REVIEW ARTICLE

A review of recent advances in quantum-inspired metaheuristics

Shahin Hakemi[1] · Mahboobeh Houshmand[1] · Esmaeil KheirKhah[1] · Seyyed Abed Hosseini[2]

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.

✉ Mahboobeh Houshmand
  houshmand@mshdiau.ac.ir

✉ Esmaeil KheirKhah
  kheirkhah@mshdiau.ac.ir

  Shahin Hakemi
  shahinhakemi@gmail.com

  Seyyed Abed Hosseini
  hosseyni@mshdiau.ac.ir

1   Department of Computer Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran

2   Department of Electrical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran

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, SienceDirect, and IEEE Xplore using keywords "quantum-inspired metaheuristic", "quantum-inspired gentic 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:

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

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 ith qubit and α_i' and β_i' are probability amplitudes of the qubit after rotation [12].
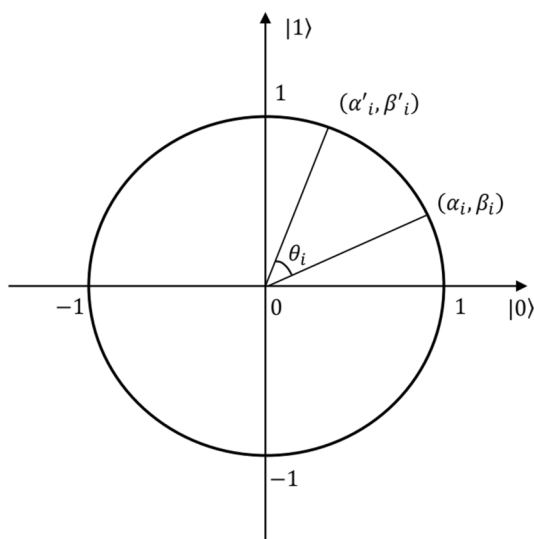
Fig. 1 Rotation operation for qubit
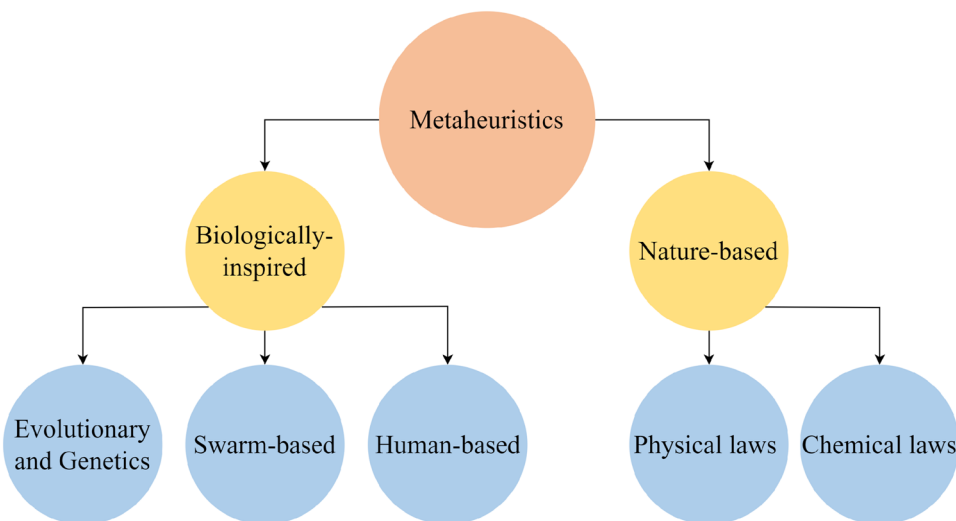
It is worth mentioning here that in the quantum-inspired metaheuristics literature, the three-dimensional model of qubits in the Bloch sphere is simplified to two-dimensional, representing the rotation angle and probability amplitudes before and after rotation. Also, the measurement of quantum bits is 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
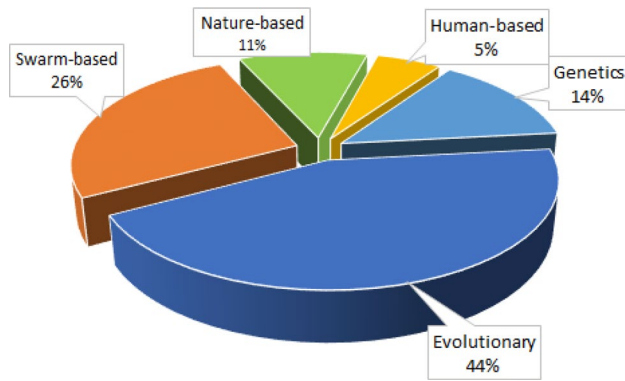

