



A review of recent advances in quantum-inspired metaheuristics

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Abstract

Quantum-inspired metaheuristics emerged by combining the quantum mechanics principles with the metaheuristic algorithms concepts. These algorithms extend the diversity of the population, which is a primary key to proper global search and is guaranteed using the quantum bits' probabilistic representation. In this work, we aim to review recent quantum-inspired metaheuristics and to cover the merits of linking the quantum mechanics notions with optimization techniques and its multiplicity of applications in real-world problems and industry. Moreover, we reported the improvements and modifications of proposed algorithms and identified the scope's challenges. We gathered proposed algorithms of this scope between 2017 and 2022 and classified them based on the sources of inspiration. The source of inspiration for most quantum-inspired metaheuristics are the Genetic and Evolutionary algorithms, followed by swarm-based algorithms, and applications range from image processing to computer networks and even multidisciplinary fields such as flight control and structural design. The promising results of quantum-inspired metaheuristics give hope that more conventional algorithms can be combined with quantum mechanics principles in the future to tackle optimization problems in numerous disciplines.

Keywords Quantum-inspired algorithms · Quantum computing · Metaheuristics · Optimization techniques · Global optimization · NP-hard problems

1 Introduction

It is too costly for conventional algorithms to find exact solutions due to real-world problems' complexity and high dimensionality. To tackle this issue, metaheuristic algorithms are proposed to provide an approximate solution with a significant cut down on computational cost. Metaheuristics are problem-independent frameworks and belong to the high-level category of algorithms that develop heuristic optimizers using a series of steps and guidelines [1].

In recent years, there has been a growing tendency to research metaheuristics [2]. The main advantage of metaheuristics is their capability to solve NP-hard problems in polynomial time. Due to the vast domain of applications and high demand for stability and accuracy, several modifications and hybridizations are applied to classical metaheuristic algorithms.

A relatively large number of metaheuristic algorithms and their modifications have been proposed, spanning from those inspired by creation-evolution to algorithms based on natural laws. This wide variety is justified by taking the No Free Lunch Theorem [3] into account. Indeed, there is no single solution to solve the problems of different disciplines. Every improvement in metaheuristic algorithms in favor of some specific problems leads to a decline in solving some other problems' performance. So, intensive study in this field and the introduction of new methods and modifications are necessary to cover the wide range of real-world problems. One of the radical variants of metaheuristics is quantum-inspired metaheuristics, which have been generated through the combination of quantum computing principles and metaheuristic algorithms concepts.

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Improvements in classical computers' computation power do not satisfy the growing demands. Moore's law is anticipated to fail by 2025 as the transistors' size lower-bound is limited to the atom's size [4]. Quantum mechanics can break through the limitations because of a property called quantum parallelism, which refers to the ability of quantum bits (qubit) to handle different processes simultaneously. For instance, utilizing only 30 qubits, it is possible to handle a billion data objects for executing parallel computing. All the data is retrievable by reading a single qubit using superposition, and entanglement [5].

The novelty and capabilities of quantum computing open a new horizon to solve optimization problems and improve the existing algorithms. Feynman [6], and Manin [7] established the quantum computing idea in the 1980s, and it has received much attention since then, especially after Shor's ground-breaking development of a super-efficient algorithm to factorize large numbers in 1994 [8]. Lov Grover proposed another outstanding work in this field: an extremely fast algorithm to search in unstructured databases in 1996 [9]. Algorithms that utilize the quantum computing concept are potentially efficient because of a quantum mechanics property called quantum parallelism which refers to the ability of quantum bits (qubit) to handle different processes simultaneously.

This work aims to conduct a review of recent quantum-inspired metaheuristic algorithms that have been presented in recent years (2017–2022) and their applications in order to help researchers identify the current research trends of this field, the state-of-the-art technologies and applications that use this approach, the limitations, and potential gaps in this scope. The reviewed works in this survey were found in Web of Science, ScienceDirect, and IEEE Xplore using keywords "quantum-inspired metaheuristic", "quantum-inspired genetic algorithm", and "quantum-inspired evolutionary algorithm".

In order to categorize the quantum-inspired metaheuristics in this study, different criteria could be applied. Type of candidate solutions, type of search, and source of inspiration are the most common criteria to categorize the metaheuristic algorithms [10]. This paper uses the latter criterion, source of inspiration, to organize the algorithms. We have divided the sources of inspiration into two major categories, namely biologically-inspired and nature-based. Biologically-inspired algorithms mimic the evolutionary process of living organisms. In contrast, the source of inspiration for nature-based algorithms is nature's laws, such as physical and chemical laws (as illustrated in Fig. 2).

In the remainder of this study, Sect. 2 introduces recent works on different types of biologically-inspired quantum metaheuristics, namely quantum-inspired genetic algorithms, quantum-inspired evolutionary algorithms, quantum-inspired swarm-based algorithms, and quantum-inspired human-based, as well as quantum-inspired nature-based

algorithms. Section 3 introduces the recent conventional metaheuristics with no quantum-inspired version and can be considered for combination with quantum-mechanics concepts for even more promising performance. Research gaps are presented in Sect. 4. Finally, this study is summarized in Sect. 5.

2 Quantum-inspired metaheuristic algorithms

Quantum-inspired metaheuristics take the principles of quantum computing to elevate the performance of metaheuristics. A proper balance between exploration/global search and exploitation/local search in metaheuristic algorithms has always been a challenge, as focusing on either of them weakens the other. The main advantage of utilizing quantum computing concepts in this field is to strengthen the global search capability without deteriorating the exploitation phase of the algorithms.

Contrary to classical computing, which is based on simple bits which are limited to either 0 or 1 values, quantum computation's fundamental unit of information is the qubit. Just like a classical bit, a qubit can be in either state of 0 or 1, but unlike a classical bit, it can be in any state of the superposition of this pair of values. This property of qubits makes them enable to faster executing of numerous processes. Mathematically, a qubit can be shown as follows:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \quad \alpha, \beta \in \mathbb{C}$$

α and β are called probability amplitudes, and the state of the qubit after measurement will be 0 with the probability of $|\alpha|^2$ and 1 with the probability of $|\beta|^2$. So as these values are probabilities:

$$|\alpha|^2 + |\beta|^2 = 1$$

An N -qubit register can hold 2^N states at the same time while an N -bit register in a traditional computer can only have a single value out of 2^N possible values. This property is the key to quantum parallelism which leads to exponential improvement in efficiency.

