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A Comprehensive Review on Quantum-inspired Metaheuristic Algorithms: Basics to Recent Advancements

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Abstract
Quantum-inspired metaheuristic approaches, often called QIMAs, basically try to mix quantum computing ideas with the usual metaheuristic search routines. In practice, they make it easier to go through tangled search spaces, and they also help maintain a broader population variety, thanks to probabilistic qubit style encodings. Because of that, these methods have drawn a lot of attention across multiple academic directions, like materials science and engineering optimization, plus areas such as drug development and cryptography. QIMAs deliver a decent alternative by stitching Quantum-inspired mechanisms into algorithms that can run on ordinary classical machines, even if actually building full universal quantum computers is still hard, because quantum states are fragile and need heavy error correction, also the hardware is just plain complicated. Theoretical underpinnings, algorithmic progress and real-world applications of QIMAs are all looked at in depth in this article, sort of in a grounded way. The literature covering primarily 2015 to 2025 is reviewed carefully, then organized by the kind of inspiration it uses, like evolutionary algorithms, swarm intelligence approaches, and also genetic algorithms that are inspired by quantum mechanics in a more direct sense. The studies we examine show quite clearly how QIMAs can be used effectively for things like structural design, image processing, flight control, feature selection, and predictive modeling. The intention behind this review is to offer scholars and practitioners a complete, operationally efficient resource on Quantum-inspired optimization methods, for tackling tricky optimization problems.

Keywords- NP-hard problems, Global optimization, Metaheuristic algorithms, Quantum computing, Quantum-inspired metaheuristic algorithms.

Abbreviation

QIMA: Quantum Inspired Metaheuristic Algorithm
QIEA: Quantum Inspired Evolutionary Algorithm
PSO: Particle Swarm Optimization
GA: Genetic Algorithm
COA: Combinatorial Optimization Problem
QIGA: Quantum Inspired Genetic Algorithm
QISBA: Quantum inspired Swarm Based Algorithm
GWO: Grey Wolf Optimization
ES: Evolutionary Strategies

1. Introduction

Quantum-Inspired Metaheuristic Algorithms (QIMAs) are often used to tackle those kinds of hard optimization problems, where normal search feels stuck or slow. They kind of blend concepts from quantum computing with more traditional optimization methods. In practice, the goal is to boost population variety and also push up solution quality, mainly through probabilistic representations, together with quantum-inspired search steps that feel like they explore things in a more guided but uncertain way.

Getting the best possible value of an objective function by doing good exploration of the solution space is kind at the main goal in an optimization process. This is usually done by using suitable optimization algorithms, that manage to keep a nice balance between exploring and exploiting, so the search doesn't get stuck too early. At the same time the method still tries to land on high quality solutions while satisfying the special constraints that belong to that particular case.

QIMAs tend to be especially practical for real-world tasks, because unlike actual quantum computing approaches, they can be run on standard computing systems. So, there is no strict need for quantum hardware which makes things simpler. A good number of QIMAs are related to swarm intelligence, genetic algorithms, and evolutionary computation, or at least they borrow from them. Because of that they form a reasonable scaffolding, for mixing ideas that are motivated by quantum mechanics into everyday optimization scenarios.

To find that ideal value of the objective function, the optimization run is basically about using the right algorithm to roam through the solution space and see what fits best. But it has to be done in a certain way, so the procedure can actually locate the answer instead of just wandering around randomly.

Recognizing crucial domains of interest comes under the ever first strategies of optimization. An objective function $f(x_1, x_2, x_3, \ldots, x_n)$ that is defined over some set of choice variables x_i, where $1 \le i \le n$, and it is paired with a bundle of constraints, makes up a pretty standard optimization problem. Basically, the core aims of optimization are to locate usable and fairly attractive regions inside the search space, and then, based on the desired goal, settle on the best possible solution. In many current engineering tasks, optimization methods are basically needed, because they help with thorny real-world issues (Pant et al., 2016, Uniyal et al., 2020).

A general optimization problem can be set up in a mathematical way like this
$f: D^n \to R^k \;\; k \ge 1$, where, $x = (x_1, x_2, x_3, \ldots, x_n) \in D^n = D_1 \times D_2 \times \ldots \times D_n$.

