
AI Techniques for Quantum Circuit Optimisation

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A B S T R A C T

Quantum computing has emerged as a powerful paradigm for addressing difficult computational tasks that classical systems cannot handle. Nevertheless, quantum algorithms are sensitive to the optimisation and design of quantum circuits, especially in noisy intermediate-scale quantum settings. This paper provides a specialised systematic literature review on the use of artificial intelligence methods in the optimisation of quantum circuits. After completing a systematic search and screening process, thirteen peer-reviewed publications from 2017 to 2026 have been selected for analysis, including machine learning, reinforcement learning, deep learning, and evolutionary algorithms. The studies discussed above show that methods based on artificial intelligence could help improve the performance of circuits by decreasing their depth, the number of gates used, and making the computations more efficient. From the above analysis, it is possible to develop an AI-based framework where all the key AI-based methodologies and optimisation goals that emerged from the analysed literature have been incorporated. Another trend in the area of optimisation process development, which is mentioned in the review, is the increasing significance of hybrid quantum-classical methods and quantum machine learning. Though there have been these improvements, issues like scarcity of hardware, problems of scaling, and non-standardised evaluation frameworks still exist. This research will give a systematic overview of the current trends and gaps in the research to inform future research in this dynamic field.

Keywords: Artificial intelligence, Machine learning, Quantum circuit optimisation, Quantum computing, Quantum machine learning

1. Introduction

Quantum computing has become a revolutionary trend with the potential to solve intricate computational problems that are impossible to solve using a classical computing system. Building on the principles of quantum mechanics, like superposition and entanglement, quantum computers can have a major benefit in fields like optimisation, cryptography, and machine learning. Nevertheless, the efficient implementation of quantum computing is limited

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by a number of technical ways, especially in designing and executing quantum circuits effectively (Kusyk et al., 2021).

Quantum algorithms rely on quantum circuits, the performance of which is directly proportional to the efficiency of quantum circuits. In realistic quantum machines, and particularly Noisy Intermediate-Scale Quantum (NISQ) systems, circuits become very susceptible to noise, decoherence, and error. Consequently, it has made quantum circuit optimisation, aimed at minimising the number of gates, circuit depth, and error resilience, an urgent research need (Karuppasamy et al., 2025). The conventional methods of optimisation are mainly rule-based and heuristic, and in most cases, they do not scale effectively as the complexity of the circuit increases.

Artificial Intelligence (AI) has become one of the potential solutions to these problems in recent years. AI, such as machine learning, reinforcement learning, and evolutionary algorithms, offers adaptive and data-based solutions to optimisation problems. Such algorithms can be used to search very large solution spaces and find the best (or near-optimal) quantum circuit models (Alexeev et al., 2025). With the incorporation of AI in the field of quantum computing, a novel branch of the discipline was created, known as quantum artificial intelligence, which aims to improve the performance of quantum systems with the use of intelligent algorithms (Dunjko & Briegel, 2018).

Recent developments in Quantum Machine Learning (QML) have suggested hybrid quantum-classical methods, that is, classical methods of optimisation coupled with quantum computation. Such techniques have proven to be of great use in enhancing the efficiency and scalability of circuits (Li et al., 2020). Irrespective of the advances, the research in this field is still divided, as numerous studies pay attention to particular approaches instead of presenting an all-inclusive overview of AI-driven optimisation tools.

The aim of this study is to perform a pertinent review of quantum circuit optimisation artificial intelligence techniques. The goals of the study include the definition of major AI strategies, the analysis of their efficiency, and the analysis of current issues and gaps in the research. This study synthesises the results of 13 chosen papers and becomes a part of a better-organised insight into the changing relationship between artificial intelligence and quantum computing.

1.1. Research Problems

This research focuses on the increasing demand for efficient quantum circuit optimisation techniques through AI. In spite of the numerous advancements achieved in AI-based optimisation techniques, the current studies available lack cohesion and usually focus only on particular techniques rather than offering a comparison between them. Therefore, this research seeks to determine the most common artificial intelligence techniques used for quantum circuit optimisation, assess their efficiency, and address some challenges in existing literature.

