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TOPICAL REVIEW

Implementation of Quantum Annealing: A Systematic Review

LENNY PUTRI YULIANTI[1], (Member, IEEE), AND KRIDANTO SURENDRO[2]

[1]Doctoral Program of Electrical Engineering and Informatics, School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Bandung 40132, Indonesia

[2]Department of Electrical Engineering and Informatics, School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Bandung 40132, Indonesia

Corresponding author: Lenny Putri Yulianti (33221007@std.stei.itb.ac.id)

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ABSTRACT Quantum annealing is a quantum computing approach widely used for optimization and probabilistic sampling problems. It is an alternative approach designed due to the limitations of gate-based quantum computing models. The method is observed to have a significant impact on different fields such as machine learning, graphics, routing, scheduling, computational chemistry, computational biology, security, portfolio, and others despite the fact that it is relatively new. This research provides a systematic review of research development trends in the field of quantum annealing and analyzes how it has been implemented in different problem domains. The results are expected to serve as the basis to identify the opportunities and challenges of research related to its implementation. The main contribution of this systematic review is to summarize different implementations of quantum annealing. It is also to analyze the prospect and opportunities in one of the problem domains with the greatest interest which is machine learning.

INDEX TERMS Quantum annealing, implementation, review.

I. INTRODUCTION

Quantum information, also known as quantum information processing (QIP), has gained great attention in different sectors such as computer science, mathematics, physics, engineering, and others [1]. It uses a different paradigm from classical information processing [2], [3]. It also applies the phenomena and principles of quantum mechanics including superposition, entanglement, and interference which provide a better way to process information than the laws of classical physics [2]–[8]. QIP provides numerous advantages over classical information processing for certain problems [2], [3], [9] as indicated by the comparisons made in previous research [2], [10].

The focus of QIP development was initially only to handle problems limited to classical information processing but was expanded to several other fields such as quantum cryptography [3]–[7], [11], quantum computation [1], [3], [10], [12]–[14], and quantum communication [4], [15]–[17] over time. Currently, numerous big companies such as IBM, Intel, Microsoft, and Google have already been involved in the area of quantum computer development. Moreover, the exploration of new areas in quantum computing has led provided certain advantages [8].

Quantum computation can be divided into two general approaches or types. These include the quantum gate model and quantum annealing (QA) [2], [4], [6], [18]–[21] which are very different in practice and have a major impact on providing practical advantages over classical computing [20]–[22]. The first approach, the quantum gate model, breaks the problem down into a sequence of primitive operations (or gates) with well-defined "digital" measurement outcomes for certain input states which is similar to the current classical approach. The second approach, QA (also referred to as adiabatic quantum computing and analog quantum computing), is a form of computing that efficiently samples the low energy configuration of a quantum system. However, the practical development of gate-based quantum computers is very limited due to the large investments made. QA is used as an alternative approach to certain problems [2], [18], [19].

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TABLE 1. Comparison between QA and other metaheuristics approach.

Methods	Concept	Advantage	Disadvantage
Quantum annealing [18], [23]	Metaheuristic that uses quantum fluctuations to find the global minimum of a given objective function.	• The quantum mechanical effects (superposition, tunneling, and entanglement) allow a direct transition between states despite a high energy barrier between them. • It can tunnel through energetic barriers to escape local minima.	• There is limited hardware and environment because the implementation of the quantum computer is more difficult than a classical computer.
Simulated annealing [24]–[26]	Local search metaheuristic that allows movement of hill-climbing to escape local optima in the hope of finding a global optimum.	• It is capable of dealing with highly nonlinear models, chaotic and noisy data, and a wide range of constraints. • It has the capability and flexibility to approach global optimality. • It is quite versatile because it does not rely on any restrictive properties of the model. • It enables complete exploration of the solution space.	• A clear trade-off exists between the quality of solutions and the time required to compute them. • The accuracy of the numbers used in SA implementation can have a significant impact on the quality of the outcome. • It has a very long computational time.
Genetic algorithm [24], [27], [28]	An evolution-based method that relies on selection, crossover, and mutation to terminate not the best solution, a group of all elements is called 'genes' which indicate a set of solutions for the optimization variables.	• It is simple to implement and employs simple operators. • It can be used to handle problems with nonlinear or discontinuous constraints and objective functions. • It can be used to handle problems with high computational complexity such as TSP.	• There is no guarantee that the global maxima will be discovered. • It lacks a standardized method for defining a good fitness function. • It can be time-consuming, specifically while dealing with problems that have a large number of variables.
Tabu search [28], [29]	The techniques that keep track of the regions of the solution space that have already been searched in order to avoid repeating searches near these areas.	• It improves local optimization capabilities • The use of memory structures enables the implementation of procedures considered to be capable of searching the solution space efficiently and effectively.	• It has a tendency to overlook some promising areas of the search space. • The static and fixed size of the tabu list can sometimes trap the exploration.
Particle swarm optimization [27], [28]	Global swarm algorithm that explores the search space using multiple individual particles to find the optimal solution.	• The calculation is simple. • It has been used widely in scientific research and engineering fields.	• All solutions converge prematurely, thereby resulting in a loss of population diversity. • It suffers from a lack of optimism.

QA can also be classified as a metaheuristic approach to handle optimization problems. There are some popular classical metaheuristic approaches such as simulated annealing, genetic algorithm, tabu search, and particle swarm optimization which are compared to QA as indicated in the following Table 1.

Table 1 shows the differences between QA and other metaheuristics. It has also been reported that QA is a promising approach to handle NP-hard optimization and probabilistic sampling problems [30], [31]. Moreover, a company, D-Wave Systems Inc., has recently successfully developed and commercialized quantum computers as an alternative approach due to the limitations of gate-based quantum computing models [21], [32]. The continuous development and improvement of this D-Wave quantum computer have also increased the research in the QA area. Therefore, this present research analyzed QA through a systematic literature review. The contribution is associated with the trends, implementation techniques, and prospect analyses for several problems focused on optimization and probabilistic sampling.

The Part II describes the research method which consists of three phases of Systematic Literature Review (SLR). The first and second were designed to form Research Questions (RQs) and find relevant pieces of literature, respectively, while the third which is the reporting phase was used to analyze the results of the SLR to answer each Research Questions (RQs). Moreover, Part III analyzes the prospects and opportunities of problem domains receiving the highest attention in QA research while Part IV describes the conclusions of this research.

II. RESEARCH METHOD

This section describes relevant findings from previous research in line with the background of this present study. The Systematic Literature Review (SLR) was conducted according to the existing guidelines from [33]. This is a research method normally used to conduct an orderly literature review to map out certain phases. It was applied through three phases which include (1) Planning and Determining Research Questions, (2) Conducting the Review, and (3) Reporting

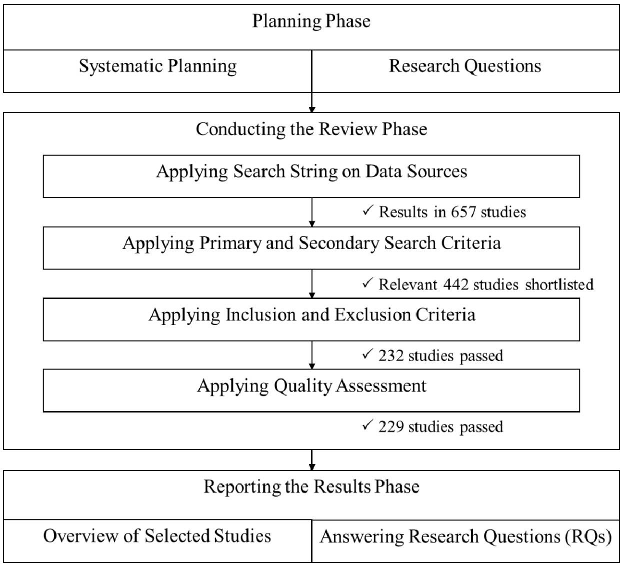

FIGURE 1. Overview of systematic literature review.

TABLE 2. PICOC and description.

PICOC	Description
Population	Quantum annealing
Intervention	Trends, techniques, and prospects of quantum annealing
Comparison	Comparison based on problem domains and methods in different research on quantum annealing
Outcomes	Problem domains and methods of quantum annealing with the potential to be explored in the future
Context	Review of the existing research on quantum annealing

TABLE 3. Research questions (RQs).