The main idea is to pick out the best solution, or well, the best choice in the domain,
$x^* = (x_1{}^*, x_2{}^*, x_3{}^*, \ldots, x_n{}^*) \in D^n$.

while still obeying the equalities $h_j(x) = 0;\; 1 \le j \le J$ and also those inequality limits $g_m(x) \ge 0; 1 \le m \le M$ and $p_l(x) \le 0; 1 \le l \le L$.

The objective is to minimize $f(x) = f(x_1, x_2, x_3, \ldots, x_n) \in R^k$, where n is the number of parameters to optimize. The domain of the objective function $f(x)$ is $D^n = D_1 \times D_2 \times \ldots \times D_n$ i.e., the choice variable space. D_i Either continuous or discrete that particular search space for optimization variable x_i, which is for the i^{th} optimization.

A solution x^* is characterized by the property of extreme values (Uniyal et al., 2022). Constraints on the task include equalities (h_j) and inequalities (g_m and p_l). A feasible solution is represented as an n-dimensional vector $x = (x_1, x_2, x_3, \dots, x_n)$, meeting all provided restrictions. The feasible decision space, is a collection of all the feasible solutions or candidate outcomes. That is the set $X \subseteq D^n$ that contains all possible solutions. Feasible criterion space is taken to mean the set of $x's$. where, f attains its maximum represented as $f(x) \subseteq R^k$.

A single solution might not be ideal for all objectives at once in multi-objective cases (k≥2). The study focuses on the solution set X_p which only contains solutions that do not meet development standards because their two objective functions $f_i(x)$ and $f_j(x)$ with $j \neq i$. The functional values determine whether any element $x^* \epsilon X_p$ gets dominated by members of $x \in X \backslash X_p$ or remains unaffected.

The mathematical expression $\forall\, x^* \epsilon X_p$, $\forall x \in X \backslash X_p$, $f_i(x^*) \leq f_i(x)$ remains valid for every index i that belongs to the set $\{1,2, \dots, k\}$. The range $f(X_p)$ from this study is known as the Pareto front according to Uniyal et al. (2022) or the Pareto border which can be observed in **Figure 1** and the set X_p contains only Pareto optimal solutions. The two solutions ${x_1}^*$ and ${x_2}^* \in X_p$ cannot be compared because one solution does not surpass the other solution in all performance areas.

Pareto dominance along with Pareto-optimal solutions basically set what "optimal" means in multi objective optimization. But in single-objective optimization it's more like we pin down one best point, a global optimum and, if that's hard to compute, we settle for some decent local optimum instead.

The global optimum solution x^* exists because $f(x^*) - f(x)$ produces results which satisfy both conditions that need to be tested across all numbers in D^n space. Non-linear programming struggles to obtain global optimal solutions because of its inherent complexity, thus programmers need to accept local optimal solutions which exist inside the open space D. A local optimal solution x^{*^*} must meet the condition $f\left(x^{*^*}\right) - f(x) \geq 0$ or $\leq 0 \quad \forall\, x \in L$. The first point selected by the user $x_0 \in L$ determines how fast local optimization methods will work, therefore choosing this point should be done with extreme caution.

This means that optimization problems are defined by the objective function, constraints, and the decision variable space. Such a real-valued programming issue will then be called an integer programming problem if its decision variable space satisfies $D^n \subseteq R^n$ (where, R is the set of real numbers) and $D^n \subseteq Z^n$ (where, Z is the set of integers). A mixed-integer programming problem occurs when $D^n \subseteq Z^n$ does not hold, yet $D^n \cap Z^n \neq \emptyset$. A combinatorial programming problem arises when each D_i , $1 \leq i \leq n$ is finite. The term combinatorial refers to the answer as one of the possible permutations or combinations of elements inside finite sets D_i.

The presence of constraints defines optimization whereas their absence creates a situation called unconstrained optimization. The synthesis process transforms into a Linear Programming Problem when both the constraints and criterion function consist of linear polynomial elements. Nonlinear programming problems are generally formulated when nonlinear components or functions appear within the objective function and constraints of the program being modelled.