Structure of an N -qubit individual is represented as following:

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_N \\ \beta_1 & \beta_2 & \dots & \beta_N \end{bmatrix}, \quad \forall i \in \{1, \dots, N\}, \quad |\alpha_i|^2 + |\beta_i|^2 = 1$$

Manipulation of qubits' states can be done using quantum gates. There are several quantum gates, such as NOT gate, CNOT gate, Rotation Gate, Toffoli Gate, Fredkin Gate and Hadamard Gate. In fact, a quantum gate is a linear transformation and consequently is reversible. A quantum gate is

shown by a unitary matrix U . A complex square matrix U is called unitary if its adjoint U^\dagger and its inverse U^{-1} are identical. Also, the rows and the columns of U are orthonormal [11]. So:

$$UU^\dagger = U^\dagger U = UU^{-1} = U^{-1}U = I$$

Updating the values of α_i and β_i using the Rotation gate can be seen in the Fig. 1 and is calculated by:

$$\begin{bmatrix} \alpha'_i \\ \beta'_i \end{bmatrix} = \begin{bmatrix} \cos \theta_i & -\sin \theta_i \\ \sin \theta_i & \cos \theta_i \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix}$$

where θ_i is the rotation angle of the i th qubit and α'_i and β'_i are probability amplitudes of the qubit after rotation [12].

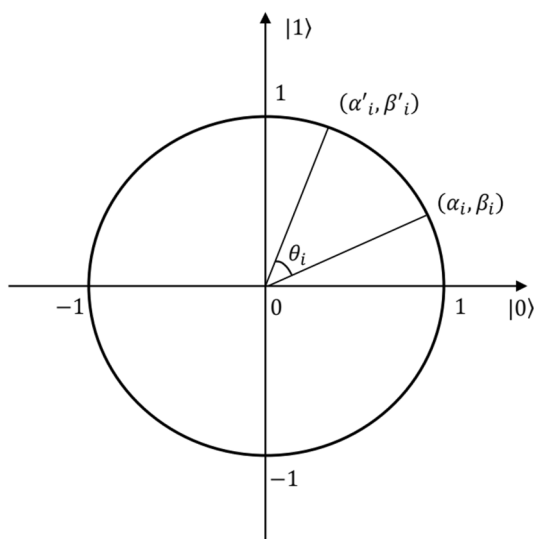
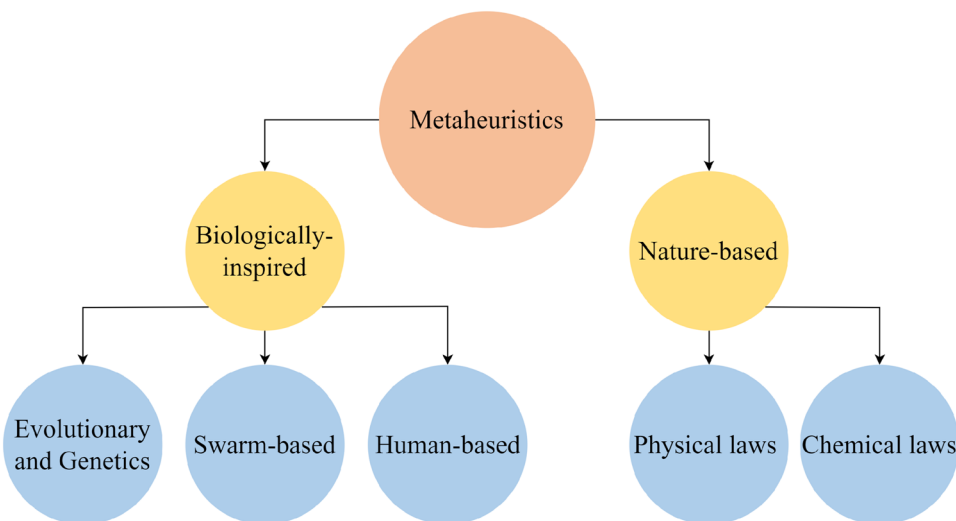


Fig. 1 Rotation operation for qubit

Fig. 2 Metaheuristics major categories



It is worth mentioning here that in the quantum-inspired metaheuristics literature, the three-dimensional model of qubits in the Bloch sphere is simplified to two-dimensional, representing the rotation angle and probability amplitudes before and after rotation. Also, the measurement of quantum bits is simulated by classical computers, considering probability amplitudes.

Like their ancestors, quantum-inspired metaheuristic algorithms' source of inspiration is divided into two main categories: biologically-inspired and nature-based (Fig. 2). Biologically inspired metaheuristics are genetic, evolutionary, swarm, and human-based algorithms. Nature-inspired algorithms are those which have taken natural laws, like physical and chemical laws, as their source of inspiration. This section reviews recent advantages and novel applications of quantum-inspired metaheuristics in recent five years. During this period, about 60% of introduced quantum-inspired metaheuristics were inspired by evolutionary and genetic algorithms, more than 25% were swarm-based, and this percentage was only about 10 and 5% for human-based and nature-inspired algorithms, respectively (see Fig. 3).

2.1 Biologically-inspired metaheuristics

2.1.1 Quantum-inspired genetic algorithms (QGAs)

The first quantum-inspired genetic algorithm was introduced by Kim and Han [13]. A quantum-inspired genetic algorithm is a variation and improvement of a classical genetic algorithm that utilizes qubit chromosome representation instead of conventional models, namely binary, numerical, and symbolic. Qubit chromosome representation is superior to its classical counterpart because of its ability to represent all states' superpositions simultaneously. Figure 4 illustrates the flowchart quantum-inspired genetic algorithm. The

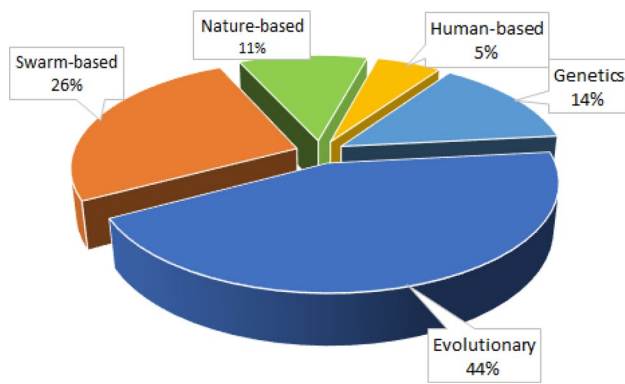


Fig. 3 Distribution of quantum-inspired metaheuristics' source of inspiration from 2017 to 2022

algorithm starts by initializing all the qubits of the qubit chromosomes with $\frac{1}{\sqrt{2}}$, which makes the representation of linear superposition of all states equally possible. Next, binary candidate solutions are generated by observing qubit chromosomes' states. The best solution is then selected and stored by evaluating candidate solutions. Until the satisfaction of the termination condition, candidate solutions are updated, considering quantum chromosomes. Finally, quantum chromosomes must be updated using quantum gates for the next generation use.