1.1.1. Research questions

RQ1: What artificial intelligence techniques are most commonly used in quantum circuit optimisation?

RQ2: How effective are artificial intelligence-based approaches in improving quantum circuit performance?

RQ3: What are the major challenges and research gaps in applying artificial intelligence to quantum circuit optimisation?

1.1.2 Research objectives

RO1: To identify the major artificial intelligence techniques applied in quantum circuit optimisation.

RO2: To evaluate the effectiveness of artificial intelligence-based methods in improving circuit efficiency, scalability, and error reduction.

RO3: To examine existing challenges, limitations, and future research directions in artificial intelligence-driven quantum circuit optimisation.

2. Literature Review

AI and quantum computing have become a hot topic in academia over the past few years, and the blending of these two fields has resulted in the creation of sophisticated optimisation algorithms to optimise the work of quantum systems. Theoretical studies by Dunjko and Briegel (2018) laid the foundations for applying machine learning to quantum systems. In these works, the advantages of AI in enhancing some of the most crucial features of quantum computing, such as quantum algorithm design, state preparation, and measurement optimisation, were discussed.

Optimisation of quantum circuits is an important field of research since it directly affects the performance and practicality of quantum computations. According to Karuppasamy et al. (2025), optimisation methods are mainly aimed at minimising the circuit depth, minimising the number of quantum gates, and improving the overall computational accuracy. These considerations are especially important in NISQ systems, where system noise and hardware limitations are the main determinants of performance. Kussyk et al. (2021) also note that it is necessary to optimise quantum circuit errors effectively to make quantum circuits more practical to use.

In order to overcome these problems, quantum circuit optimisation has been looking at increasing the use of artificial intelligence methods. Machine learning has found extensive applications to estimate the most efficient circuit configurations and enhance design efficiency. Specifically, reinforcement learning has been popular because of its capability to acquire the best gate sequences as a result of repetitive interactions with the surrounding world. Also, Krenn et al. (2023) prove that neural networks and deep learning models could effectively explore complicated optimisation spaces, thus discovering high-quality solutions that are not achievable using conventional techniques.

In addition to machine learning, genetic algorithms are also evolutionary algorithms, and they have been used to optimise quantum circuits. These techniques incrementally improve candidate solutions and can especially be used to solve large and complicated search spaces. Alexeev et al. (2025) also state that AI-inspired optimisation methods provide a large increase in quantum computing performance by making the process of quantum circuit design more efficient and scalable.

Another dimension that is of importance to quantum machine learning is QML. QML combines machine learning with quantum computing ideas to create superior optimisation models. Olaitan et al. (2025) emphasise that QML algorithms utilise the quantum properties of superposition and entanglement to enhance computation efficiency and optimisation results. It is also the case that Li et al. (2020) address the role of variational quantum algorithms that use the combination of a classical optimisation procedure with quantum circuits to attain high performance in addressing complex problems.

Besides the optimisation of the circuits, there is contemporary research that has investigated more extensive uses of AI in quantum technologies. As an illustration, Mahmud and Abdelhadi (2025) discuss the usage of AI in quantum communication systems, where the issue is enhancing error correction and resource distribution. Baiocchi et al. (2025) also comment on how AI can be implemented into quantum systems, noting that there is a prospect of interdisciplinary developments. Furthermore, according to Mukhanbet et al. (2026), some of the trends under development include quantum neural networks and quantum convolutional models that provide new possibilities to optimise the circuit and increase its scalability.

Although these achievements have been made, there are still a number of research gaps. A significant number of the available studies concentrate on a single type of AI technique without a comparative analysis of their effectiveness. Also, the empirical support for these techniques with actual quantum devices is small, with most findings relying on simulations. Moreover, scalability issues, availability of data, and complexity of computations are still obstacles to the development of this field. Such drawbacks highlight why AI-based quantum circuit optimisation methods should be evaluated more thoroughly and systematically.