Depending on how many objective functions it contains, the optimization issue can be sort of categorized as either a single-objective optimization problem, SOOP or a multi-objective optimization problem MOOP (Byrne, 2014).

Convex optimization involves the process of minimizing an objective function while following convexity restrictions. The search space together with the function f shows convex properties which make local minima sufficient to prove global minima existence (Boyd and Vandenberghe, 2004).

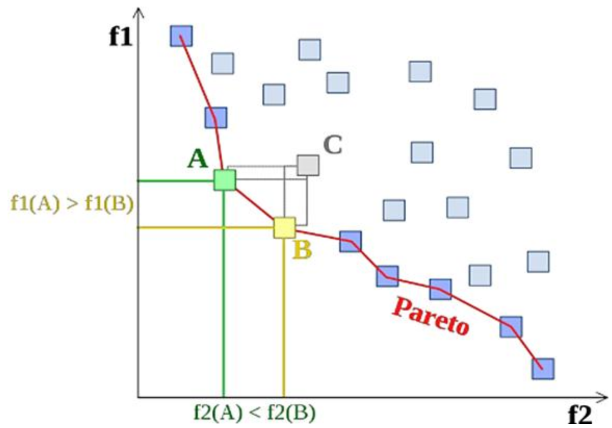

Figure 1. Point C lies between points A and B in the pareto frontier represented by red lines.

In practical engineering challenges, an objective function becomes discontinuous, nonlinear, nonconvex, and multimodal. The other side of the coin is that these challenges are all multidimensional with more variables of many types' integer real, discrete and binary. This means one can say that the search space is not very smooth. Look-up table data might be required for evaluating the objective functions. The constraints are very complicated, so they have to be normalized due to the varying degrees of violation of each constraint.

The mathematical programming may be used together with some meta-heuristic approaches to solve optimization problems but derivative-based mathematical programming methods are constrained by their inability to solve nonlinear problems also Classical optimization techniques become ineffective in the presence of multi-modal search space, leading to premature convergence and local optima. They also require formulation of clear objective and constraint functions, whose gradients are needed for both. They struggle with mixed-variable problems.

In the concrete optimization, possible local minima and peaks seen in the surface plot arise due to the optimization of two design variables. A surface plot which defines the optimization of design on the distribution transformer problem with two decision variables of reducing the lifespan cost of transformers, namely width of core leg and height of core window (Tamilselvi, 2022).

With the numerous decision variables coming in with the multi-dimensionality problems in engineering, it can be said that the multi-modal optimization fails to address the problem. Since the standard derivative-based mathematical programming techniques cannot cope with such a complex optimization problem effectively, it can give out designs in theory but not effective ones in practice. When knowledge in this area exists only vaguely or not at all about how global minima, local minima, feasible regions, and infeasible regions behave in multidimensional parameter space, the metaheuristic techniques with a basis of stochastic strategy would be the best alternative.