Recent works using the quantum-inspired genetic approach and their application and improvements are listed in Table 1.

2.1.2 Quantum-inspired evolutionary algorithms (QEAs)

Han and Kim proposed quantum-inspired evolutionary algorithms two years after the introduction of QGAs in 2002 [24]. Just like Evolutionary algorithms (EAs), QEAs are based on individual representation, fitness function, and the population dynamics such as the number of the initial population, selection, crossover, mutation operations, and so forth. QEAs utilize qubits which are defined as the smallest information units. A qubits individual consists of a string of qubits. Search diversification is performed more properly using qubit representation thanks to its probabilistic representation. The first steps of QEA lead to a diverse population as the qubit individuals are in the superposition of all possible states with equal probability. As the algorithm carries on, the convergence of individuals to a single state intensifies the search. An elegant balance between exploration and exploitation phases is achieved by this behavior of QEA. It is worth mentioning that despite being inspired by quantum computing, QEA is not actually a quantum algorithm and is just a new evolutionary algorithm for classical computers.

The flowchart of quantum-inspired evolutionary is shown in Fig. 5.

Table 2 summarizes works using the QEA idea in recent five years and improvements and modifications made on QEA.

2.1.3 Quantum-inspired swarm-based algorithms

Swarm-based optimization algorithms take the behavior of swarms of animals as their source of inspiration. This approach is called swarm intelligence. The introduction of term “swarm intelligence” backs to 1989 by Beni and Wang [58]. Swarm-based algorithms that have been modified and improved by quantum computing approach in recent years are as follows:

The most swarm-based eminent algorithm is Particle Swarm Optimization (PSO) which was introduced by Kennedy and Eberhart [59]. PSO is a stochastic optimization algorithm that simulates the social behavior of birds in a flock. Krill Herd (KH) [60] which simulates of the krill individuals herding behavior, Firefly Algorithm (FA) [61] inspired by flashing characteristics of fireflies, Grey Wolf Optimizer (GWO) [62] which is inspired by hierarchical leadership and hunting of grey wolves, Ant Colony Optimization (ACO) [63] inspired by foraging behavior of some ants species, Bat Algorithm (BA) [64] which mimics the echolocation or bio-sonar characteristics of bats, Glowworm Swarm Optimization (GSO) [65] that simulates the lighting worms behavior, Monarch Butterfly Optimization (MBO) [66] which is proposed by simplifying the monarch butterflies migration, Spider Monkey Optimization (SMO) [67] that simulates the social behavior and foraging of spider monkeys, Whale Optimization Algorithm (WOA) [68] inspired by hunting method of humpback whales, Salp Swarm Algorithm (SSA) [69] which mimics the swarming behavior of salps, Satin Bowerbird Optimization (SBO) [70] inspired by breeding behavior of satin birds, Sperm Motility Algorithm (SMA) which simulates the fertilization process [71], Squirrel Search Algorithm (SSA) [72] which mimics the flying squirrel's foraging, and Reptile Search algorithm [73] which is inspired by hunting behavior of crocodiles.

Quantum-inspired particle swarm optimization algorithm (QPSO) was proposed by Yang et al. [74]. QPSO utilizes concepts of quantum mechanics to boost the performance of classic PSO. Figure 6 illustrates the flowchart of QPSO.

Quantum-inspired swarm-based metaheuristic algorithms were introduced in the last five years, and their applications are listed in Table 3.

2.1.4 Quantum-inspired human-based algorithms

Human-based heuristics are inspired by human behavior. Harmony search (HS) [94] and Tabu Search (TS) [95, 96]

Fig. 4 Flowchart of QGA [13]