RQs	Statements
RQ1	What is the trend of quantum annealing research?
RQ2	How is quantum annealing implemented in several optimizations and probabilistic sampling problems?
RQ3	What are the challenges and opportunities of quantum annealing?

the Results as explained in the following subsections. Meanwhile, an overview of the SLR is presented in Figure 1.

A. PLANNING PHASE

Good planning is the basis for a smooth SLR implementation serves as the foundation to derive the RQs which is an important step in any SLR. Moreover, the criteria used in formulating the RQs in this research were based on PICOC (Population, Intervention, Comparison, Outcomes, and Context) as shown in the following Table 2 [34].

This research focuses on analyzing previous studies related to QA with attention on its trends, implementation techniques, and prospects as indicated in the table. Moreover, different techniques and problem domains in the QA area were analyzed and this led to the formulation of the RQs presented in Table 3.

This means three RQs were answered and used as the basis for the systematic literature review. RQ1 was designed to review the development trend of QA from year to year and the most dominant research type. RQ2 focused on reviewing the problem domains of QA implementation and how the QA approach is used to handle these problems. RQ3 was used to analyze the prospect of quantum annealing research in the future based on the results of RQ1 and RQ2.

TABLE 4. List of keywords and synonyms.

Keywords	Synonyms
Quantum annealing	Adiabatic quantum computing, analog quantum computing
Implementation	Implementations, application, implement, apply, using
Challenges	Questions, issues
Opportunities	Prospects

TABLE 5. Search string categories.

Category	Mapping on RQs	Search String
1	Quantum annealing	"quantum annealing" OR "adiabatic quantum computing" OR "analog quantum computing"
2	Implementation of quantum annealing	("implement*" OR "application*" OR "apply*" OR "using") AND ("quantum annealing" OR "adiabatic quantum computing" OR "analog quantum computing")
3	Challenges and opportunities in quantum annealing	(("challenge*" OR "question*" OR "issue*") OR ("opportunities" OR "prospects")) AND ("quantum annealing" OR "adiabatic quantum computing" OR "analog quantum computing")

B. CONDUCTING THE REVIEW PHASE

Conducting the Review phase consists of search strategy, study selection, study quality assessment, and data extraction.

1) SEARCH STRATEGY

The purpose of the search strategy is to find research that can assist in answering the defined RQs. It involves three phases which include identifying the keywords and determining search strings, selecting data sources, and searching the data sources.

a: KEYWORDS IDENTIFICATION AND SEARCH STRING DETERMINATION

According to [33], the search string can be determined by analyzing the main keywords in the RQs, their synonyms, and

TABLE 6. Relevant search results based on data sources.

Data Sources	Search of Results
SpringerLink	177
IEEE Explore	16
ACM Digital Library	8
Elsevier Science Direct	123
Nature	118
Total	442

TABLE 7. Inclusion and exclusion criteria.

Inclusion Criteria
1. Research related to the analysis of QA methods
2. Research related to the implementation of QA
3. Research related to the improvement of QA algorithms
4. Research related to challenges and opportunities of QA
5. Written in English
6. Peer-reviewed papers
Exclusion Criteria
1. Research related to the quantum gate model
2. Research related to the classical annealing approach
3. Research related to analysis, implementation, or improvement of QA hardware
4. Research not written in English

other spellings of the word. The summary of keywords and synonyms identified in this research is presented in Table 4.

The keywords in Table 3 were used to obtain the search string through the combination of the synonymous terms using logical 'OR', other keywords using 'AND', and wildcard characters ('*'). The search strings are categorized into three according to the identified RQ and presented in the following Table 5.

b: DATA SOURCES

The digital databases used to search the keywords were SpringerLink, IEEE Explore, ACM Digital Library, Elsevier Science Direct, and Nature.

c: SEARCH PROCESS IN DATA SOURCES

All the search strings discovered were applied to predefined digital data sources to find related research and the data were collected up to December 2021. This phase was divided into 2 sub-activities which include the primary and secondary search. In the primary phase, 657 results were obtained from the selected search string restricted to only journals and further refined to have better results through the removal of duplicated titles. The technique used in the secondary phase is called snowball tracking and was applied to further explore all primary references to increase the likelihood of finding important research for SLR. The results for both phases are presented in Table 6.

Table 6 shows that 442 research were found with the highest, 40%, obtained from SpringerLink followed by Elsevier Science Direct, Nature, IEEE Explore, and the lowest in ACM Digital Library.

2) RESEARCH SELECTION

The results obtained through the search string were analyzed based on the inclusion/exclusion criteria presented in the following Table 7.

Relevant research were selected by marking each research as In (Include), Un (Uncertain), and Ex (Exclude). This analysis was conducted in two stages starting with the review of the titles and abstracts to ensure they match the information required for each RQs. This was followed by the review of the entire content of the research, specifically the conclusion section. This led to the selection of 232 relevant research from the 442 previously retrieved.

3) RESEARCH QUALITY ASSESSMENT

This activity was used to assess the quality of primary research obtained through inclusion and exclusion criteria analysis. This was achieved through a set of five questions presented in a questionnaire form in line with the guidelines used by [33] as follows:

Q1. Are the goals clearly defined?

Q2. Was the research designed to attain the aims or questions?

Q3. Is the quantum annealing implementation well defined?

Q4. Are all research questions answered sufficiently?

Q5. Are the main findings clearly defined in terms of credibility, validity, and reliability?

This led to the exemption of three research and this means only 229 were included in the next phase of the analysis.

4) DATA EXTRACTION

The data extraction describes the data selected due to their ability to answer the RQs and this was conducted using Microsoft Excel.

C. REPORTING THE RESULTS PHASE

This section presents the results for each of the RQs in the systematic literature review in a tabular form.

1) OVERVIEW OF SELECTED RESEARCH

Figure 2 shows the distribution of the selected research based on their data sources. It was discovered that 111 (48.47%) are from SpringerLink, 50 (21.83%) from Elsevier Science Direct, 49 (21.40%) from Nature, 12 (5.24%) from IEEE Explore, and 7 (3.06%) from the ACM Digital Library. Moreover, the distribution based on the year of publication presented in Figure 3 showed that those related to QA increased over the years and 2021 was observed to have the highest with 71 research.

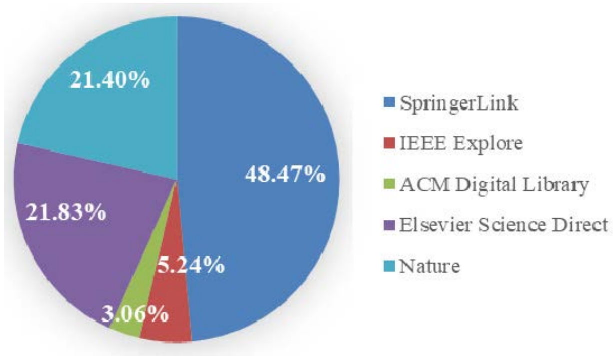

FIGURE 2. Distribution of selected studies from data sources.

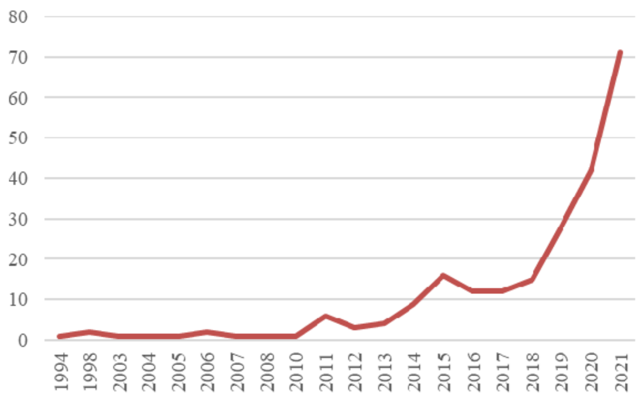

FIGURE 3. Distribution of selected studies by year of publication.

TABLE 8. Mapping of research types.