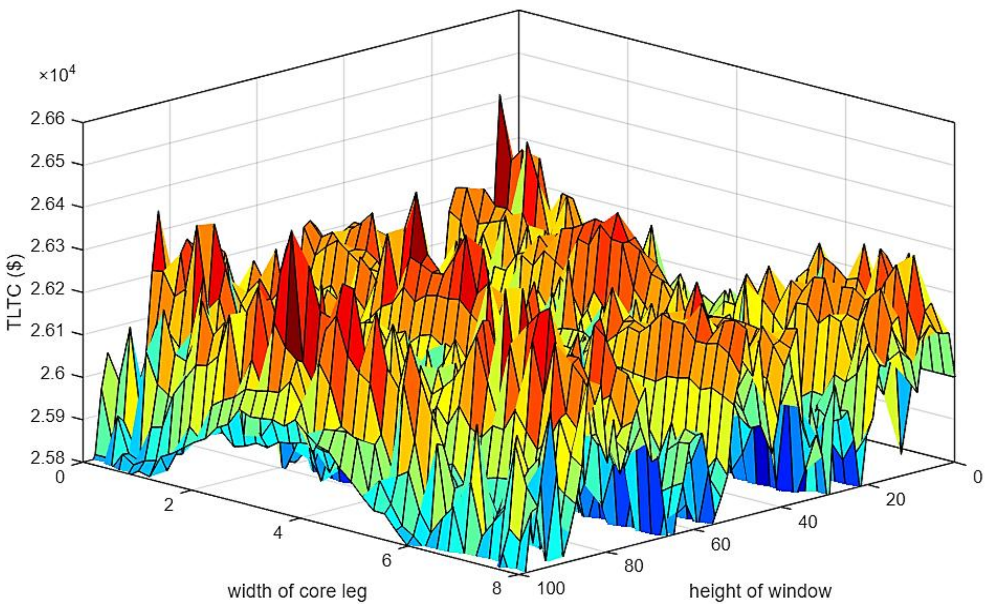

Figure 2. Search space for optimizing the two decision variables in minimization of the objectives of TLTC (Tamilselvi, 2022).

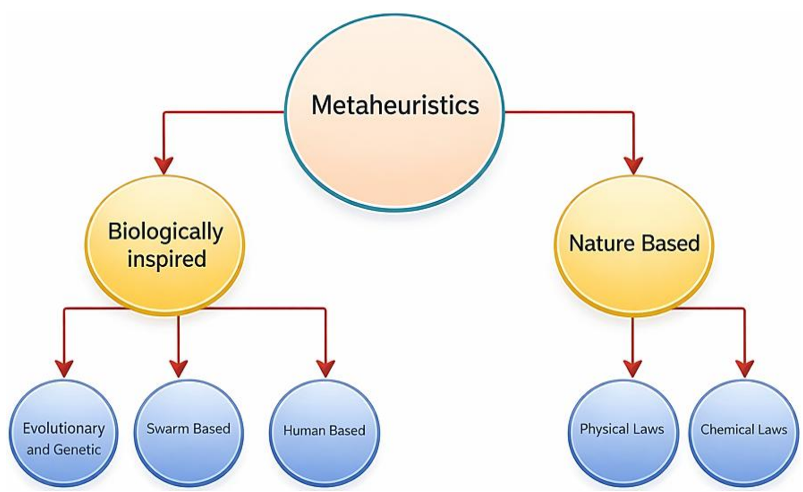

Figure 3. Metaheuristics categories.

The theory of metaheuristics demonstrates its value because it provides results that closely resemble actual natural processes which have developed through biological evolution during millions of years. The two most significant traits are the selection of the fittest and adaptation to the environment. The main features which define modern metaheuristics research can be measured through two numerical values which represent intensification and diversification. The process of intensification uses local search methods to examine nearby solutions while the system accepts better solutions, whereas the process of diversification ensures that the algorithm explores enough of the search area (Pétrowski and Ben-Hamida, 2017).

Metaheuristic algorithms provide fast solutions to worldwide problems because they develop strong algorithms through their independent problem-solving capabilities and their ability to learn. The metaheuristic category of algorithms includes most algorithms whose solutions originate from natural physical and biological processes (**Figure 3**). The genetic algorithm and ant colony optimization and bee colony optimization algorithms represent bio-inspired algorithms whereas water-filling algorithms and particle swarm optimization and gravitation search algorithms operate as algorithms that study physical phenomena.

Optimal solutions are necessary for handling real-life complexity, where gaining exact solutions was presumed to be impossible or extremely hard. Most areas in math and engineering such as structural design, aerospace modelling, travel postman problems, etc. have their share of optimization techniques. The exact solution-finding techniques of branch and bound and dynamic programming become inefficient because their solution time increases exponentially with additional variables in the problem instance. Meta-heuristics serve as the most effective solution algorithm options because they utilize their computational power to deliver results that meet acceptable accuracy thresholds within fixed operational periods.

Evolutionary optimization techniques, also known as search algorithms, are techniques that minimize or maximize some objective function. The method evaluates the entire search space according to **Figure 2** to identify different possible solutions which it will use to determine the most effective choice (Tamilselvi, 2022). The process of optimization holds vital importance for both personal life and professional development.