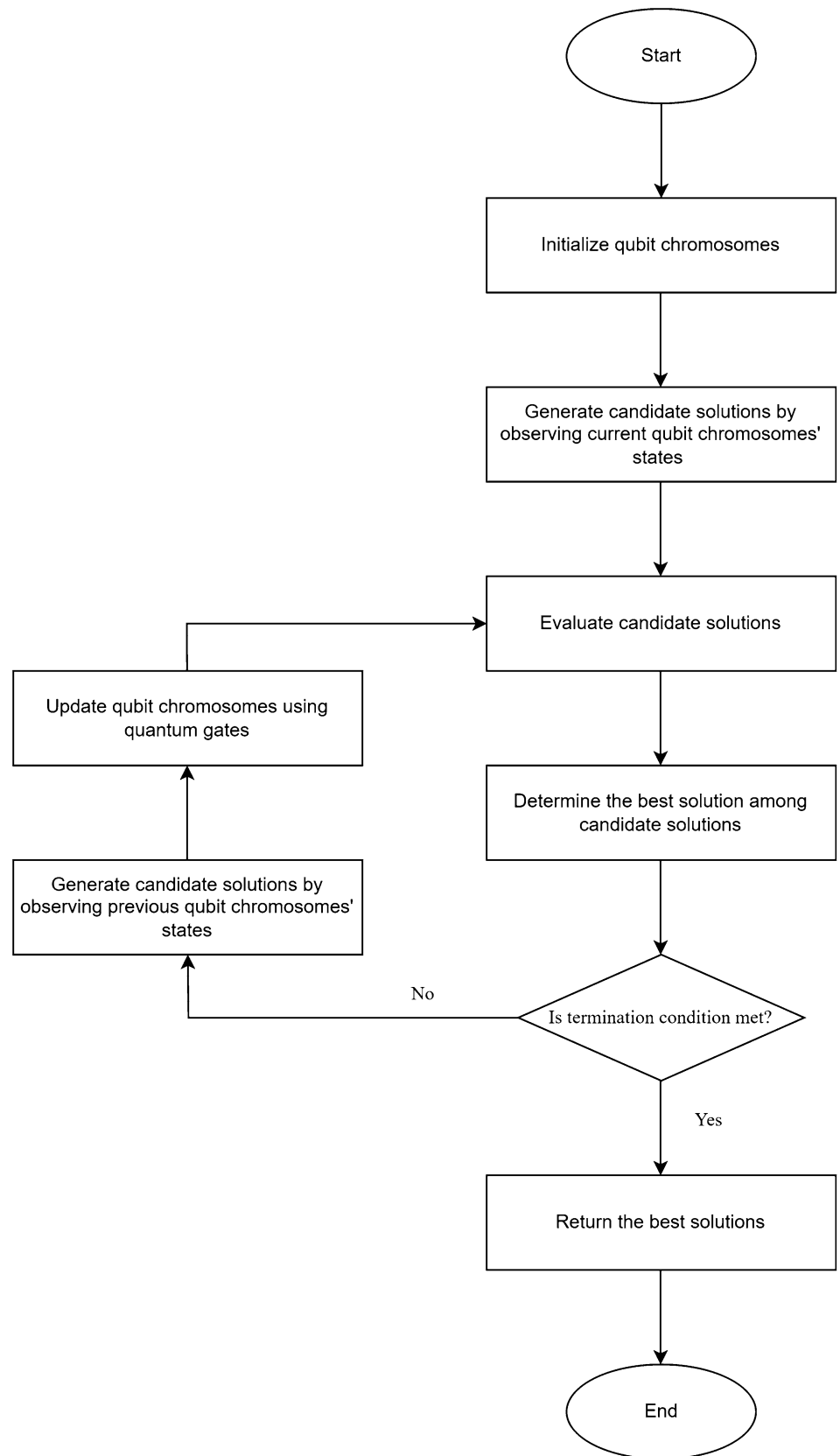


Table 1 Quantum-inspired genetic algorithms (QGA) applications (2016–2022)

| Applications | Year | Contributions/innovations/modification | References |
|--|------|--|---------------------|
| Real-time task scheduling | 2017 | Association of evaluation function with heuristic earlier deadline first (EDF) | Konar et al. [14] |
| Precedence constrained job scheduling | 2018 | Minimization of both load imbalance and load balance cost ratio simultaneously | Alam et al. [15] |
| Multimodal optimization of flight control system | 2019 | Generating new chromosomes using stratification method | Bian et al. [16] |
| The RNA secondary structure prediction | 2019 | | Shi et al. [17] |
| Double digest problem | 2020 | DNA mapping (converting the binary qubit representation to mapping sequences) | Suo et al. [18] |
| Modified traveling purchaser problem | 2020 | Introducing in vitro fertilization (IVF) crossover method | Pradhan et al. [19] |
| Crude oil scheduling | 2020 | Integration of grammar-based, linear, and quantum-inspired genetic programming | Pereira et al. [20] |
| Segmentation and optimization | 2020 | | Sabeti et al. [21] |
| Resource-constrained project-scheduling | 2021 | | Saad et al. [22] |
| Predictive BPaaS Management | 2021 | Utilizing the QGA for optimization the training phase of a neural network prediction model | Hedhli et al. [23] |

are among the most famous human-based metaheuristic algorithms. Harmony search mimics the improvisations of musicians in pursuit of more satisfying harmony. Tabu Search relies on two key elements: classifying particular moves in search space as forbidden or 'tabu' and 'strategic forgetting', allowing individuals to temporarily break loose from constraints. Some novel quantum-inspired algorithms developed recently concerning these concepts, which are listed in Table 4.

2.2 Nature-based metaheuristics

Nature has always been an infinite source of inspiration for humankind. Metaheuristics are no exception. Several nature-based metaheuristics are based on natural phenomena and laws of physics and chemistry. Quantum-inspired versions of Gravitational Search Algorithm (GSA) [101] that is based on the law of gravity, Colliding Bodies Optimization (CBO) [102] which imitates the collision between objects, and Charged System Search (CSS) [103] which is based on Coulomb law from electrostatics and Newtonian laws from mechanics have been proposed recently. In 2019 Multi-scale Quantum Harmonic Oscillator Algorithm (MQHOA) was originally introduced as a quantum-inspired algorithm [104]. Quantum versions of nature-inspired metaheuristic algorithms between 2017 and 2022 are summarized in Table 5.

2.3 Numerical optimization comparison

As the recent proposed quantum-inspired metaheuristic algorithms are applied to different applications, it is impossible to compare their effectiveness fairly. In addition, the algorithms that are proposed for the same applications may differ in the methods and datasets they use.

However, numerical optimization is a relatively more common application among the proposed quantum-inspired metaheuristics. So, we conduct a comparison between some of the algorithms. The algorithms in this comparison are Entanglement-Enhanced Quantum-inspired Tabu Search Algorithm (Entanglement-QTS) [98], Multi-scale Quantum Harmonic Oscillator Algorithm (MQHOA) [104], Multi-scale Quantum Harmonic Oscillator Algorithm With Multi-Harmonic Oscillators (MHO-MQHOA) [110], Quantum Salp Swarm Algorithm (QSSA) [89], Half Significant Bit QEA (HSBQEA) [25], Stepwise Real QEA [25], enhanced Quantum behaved Particle Swarm Optimization (e-QPSO) [77], Quantum-Inspired Acromyrmex Evolutionary Algorithm (QIAEA), and Quantum Enhanced Colliding Bodies Optimization (QECBO) [108]. Six well-known benchmark functions are selected for this comparison. The benchmark functions consist of two unimodal functions, namely the Sphere function and Rosenbrock function, and four multimodal functions, Schewel function, Rastrigin function, Ackley function, and Griewank, and the reported results have been compared.

It is worth mentioning that unimodal benchmark functions are mainly used to examine the exploitation power of the algorithms, while multimodal benchmark functions are suitable to evaluate the exploration abilities.

The reported results are taken from the original papers and are collected in Table 6. Although the experiments have been conducted on different dimensions using different maximum fitness function evaluations, the number of evaluations is somehow proportionate to the number of dimensions so that the results can be roughly compared together. From the results, it can be concluded that all the algorithms successfully solved the unimodal test functions except the HSBQEA. The Schwefel function was the