Fig. 2 Metaheuristics major categories

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 inpired 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 bt 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]
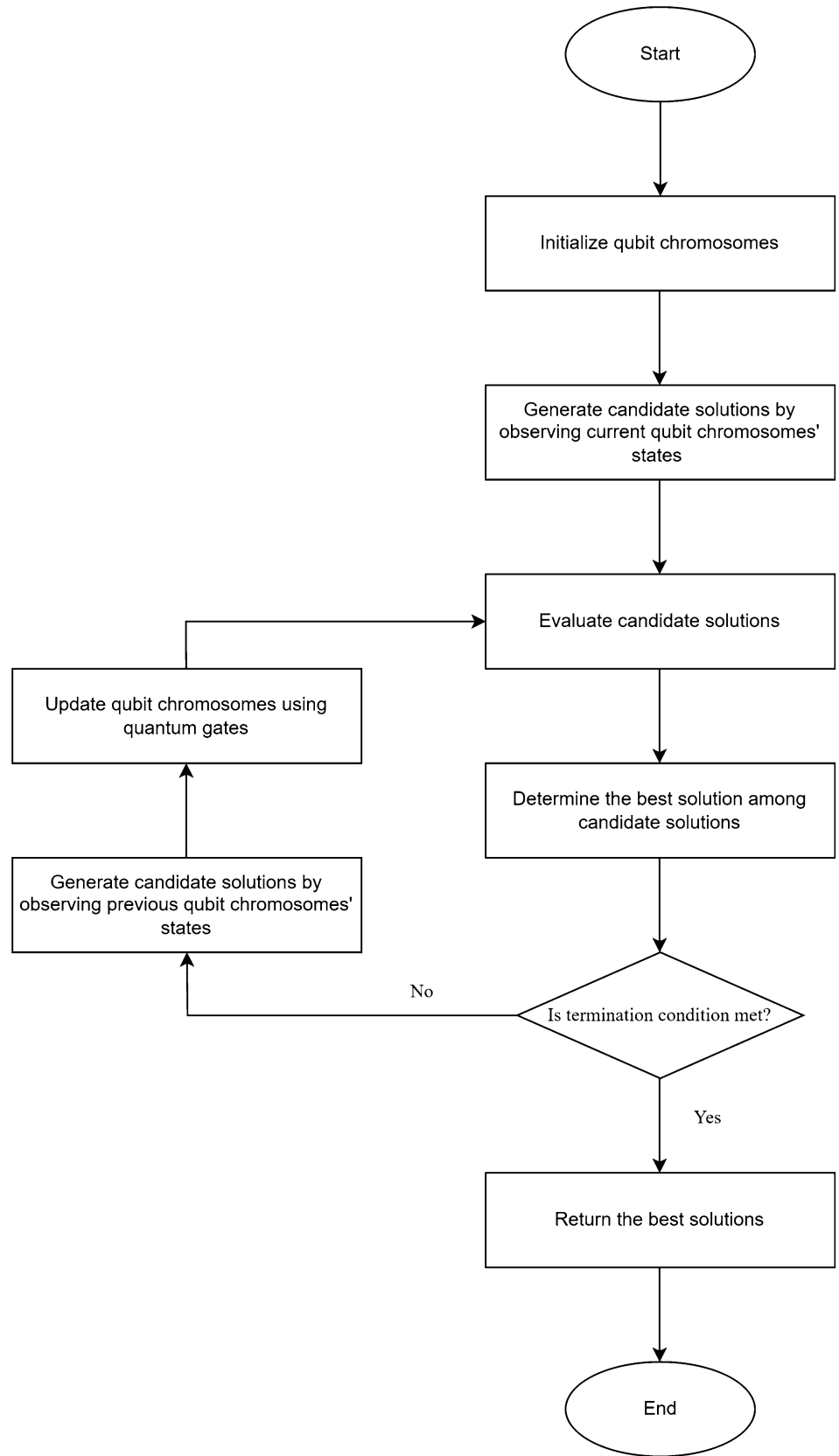
Fig. 4 Flowchart of QGA [13]

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 is 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
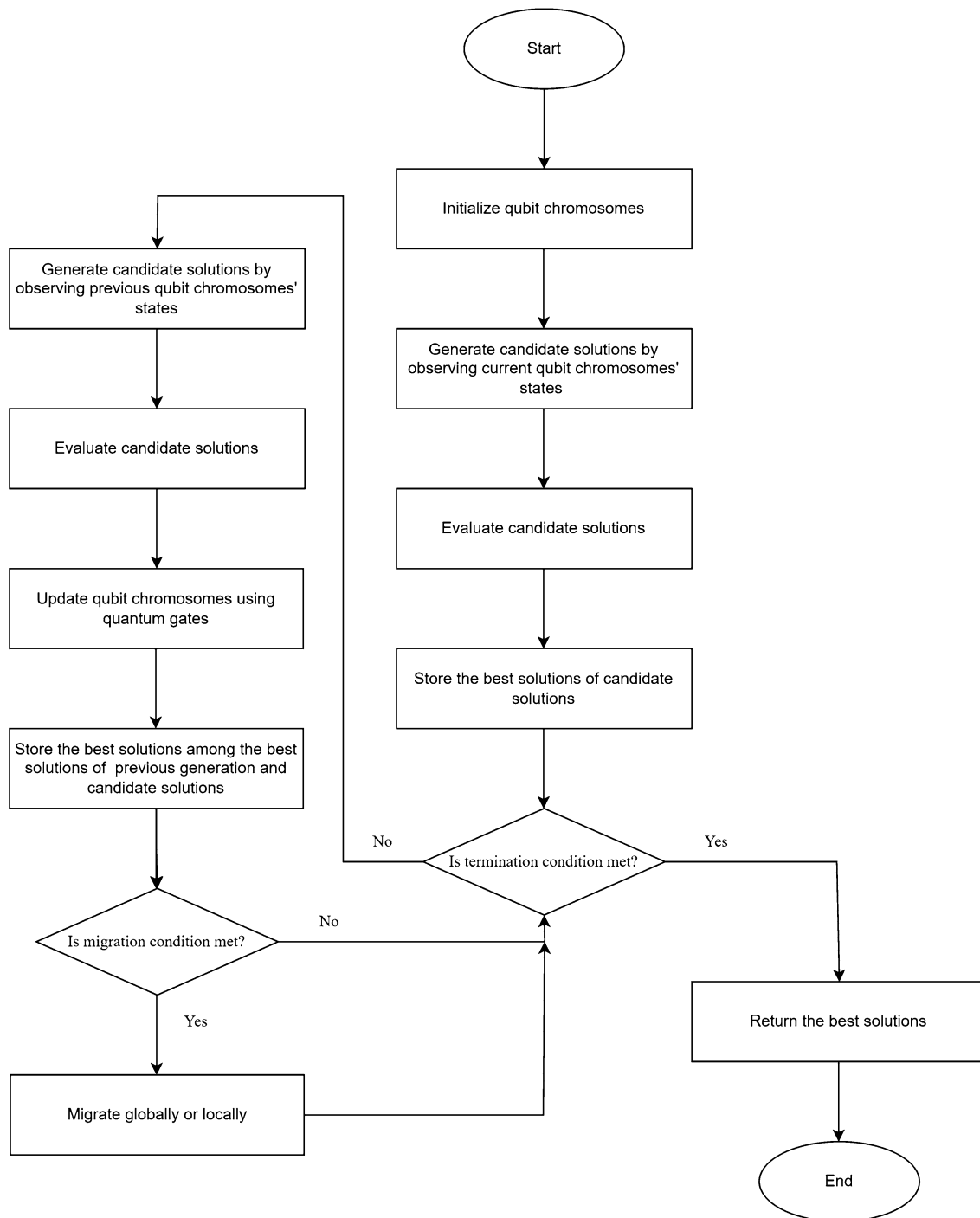
Fig. 5 Flowchart of QEA [24]