Research Type	Number of Research	References
Analysis	100	[8], [12], [18], [19], [30], [32], [35]–[128]
Implementation	121	[20], [22], [129]–[247]
Evaluation	8	[248]–[255]

2) RESULTS REPORTING ON RQ1

All the 229 selected research were able to provide answers to RQ1. Moreover, the trend based on the number from year to year shows a significant exponential increase with several peak points observed most notably in 2011, 2015, and 2021 as indicated in Figure 3. The increase in 2011 is associated with the release of the first commercial quantum computer that uses QA for its processing by D-Wave Systems. The increase in 2015 is related to the release of the D-Wave 2X quantum computer with approximately 10 times the number of qubits in the D-Wave One. Meanwhile, the increase recorded in 2020 was characterized by the launching of the D-Wave Advantage quantum computer with approximately 5 times the number of qubits in the D-Wave 2X. These events possibly contributed to the continuous increase in the development trend of QA research.

Apart from the number of publications, the development trend based on the type of research was also analyzed using three categories which include analysis, implementation, and evaluation. This was conducted to determine the main concern and contributions of existing studies. The results are presented in the following Table 8.

The results from the table show that 52.84% of research focus on implementing QA methods in different problem domains. This is reasonable due to the growing number of quantum computers that support the implementation of QA, especially the D-Wave. Moreover, the trend of these publications is predicted to continue to increasing because quantum computers are still developing and the problem space being researched is increasingly complex. It was also discovered that 43.67% are on the analysis of the working principles, the potential for performance improvement, or the idea of its application in different problem domains conceptually. This type is also studied extensively due to the fact that QA is a topic with several challenges, both from the aspect of quantum physics and quantum information technology. The analysis in this aspect is also predicted to continue increasing and has the ability to cause a new quantum revolution. The remaining 3.49% focus on evaluation which does not have a very significant portion in the current development trend. This is due to the fact that the QA research usually tend to incorporate the evaluation aspect into the implementation process as a performance parameter.

3) RESULTS REPORTING ON RQ2

The determination of the answer to RQ2 which focuses on analyzing the evolution of QA implementation in different optimization and probabilistic sampling problems led to the selection of 171 out of 229 research. The answer was provided through further analysis of two aspects which include the problem domains of QA implementation and the specific method used. These problem domains were grouped into 13 which include machine learning, graphics, mathematics, routing, scheduling, computational chemistry, computational biology, security, portfolio, big data, hydrology, database, and sensors. The findings are presented in the following Table 9.

The table shows that eight research including [37], [93], [179], [208], [210], [222], [228] are categorized under two problem domains. Meanwhile, machine learning was found to be the most investigated topic using the QA approach as indicated by 26.40% and this was followed by graphics with 24.72%, mathematics with 17.98%, routing with 6.74%, scheduling 6.74%, chemistry computation 5.06%, biology computation 3.37%, security 2.25%, portfolio 1.69%, big data 1.69%, hydrology 1.12%, database 1.12%, and sensors with 1.12%. The descriptions of the findings from the 13 domains are stated as follows:

1) Machine learning: This includes optimization of the training process, improving the quality of predictions, image recognition, improving the quality of classification (clustering), and optimizing neural networks.

TABLE 9. Mapping of problem domains.

Domain	Number of Research	References
Machine learning	47	[36]–[38], [56], [61], [77], [82], [83], [85], [87], [89]–[91], [100], [110], [121], [129], [133], [134], [137], [139], [147], [155], [158], [161], [164], [172], [173], [191], [199], [200], [203], [204], [208]–[211], [214], [217], [221], [222], [224], [229], [232], [236], [239], [254]
Graphics	44	[19], [53], [58], [74], [88], [92], [104], [125], [128], [136], [138], [140], [141], [144], [145], [151], [152], [160], [163], [165], [168], [174], [175], [177], [180], [184]–[187], [190], [193], [196], [197], [207], [215], [225], [226], [230], [241], [242], [244], [245], [248], [250]
Mathematics	32	[20], [22], [42], [75], [79], [93], [94], [96], [107], [119], [143], [148], [153], [154], [159], [162], [169]–[171], [181]–[183], [192], [201], [202], [205], [213], [227], [228], [234], [235], [240]
Routing	12	[72], [127], [130], [149], [150], [156], [179], [189], [195], [216], [223], [228]
Scheduling	12	[37], [40], [132], [135], [146], [179], [188], [206], [233], [243], [247], [249]
Chemistry computation	9	[41], [86], [93], [176], [208], [210], [218], [222], [231]
Biology computation	6	[106], [114], [115], [220], [238], [246]
Security	4	[35], [98], [131], [157]
Portfolio	3	[166], [194], [219]
Big data	3	[43], [103], [105]
Hydrology	2	[39], [237]
Database	2	[55], [198]
Sensor	2	[178], [212]

2) Graphics: This includes optimization of different graphs such as chimera graph, max-cut problem, satisfiability problem, graph isomorphism problem, maximum clique, max-flow problem, and hardware graph as well as the formulation of real-world problems using graphs such as smart-charging of electric vehicles [138] and air traffic management [193].
3) Mathematics: This includes optimization of mathematical problems such as number partitioning problem, distribution measurement, polynomial equations, factorization, integer-to-binary mapping, counting problem, Hamiltonian equation, Jarzynski equality, linear equation, and Hadamard matrices problem.
4) Routing: This includes optimization of route determination in real-world problems, such as track reconstruction, Chinese postman problem, Traveling Salesman Problem (TSP), traffic signals control problem, social trust path problem, and vehicle routing problems.
5) Scheduling: This includes optimization scheduling problems such as garden optimization problem, refinery scheduling process, job scheduling problem, logistic network design, wireless network scheduling, agile earth observation satellite scheduling, network shortest path problem, nurse scheduling problem, and network scheduling problem.
6) Chemistry computation: This includes optimization of computation related to chemistry such as molecule structures, drug discovery, fault detection in the chemistry process, and chemical vapor deposition.
7) Biology computation: This involves optimization of computation related to biology such as neurosurgery, genome assembly, protein folding, transcription factor-DNA binding, and lattice protein modeling problem.
8) Security: This includes optimization in security problems such as cryptography, DDOS attack identification and mitigation, and cybersecurity.
9) Portfolio: This focuses on the optimization of the portfolio specifically in the trading trajectory problem.
10) Big data: This involves the optimization of big data in terms of its accuracy and efficiency.
11) Hydrology: This entails the optimization of aquifer composition determination from pressure readings and prediction of flow and transport in aquifers.
12) Database: This emphasizes the optimization of the Grover search algorithm and multiple query problems.
13) Sensor: This centers on the optimization of sensor utilization in terms of fault detection and cost-efficiency.

The analysis of this problem domain aspects showed that QA can be implemented in different optimization problems and probabilistic sampling. Moreover, it was discovered that the case studies studied in each problem domain also vary. This means the types of problems being handled as well as the problem domain tend to continue increasing.

The specific methods used to implement the QA in a particular problem domain were also analyzed using four groups which include QA, hybrid QA, reverse QA, and improved QA. It is important to note that the hybrid QA, reverse QA, and improved QA are three groups related to the modification of QA. The hybrid QA is fundamentally based on the combination of QA and classical methods to handle optimization problems [256]. This can be in the form of the 1) decomposition of QA and classical methods in the completion process as well as their integration into a complete solution, 2) application of the classical approach to qubits, and 3) application of the QA approach to classical computers. Meanwhile, the reverse QA is based on the concept that if the system is initialized in the S state according to the local minimum of the objective function, then the interaction of quantum and thermal fluctuations can help the state escape the energy trap during reverse annealing. In this method, the quantum fluctuation first increases and only then decreases [185], [257]. Moreover, the improved QA is basically focused on adding certain parameters to improve the quality of a previously conducted QA. It is important to note that the hybrid QA and improved QA group different forms of implementation that meet their fundamental requirements. Meanwhile,

TABLE 10. Mapping of methods.

Method	Number of Research	References
QA (adiabatic)	115	[19], [20], [22], [35]–[39], [41]–[43], [53], [55], [56], [58], [61], [72], [74], [75], [79], [82], [83], [85]–[87], [89]–[92], [94], [96], [98], [100], [103]–[106], [110], [114]–[115], [121], [125], [127], [129]–[132], [134], [141], [144], [149], [151]–[155], [160]–[163], [165], [168]–[173], [176]–[179], [181], [183]–[184], [187]–[190], [193]–[194], [196], [198], [199], [203], [204], [206], [207], [211], [212], [215]–[218], [221], [223], [224], [227], [229], [230], [234], [235], [237]–[239], [241]–[250], [254]
Hybrid QA	44	[40], [77], [88], [93], [107], [119], [133], [135]–[139], [143], [145]–[148], [156]–[159], [164], [182], [191], [192], [195], [197], [200]–[202], [205], [208]–[210], [213], [219], [220], [222], [225], [226], [228], [231], [232], [240]
Reverse QA	3	[166], [233], [236]
Improved QA	9	[128], [140], [150], [174], [175], [180], [185], [186], [214]

reverse QA is a specific method published in several research as a QA modification method. These findings are presented in the following Table 10.