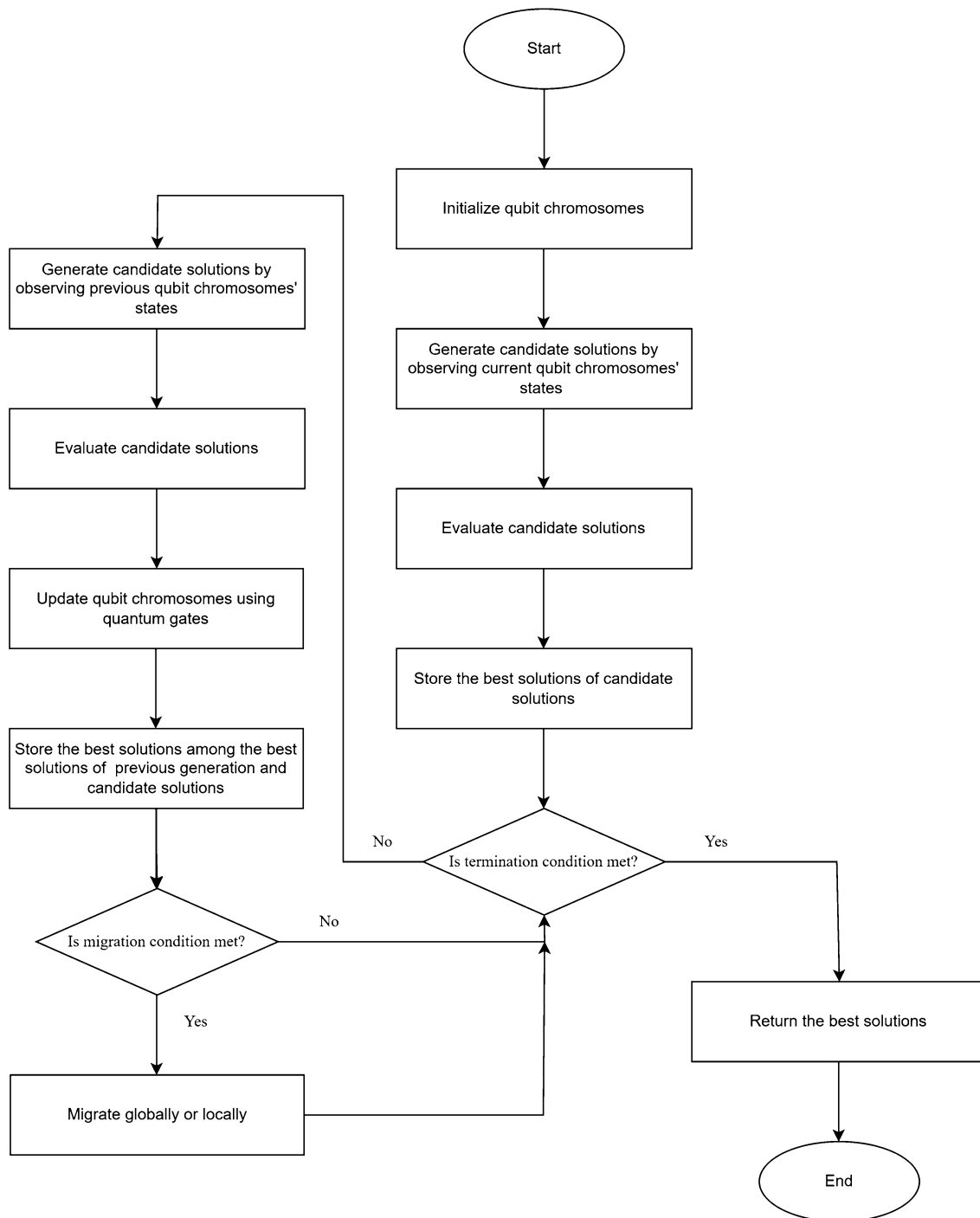


Fig. 5 Flowchart of QEA [24]

most challenging in the multimodal functions, and QSSA, HSBQEA, and e-QPSO algorithms could not converge into the global minimum. However, it is not a significant drawback since several well-known metaheuristics fail to

avoid the tricky local optima of the Schwefel benchmark function’s search space. The error result for the Rastrigin, Ackley, and Griewank functions was acceptable for all algorithms and was at least near zero.

Table 2 Quantum-inspired evolutionary algorithms (QIEAs) applications (2017–2022)