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 cha-otic 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]
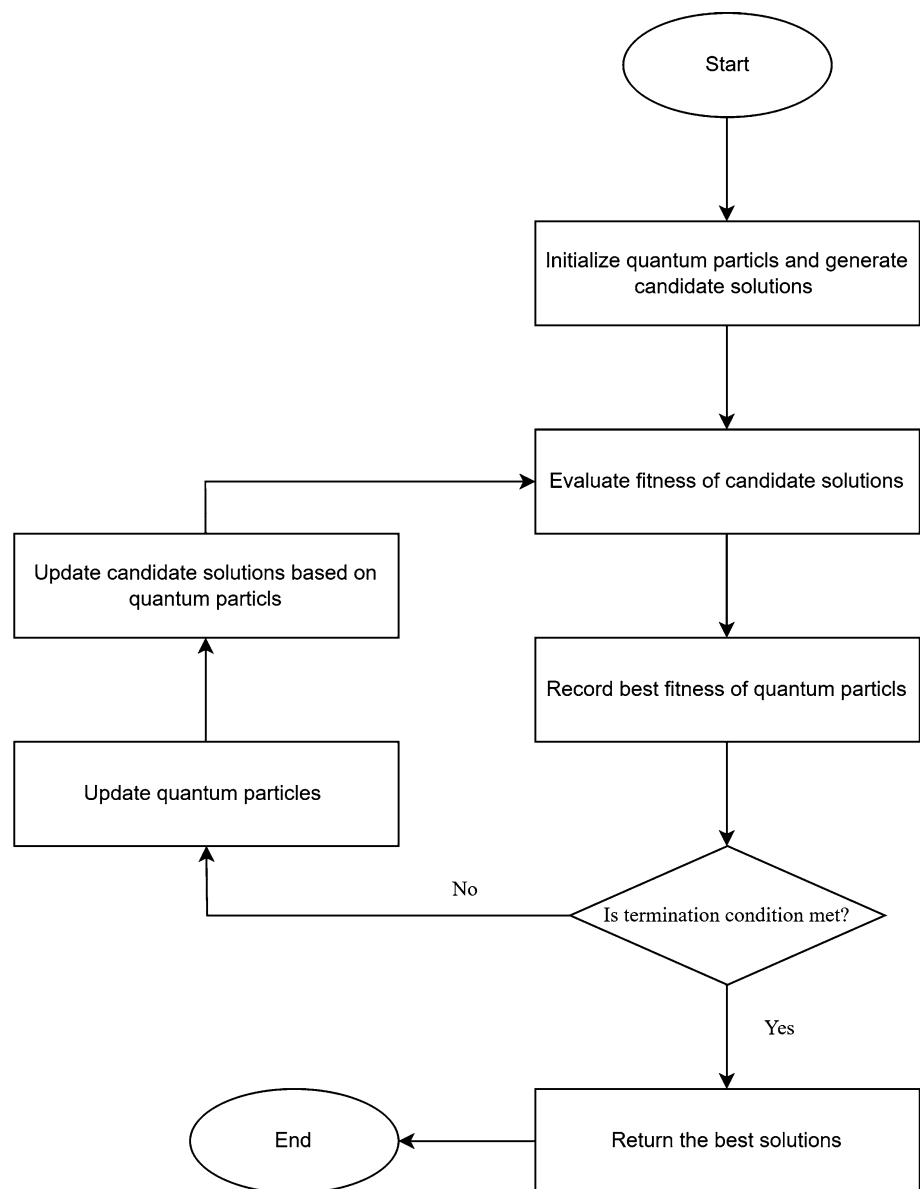
behaviour. Equilibrium Optimizer (EO) [115] is a physics-based optimization algorithm inspired by a volume mass balance equation. Social Engineering Optimizer (SEO) [116] is inspired by human social behavior. Red Deer Algorithm (RDA) [117] mimics the Scottish red deer's mating behavior. Other examples 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
		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]
	Text document clustering	2022	Abualigah et al. [124]
Aquila optimizer (AO)	Hyperspectral image classification	2022	Subha et al. [125]
	Automatic voltage regulation	2022	Ekinci et al. [126]
	Wind forcasting	2022	Xing et al. [127]
Red Deer Algorithm (RDA)	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.

Declarations

Consent for publication Not applicable.