The table shows that the majority of research related to QA implementation, represented by 67.25%, use the basic QA approach to handle problems. QA is most widely used because it is the basic annealing-based quantum approach which is easier to be implemented using the current quantum annealer. Meanwhile, most research, represented by 25.73%, started to improve QA performance by combining the QA with the classical approach. They are usually driven by the goal of maximizing the potential of existing resources which include both classical and quantum computers. This was followed by research on the improved QA with 5.26% and reverse QA with 1.76%.

The implementation method and problem domain were also mapped as presented in Table 11 to comprehensively determine the specific method used in each problem domain. The result shows that there are potentials to apply several implementation methods to different problem domains in order to improve QA performance. Several problem domains have been handled using more than one method while machine learning was found to be the only domain analyzed and/or implemented using the four methods. Those investigated using at least three methods are only 5 which include machine learning, graphics, routing, scheduling, and portfolio domains. Moreover, some case studies with the same specific problem like the Traveling Salesman Problem were analyzed using different methods which include QA [72], [127] and improved QA [150]. This means further analysis and exploration of QA methods to be implemented in different/same domains and case studies can become an interesting challenge in the future.

This research also compares the QA performance with other methods based on 90 relevant research presented in Table 8 to determine their results based on the four specific methods of QA. These research were mapped based on the implementation and evaluation types. The number of research were reduced from a total of 129 to 90 because 39 did not compare performance with other methods. An overview of the metrics and the method used for the comparison is presented in Figure 4.

The figure shows three broad groups of state-of-the-art methods which include heuristics, machine learning, and others apart from these two. Heuristics and machine learning methods are the two groups that are mostly used as comparisons. Moreover, the figure shows different metrics used in the implementation and evaluation of the four specific methods. Accuracy and time metrics were found to be the two main factors considered in each specific method. The figure also assists in simplifying the comparative analysis between the performance of these four specific methods and the three groups of state-of-the-art methods based on these defined metrics as indicated in the findings presented in Figures 5, 6, and 7.

Figure 5 compares QA and state-of-the-art methods using 50 research found to be relevant to the concept. It was discovered that 75 combinations of metrics and state-of-the-art methods were mapped and compared out of which 60 (80%) stated that the QA performed better, 7 (9.33%) stated they have equivalent performance, and 8 (10.67%) showed that QA has lower performance. The most widely used state-of-the-art method for comparison was found to be simulated annealing as indicated by 21 (42%) of the 50 research which include [130], [149], [152], [154], [161], [168], [171], [189], [212], [217], [218], [223], [229], [238], [239], [242], [243], [246], [249], [251], and [252]. This is due to the fact that QA is analogous to simulated annealing (classical approach) but in substitution of thermal activation by quantum tunneling. Moreover, the three metrics widely used for the comparison include the quality of solution (13 comparisons), accuracy (12 comparisons), and efficiency (9 comparisons). The QA performance was generally found to be analyzed better than the current state-of-the-art methods including heuristics, machine learning, and the others. However, 15 (20%) studies showed that it has not been able to outperform the state-of-the-art approach mainly due to the limitations of the D-Wave architecture used [130], [134], [172]. Reference [130] reported that the QA implementation only fits up to 500 tracks in problems associated with charged particle tracking due to the limited size of the D-Wave 2X (33 fully connected logical qubits). Furthermore, [134] showed that the QA approach has a slower run time in all cases used in the balanced k-means clustering problem because the quantum run time was dominated by the embedding time. This is because embedding is extremely difficult on modern quantum computers due to limited qubit connectivity in D-Wave 2000Q. Another research [172] showed that the use of QA is only feasible for small matrices which are up to 6×6 instance size

TABLE 11. Mapping of problem domains and methods.

Domain	Method	Number of Research	References
Machine learning	QA (adiabatic)	32	[36]–[38], [56], [61], [82]–[83], [85], [87], [89]–[91], [100], [110], [121], [129], [134], [139], [155], [161], [172], [173], [199], [203], [204], [211], [217], [221], [224], [229], [239], [254]
	Hybrid QA	13	[77], [133], [137], [147], [158], [164], [191], [200], [208]–[210], [222], [232]
	Reverse QA	1	[236]
	Improved QA	1	[214]
Graphics	QA (adiabatic)	30	[19], [53], [58], [74], [92], [104], [125], [141], [144], [151], [152], [160], [163], [165], [168], [177], [184], [187], [190], [193], [196], [207], [215], [230], [241], [242], [244], [245], [248], [250]
	Hybrid QA	7	[88], [136], [138], [145], [197], [225], [226]
	Improved QA	7	[128], [140], [174], [175], [180], [185], [186]
Mathematics	QA (adiabatic)	18	[20], [22], [42], [75], [79], [94], [96], [153], [154], [162], [169]–[171], [181], [183], [227], [234], [235]
	Hybrid QA	14	[93], [107], [119], [143], [148], [159], [182], [192], [201], [202], [205], [213], [228], [240]
Routing	QA (adiabatic)	8	[72], [127], [130], [149], [179], [189], [216], [223]
	Hybrid QA	3	[156], [195], [228]
	Improved QA	1	[150]
Scheduling	QA (adiabatic)	8	[37], [132], [179], [188], [206], [243], [247], [249]
	Hybrid QA	3	[40], [135], [146]
	Reverse QA	1	[233]
Chemistry computation	QA (adiabatic)	4	[41], [86], [176], [218]
	Hybrid QA	5	[93], [208], [210], [222], [231]
Biology computation	QA (adiabatic)	5	[106], [114], [115], [238], [246]
	Hybrid QA	1	[220]
Security	QA (adiabatic)	3	[35], [98], [131]
	Hybrid QA	1	[157]
Portfolio	QA (adiabatic)	1	[194]
	Hybrid QA	1	[219]
	Reverse QA	1	[166]
Big data	QA (adiabatic)	3	[43], [103], [105]
Hydrology	QA (adiabatic)	2	[39], [237]
Database	QA (adiabatic)	2	[55], [198]
Sensor	QA (adiabatic)	2	[178], [212]

in bi-clustering problems. This is due to the limited number of qubits accommodated by the D-Wave 2X architecture. It was also observed that the D-Wave architecture is developing with the latest version found to be the D-Wave Advantage which has approximately 5 times more qubits than D-Wave 2X and 2.7 times more than D-Wave 2000Q. It also has a significant increase in the number of couplers which is estimated to be 12 times more than the D-Wave 2X and 6.7 times more than the D-Wave 2000Q. This means further developments of the D-Wave machine including the use of a larger number of qubits with higher connectivity can potentially improve the performance of QA on large scale problems.