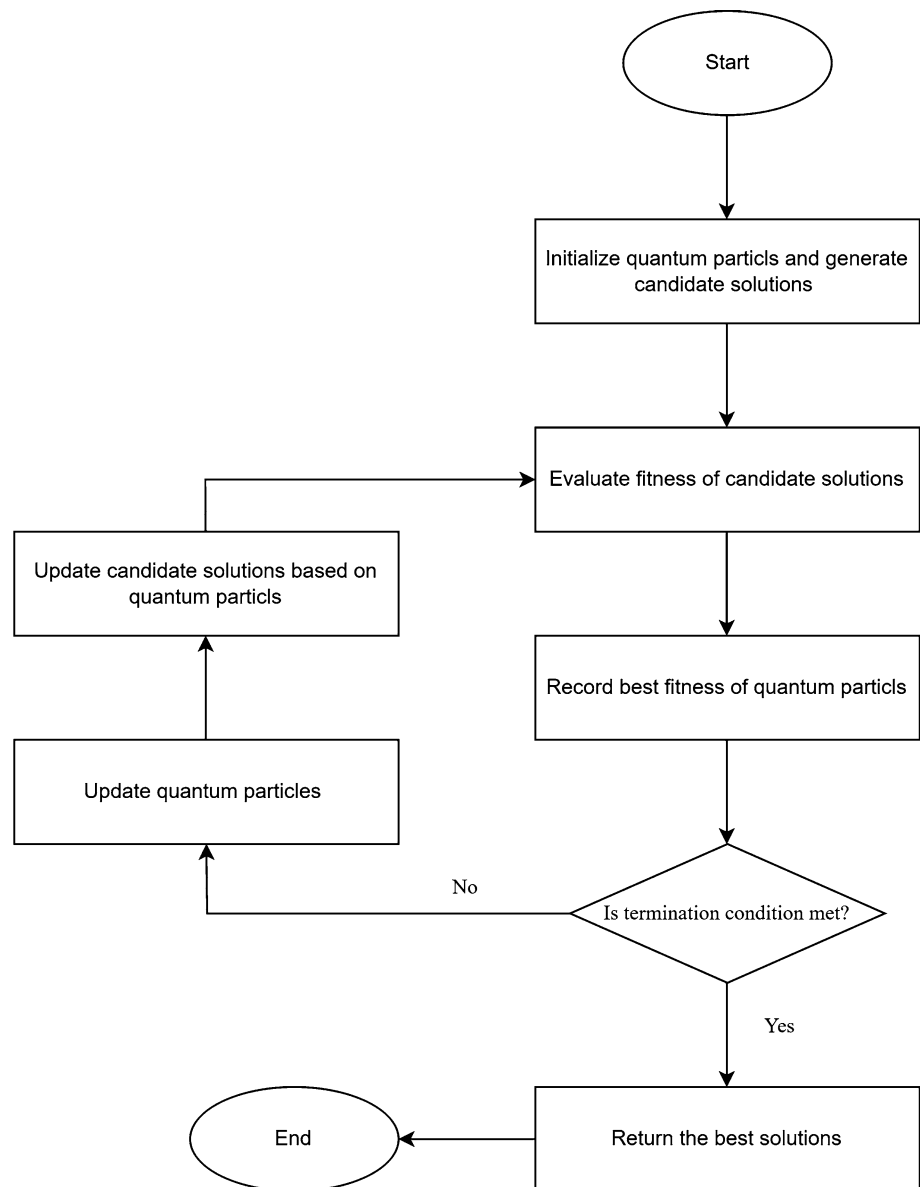
| Applications | Year | Contributions/innovations/modification | References |
|---|------|---|------------------------|
| Numerical optimization | 2017 | Rotation gates improvement | Wright et al. [25] |
| Robotic flow shop scheduling | 2017 | Utilizing adaptive crossover and mutation operators | Lei et al. [26] |
| Continuous optimization | 2017 | | Talbi et al. [27] |
| Flexible job-shop scheduling | 2017 | Applying elitist attitude to boost convergence speed | Wu et al. [28] |
| Disruption management in cloud manufacturing | 2017 | Integration of QEA with group leader optimization algorithm and chaotic mapping | Liu et al. [29] |
| Social networks' community detection | 2017 | Using the QEA for parallel implementation of community detection algorithms | Gupta et al. [30] |
| Heterogeneous cellular networks design | 2017 | Introducing in vitro fertilization (IVF) crossover method | Xie et al. [31] |
| Ordering problems | 2017 | Using the QEA solution to initialize a traditional order-based genetic algorithm population | Silveira et al. [32] |
| Numerical optimization problems | 2018 | | Tirumala et al. [33] |
| Optimal view selection | 2018 | | Kumar et al. [34] |
| Optimization of electromagnetic devices | 2018 | Keeping only promising solutions for performance checking mechanism | Yang et al. [35] |
| Fuzzy controller design | 2018 | | Yu et al. [36] |
| Constrained fuel loading pattern optimization | 2018 | | Oktavian et al. [37] |
| Hand gesture recognition | 2018 | Applying minimum redundancy maximum relevance criterion to QEA | Ryu et al. [38] |
| Quadratic assignment problem | 2018 | | Chmiel et al. [39] |
| Fuzzy clustering parameters optimization | 2018 | Integration with fuzzy c-means algorithm | Bharill et al. [40] |
| Complex networks' community detection | 2018 | Use of conventional partitioning algorithm solution as a guiding quantum individual | Yuanyuan et al. [41] |
| Process planning and scheduling | 2018 | Integration with group leader optimization algorithm and chaotic mapping | Liu et al. [42] |
| Hybrid laminated composites design | 2018 | Using rank-based dynamical version of QEA | Kaveh et al. [43] |
| Pitched roof frames design | 2019 | Using different quantum gate for exploitation improvement | Arzani et al. [44] |
| Multi-objective fuzzy classifier | 2019 | Implementing QEA with categorical variables | Nunes et al. [45] |
| Reactor loading design | 2019 | Using self-regulated learning | Hsieh et al. [46] |
| Sensor placement optimization | 2019 | Development of a dynamic version of QEA | Kaveh et al. [47] |
| Fuzzy cognitive maps | 2019 | Integration of QEA with particle swarm optimization algorithm | Kolahdoozi et al. [48] |
| Efficient data clustering | 2019 | Combination of QEA with fuzzy c-means algorithm | Bharill et al. [49] |
| Complex systems optimization problems | 2019 | Modification of QEA by inspiration from colony evolution of acromyrmex ants | Montiel et al. [50] |
| Multi-carrier communication | 2020 | Utilizing multi objective fitness function and characteristics information ranking | Hou et al. [51] |
| Robot path planning | 2020 | Handling discretized environment | Gao et al. [52] |
| Network resource optimization | 2020 | Using self-adaptive evolution mechanism | Qu et al. [53] |
| Feature selection | 2020 | Utilizing chaotic maps | Ramos et al. [54] |
| Multi-objective optimization | 2020 | Implementing parallelism to solve large-scale problems | Cao et al. [55] |
| Airport gate allocation | 2021 | Combination of cooperative co-evolution, random rotation direction, and hamming adaptive rotation angle | Cai et al. [56] |
| Predictive BPaaS Management | 2021 | Applying biological coevolution for sub-populations evolution | Dias et al. [57] |

3 Recent metaheuristics without quantum version

This section introduces some novel conventional metaheuristics and their applications. To our best knowledge, these algorithms have not been combined with

quantum mechanics notions yet. So, quantum-inspired versions of these approaches can be developed in future.

One of the most prominent examples is the Arithmetic Optimization Algorithm (AOA) [113], which utilizes arithmetic operators to solve arithmetic problems. The Aquila Optimizer (AO) [114] is a state-of-the-art nature-inspired metaheuristic inspired by Aquila's hunting

Fig. 6 Flowchart of QPSO [59]

behaviour. Equilibrium Optimizer (EO) [115] is a physics-based optimization algorithm inspired by a volume mass balance equation. Social Engineering Optimizer (SEO) [116] is inspired by human social behavior. Red Deer Algorithm (RDA) [117] mimics the Scottish red deer's mating behavior. Other examples of nature-inspired metaheuristics are Keshtel Algorithm [118] (KA), African Vultures Optimizer (AVO) [119], and Harris Hawks Optimizer (HHO) [120].

Table 7 gives the metaheuristics without quantum-inspired versions till now and some of their recent applications.

4 Research gaps

Searching through several recent quantum-inspired metaheuristics, we came across some areas that have not been covered thoroughly. The literature is full of innovative and elegant contributions in terms of combining quantum mechanics notions with conventional metaheuristic algorithms. However, the literature suffers from several gaps.