References

1. Salcedo-Sanz S (2016) Modern meta-heuristics based on nonlinear physics processes: a review of models and design procedures. Phys Rep 655:1–70
2. Hussain K, Mohd Salleh MN, Cheng S, Shi Y (2019) Metaheuristic research: a comprehensive survey. Artif Intell Rev 52(4):2191–2233
3. Wolpert DH, Macready WG (1997) No free lunch theorems for optimization. IEEE Trans Evol Comput 1(1):67–82
4. Shalf J (2020) The future of computing beyond Moore's law. Philos Trans R Soc A 378(2166):20190061
5. Prakash KB, Kanagachidambaresan GR, Srikanth V, Vamsidhar E (2021) Cognitive engineering for next generation computing: a practical analytical approach. Wiley. https://books.google.com/books?id=jOEmEAAAQBAJ
6. Feynman RP (1982) Simulating physics with computers. Int J Theor Phys 21(6):467–488. https://doi.org/10.1007/BF02650179
7. Manin Y (1980) Computable and uncomputable, vol 128. Sovetskoye Radio, Moscow
8. Shor PW (1998) Quantum computing. Doc Math 1(1000):467–486
9. GroverL K (1996) Afastquantum mechanicalalgorithmfordatag basesearch. In: Proceedings of the 28th annual ACM symposium on theory of computing. ACM
10. Dragoi EN, Dafinescu V (2021) Review of metaheuristics inspired from the animal kingdom. Mathematics 9(18):2335
11. Sutor RS (2019) Dancing with qubits: how quantum computing works and how it can change the world. Packt Publishing Ltd
12. Dey A, Dey S, Bhattacharyya S, Platos J, Snasel V (2020) 5 quantum inspired automatic clustering algorithms: a comparative study of genetic algorithm and bat algorithm. Quantum Mach Learn 6:89
13. Han K-H, Kim J-H (2000) Genetic quantum algorithm and its application to combinatorial optimization problem. In: Proceedings of the 2000 congress on evolutionary computation. CEC00 (Cat. No. 00TH8512), vol 2 . IEEE, pp 1354–1360
14. Konar D, Bhattacharyya S, Sharma K, Sharma S, Pradhan SR (2017) An improved hybrid quantum-inspired genetic algorithm (HQIGA) for scheduling of real-time task in multiprocessor system. Appl Soft Comput 53:296–307
15. Alam T, Raza Z (2018) Quantum genetic algorithm based scheduler for batch of precedence constrained jobs on heterogeneous computing systems. J Syst Softw 135:126–142
16. Qi B, Nener B, Xinmin W (2019) A quantum inspired genetic algorithm for multimodal optimization of wind disturbance alleviation flight control system. Chin J Aeronaut 32(11):2480–2488
17. Shi S, Zhang X-L, Zhao X-L, Yang L, Du W, Wang Y-J (2019) Prediction of the RNA secondary structure using a multi-population assisted quantum genetic algorithm. Hum Hered 84(1):1–8
18. Suo J, Gu L, Pan Y, Yang S, Hu X (2020) Quantum inspired genetic algorithm for double digest problem. IEEE Access 8:72910–72916
19. Pradhan K, Basu S, Thakur K, Maity S, Maiti M (2020) Imprecise modified solid green traveling purchaser problem for substitute items using quantum-inspired genetic algorithm. Comput Ind Eng 147:106578
20. Pereira CS, Dias DM, Pacheco MAC, Vellasco MMR, da Cruz AVA, Hollmann EH (2020) Quantum-inspired genetic programming algorithm for the crude oil scheduling of a real-world refinery. IEEE Syst J 14(3):3926–3937
21. Sabeti M, Karimi L, Honarvar N, Taghavi M, Boostani R (2020) Quantumized genetic algorithm for segmentation and optimization tasks. Biomed Eng: Appl, Basis Commun 32(03):2050022
22. Saad HM, Chakrabortty RK, Elsayed S, Ryan MJ (2021) Quantum-inspired genetic algorithm for resource-constrained project-scheduling. IEEE Access 9:38488–38502
23. Hedhli A, Mezni H, Said LB (2021) A quantum-inspired neural network model for predictive BPaaS management. In: International conference on database and expert systems applications. Springer, pp 91–103
24. Han K-H, Kim J-H (2002) Quantum-inspired evolutionary algorithm for a class of combinatorial optimization. IEEE Trans Evol Comput 6(6):580–593
25. Wright J, Jordanov I (2017) Quantum inspired evolutionary algorithms with improved rotation gates for real-coded synthetic and real world optimization problems. Integr Comput-Aided Eng 24(3):203–223
26. Lei W, Manier H, Manier M-A, Wang X (2017) A hybrid quantum evolutionary algorithm with improved decoding scheme for a robotic flow shop scheduling problem. Math Probl Eng 2017:1–13
27. Talbi H, Draa A (2017) A new real-coded quantum-inspired evolutionary algorithm for continuous optimization. Appl Soft Comput 61:765–791
28. Wu X, Wu S (2017) An elitist quantum-inspired evolutionary algorithm for the flexible job-shop scheduling problem. J Intell Manuf 28(6):1441–1457
29. Liu M, Yi S, Wen P, Song H (2017) Disruption management for predictable new job arrivals in cloud manufacturing. J Intell Syst 26(4):683–695
30. Gupta S, Mittal S, Gupta T, Singhal I, Khatri B, Gupta AK, Kumar N (2017) Parallel quantum-inspired evolutionary algorithms for community detection in social networks. Appl Soft Comput 61:331–353
31. Xie R, Li Z, Huang T, Liu Y (2017) Energy-efficient joint content caching and small base station activation mechanism design in heterogeneous cellular networks. China Commun 14(10):70–83
32. da Silveira LR, Tanscheit R, Vellasco MM (2017) Quantum inspired evolutionary algorithm for ordering problems. Expert Syst Appl 67:71–83
33. Tirumala SS (2018) A quantum-inspired evolutionary algorithm using gaussian distribution-based quantization. Arab J Sci Eng 43(2):471–482
34. Kumar S, Vijay Kumar T (2018) A novel quantum-inspired evolutionary view selection algorithm. Sādhanā 43(10):1–20
35. Yang W, Ho SL, Yang S (2017) An efficient direct search methodology for robust optimization of electromagnetic devices. IEEE Trans Magn 54(3):1–4
36. Yu G-R, Huang Y-C, Cheng C-Y (2018) Optimally robust h-inf polynomial fuzzy controller design using quantum-inspired evolutionary algorithm. Int J Syst Sci 49(12):2601–2617
37. Oktavian MR, Agung A, Harto AW (2018) Fuel loading pattern optimization with constraint on fuel assembly inventory using quantum-inspired evolutionary algorithm. In: E3S web of conferences, vol 42. EDP Sciences, p 01007
38. Si-Jung R, Jun-Seuk G, Seung-Hwan B, Songcheol H, Jong-Hwan K (2018) Feature-based hand gesture recognition using an FMCW radar and its temporal feature analysis. IEEE Sens J 18:7593–7602
39. Wu B, Gao Y, Feng S, Chanwimalueang T (2018) Sparse optimistic based on lasso-LSQR and minimum entropy de-convolution with FARIMA for the remaining useful life prediction of machinery. Entropy 20(10):747