3. Methodology

This study adopts a Systematic Literature Review (SLR) approach to investigate artificial intelligence techniques for quantum circuit optimisation. The study selection and synthesis process were informed by the methodological framework proposed by Arksey and O'Malley (2005) and further discussed by Levac et al. (2010).

A structured search was conducted using academic databases including IEEE Xplore, Google Scholar, and ScienceDirect. Relevant studies were identified using keywords such as “quantum circuit optimisation,” “artificial intelligence in quantum computing,” and “quantum machine learning” to identify literature relevant to the study topic. The search was conducted only for English-language literature during the time period of 2017 to 2026, including both journal articles and conference papers. The retrieved papers were initially screened based on titles and abstracts, after which the eligibility of full texts was assessed.

Search terms were used in different combinations to identify studies pertaining to the topic of artificial intelligence and quantum circuit optimisation. Major search terms used include “Quantum Circuit Optimisation”, “Artificial Intelligence in Quantum Computing”, and “Quantum Machine Learning”. The above search terms were used in selected databases, and records identified were further screened based on the specified criteria.

Inclusion criteria required that the studies should have been published between 2017 and 2026 in English. The criteria also required the use of AI and/or any other machine learning technique in the fields of quantum computing, quantum circuit optimisation, and their related optimisation tasks. The exclusion criteria included non-relevant studies regarding quantum computing, AI and/or related machine learning techniques, and quantum circuit optimisation. Duplicate records were also removed before the screening process.

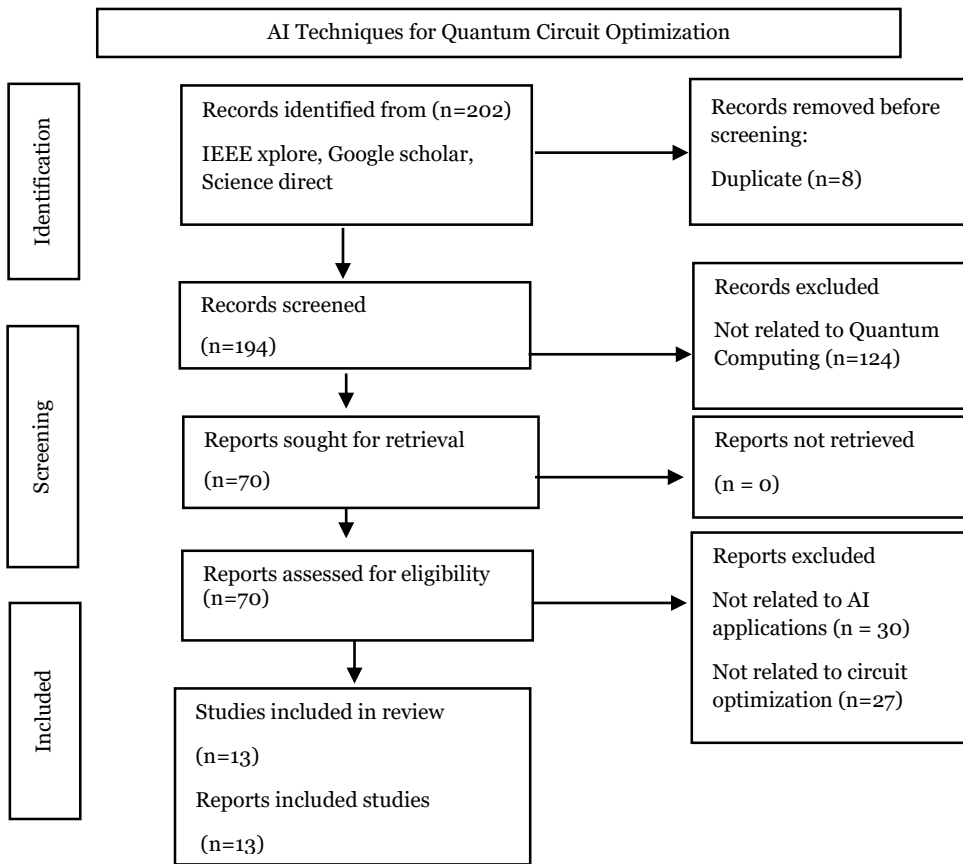


Figure 1: PRISMA Flow Diagram of the Study Selection Process

The relevance of the included studies to the research questions, as well as the quality of the methodology used in them, was checked. The quality of the selected studies was assessed based on four factors: the clarity of the AI technique used, the clarity of the optimisation of the quantum circuit problem, the sufficiency of the reported optimisation results, and the methodological transparency of the study. Studies with relevant data according to these criteria were considered appropriate for a more detailed study, while others were excluded from the analysis due to insufficient information on the methodology or incompatibility with the research goals.