First, most of these algorithms perform a simulation of quantum bits and quantum gates manipulating their

Table 3 Quantum-inspired swarm-based algorithms applications (2017–2022)

| Source of inspiration | Application | Year | References |
|--|--|------|-----------------------|
| Particle swarm optimization (PSO) | Engineering inverse problems | 2017 | Rehman et al. [75] |
| | Grey level image clustering | 2020 | Dey et al. [76] |
| | Numerical optimization | 2021 | Agrawal et al. [77] |
| | Multimodal multi-objective problems | 2021 | Li et al. [78] |
| | Virtual machines in smart computing cloud placement optimization | 2022 | Balicki et al. [79] |
| Krill herd optimization algorithm (KH) | Multi-objective optimization problems | 2020 | Liu et al. [80] |
| Firefly algorithm (FA) | Segmentation of hippocampus images | 2021 | Choudhury et al. [81] |
| Grey wolf optimizer (GWO) | Unit commitment problem | 2021 | Srikanth et al. [82] |
| | 0–1 Knapsack problem | 2021 | Wang et al. [83] |
| Ant colony optimization (ACO) | Multi-objective routing in WSN | 2019 | Li et al. [84] |
| Bat inspired algorithm (BA) | Classification of leukocytes in blood smear | 2021 | Sharma et al. [85] |
| Glowworm swarm optimization (GSO) | Discrete optimization | 2017 | Gao et al. [86] |
| Monarch butterfly optimization (MBO) | Air vehicle path planning navigation | 2020 | Yi et al. [87] |
| Spider Monkey optimization (SMO) | Grey level image clustering | 2020 | Dey et al. [76] |
| Whale optimization algorithm (WOA) | Wrapper feature selection clustering | 2020 | Agrawal et al. [88] |
| Salp swarm algorithm (SSA) | Mechanical design | 2019 | Chen et al. [89] |
| Satin bowerbird optimization (SBO) | Constrained structural optimization | 2021 | Zhang et al. [90] |
| Sperm motility algorithm (SMA) | General optimization | 2022 | Hezam et al. [91] |
| Squirrel search algorithm (SSA) | Global optimization problems | 2022 | Zhang et al. [92] |
| Reptile search algorithm (RSA) | Global optimization and data clustering | 2022 | Almodfer et al. [93] |

Table 4 Quantum-inspired human-based algorithms (2017–2022)

| Source of inspiration | Application | Year | References |
|-----------------------|------------------------------|------|---------------------------|
| Harmony search (HS) | Multi-objective optimization | 2021 | Sadeghi Hesar et al. [97] |
| Tabu search (TS) | Function optimization | 2017 | Kuo et al. [98] |
| | Portfolio optimization | 2019 | Chou et al. [99] |
| | Portfolio optimization | 2021 | Chou et al. [100] |

Table 5 Quantum-inspired nature-based algorithms (2017–2022)

| Source of inspiration | Application | Year | References |
|---|------------------------------|------|--------------------------|
| Gravitation search algorithm (GSA) | Job-scheduling | 2017 | Singh et al. [105] |
| | Feature subset selection | 2017 | Barani et al. [106] |
| | Wireless sensor networks | 2021 | Mirhosseini et al. [107] |
| Colliding bodies optimization (CBO) | Numerical optimization | 2020 | Kaveh et al. [108] |
| Charged system search (CSS) | Large-scale structure design | 2022 | Talatahari et al. [109] |
| Multi-scale quantum harmonic oscillator algorithm (MQHOA) | Numerical optimization | 2018 | Wang et al. [104] |
| | Numerical optimization | 2019 | Li et al. [110] |
| | Numerical optimization | 2019 | Mu [111] |
| | Numerical optimization | 2020 | Mu et al. [112] |

states. The emergence of real quantum computers and the implementation of quantum-inspired metaheuristics on them is a significant issue to be considered. One solution is to use a hybrid approach, using quantum circuits to implement quantum population and the quantum gates and utilizing conventional computers for fitness function

evaluation. However, we cannot take advantage of the super-fast quantum computation, and we only profit from the true probabilistic nature of qubits which might not significantly outperform the simulated qubits in classical computers. In this manner, we will still struggle with the massive amount of time needed to run the metaheuristic

Table 6 Error results of quantum-inspired metaheuristic algorithms applied on benchmark functions

| Algorithm | Maximum evaluations | Dim. | Metric | Sphere function | Rosenbrock | Schwefel function | Rastrigin function | Ackley function | Griewank |
|-----------------------|---------------------|------|--------|-----------------|------------|-------------------|--------------------|-----------------|----------|
| Entanglement-QTS [98] | 15,000 | 30 | Mean | 0.00E+00 | 0.00E+00 | 8.27E-07 | 0.00E+00 | 0.00E+00 | 0.00E+00 |
| | | | SD | 0.00E+00 | 0.00E+00 | 2.18E-11 | 0.00E+00 | 0.00E+00 | 0.00E+00 |
| | 300,000 | 40 | Mean | 0.00E+00 | 0.00E+00 | 1.10E-06 | 0.00E+00 | 0.00E+00 | 0.00E+00 |
| | | | SD | 0.00E+00 | 0.00E+00 | 1.22E-11 | 0.00E+00 | 0.00E+00 | 0.00E+00 |
| | | 50 | Mean | 0.00E+00 | 0.00E+00 | 1.38E-06 | 0.00E+00 | 0.00E+00 | 0.00E+00 |
| | | | SD | 0.00E+00 | 0.00E+00 | 1.38E-11 | 0.00E+00 | 0.00E+00 | 0.00E+00 |
| MQHOA [104] | 300,000 | 30 | Mean | 4.65E-84 | 4.91E-01 | NA | NA | 1.70E-01 | 2.51E-03 |
| | | | SD | 4.82E-84 | 3.76E-01 | NA | NA | 5.01E-01 | 4.87E-03 |
| | 600,000 | 60 | Mean | 2.50E-86 | 6.09E-01 | NA | NA | 1.93E+00 | 2.75E-03 |
| | | | SD | 4.20E-86 | 5.79E-01 | NA | NA | 7.27E-01 | 5.74E-03 |
| MHO-MQHOA [110] | 300,000 | 30 | Mean | 1.58E-177 | 2.17E+00 | NA | NA | 4.50E-15 | 1.64E-04 |
| | | | SD | 0.00E+00 | 9.65E+00 | NA | NA | 4.59E-16 | 1.27E-03 |
| | 600,000 | 60 | Mean | 8.40E-161 | 4.15E+00 | NA | NA | 1.15E-14 | 3.70E-18 |
| | | | SD | 6.51E-143 | 1.25E+01 | NA | NA | 5.59E-15 | 2.01E-17 |
| QSSA [89] | 15,000 | 30 | Mean | 0.00E+00 | 3.42E+00 | 5.56E+03 | 2.47E-323 | 8.88E-16 | 0.00E+00 |
| | | | SD | 0.00E+00 | 3.72E+00 | 1.18E+02 | 0.00E+00 | 2.01E-31 | 0.00E+00 |
| HSBQEA [25] | 500,000 | 50 | Mean | 1.63E+03 | 9.17E+07 | 1.88E+02 | 7.99E+01 | 1.72E+01 | 1.53E+01 |
| | | | SD | 7.16E+02 | 7.77E+07 | 8.73E+01 | 1.82E+01 | 1.12E+00 | 5.86E+00 |
| SRQEA [25] | 500,000 | 50 | Mean | 0.00E+00 | 4.34E+01 | 0.00E+00 | 0.00E+00 | 5.63E-07 | 1.48E-02 |
| | | | SD | 0.00E+00 | 3.09E+01 | 0.00E+00 | 0.00E+00 | 3.26E-06 | 2.59E-02 |
| e-QPSO [77] | 15,000 | 30 | Mean | 8.23E-95 | 2.76E+01 | 4.82E+03 | 0.00E+00 | 1.42E-15 | 0.00E+00 |
| | | | SD | 8.15E-94 | 3.76E-01 | 8.05E+02 | 0.00E+00 | 1.27E-15 | 0.00E+00 |
| QIAEA [50] | 2000 | 2 | Mean | NA | 2.48E-02 | 4.17E-04 | 3.81E-04 | NA | 3.52E-03 |
| | | | SD | NA | 6.48E-02 | 5.11E-04 | 4.34E-04 | NA | 3.75E-03 |
| QECBO [108] | 10,000 | 10 | Mean | NA | NA | 0.00E+00 | 1.05E+00 | 2.45E-01 | 4.52E-01 |
| | | | SD | NA | NA | 6.65E-01 | 9.24E-01 | 6.93E-02 | 1.19E-01 |
| | 20,000 | 30 | Mean | 2.90E-06 | 1.60E-01 | NA | NA | NA | NA |
| | | | SD | 1.05E-05 | 8.93E-02 | NA | NA | NA | NA |