40. Bharill N, Patel OP, Tiwari A (2018) Quantum-inspired evolutionary approach for selection of optimal parameters of fuzzy clustering. Int J Syst Assur Eng Manag 9(4):875–887

41. Yuanyuan M, Xiyu L (2018) Quantum inspired evolutionary algorithm for community detection in complex networks. Phys Lett A 382(34):2305–2312

42. Liu M, Yi S, Wen P (2018) Quantum-inspired hybrid algorithm for integrated process planning and scheduling. Proc Inst Mech Eng, Part B: J Eng Manuf 232(6):1105–1122

43. Kaveh A, Dadras A, Geran Malek N (2019) Robust design optimization of laminated plates under uncertain bounded buckling loads. Struct Multidiscipl Optim. https://doi.org/10.1007/s00158-018-2106-0

44. Arzani H, Kaveh A, Kamalinejad M (2019) Optimal design of pitched roof rigid frames with non-prismatic members using quantum evolutionary algorithm. Period Polytech Civil Eng 63(2):593–607

45. Nunes W, Vellasco M, Tanscheit R (2019) Quantum-inspired evolutionary multi-objective fuzzy classifier with real and categorical representation. J Intell Fuzzy Syst 36(6):5875–5887

46. Hsieh M-S, Wu S-C (2019) Modified quantum evolutionary algorithm and self-regulated learning for reactor loading pattern design. Ann Nucl Energy 127:268–277

47. Kaveh A, Dadras Eslamlou A (2019) An efficient two-stage method for optimal sensor placement using graph-theoretical partitioning and evolutionary algorithms. Struct Control Health Monit 26(4):2325

48. Kolahdoozi M, Amirkhani A, Shojaeefard MH, Abraham A (2019) A novel quantum inspired algorithm for sparse fuzzy cognitive maps learning. Appl Intell 49(10):3652–3667

49. Bharill N, Patel OP, Tiwari A, Mu L, Li D-L, Mohanty M, Kaiwartya O, Prasad M (2019) A generalized enhanced quantum fuzzy approach for efficient data clustering. IEEE Access 7:50347–50361

50. Montiel O, Rubio Y, Olvera C, Rivera A (2019) Quantum-inspired acromyrmex evolutionary algorithm. Sci Rep 9(1):1–10

51. Hou J, Wang W, Zhang Y, Liu X, Xie Y (2020) Multi-objective quantum inspired evolutionary SLM scheme for PAPR reduction in multi-carrier modulation. IEEE Access 8:26022–26029

52. Gao L, Liu R, Wang F, Wu W, Bai B, Yang S, Yao L (2020) An advanced quantum optimization algorithm for robot path planning. J Circuits, Syst Comput 29(08):2050122

53. Qu Z, Li T, Tan X, Li P, Liu X (2020) A modified quantum-inspired evolutionary algorithm for minimising network coding operations. Int J Wirel Mob Comput 19(4):401–410

54. Ramos AC, Vellasco M (2020) Chaotic quantum-inspired evolutionary algorithm: enhancing feature selection in BCI. In: 2020 IEEE congress on evolutionary computation (CEC). IEEE, pp 1–8

55. Cao B, Fan S, Zhao J, Yang P, Muhammad K, Tanveer M (2020) Quantum-enhanced multiobjective large-scale optimization via parallelism. Swarm Evol Comput 57:100697

56. Cai X, Zhao H, Shang S, Zhou Y, Deng W, Chen H, Deng W (2021) An improved quantum-inspired cooperative co-evolution algorithm with muli-strategy and its application. Expert Syst Appl 171:114629

57. Dias EDM, Vellasco MMBR, da Cruz AVA (2021) Quantum-inspired neuro coevolution model applied to coordination problems. Expert Syst Appl 167:114133

58. Beni G, Wang J (1993) Swarm intelligence in cellular robotic systems. In: Robots and biological systems: towards a new bionics? Springer, pp 703–712

59. Kennedy J, Eberhart R (1995) Particle swarm optimization. In: Proceedings of ICNN'95-international conference on neural networks, vol 4 IEEE, pp 1942–1948