Initially, 202 studies were identified. After removing duplicates (8), 194 studies were screened based on titles and abstracts. A total of 124 studies were excluded as irrelevant, leaving 70 studies for full-text assessment. During the eligibility stage, 30 studies were excluded as they were not related to AI applications, and 27 studies were excluded as they did not focus on quantum circuit optimisation. Finally, 13 studies were selected for detailed analysis.

4. Data Analysis and Findings

4.1 Overview of Selected Studies

This part presents a discussion of the 13 chosen articles concerning the techniques of artificial intelligence optimisation of quantum circuits. The chosen articles are between 2017 and 2026, and encompass the theoretical background as well as the current developments in the field of integration of artificial intelligence and quantum computing. Some of the earliest reports give theoretical foundations of machine learning in quantum systems (Dunjko & Briegel, 2018), and the latest work is in practical implementations and new optimisation methods (Alexeev et al., 2025). The chosen articles all point to the increased relevance of artificial intelligence in the improved operation of quantum circuits, especially under noisy intermediate-scale quantum (NISQ) conditions (Kusyk et al., 2021).

4.2 Techniques of Artificial Intelligence Identified

As can be seen in the analysis, quantum circuit optimisation has been studied using a wide variety of artificial intelligence methods. The most popular machine learning architectures to predict the best circuit settings are supervised and unsupervised machine learning models (Dunjko & Briegel, 2018). Reinforcement learning has emerged as an efficient method because it allows learning the optimal sequence of gates adaptively by interacting with the environment (Alexeev et al., 2025). Also, deep learning algorithms and neural networks are employed to investigate the complicated optimisation space and produce effective solutions (Krenn et al., 2023). Genetic algorithms and other evolutionary algorithms are also popular because they allow exploration of broad solution spaces and improvement of circuit designs through a sequence of steps (Baiocchi et al., 2025).

Table 1 summarises the main AI techniques identified in the reviewed literature based on their advantages, disadvantages, areas of application, and relevant research works.

Table 1: Comparison of AI Techniques for Quantum Circuit Optimisation

Techniques	Strength	Limitation	Typical Application	Supporting References
Machine Learning	Data-driven optimisation	Requires training data	Small-scale circuits	Dunjko and Briegel (2018); Karuppasamy et al. (2025)
Reinforcement Learning	Flexible	High training time	Dynamic environments	Karuppasamy et al. (2025); Alexeev et al. (2025)
Deep Learning	Effective for Complex Optimisation	Computationally expensive	Complex circuits	Krenn et al. (2023); Alexeev et al. (2025)
Evolutionary Algorithms	Broad Search Capability	Time consuming	Large search spaces	Baiocchi et al. (2025); Kusyk et al. (2021)

From the literature survey, it is evident that different AI methods are used for different aspects of optimisation of quantum circuits. Machine learning is useful in identifying the features of the circuits from data, while reinforcement learning allows for adaptive optimisation through the interaction of the algorithm with the environment. Deep learning is useful in dealing with complex optimisation tasks, while evolutionary algorithms are useful for exploring a wide search space. However, it must be noted that none of the examined works proves the universality of any AI method.

4.3 Quantum Circuit Optimisation Applications

The chosen studies indicate that the artificial intelligence techniques are used mostly to decrease the depth of the circuits, decrease the number of gates, and enhance the total efficiency of the computation (Karuppasamy et al., 2025). The improvements can contribute to better performance of quantum algorithms on real hardware. The use of AI-based optimisation techniques is especially useful when the problem is noise and error rates in NISQ devices (Kusyk et al., 2021). Moreover, variational quantum algorithms are another example of optimising circuits using a hybrid quantum-classical algorithm; they are frequently employed to formulate optimistic predictions of quantum circuits (Li et al., 2020).

