelligence in physical design. This also leads to the participation of an increasing number of experts in this field and motivates many experts to apply ML techniques to achieve automated routing.

Early in 2017, [20] explored a learning-based routing solution. A fully convolutional network-based router is proposed in an attempt to learn the design rules from the given data and perform routing. In 2019, [34] first introduced deep reinforcement learning to solve the global routing problem. They cast the global routing problem as a sequential version of a maze game. Each net is decomposed into a two-pin net and the agent is trained to determine a routing path that is as short as possible. In addition, to achieve fast convergence, [34] proposes a burn-in memory technique using data from the A* search algorithm. The flow of the proposed algorithm in [34] is presented in Fig. 4. Later, [37] introduced a second-order Nesterov's accelerated quasi-Newton method to speed up the training of the model based on [34]. Then, [38] transforms the global routing problem into a classical image-to-image processing problem. A neural network is trained to identify whether the tile can be used to construct the routing path for the input net. In addition, to achieve further efficiency, parallel techniques on GPU hardware are also incorporated. The experimental results show a shorter runtime compared with the FastRoute router.

From the current development in intelligent routing, we can observe that most of the research focuses on solving the global routing problem, while to the best of our knowledge, algorithms related to intelligent detailed routing have not been studied. For the existing ML-based global routing methods, applying the learning model to solve different real circuit designs still faces difficulty. The algorithms in [20,34] use the generated layouts to evaluate their router, and the complexity of these layouts may have significant differences from the complexity of real circuit designs. [38] evaluates their router on parts of the net of a circuit design from the ISPD'98 benchmark. Additionally, compared with traditional methods, the routability of the current ML-based global routing techniques still has to be further improved.

The development of intelligent routing algorithms show some future trends. Specially, prediction will still play an essential role in ML-based routing. More advanced ML techniques can be used to learn the features of well-performing routing paths and design rules to predict the solution with fewer violations. It is also possible to obtain the global optimal solution for a net by predicting and comparing the solutions of other nets after each routing solution of the input net is executed. In addition, parallel computing is still an important strategy to accelerate routing, including cooperation with multicore techniques or GPUs. On the whole, ML may only play a supporting role in routing problems in the short term. It will play an important role mainly in details that require intensive manual efforts or computationally tedious parts in the algorithms, such as calculating net order and optimizing cost function. Although the existing intelligent routers are still unable to completely surpass the traditional algorithms, the research time of intelligent routing is far shorter compared with the traditional algorithms, and we can still expect the subsequent breakthroughs.

4. Conclusion

In this paper, we surveyed some recently proposed machine learning-based routing algorithms and divided them into three types: routing violation prediction, routing optimization and intelligent routing. As technology advances, there is a clear trend to integrate machine learning to solve the routing problem. In this development, instead of introducing advanced techniques to routing problems just for the sake of applying machine learning, we look forward to the development of suitable machine learning methods tailored to the characteristics of the routing problem.

CRediT authorship contribution statement

Lin Li: Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Yici Cai:** Conceptualization, Supervision. **Qiang Zhou:** Conceptualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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