60. Gandomi AH, Alavi AH (2012) Krill herd: a new bio-inspired optimization algorithm. Commun Nonlinear Sci Numer Simul 17(12):4831–4845

61. Yang X-S (2010) Firefly algorithm, stochastic test functions and design optimisation. International J Bio-inspired Comput 2(2):78–84

62. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. Adv Eng Softw 69:46–61

63. Dorigo M, Birattari M, Stutzle T (2006) Ant colony optimization. IEEE Comput Intell Mag 1(4):28–39

64. Yang X-S (2010) A new metaheuristic bat-inspired algorithm. In: Nature inspired cooperative strategies for optimization (NICSO 2010). Springer, pp 65–74

65. Krishnanand K, Ghose D (2009) Glowworm swarm optimisation: a new method for optimising multi-modal functions. Int J Comput Intell Stud 1(1):93–119

66. Wang G-G, Deb S, Cui Z (2019) Monarch butterfly optimization. Neural Comput Appl 31(7):1995–2014

67. Sharma H, Hazrati G, Bansal JC (2019) Spider monkey optimization algorithm. In: Evolutionary and swarm intelligence algorithms. Springer, pp 43–59

68. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67

69. Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM (2017) Salp swarm algorithm: a bio-inspired optimizer for engineering design problems. Adv Eng Softw 114:163–191

70. Moosavi SHS, Bardsiri VK (2017) Satin bowerbird optimizer: a new optimization algorithm to optimize ANFIS for software development effort estimation. Eng Appl Artif Intell 60:1–15

71. Raouf OA, Hezam IM (2017) Sperm motility algorithm: a novel metaheuristic approach for global optimisation. Int J Oper Res 28(2):143–163

72. Jain M, Singh V, Rani A (2019) A novel nature-inspired algorithm for optimization: squirrel search algorithm. Swarm Evol Comput 44:148–175

73. Abualigah L, Abd Elaziz M, Sumari P, Geem ZW, Gandomi AH (2022) Reptile search algorithm (RSA): a nature-inspired metaheuristic optimizer. Expert Syst Appl 191:116158

74. Yang S, Wang M, et al (2004) A quantum particle swarm optimization. In: Proceedings of the 2004 congress on evolutionary computation (IEEE Cat. No. 04TH8753), vol 1. IEEE, pp 320–324

75. Rehman OU, Yang J, Zhou Q, Yang S, Khan S (2017) A modified QPSO algorithm applied to engineering inverse problems in electromagnetics. Int J Appl Electromagnet Mech 54(1):107–121

76. Dey A, Dey S, Bhattacharyya S, Platos J, Snasel V (2020) Novel quantum inspired approaches for automatic clustering of gray level images using particle swarm optimization, spider monkey optimization and ageist spider monkey optimization algorithms. Appl Soft Comput 88:106040

77. Agrawal R, Kaur B, Agarwal P (2021) Quantum inspired particle swarm optimization with guided exploration for function optimization. Appl Soft Comput 102:107122

78. Li G, Wang W, Zhang W, You W, Wu F, Tu H (2021) Handling multimodal multi-objective problems through self-organizing quantum-inspired particle swarm optimization. Inf Sci 577:510–540

79. Balicki J (2021) Many-objective quantum-inspired particle swarm optimization algorithm for placement of virtual machines in smart computing cloud. Entropy 24(1):58

80. Liu Z, Li S (2020) A coevolutionary quantum krill herd algorithm for solving multi-objective optimisation problems. Int J Model Ident Control 34(4):350–358

81. Choudhury A, Samanta S, Pratihar S, Bandyopadhyay O (2022) Multilevel segmentation of hippocampus images using

global steered quantum inspired firefly algorithm. Appl Intell 52(7):7339–7372

82. Srikanth K, Panwar LK, Panigrahi BK, Herrera-Viedma E, Sangaiah AK, Wang G-G (2018) Meta-heuristic framework: quantum inspired binary grey wolf optimizer for unit commitment problem. Comput Electr Eng 70:243–260

83. Wang Y, Wang W (2021) Quantum-inspired differential evolution with grey wolf optimizer for 0–1 knapsack problem. Mathematics 9(11):1233

84. Li F, Liu M, Xu G (2019) A quantum ant colony multi-objective routing algorithm in WSN and its application in a manufacturing environment. Sensors 19(15):3334

85. Sharma P, Sharma K (2022) A novel quantum-inspired binary bat algorithm for leukocytes classification in blood smear. Expert Syst 39(3):12813

86. Gao H, Du Y, Diao M (2017) Quantum-inspired glowworm swarm optimisation and its application. Int J Comput Sci Math 8(1):91–100

87. Yi J-H, Lu M, Zhao X-J (2020) Quantum inspired monarch butterfly optimisation for UCAV path planning navigation problem. Int J Bio-Inspired Comput 15(2):75–89

88. Agrawal R, Kaur B, Sharma S (2020) Quantum based whale optimization algorithm for wrapper feature selection. Appl Soft Comput 89:106092

89. Chen R, Dong C, Ye Y, Chen Z, Liu Y (2019) QSSA: quantum evolutionary salp swarm algorithm for mechanical design. IEEE Access 7:145582–145595

90. Zhang S, Zhou G, Zhou Y, Luo Q (2021) Quantum-inspired satin bowerbird algorithm with Bloch spherical search for constrained structural optimization. J Ind Manag Optim 17(6):3509

91. Hezam IM, Abdul-Raof O, Foul A, Aqlan F (2022) A quantum-inspired sperm motility algorithm. AIMS Math 7(5):9057–9088

92. Zhang Y, Wei C, Zhao J, Qiang Y, Wu W, Hao Z (2022) Adaptive mutation quantum-inspired squirrel search algorithm for global optimization problems. Alex Eng J 61(9):7441–7476