4.4 Improvements in Performance were Observed

These studies reveal the capabilities of AI-based methods to improve quantum circuit performance by reducing circuit complexity, the number of gates, and circuit depth, while also supporting error and noise management. Reinforcement learning can be used for adaptive optimisation by finding suitable gate sequences, whereas deep learning can help explore complex optimisation landscapes for better circuits (Alexeev et al., 2025; Krenn et al., 2023). Machine learning and quantum-classical hybrid approaches are also candidates for optimising circuits and computations (Dunjko & Briegel, 2018; Li et al., 2020).

The efficiency of such approaches depends on the optimisation goal, on circuit parameters, on available information, and on the hardware configuration. Thus, from the presented results, it follows that AI can help improve certain aspects of the performance of quantum circuits; however, the considered papers lack sufficient standardised data to conclude that any of the considered AI techniques is universally superior to conventional optimisation methods.

4.5 Application of Quantum Machine Learning

Quantum machine learning (QML) is essential in the development of optimisation. The quantum properties of superposition and entanglement are used in QML algorithms in order to increase the efficiency of computations (Olaitan et al., 2025). QML combined with classical AI techniques can be more effectively used to optimise quantum circuits (Li et al., 2020). The newer methods such as quantum neural networks and quantum convolutional models also lead to better circuit design and scalability (Mukhanbet et al., 2026). These advancements show that QML is a major innovation in the field of quantum circuit optimisation.

4.6 Challenges and Limitations

Although these are positive outcomes, there are a number of issues when it comes to the use of artificial intelligence to optimise the quantum circuit. The limited access to quantum hardware is one of the major constraints that restricts real-life testing and validation (Kusyk et al., 2021). There are numerous experiments based on simulation results that do not necessarily represent real-life situations. Also, scaling is another significant problem, and optimisation of larger quantum systems is more complicated (Karuppasamy et al., 2025). The absence of data and non-standardised evaluation metrics is also a further deterrent to the creation of strong AI models (Li et al., 2020).

4.7 New Trends and Research Areas

The review singles out a number of new trends such as the growing popularity of reinforcement learning, deep learning, and mixed quantum-classical optimisation (Alexeev et al., 2025). The growth of interest in building quantum-native AI models, including quantum neural networks (Mukhanbet et al., 2026), also exists. Nevertheless, serious gaps in research exist, namely, the absence of comparative studies to assess various AI methods in a single framework (Li et al.,

2020). Moreover, little empirical research has been done on the feasible use and application of these techniques in reality (Kusyk et al., 2021). These gaps will be critical to address as far as the practical implementation of AI in quantum circuit optimisation is concerned.

5. Discussion and Conclusion

5.1 Discussion

The results of this paper indicate that artificial intelligence plays an important role in quantum circuit optimisation. From the analysis of the articles, one can easily see that there are efficient ways of optimising quantum circuits using artificial intelligence. Specifically, reinforcement learning and machine learning models have demonstrated potential for identifying optimised circuit configurations and reducing circuit complexity (Alexeev et al., 2025).

Among the important lessons learned during the analysis, it is important to note that AI approaches are useful in overcoming the shortcomings of noisy intermediate-scale quantum (NISQ) machines. NISQ quantum systems are strongly prone to noise and error, both of which have detrimental impacts on performance. AI-based optimisation approaches that include deep learning and quantum-classical hybrids have shown the promise of improving performance by reducing circuit depth and the number of gates, which can improve execution efficiency (Karuppasamy et al., 2025). The results suggest that AI could be a useful tool to make quantum computing more efficient.

Moreover, quantum machine learning (QML) has created new optimisation possibilities. QML techniques make use of quantum properties such as superposition and entanglement to investigate potential improvements in computation efficiency and optimisation (Olaitan et al., 2025). The development of quantum neural networks and quantum convolutional models also contributes to the development of optimisation methods and emphasises the increasing significance of hybrid methods in this direction (Mukhanbet et al., 2026).