Figure 6 shows the comparison between hybrid QA and state-of-the-art methods using 32 relevant research. It was discovered that 55 combinations of metrics and state-of-the-art methods were mapped and compared. The result shows 50 (90.91%) stated that the hybrid QA performed better, 3 (5.45%) found an equivalent performance, and 2 (3.64%) showed that it has lower performance. This shows that the hybrid QA has better quality than QA. Moreover, the state-of-the-art method widely used for the comparison is also the simulated annealing as indicated by 7 (21.87%) out of the 32 research which include [146], [156], [162], [164], [192], [213], and [255]. This was followed by QA with

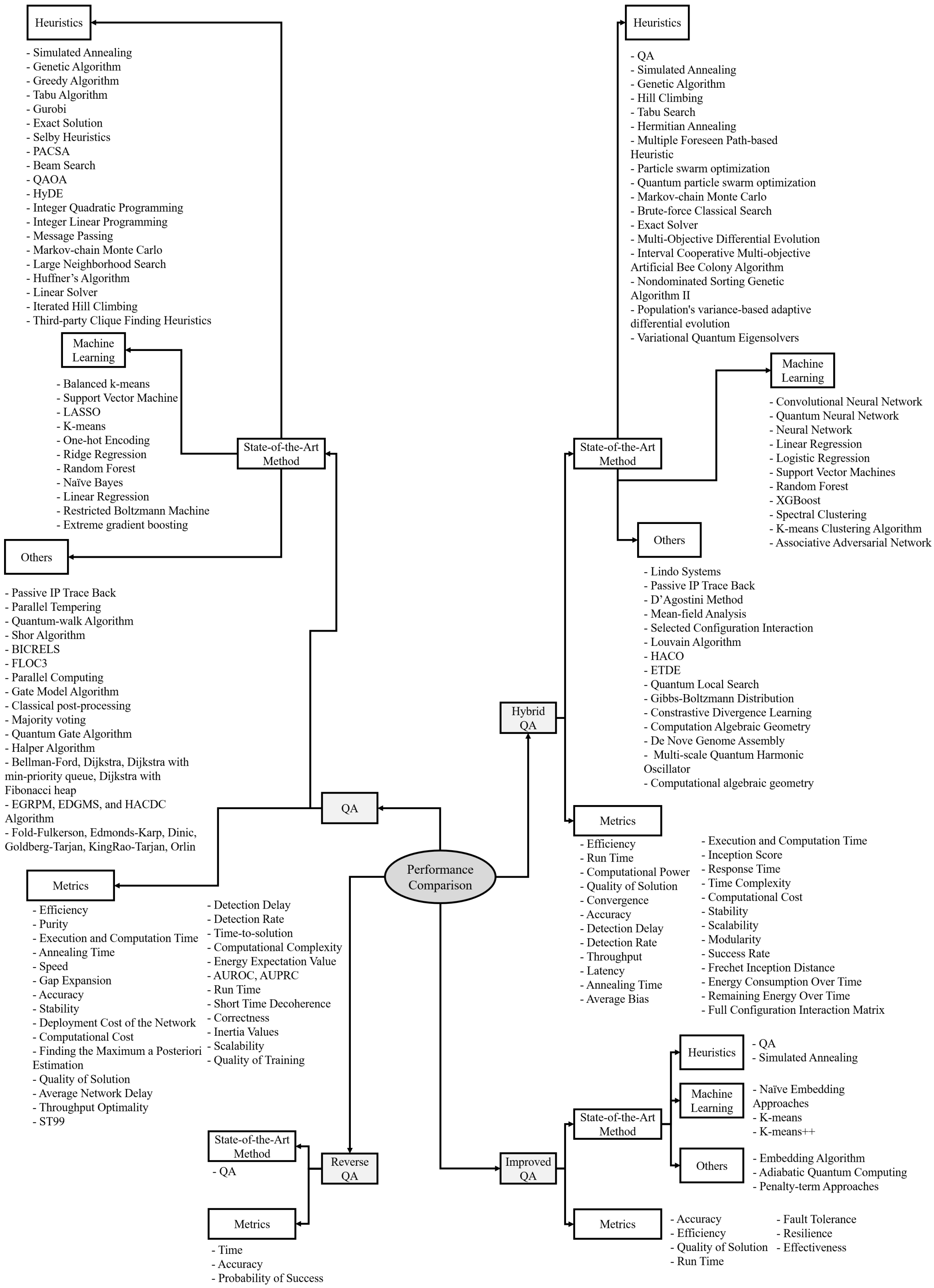

FIGURE 4. Overview of benchmarking performance methods and metric.

3 32 (9.37%) including [142], [226], and [255]. Furthermore, the three metrics most widely used for the comparison were observed to include efficiency (11 comparisons), quality of solutions (6 comparisons), and execution and computation time (5 comparisons). The difference in these metrics is due to the fact that the main goal of hybrid QA is to overcome

Metrics	State-of-the-Art Methods								
	Heuristics			Machine Learning			Others		
	QA								
Efficiency	[161], [149], [178], [229]		[130]	[139], [204]			[170], [235]		
Purity		[161]	[130]						
Execution and Computation Time	[152], [154]					[134]			[245]
Annealing Time	[206]		[242]						
Speed	[168], [189], [252], [253]						[189]		
Gap Expansion	[249]								
Accuracy	[171], [189], [237], [252]	[154], [251]			[134,139]		[170], [189], [227]	[251]	
Stability	[171]								
Deployment Cost of the Network	[212]								
Computational Cost	[218]								
Finding the Maximum a Posteriori Estimation	[217]								
Quality of Solution	[151], [155], [188], [223], [238], [239], [248], [253], [254]	[206]	[246]	[238]			[199]		
Average Network Delay	[243]								
Throughput Optimality	[243]								
ST99	[243]								
Detection Delay							[131]		
Detection Rate							[131]		
Time-to-solution	[188], [198]								
Computational Complexity				[221]			[181], [190], [247]		[172]
Energy Expectation Value	[248]								
AUROC, AUPRC				[211]					
Run Time	[151], [196]								
Short Time Decoherence							[227]		
Correctness							[245]		[172]
Inertia Values				[173]					
Scalability							[227], [250]		
Quality of Training				[224]					

Performance
QA has a better performance — QA has a comparable performance — QA has a worse performance

FIGURE 5. Comparative analysis between QA and state-of-the-art methods.

the limitations of the current quantum annealer, especially the D-Wave. This quantum-classical hybrid approach allows more efficient performance either in terms of the number of iterations performed or the number of resources used on the hybrid QA implementation. Moreover, efficient performance is required to be accompanied by a good and reasonable quality of solutions and time, and this is the reason they are widely used for comparison. Figure 6 shows a research [147] that did not find any improvement in the performance of the hybrid QA which is a Quanvolutional Neural Network when compared to the classical method which is a Convolutional Neural Network. The main challenging factor in [147] is how to deal with noise in the developed quantum circuits. It is, however, important to note that the hybrid QA generally contributes significantly to the efforts toward dealing with optimization and probabilistic sampling problems, especially in relation to efficiency.

Figure 7 shows two types of comparisons between 1) reverse QA and state-of-the-art methods and 2) improved QA and state-of-the-art methods. The result shows only 2 research comparing on reverse QA and state-of-the-art methods with a focus on portfolio optimization [166] and nurse scheduling [233] problems. It was discovered that 3 combinations of metrics and state-of-the-art methods were mapped and compared. The result shows 2 (66.67%) stated that the reverse QA performed better while 1 (33.33%) showed they had an equivalent performance. The only state-of-the-art method used for comparison was QA [166], [233]. Moreover, the proposed modification of the QA approach to reverse QA caused a significant increase in time and probability of success. This means the method is very promising with a protocol that focuses on path modification of QA. Its accuracy is comparable to state-of-the-art methods because the proposed reverse QA is intended to increase the acceleration of the annealing process in QA without any attempt to increase the accuracy significantly.

Figure 7 also shows 6 research compared the performance of improved QA with the state-of-the-art methods. It was discovered that 8 combinations of metrics and state-of-the-art methods were mapped and compared. They all showed an increase in the performance of the improved QA compared to the state-of-the-art methods. Moreover, two metrics observed to be widely used for the comparison include efficiency (2 comparisons) and running time (2 comparisons). The results obtained are reasonable because the main purpose of an improved QA is to improve the quality of a previous QA implementation. This is indicated in [150] that proposed the application of the INQA (Improved Noise QA) method to deal with the possibility of QA falling into the local optimum during the process of solving TSP problems. The INQA

Metrics	State-of-the-Art Methods		
	Heuristics	Machine Learning	Others
Hybrid QA			
Efficiency	[142], [146], [162], [219], [226]	[147]	[146], [162], [200], [208], [228]
Run Time	[164], [226], [219]		
Computational Power	[255]		
Quality of Solution	[156], [192], [202], [219]	[197]	[200]
Convergence	[143], [148], [164], [213]		
Accuracy	[213]	[158] [147]	
Detection Delay			[157]
Detection Rate			[157], [208]
Throughput			[157]
Latency			[157]
Annealing Time	[182]		
Average Bias		[191]	
Execution and Computation Time	[195], [231]		[133], [201], [220]
Inception Score		[137]	
Response Time			[200]
Time Complexity	[205]		[205]
Computational Cost	[205]		[205]
Stability	[143], [209]		
Scalability			[240]
Modularity			[133]
Success Rate	[231]		
Frechet Inception Distance		[137]	
Energy Consumption Over Time			[157]
Remaining Energy Over Time			[157]
Full Configuration Interaction Matrix			[222]

Performance
Hybrid QA has a better performance | Hybrid QA has a comparable performance | Hybrid QA has a worse performance

FIGURE 6. Comparative analysis between hybrid QA and state-of-the-art methods.