Evolutionary algorithms like genetic algorithm (GA) uses population of some possible random solutions that are individually modelled as chromosomes (Talbi, 2009). These chromosomes are assigned finesses in order to organize the competition among them from which the most fit chromosomes or solutions are selected as winner chromosomes. The first filtration stage is parent selection, where chromosomes are filtered by their fitness values. The rest of the selected individuals, parents, are used as sources from which children may be produced through genetic inheritance, i.e., recombination and mutation. Such operators search for different configurations. A few pairs of chromosomes are picked randomly for crossover chance to yield children.

The development of QIMAs improved after researchers integrated quantum computing principles into their work. The process of achieving proper balance between local search and global search in metaheuristic algorithms presents its users with extreme difficulty. The process of improving one element causes the other element to become worse. The techniques provide their main benefit because they enable better global search abilities while maintaining existing algorithm extraction methods. Quantum computing uses specialized bits called qubits to create its computational system instead of using traditional bits that represent 0 and 1 (McMahon, 2008). The qubit functions like a classical bit because it can exist in both zero and one states, but it additionally possesses the ability to exist in two states simultaneously. The special characteristics of qubits enable fast computational processes that use them as operational units. A qubit exists in mathematical terms as follows:
$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle$; $\alpha, \beta \in C$ and must satisfy the relation $|\alpha|^2 + |\beta|^2 = 1$.

where, α is the probability of finding the quantum bit $|\varphi\rangle$ in state $|0\rangle$ and β is the probability of finding the quantum bit $|\varphi\rangle$ in state $|1\rangle$.

The basic gates of quantum computation perform all fundamental quantum mathematical functions required to process qubits. People need to comprehend how quantum systems change their states because this knowledge helps them comprehend quantum system behavior. The Pauli Operators consist of four basic quantum operators which include identity operator (I) NOT operator (X) scalar product operator (Y) and quaternion product operator (Z). **Table 1** provides a clear summary of these Pauli operations and associated matrices. The quantum gates provide active operations through their implementation of CNOT phase Hadamard Toffoli Feynman Fredkin swap and Peres gates (Boyd and Vandenberghe, 2004). The rotation gates enable qubit rotation around three different axes which include X axis Y axis and Z axis (**Figure 4**).

Table 1. Some of the two qubit gates (Pauli and Rotation) along with respective matrices (McMahon, 2008).

Gate	Matrix
I -Identity	$\begin{pmatrix}1 & 0\\0 & 1\end{pmatrix}$
X-gate	$\begin{pmatrix}0 & 1\\1 & 0\end{pmatrix}$
Y-gate	$\begin{pmatrix}0 & -i\\i & 0\end{pmatrix}$
Z-gate	$\begin{pmatrix}1 & 0\\0 & -1\end{pmatrix}$
Phase (θ) (Rotation gate)	$\begin{pmatrix}1 & 0\\0 & e^{i\theta}\end{pmatrix}$

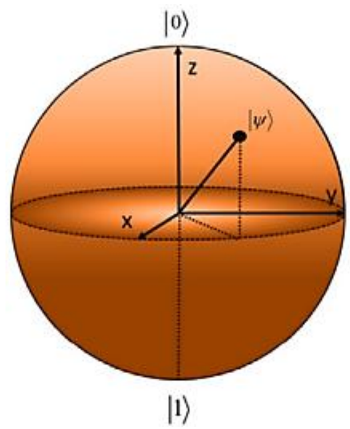

Figure 4. Bloch sphere.

A quantum gate has the ability to change a qubit's state as its fundamental characteristic. Any reversible process that operates as a linear change on the quantum state is called a quantum gate. Therefore, all quantum gates need a unitary matrix U to be their gate operator. A matrix becomes unitary when its complex square matrix U† matches its inverse through the process of finding its adjoint. Also, the rows and columns of U are orthonormal 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 (McMahon, 2008) can be seen in the **Figure 5** 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 i^{th} qubit and $\begin{bmatrix}\alpha_i{}'\\\beta_i{}'\end{bmatrix}$ is the qubit after rotation of the qubit $\begin{bmatrix}\alpha_i\\\beta_i\end{bmatrix}$.