algorithms since classical computers are in charge of fitness function evaluations. In addition, this approach only works for binary-coded algorithms, and the issue for real-coded algorithms is much more complicated. So, there is a considerable demand for translating quantum-inspired metaheuristics to real quantum computers.

Second, optimizing the current algorithm’s parameters has gotten inadequate attention. For instance, in a quantum-inspired genetic algorithm, the number of the qubits in chromosomes, the state of being static or dynamic of chromosomes’ length, and the impact of the size and direction of rotation gates are potential subjects for further research.

Third, comparing and using the current quantum-inspired optimization algorithms on new applications is tedious because there is no programming library with comprehensive implementation of quantum-inspired optimization algorithms like the libraries implemented for conventional metaheuristics (see [146]).

5 Conclusions

This review covers quantum-inspired metaheuristics proposed between 2017 and 2022 and organizes these algorithms concerning their source of inspiration. The algorithms’ modifications, innovations, and contributions are also introduced in tabular format for readability and quick reference.

The dominant sources of inspiration for quantum-inspired metaheuristics are evolutionary and genetic algorithms. The swarm-based inspired algorithms are the following most widely-used techniques. The quantum-inspired metaheuristic concept has been adapted to some classical problems such as time scheduling travelling salesperson, and 0-1 knapsack as well as numerous applications, namely image segmentation, RNA prediction, cloud computing, flight control, network community detection, network design, network routing, view selection, fuzzy controller design, multi-agent systems, airport gate allocation, and structural design. There has been

Table 7 Recent applications of some conventional metaheuristics with no quantum-inspired version

| Algorithm | Application | Year | References |
|---|---|------|----------------------------|
| Arithmetic optimization algorithm (AOA) | Numerical optimization and engineering problems | 2022 | Zhang et al. [121] |
| | Solving industrial engineering problems | 2022 | Fang et al. [122] |
| | Internet of healthcare things (IoHT) | 2022 | Dahou et al. [123] |
| Aquila optimizer (AO) | Text document clustering | 2022 | Abualigah et al. [124] |
| | Hyperspectral image classification | 2022 | Subha et al. [125] |
| | Automatic voltage regulation | 2022 | Ekinci et al. [126] |
| Red Deer Algorithm (RDA) | Wind forecasting | 2022 | Xing et al. [127] |
| | Closed-loop supply chain network | 2021 | Chohan et al. [128] |
| Social engineering optimizer (SEO) | Decision-making model design | 2022 | Chohan et al. [129] |
| | Supply chain network design | 2021 | Mousavi et al. [130] |
| | Relief supply chain for SARS-COV-2 pandemic | 2021 | Zahedi et al. [131] |
| Equilibrium optimizer (EO) | Feature selection | 2022 | Varzaneh et al. [132] |
| | Renewable energy systems design | 2022 | Zhao et al. [133] |
| | Power flow optimization | 2022 | Houssein et al. [134] |
| Keshtel algorithm (KA) | Shrimp supply chain design | 2021 | Mosallanezhad et al. [135] |
| | Multitask supply chain network | 2021 | Zahedi et al. [136] |
| | Sustainable agricultural supply chain network | 2021 | Hamdi et al. [137] |
| | Multi objecti supply chain design | 2021 | Fasihi et al. [138] |
| African vultures optimizer (AVO) | Skin cancer detection | 2022 | Hu et al. [139] |
| | Combined systems modeling | 2022 | Chen et al. [140] |
| | Feature selection | 2022 | Balakrishnan et al. [141] |
| Harris Hawks optimizer (HHO) | Fault diagnosis of wind turbine | 2022 | Long et al. [142] |
| | Numerical optimization and engineering problems | 2022 | Li et al. [143] |
| | Hybrid energy systems optimization | 2022 | Anand et al. [144] |
| | Image segmentation | 2022 | Dong et al. [145] |

a vast interest in the field of quantum-inspired metaheuristics recently. Quantum computing elevates metaheuristics' performance by its characteristics, such as parallelism and qubit probabilistic representation, which are in favour of efficiency and accuracy, respectively. However, quantum-inspired metaheuristic algorithms adapt quantum mechanics concepts and are mostly executed on classical computers. Therefore, quantum qubits must be simulated on classical bits, and practically it leads to inefficiency. State-of-the-art quantum computers still have a limited number of qubits. So, it is impossible to execute most of these algorithms on real quantum computers for the time being. However, concerning the pace of improvements in quantum hardware, the development of powerful quantum computers does not seem unachievable in the early future. Finally, although there have been remarkable works considering quantum-inspired metaheuristics, the literature lacks a comprehensive comparison between the algorithms in terms of performance and time complexity.

The potential future works consist of further studies on metaheuristic algorithms to be implemented solely on real quantum computers or at least to harness the quantum

computing capabilities in favour of performance improvement. Real-coded quantum-inspired algorithms also need more attention, as binary-coded algorithms require extra computations to convert binary and decimal representations for fitness function evaluation in numerical optimization problems. Moreover, the proposal of the quantum-inspired version of the conventional metaheuristics presented in Sect. 3 can be considered for future studies.

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