Metrics	State-of-the-Art Methods		
	Heuristics	Machine Learning	Others
Reverse QA			
Time	[166]		
Accuracy	[166]		
Probability of Success	[233]		
Improved QA			
Accuracy	[150]		
Efficiency	[150]		[175]
Quality of Solution			[174]
Run Time			[175], [185]
Fault Tolerance			[175]
Resilience		[180]	
Effectiveness		[214]	

Performance
Reverse/Improved QA has a better performance | Reverse/Improved QA has a comparable performance | Reverse/Improved QA has a worse performance

FIGURE 7. Comparative analysis between reverse QA-improved QA and state-of-the-art methods.

added noise parameters to the QA in order to enhance the solution quality and reduce errors caused by the noise. The two parameters included are O which is the threshold value for noise in the inner loop and K which is the threshold value for noise in the outer loop.

The findings generally showed that 73 out of the 90 research (81.11%) reported QA and its variant methods had a better performance than other state-of-the-art methods. Accuracy and time metrics were mainly focused on in the process of analyzing the performance of all different methods of QA. This means the methods empirically and exponentially speed up the process of dealing with optimization problems and probabilistic sampling without neglecting their accuracy. The other metrics mostly used as the comparison parameters include the efficiency and quality of the solution. These findings showed that the QA approach is empirically superior to the classical or other heuristic approaches.

4) RESULTS REPORTING ON RQ3

RQ3 focuses on analyzing the challenges and opportunities of QA in the future and a total of 10 out of the 229 selected research were used specifically because they explicitly describe the challenges and/or opportunities of QA. Moreover, the analysis was also based on the findings of RQ1 and RQ2, and the challenges observed to remain in the research area are stated as follows:

1) Numerous challenging computational problems have not been handled effectively [102]
2) There are limitations on precision and error mitigation [94]
3) The maintenance of fragile quantum correlations in the macroscopic environment [99]
4) The scalability in larger problem domains
5) The improvement of efficiency and accuracy of QA in several domains
6) The improvement of algorithm acceleration

These challenges were used to identify the following research opportunities:

1) How to implement alternative methods related to QA in problem domains that have not been investigated.
2) How to improve performance using different QA methods.

III. DISCUSSION

The problem domain with the greatest interest in the QA research area was found to be machine learning with 47 out of 171 research analyzed discovered to have focused on the domain. The findings also showed that 30 out of the 47 focus on the implementation of QA using quantum annealer. Moreover, 20 research indicates the QA approach provides better performance than the benchmark state-of-the-art approach, 3 provide equivalent performance, while 7 fail to outperform. These are considered to be ''recent'' because they were published between 2018 and 2021. The approach fails to outperform the benchmark means there are several limitations and opportunities to improve the performance of different QA methods for machine learning problems. The hardware and datasets used were also analyzed to deepen the knowledge of the implementation of QA in machine learning. It was discovered that only 21 out of the 30 research provide complete information regarding the hardware and datasets used. The details of the analysis are presented in the following Table 12.

The table has 8 columns which include the references, year, specific problems, methods, hardware, datasets, QA applications, as well as metrics and performance. The reference column was used to analyze the research conducted in a particular year while the year column emphasizes the trend of those on machine learning over the years. The specific problems aspect was intended to determine the context of the problem studied concerning the machine learning domain in detail. The method aspect focused on the particular approach used to deal with the specific problem. Meanwhile, the hardware, tools, and datasets were analyzed to have an insight into the effect of hardware, tools, and datasets used on the method performance. QA applications aspect was used to identify the specific objectives of implementing QA on the specific problems. Finally, the metrics and performance columns were intended to comprehensively analyze the method's performance in solving specific problems based on the hardware limitations and the dataset used.

A. RESEARCH TRENDS ON QA-ML

The results show that the highest studies on QA implementation for machine learning (QA-ML) were published in 2021 with 11 research (52.38%), followed by 5 (23.81%) in 2020, 1 (4.76%) in 2019, 3 (14.29%) in 2018, and 1 (4.76%) in 2017. This significant percentage difference indicates 2021 was the initial peak of the QA-ML field which is expected to grow further in the future.

It was also discovered that some of the most optimized ML models for the specific problems handled using the QA approach include restricted Boltzmann machines [155], [158], [200], [208], [224], k-means clustering [134], [173], and neural networks [147], [236]. Meanwhile, certain differences were observed in the specifics of optimized QA even though several studies focused on the same problem as indicated in the QA Application column. For example, several optimizations were made on the restricted Boltzmann machine model in five studies which include optimization of the process of reconstructing missing labels from test images [155], optimization of the classification process of subtypes of non-small-cell lung cancer patients [158], optimization of fault diagnosis results [200] and multiple faults [208], and optimization of hyperparameters on RBM training [224]. This means there is a significant opportunity to discover the potential of applying new optimizations through the analysis of the possible new conditions or cases in the specific problems presented in Table 12. Moreover, this research also analyzes two types of machine learning problems that are handled based on the 21 specific problems found, which include classification and clustering. The findings are presented in the following Figure 8.

From the aspect of the method used, the findings showed that most of the studies used QA but modifications were proposed to this method and implemented in 2018. This is indicated by the proposed application of the reverse QA method to enhance generalization in neural networks in 2018 [236]. Improved QA was also applied in 2018 to improve the performance of the harmonic average of purity and inverse purity of the k-means clustering method [214] but the information on the hardware and tools used was not included, thereby, leading to the exclusion of the research from Table 12. Meanwhile, a hybrid QA method was proposed in 2019 to streamline the partitioning of large integer optimization problems by extracting subproblems with as many feasible solutions as possible [232]. These findings showed that the proposal to modify QA is still relatively new and has the potential to continue improving in the future. This phenomenon was observed to have also been driven by the limitations of the quantum annealer expected to be handled by the modifications. Furthermore, it is possible to propose a new form of modification for QA to improve its current performance.

TABLE 12. Analysis of QA implementation in machine learning.

References	Year	Specific Problems	Method	Hardware and Tools	Dataset	QA Application	Metrics and Performance
[129]	2021	Election polls forecasting	QA	D-Wave Advantage	Latest 200 likes, retweets, and comments amongst ten anonymous Twitter volunteers	Predicting votes from individuals	Accuracy: There is no benchmark evaluation but this approach was evaluated qualitatively using Twitter data
[133]	2021	k-community detection	Hybrid QA	D-Wave 2000Q, qbsolv	Quantum modularization from Github [258]	Determining the partition of a graph into distinct communities	Modularity, time: Equal modularity performance, but there is no quantum acceleration yet
[134]	2021	Balanced k-means clustering	QA	D-Wave 2000Q	Synthetic classification data sets from make_classification function in the Scikit-learn datasets package	Finding the global solution to the training problem	Time complexity, average total computing time, accuracy: Theoretically, the time complexity is better. Empirically, the performance is slower but the accuracy is similar.
[137]	2021	GAN	Hybrid QA	D-Wave 2000Q	MNIST, LSUN	Sampling from graphical model to train the Boltzmann machine	Inception score, Frechet Inception Distance (FID): Better performance for models with higher connectivity. The image becomes less intuitive when trained through sampling with QA.
[139]	2021	Time-series construction and semi-supervised classification	QA	D-Wave 2000Q	SonyAIBORobotSurface1, GunPoint, TwoLeadECG, ECG200, BeetleFly, Chinatown	Reconstructing and classifying time-series	Efficiency, accuracy: Competitive and superior in some cases
[147]	2021	Geospatial data processing	Hybrid QA	Universal Quantum Computing by Rigetti Computing	SAT-4	Classifying satellite image	Efficiency, accuracy: There are no practical advantages
[200]	2021	Fault diagnosis	Hybrid QA	D-Wave 2000Q	IEEE 30-bus system	Analyzing and diagnosing faults in electrical power systems	Computational result, response time, efficiency: Better computation result and efficiency performance and faster response time
[203]	2021	Particle track classification	QA	D-Wave 2000Q	Particle tracks dataset	Performing QAMM and QCAM recall for track recognition	Efficiency, accuracy: Accuracy performance is quite high and efficiency is competitive
[204]	2021	Biomedical science	QA	D-Wave 2x and D-Wave 2000Q	TCGA	Comparing the performance of Ising models to ML algorithms	Efficiency: Better performance for small amounts of data
[222]	2021	Community detection	Hybrid QA	D-Wave 2000Q, qbsolv	Molecule point groups, FCI energies, and cluster energies	Reducing the molecular Hamiltonian matrix in Slater determinant basis without chemical knowledge	Full configuration interaction (FCI): Can be an alternative to the classic approach
[224]	2021	RBM	QA	D-Wave 2000Q	1000 7 x 7 pixels of black and white Bars and Stripes (BAS) images	Optimizing hyperparameter to train RBM	Running time and accuracy: Faster training and reaching the lowest asymptotic error
[155]	2020	Restricted Boltzmann Machine (RBM) model	QA	D-Wave 2000Q	OptDigits	Reconstructing missing labels of test images	Speed, error classification: Faster performance and twice the error rate for incomplete image classification
[158]	2020	Hybrid RBM model	Hybrid QA	D-Wave 2000Q	Geo lung cancer dataset from Kuner and Golumbic	Classifying two subtypes of non-small-cell lung	Accuracy: Equal performance