A comparison of AI methods studied above reveals the existence of unique advantages and disadvantages of each method. Machine learning can be used to identify the best configuration of circuits, while the reinforcement learning method is very suitable for solving the optimisation problem that requires sequential decision-making (Alexeev et al., 2025). The deep learning method is able to solve more complicated optimisation problems through learning from the existing data, but the applicability of deep learning will be limited by the presence of necessary training data. Evolutionary algorithms represent another way of solving optimisation problems by exploring different types of circuit configurations. As a result, the reviewed papers do not prove the superiority of any AI method; the appropriate method depends on the specific optimisation problem.

The review highlights a number of key areas where research is lacking. Many of the reviewed studies rely on the findings of simulations rather than practical testing of AI optimisation techniques implemented on real quantum hardware, thus limiting the performance assessment (Kusyk et al., 2021). Scalability remains an important issue, with quantum circuits becoming more complicated (Karuppasamy et al., 2025). Moreover, the lack of adequate data and the absence of an evaluation framework prevent the creation and comparison of AI models (Li et al., 2020). The lack of a benchmark makes it difficult to assess the generalisation of obtained results in relation to different quantum circuits. Overall, it highlights the importance of future research conducted through the use of real quantum hardware and datasets.

On the whole, it is possible to state that the discussion has highlighted that although artificial intelligence has shown potential in quantum circuit optimisation, more studies are necessary to solve the existing issues and improve the practical application. Further scaling model

development, validation in practice, and the participation of other disciplines will be key to the future of AI and quantum computing integration.

5.2 Proposed Framework

This paper offers an AI-based framework for quantum circuit optimisation based on the review of thirteen studies. The suggested framework is a result of the synthesis of AI-based tools, optimisation goals, and performance parameters that are used in the papers considered. In particular, the papers reveal that machine learning, reinforcement learning, and deep learning are relevant AI-based methods for quantum circuit optimisation, while the optimisation goals include circuit depth, gate count, minimisation of errors, and computational speed. In accordance with the proposed framework, the input is a quantum circuit, which should first be assessed by determining its basic properties, such as gate count and circuit depth. Based on these properties, machine learning, reinforcement learning, and deep learning can be applied for optimisation purposes.

These techniques were selected based on their relevance to the optimisation approaches identified in the reviewed studies and their potential to address different optimisation objectives. The optimisation process aims to improve circuit performance by reducing circuit complexity, minimising errors, and improving efficiency. The resulting circuit is then evaluated using performance measures such as circuit depth, error rates, and overall efficiency. Therefore, the proposed framework provides a structured approach for applying the findings of the systematic literature review to the optimisation of quantum circuits.

5.3 Conclusion

This study conducted a targeted systematic review of the literature on the use of AI methods for quantum circuit optimisation. In the process of conducting the analysis of 13 chosen studies (published in 2017-2026), the review identified several important AI strategies, such as machine learning, reinforcement learning, deep learning, and evolutionary algorithms, which are extensively applied to optimise the work of quantum circuits. The reviewed studies indicate that AI-based optimisation methods can contribute to minimising circuit depth and the number of gates used, and can improve computational efficiency, particularly in noisy intermediate-scale quantum (NISQ) settings (Kusyk et al., 2021).

In spite of these developments, there are still a few limitations and challenges. The lack of quantum hardware limits the feasibility of AI-based optimisation methods, while scalability, lack of data, and standardised assessment remain challenges (Kusyk et al., 2021; Li et al., 2020). Furthermore, the reviewed literature provides limited direct comparison between different AI techniques, making it difficult to determine whether one approach is universally more effective than another.

Overall, the findings indicate that AI techniques have potential to support quantum circuit optimisation, but their effectiveness depends on factors such as the optimisation objective, circuit characteristics, available data, and hardware conditions. Although there has been substantial advancement, additional studies are needed to create scalable models, test methods on actual quantum hardware, and create standardised evaluation methods. Further integration of AI and quantum computing may support future developments towards more practical and efficient quantum systems.

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