93. Almodfer R, Mudhsh M, Chelloug S, Shehab M, Abualigah L, Abd Elaziz M (2022) Quantum mutation reptile search algorithm for global optimization and data clustering. Hum-Centr Comput Inf Sci 12

94. Geem ZW, Kim JH, Loganathan GV (2001) A new heuristic optimization algorithm: harmony search. Simulation 76(2):60–68. https://doi.org/10.1177/003754970107600201

95. Glover F (1989) Tabu search-part I. ORSA J Comput 1(3):190–206

96. Glover F (1990) Tabu search-part II. ORSA J Comput 2(1):4–32

97. Sadeghi Hesar A, Kamel SR, Houshmand M (2021) A quantum multi-objective optimization algorithm based on harmony search method. Soft Comput 25(14):9427–9439

98. Kuo S-Y, Chou Y-H (2017) Entanglement-enhanced quantum-inspired Tabu search algorithm for function optimization. IEEE Access 5:13236–13252

99. Chou Y-H, Kuo S-Y, Jiang Y-C (2018) A novel portfolio optimization model based on trend ratio and evolutionary computation. IEEE Trans Emerging Top Comput Intell 3(4):337–350

100. Chou Y-H, Lai Y-T, Jiang Y-C, Kuo S-Y (2021) Using trend ratio and GNQTS to assess portfolio performance in the us stock market. IEEE Access 9:88348–88363

101. Rashedi E, Nezamabadi-Pour H, Saryazdi S (2009) GSA: a gravitational search algorithm. Inf Sci 179(13):2232–2248

102. Kaveh A, Mahdavi VR (2014) Colliding bodies optimization: a novel meta-heuristic method. Comput Struct 139:18–27

103. Kaveh A, Talatahari S (2010) A novel heuristic optimization method: charged system search. Acta Mech 213(3):267–289

104. Wang P, Ye X, Li B, Cheng K (2018) Multi-scale quantum harmonic oscillator algorithm for global numerical optimization. Appl Soft Comput 69:655–670

105. Singh KV, Raza Z (2017) A quantum-inspired binary gravitational search algorithm-based job-scheduling model for mobile computational grid. Concurr Comput: Pract Exp 29(12):4103

106. Barani F, Mirhosseini M, Nezamabadi-Pour H (2017) Application of binary quantum-inspired gravitational search algorithm in feature subset selection. Appl Intell 47(2):304–318

107. Mirhosseini M, Fazlali M, Malazi HT, Izadi SK, Nezamabadi-pour H (2021) Parallel quadri-valent quantum-inspired gravitational search algorithm on a heterogeneous platform for wireless sensor networks. Comput Electr Eng 92:107085

108. Kaveh A, Kamalinejad M, Arzani H (2020) Quantum evolutionary algorithm hybridized with enhanced colliding bodies for optimization. In: Structures, vol 28. Elsevier, pp 1479–1501

109. Talatahari S, Azizi M, Toloo M, Baghalzadeh Shishehgarkhaneh M (2022) Optimization of large-scale frame structures using fuzzy adaptive quantum inspired charged system search. Int J Steel Struct 1–22

110. Li B, Wang P (2019) Multiscale quantum harmonic oscillator algorithm with multi-harmonic oscillators for numerical optimization. IEEE Access 7:51159–51170

111. Mu L (2019) Dynamic scale quantum-inspired optimisation algorithm under harmonic oscillator potential well. Electron Lett 55(18):1012–1015. https://doi.org/10.1049/el.2019.1681

112. Mu L, Wang P, Xin G (2020) Quantum-inspired algorithm with fitness landscape approximation in reduced dimensional spaces for numerical function optimization. Inf Sci 527:253–278

113. Abualigah L, Diabat A, Mirjalili S, Abd Elaziz M, Gandomi AH (2021) The arithmetic optimization algorithm. Comput Methods Appl Mech Eng 376:113609

114. Abualigah L, Yousri D, Abd Elaziz M, Ewees AA, Al-Qaness MA, Gandomi AH (2021) Aquila optimizer: a novel meta-heuristic optimization algorithm. Comput Ind Eng 157:107250

115. Faramarzi A, Heidarinejad M, Stephens B, Mirjalili S (2020) Equilibrium optimizer: a novel optimization algorithm. Knowl-Based Syst 191:105190

116. Fathollahi-Fard AM, Hajiaghaei-Keshteli M, Tavakkoli-Moghaddam R (2018) The social engineering optimizer (SEO). Eng Appl Artif Intell 72:267–293

117. Fathollahi-Fard AM, Hajiaghaei-Keshteli M, Tavakkoli-Moghaddam R (2020) Red deer algorithm (RDA): a new nature-inspired meta-heuristic. Soft Comput 24(19):14637–14665

118. Hajiaghaei-Keshteli M, Aminnayeri M (2013) Keshtel algorithm (ka); a new optimization algorithm inspired by Keshtels' feeding. In: Proceeding in IEEE conference on industrial engineering and management systems, pp 2249–2253

119. Abdollahzadeh B, Gharehchopogh FS, Mirjalili S (2021) African vultures optimization algorithm: a new nature-inspired metaheuristic algorithm for global optimization problems. Comput Ind Eng 158:107408

120. Heidari AA, Mirjalili S, Faris H, Aljarah I, Mafarja M, Chen H (2019) Harris hawks optimization: algorithm and applications. Futur Gener Comput Syst 97:849–872