TABLE 12. ***(Continued.)*** **Analysis of QA implementation in machine learning.**

References	Year	Specific Problems	Method	Hardware and Tools	Dataset	QA Application	Metrics and Performance
						cancer patients	
[161]	2020	Pattern recognition	QA	D-Wave 2X	TrackML	Recognizing patterns in events representative of expected conditions at the HL-LHC	Purity, efficiency: Better purity and efficiency performance for small amounts of data
[208]	2020	Fault detection	Hybrid QA	D-Wave 2000Q	Records of continuous stirred tank reactor and Tennessee Eastman process	Detecting and diagnosing multiple faults	Fault detection rates, efficiency: Better training performance in many cases
[211]	2020	SVM	QA	D-Wave 2000Q	Mad50, Max50, Myc50, Mad70, Max70, Myc70, Mad80, Max80, Myc80	Producing an ensemble of classifiers	AUROC, AUPRC, accuracy: Better training performance for small amounts of data
[232]	2019	Integer partition with one-hot encoding	Hybrid QA	D-Wave 2000Q	Ferromagnetic, anti-ferromagnetic, Potts glass, and Potts gauge glass models	Partitioning large integer optimization problem	Efficiency: Hybrid performance with binary partition has the highest performance
[172]	2018	Biclustering	QA	D-Wave 2X	Synthetic data set composed by 10 x 10 matrices with a constant random-positioned bicluster that occupies the 25 percent of the elements, data from [259]	Solving biclustering problems	Correctness and complexity: It is only feasible for small matrices
[173]	2018	Clustering with one-hot encoding and k-means	QA	D-Wave 2X	Clustering samples of N = 40, N = 200, N = 1000, and N = 2000	Solving clustering problems	Inertia values: QA performance on k-means is better than one-hot encoding
[236]	2018	Deep neural networks	Reverse QA	D-Wave 2000Q	MNIST, Olivetti	Enhancing generalization in neural networks	Generalization: Generalization performance with higher finite value induction
[239]	2017	Higgs optimization	QA	D-Wave 2X	Synthetic 18 data sets of simulated collision events	Solving Higgs-signal-versus-background ML optimization problems	Robustness to error: Equal performance

B. HARDWARE, TOOLS, AND DATASETS USED FOR QA-ML IMPLEMENTATION

The hardware, tools, and datasets used in the research were also analyzed because they are related to the performance of the QA. The results show that D-Wave 2000Q is the most widely used quantum annealer version as indicated by its application in 15 research (71.43%). It was discovered that the research analyzed ranged from 2018-2021 while the D-Wave 2000Q was released in 2017. Moreover, this version of D-Wave was found to be the most popular quantum annealer hardware when compared to the D-Wave 2X released in 2015 and the D-Wave Advantage released in 2020 as indicated in Table 12. The D-Wave 2X was also observed to be the second most used due to its application in 5 research (23.81%). This means some research did not use the latest version of D-Wave even though they were published after 2017. Furthermore, only one research [129] was observed to have used D-Wave Advantage, which is the

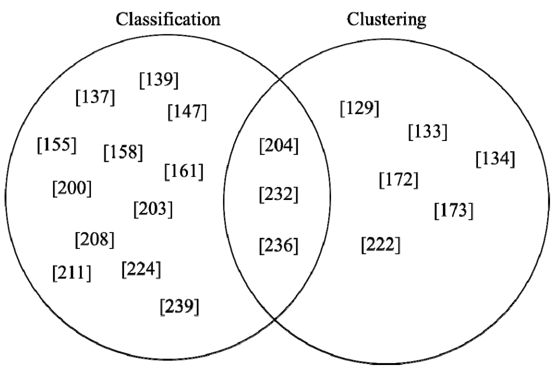

FIGURE 8. **Distribution of common types of machine learning problems.**

latest version. Research [147] also prefers universal quantum computers by Rigetti Computing to quantum annealers in implementing QA. This means QA can be applied both using the quantum annealer and universal quantum computer.

Table 12 also shows the different types of datasets used in 21 studies and none was found to be exactly the same. Some of the methods observed to have been applied in creating and using the datasets include building personal datasets [129], [134], [172], [173], [203], [208], [222], [224], [232], [239], using a representative dataset on a specific problem [133], [147], [155], [161], [200], [204], and applying several representative datasets [137], [139], [158], [211], [236]. The difference in the modes of creating and using these datasets is reasonable due to the variations in the specific issues focused on in each of those studies. In fact, it was found that the shape of the dataset used to optimize the same ML model was different due to the variations in the concerns and focus of the QA implementation. It is important to note that the information concerning the dataset can also provide an idea of the quantity of data a quantum annealer has the ability to handle.

C. METRICS AND PERFORMANCE OF QA-ML

The different methods of QA and their performance have been generally identified in the early part of the discussion. This section focuses on analyzing the metrics used and the role of hardware in the results of each method comprehensively using the information in Figure 9 which shows the 36 combinations of performance results based on the metrics, methods, and hardware used in 21 research from Table 12. Research [129] was observed not to have compared the QA with state-of-the-art methods and this led to its exclusion in Figure 9.

The results show that D-Wave 2000Q is the only hardware used to implement more than one specific method of QA including the QA, hybrid QA, and reverse QA. Meanwhile, D-Wave 2X and Universal Quantum Computing by Rigetti Computing were applied to only QA. Moreover, the implementation of QA on three different hardware was analyzed and the application of D-Wave 2000Q was found to have a better performance. This is indicated from 12 research (80%) which showed it performs better than state-of-the-art methods, 2 (13.33%) indicated comparable performance, and 1 (6.67%) showed a lesser performance. Furthermore, the percentage of success achieved using D-Wave 2000Q was observed to be much higher than using D-Wave 2X. This was proven by only 4 research (57.14%) that showed D-Wave 2X provides better QA performance, 1 (14.29%) indicated comparable QA performance, and 2 (28.57%) showed it is worse. This is reasonable because D-Wave 2000Q is a newer version with improved performance (better solutions and time-to-solution), annealing quantum processor design (qubits, couplers, couplers per qubit), and topology (graph, graph size, connectivity, lattice, and chain length) [260]. The findings also showed that the implementation of QA in Universal Quantum Computing by Rigetti Computing did not provide better or even equivalent performance than the state-of-the-art methods. This is due to the fact that the Universal Quantum Computing is actually more suitable for the gate-based quantum computing approach but can also be used in QA.

The emergence of D-Wave 2000Q close to the initiation of implementing QA in machine learning (2018) led to the proposed modification of QA through hybrid and reverse methods. It was discovered that the implementation of hybrid QA using D-Wave 2000Q has not shown significant performance compared to the QA. This was confirmed by the findings of only 6 research (50%) that the hybrid approach has better performance, 5 (41.67%) indicated a competitive performance, and 1 (8.33%) showed it performed worse. Moreover, only [236] used reverse QA on D-Wave 2000Q and a better result was reported.