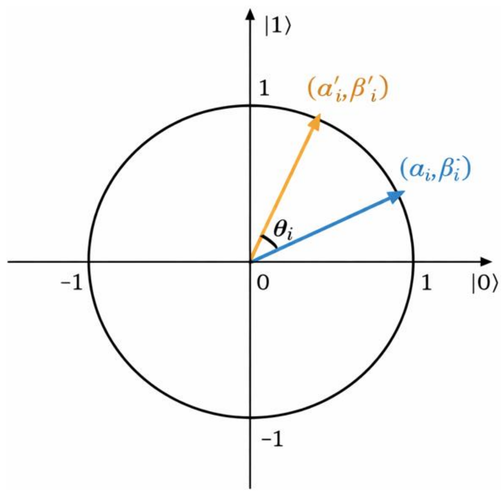

Figure 5. Rotation operation for qubit.

The creation of QIMA began with the use of three fundamental components based on the principles of quantum computing. The system can handle m qubits because it has the ability to display all possible 2^m states at once. A quantum state becomes permanent when an observation occurs because it forces the state to collapse into one definite state.

Metaheuristic computation enables solution representation through multiple methods because solutions can be transformed into different forms that serve as individual solutions. The representations used in this study can be categorized into three main types which are binary numeric and symbolic according to Hinterding (1999). The QIMA system uses probabilistic representation which combines concepts from qubits and Q-bit individual representation through the Q-bit string that follows.

A Q-bit individual as a string of m qubits is defined as

$$\left[\begin{array}{c|c|c} -\sqrt{3}/_3 & \sqrt{2}/_3 & -\sqrt{5}/_3 \\ \sqrt{6}/_3 & \sqrt{7}/_3 & -2/_3 \end{array}\right]$$

then the states of the system can be represented as

$$\frac{\sqrt{30}}{27}|000\rangle + \frac{\sqrt{24}}{27}|001\rangle - \frac{\sqrt{105}}{27}|010\rangle + \frac{\sqrt{84}}{27}|011\rangle + \frac{\sqrt{60}}{27}|100\rangle - \frac{\sqrt{48}}{27}|101\rangle + \frac{\sqrt{210}}{27}|110\rangle - \frac{\sqrt{168}}{27}|111\rangle$$

the above result means that the probabilities to represent the states $|000\rangle$, $|001\rangle$, $|010\rangle$, $|100\rangle$, $|101\rangle$, $|011\rangle$, $|110\rangle$, $|111\rangle$ are $\frac{30}{729}, \frac{24}{729}, \frac{105}{729}, \frac{84}{729}, \frac{60}{729}, \frac{48}{729}, \frac{210}{729}, \frac{168}{729}$ respectively. The three qubit system stores information about eight different states.

Multivalued qubits enable systems to exist in multiple states through their probabilistic linear superposition, which enables systems to achieve more diverse outcomes in evolutionary computing experiments. The binary encoding of data requires only one qubit to represent eight different strings. The evolutionary computing system employs qubit representation because its states can be created through probabilistic linear superposition, which provides greater population diversity than other systems. The system requires eight states because three qubits need to represent eight different strings that encode the same information. (000), (001), (010), (100), (101), (011), (110), (111) are needed (**Table 2**).

Table 2. Binary encoding (4 integer bits and 3 fractional bits).

Sign	2^3	2^2	2^1	2^0	2^{-1}	2^{-2}	2^{-3}	Number
1	1	0	0	0	0	1	0	-8.25
0	0	0	1	0	1	1	0	2.75
1	0	0	0	1	0	1	0	-1.25

The algorithm uses this probabilistic model to keep different solutions active, which allows it to search for multiple possible solutions at once, resulting in better exploration results and decreased chances of early solution convergence when compared to standard binary methods.

QIMA's yield approximated results with reduced processing costs. QIMA is a high-level algorithm to formulate heuristic optimizers based on a previously set of steps and principles, independent of the situation. Recent years have seen greater attention being paid to the research on QIMA (Messiah, 1961; Schuld and Petruccione, 2018; Dias et al., 2021).

Metaheuristic algorithms provide an effective framework for solving NP-hard optimization problems which require only reasonable computation time for their resolution. Stochastic search mechanisms of these algorithms enable them to navigate challenging search spaces while reaching solutions that are almost optimal for problems which exact optimization methods fail to solve. The rising need for stability and accuracy together with robust operation in various engineering fields has led to continuous enhancements and new hybrid approaches for traditional metaheuristic algorithms. Researchers have developed new quantum-inspired metaheuristic methods by integrating quantum mechanics concepts into traditional optimization algorithms.