121. Zhang Y-J, Wang Y-F, Yan Y-X, Zhao J, Gao Z-M (2022) Lmraoa: an improved arithmetic optimization algorithm with multi-leader and high-speed jumping based on opposition-based learning solving engineering and numerical problems. Alex Eng J 61(12):12367–12403

122. Fang H, Fu X, Zeng Z, Zhong K, Liu S (2022) An improved arithmetic optimization algorithm and its application to determine the parameters of support vector machine. Mathematics 10(16):2875

123. Dahou A, Al-qaness MA, Abd Elaziz M, Helmi A (2022) Human activity recognition in ioht applications using arithmetic optimization algorithm and deep learning. Measurement 199:111445

124. Abualigah L, Almotairi KH, Al-qaness MA, Ewees AA, Yousri D, Abd Elaziz M, Nadimi-Shahraki MH (2022) Efficient text document clustering approach using multi-search arithmetic optimization algorithm. Knowl-Based Syst 248:108833

125. Reddy TS, Harikiran J, Enduri MK, Hajarathaiah K, Almakdi S, Alshehri M, Naveed QN, Rahman MH (2022) Hyperspectral image classification with optimized compressed synergic deep convolution neural network with aquila optimization. Comput Intell Neurosci 2022:6781740

126. Ekinci S, Izci D, Eker E, Abualigah L (2022) An effective control design approach based on novel enhanced aquila optimizer for automatic voltage regulator. Artif Intell Rev 1–32

127. Xing Q, Wang J, Lu H, Wang S (2022) Research of a novel short-term wind forecasting system based on multi-objective aquila optimizer for point and interval forecast. Energy Convers Manag 115583

128. Chouhan VK, Khan SH, Hajiaghaei-Keshteli M (2021) Metaheuristic approaches to design and address multi-echelon sugarcane closed-loop supply chain network. Soft Comput 25(16):11377–11404

129. Chouhan VK, Khan SH, Hajiaghaei-Keshteli M (2022) Sustainable planning and decision-making model for sugarcane mills considering environmental issues. J Environ Manage 303:114252

130. Mousavi R, Salehi-Amiri A, Zahedi A, Hajiaghaei-Keshteli M (2021) Designing a supply chain network for blood decomposition by utilizing social and environmental factor. Comput Ind Eng 160:107501

131. Zahedi A, Salehi-Amiri A, Smith NR, Hajiaghaei-Keshteli M (2021) Utilizing IoT to design a relief supply chain network for the SARS-COV-2 pandemic. Appl Soft Comput 104:107210

132. Varzaneh ZA, Hossein S, Mood SE, Javidi MM (2022) A new hybrid feature selection based on improved equilibrium optimization. Chemom Intell Lab Syst 228:104618

133. Zhao M, Huan J, Huang X, Yu T, Ding Q (2022) Optimal coordinated frequency regulation of renewable energy systems via equilibrium optimizer. Front Energy Res 976

134. Houssein EH, Hassan MH, Mahdy MA, Kamel S (2022) Development and application of equilibrium optimizer for optimal power flow calculation of power system. Appl Intell 1–22

135. Mosallanezhad B, Hajiaghaei-Keshteli M, Triki C (2021) Shrimp closed-loop supply chain network design. Soft Comput 25(11):7399–7422

136. Zahedi A, Salehi-Amiri A, Hajiaghaei-Keshteli M, Diabat A (2021) Designing a closed-loop supply chain network considering multi-task sales agencies and multi-mode transportation. Soft Comput 25(8):6203–6235

137. Hamdi-Asl A, Amoozad-Khalili H, Tavakkoli-Moghaddam R, Hajiaghaei-Keshteli M (2021) Toward sustainability in designing agricultural supply chain network: a case study on palm date. Sci Iran

138. Fasihi M, Tavakkoli-Moghaddam R, Najafi SE, Hajiaghaei M (2021) Optimizing a bi-objective multi-period fish closed-loop supply chain network design by three multi-objective meta-heuristic algorithms. Sci Iran

139. Hu L, Zhang Y, Chen K, Mobayen S (2022) A computer-aided melanoma detection using deep learning and an improved African vulture optimization algorithm. Int J Imaging Syst Technol

140. Chen L, Huang H, Tang P, Yao D, Yang H, Ghadimi N (2022) Optimal modeling of combined cooling, heating, and power systems using developed African vulture optimization: a case study in watersport complex. Energy Sour, Part A: Recov, Util, Environ Effects 44(2):4296–4317

141. Balakrishnan K, Dhanalakshmi R, Seetharaman G (2022) S-shaped and v-shaped binary African vulture optimization algorithm for feature selection. Expert Syst 13079

142. Long W, Jiao J, Liang X, Xu M, Wu T, Tang M, Cai S (2022) A velocity-guided Harris Hawks optimizer for function optimization and fault diagnosis of wind turbine. Artif Intell Rev 1–43

143. Li W, Shi R, Dong J (2022) Harris hawks optimizer based on the novice protection tournament for numerical and engineering optimization problems. Appl Intell 1–26

144. Anand P, Kamboj VK, Alaraj M, Rizwan M, Mwakitalima IJ (2022) Optimal sizing of hybrid energy system using random exploratory search-centred Harris hawks optimizer with improved exploitation capability. Math Probl Eng 2022:5348017. https://doi.org/10.1155/2022/5348017

145. Dong W, Chen Y, Hu X (2022) Image multithreshold segmentation method based on improved Harris hawk optimization. Math Probl Eng 2022:7401040. https://doi.org/10.1155/2022/7401040

146. Thieu NV, Mirjalili S. MEALPY: a framework of the state-of-the-art meta-heuristic algorithms in python. https://doi.org/10.5281/zenodo.6684223