These findings showed that the continuous development of the D-Wave quantum annealer provides an opportunity to improve the performance and different methods of QA better than the application of D-Wave 2000Q. There are currently newer quantum annealers such as D-Wave Advantage which provides better quality than the D-Wave 2000Q. This means the variant QA methods including the hybrid QA, reverse QA, and improved QA are very likely to provide better performance. Moreover, the proposed new modification of QA is also projected to be interesting to address the limitations of the current specific methods.

D. CHALLENGES AND SUGGESTIONS

Machine learning has been widely applied in different sectors such as health, finance, autonomous driving, security, and others [38]. However, it was observed in Table 12 to be facing different challenges stemming from several factors such as the scale of the data generated, hardware limitations, computational complexity, and cost. Hardware technology is also growing increasingly due to the significant advancement in computing capabilities but it has certain difficulties in handling the data projected to be increasing rapidly at 20% per year [38], [261].

The main characteristic of machine learning algorithms is their ability to be implemented and applied after the training process. This training process requires setting the model parameters to extract meaningful information from the data [221]. The tendency of the data to increase causes the training process to have high computational complexity. It was discovered from Table 12 QA research in the machine learning domain generally focuses mostly on improving the optimization of the training process. The analysis also showed two opportunities to develop QA algorithms in order to increase the optimization of machine learning processes as follows:

1) Implementation of QA to handle new problems

This research analyzed the potential of QA to be applied in different optimization and probabilistic sampling problems that have not been investigated. Several machine learning models have not been previously

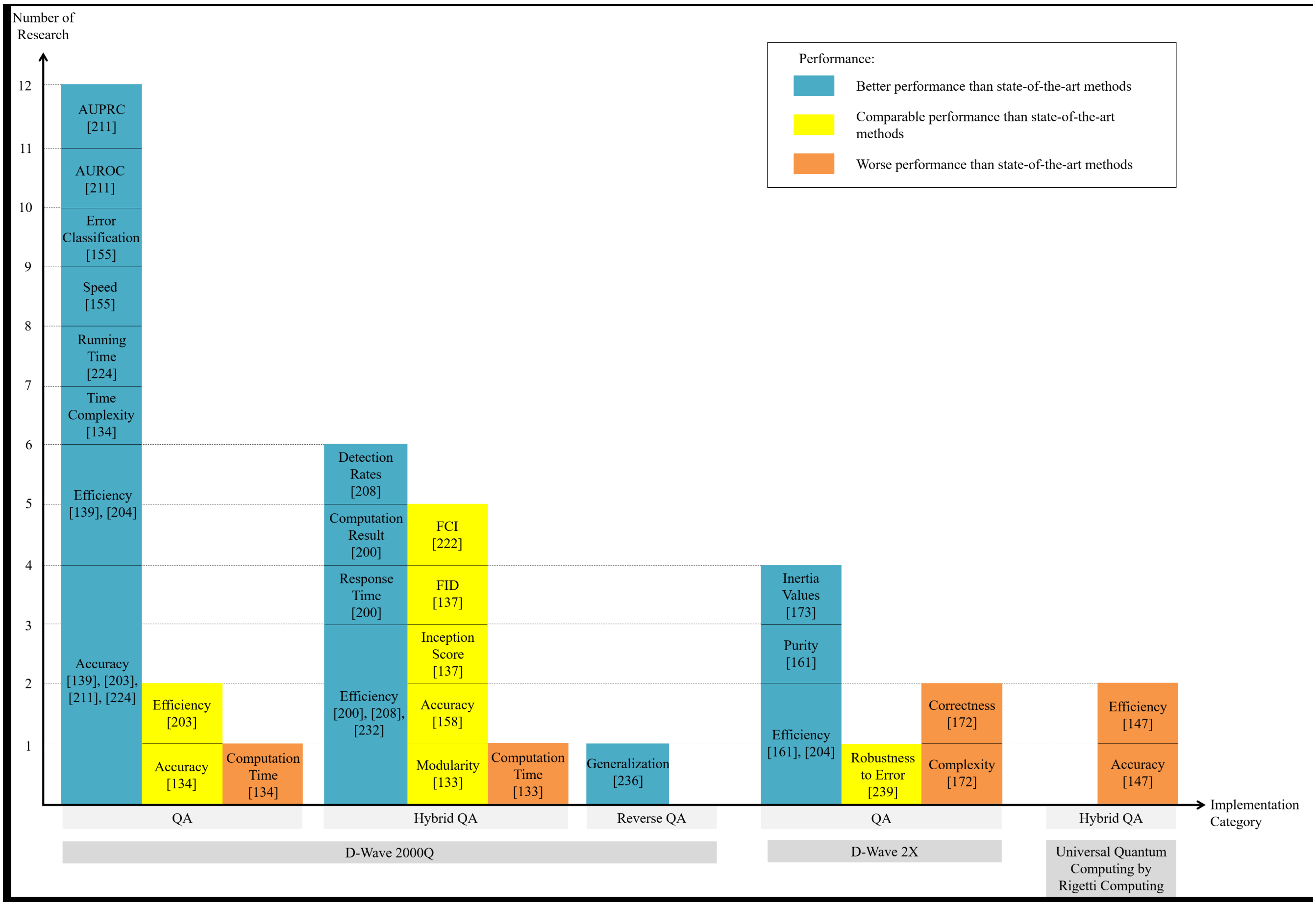

FIGURE 9. **Metrics and performance based on method and hardware used.**

investigated. It was discovered that the implementation of QA in the machine learning domain has the ability to optimize several supervised learning models such as k-Nearest Neighbor, decision tree, random forest, Linear Discriminant Analysis (LDA), ridge regression, LASSO, and others as well as unsupervised, semi-supervised, and reinforcement learning models. It will also be interesting to further explore the use of QA methods in optimizing different forms of ensemble learning models. Moreover, many machine learning problems, especially in machine learning training, lead to optimization problems, such as optimization of hyperparameters and optimization of features.

2) Modification of QA to improve its performance
There is a need for continuous improvement of the QA performance due to the fact that some were discovered not to outperform other state-of-the-art approaches. This can be achieved by combining the QA method with other approaches to form a hybrid QA or modifying it to have reverse and improved QAs. There is a possibility of proposing a new form of modification to assist in improving the performance of existing or variant methods of QA to deal with optimization problems and probabilistic sampling, especially in the machine learning domain. The improvement of the algorithm quality (as well as hardware which is not the scope of this research) can lead to the application of QA to handle optimization and probabilistic sampling problems on a larger scale.

This research shows that the research concerning QA-ML is expected to continue growing because each of the two fields has very large growth. There is also an increasing need for multidisciplinary research between QA-ML and other fields such as chemistry, biology, security, and others, and this can serve as a research opportunity in the future.

IV. CONCLUSION

QA is a new promising approach to handle NP-hard problems, specifically those related to optimization and probabilistic sampling. The QA-related research trend tends to increase due to the growth of the quantum annealer with their impact significantly observed in 13 domains which include machine learning, graphics, mathematics, routing, scheduling, computational chemistry, computational biology, security, portfolio, big data, hydrology, database, and sensors. Moreover, four specific methods were used in QA research and these include basic, hybrid, reverse, and improved QA. This research also mapped the implementation methods and problem domains to find gaps for future research. Comparative analysis of QA performance with other state-of-the-art methods was also conducted to deepen the analysis. In addition, machine learning, as a domain with the greatest interest in QA-related research, was explored comprehensively in relation to the hardware and dataset used, detailed application of QA, and method performances. It is important to note that the results of this systematic review can be used as the basis to identify the opportunities and challenges in the research area related to the implementation of QA in the future.

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LENNY PUTRI YULIANTI (Member, IEEE) received the B.Sc. degree in information system and technology and the M.Sc. degree in informatics from Institut Teknologi Bandung (ITB), Indonesia, in 2017 and 2018, respectively, where she is currently pursuing the Ph.D. degree in informatics. Since 2019, she has been a Lecturer with the School of Electrical Engineering and Informatics, ITB. Her current research interests include information systems, machine learning, and quantum annealing.

KRIDANTO SURENDRO received the Ph.D. degree in computer science from Keio University, Japan, in 1999. He is currently working with Institut Teknologi Bandung, Indonesia. He is working in the area of information systems, information and knowledge analytic, and information governance. His research interests include the application of artificial intelligence to enterprise engineering and quantum computing.