Quantum-inspired metaheuristic algorithms (QIMAs) create a new research area which studies how quantum computing principles connect with evolutionary optimization techniques. The algorithms enable classical computer operation while they use quantum concepts which include qubit representation and superposition and probabilistic state updates to improve search exploration and diversity. Researchers have shown significant interest in QIMAs because they can enhance the effectiveness of standard metaheuristic algorithms. Researchers have developed multiple quantum-inspired optimization techniques which each follow distinct algorithm design principles.

Researchers have conducted extensive studies on complex optimization problems encountered in engineering design and reliability analysis, as these problems require solutions to handle their nonlinear nature and multiple constraints and extensive search areas. Conventional optimization techniques encounter difficulties with these problems because they tend to find only local solutions while unable to search through high-dimensional solution spaces. Engineers today use metaheuristic algorithms as their main solution method for difficult optimization problems. The development of quantum-inspired metaheuristic algorithms has attracted a lot of attention since these algorithms enhance their search capabilities by utilizing concepts from quantum computing, such as probabilistic state superposition and qubit representation. The algorithms use their properties to solve optimization challenges which involve multiple decision variables and complex constraints. The research investigates an optimization framework which incorporates quantum mechanics to enhance system robustness and convergence efficiency and solution effectiveness in solving complex engineering optimization challenges.

The study is divided into 6 sections, with Section 1 providing a thorough overview of QIMAs. Section 2 describes the information gathering process. Section 3 focuses on the different categories and applications of QIMAs. The bibliometric study appears in Section 4. Section 5 presents findings, difficulties, and future directions. The article is finally concluded in Section 6.

2. Collecting Information

In this section, a detailed explanation of the inclusion criteria, exclusion criteria, and the resulted studies is provided.

2.1 Selection Criterion for Research Studies

To avoid overlapping results frequently encountered in digital libraries during preliminary searches, we concentrated our efforts on primary databases:
1) Science Direct
2) Springer Nature Link
3) Web of Science

The reason for selecting these databases is due to the coverage criteria of literature in areas of interest, seeking to avoid duplication.

The search covered the period from **2015 to 2025**, with the exception of a few earlier studies that were included to provide the necessary background and facilitate a comprehensive understanding of the topic. We chose this time range because it captured very recent developments with regard to QIMAs. Considering that most of the metaheuristics have undergone dramatic development since 2018.

We construct an effective search query using the keywords identified about ("Quantum-inspired Metaheuristic Algorithms"). The defined search query would then be: ("Quantum-inspired Evolutionary Algorithms") AND ("Quantum-inspired metaheuristic algorithms").

This query was designed to be as specific as possible to the topics of QIMAs while still retrieving a significant number of relevant studies. The results obtained, as well as the exact query passed to each database, are presented in **Table 3** (Kitchenham and Charters, 2007).

Table 3. Selection criteria.

Stage	Description	Criteria
1	Identification	Records identified after searching 1) Science Direct 781 papers 2) Web of Science 425 papers 3) Springer Nature link 346 papers
2	Screening	1033 unique papers after removing duplicates and 835 papers after applying date range and language criteria
3	Eligibility	484 papers after title/keywords screening 286 papers after applying exclusion criteria 192 papers after reading the abstract 162 papers after reading introduction 141 papers after reading introduction with conclusion 14 papers after backward snowballing
4	Included	155 full text articles included in the systematic literature review

2.2 Inclusion and Exclusion Criteria

The study established specific guidelines to include or exclude research studies which ensured that only high-quality studies would be selected for the research. Our research questions established three specific application domains and two contexts and eight different types of outcomes which served as our inclusion criteria.

Inclusion Criteria:

- ✓ Peer-reviewed journal articles and conference papers.
- ✓ Studies focusing on the applications of QIMAs.
- ✓ Papers that report original research, case studies, comprehensive reviews.
- ✓ Publication dates: primarily 2015 to 2025 with few exceptions.
- ✓ Language: English.

Exclusion criteria: non-Peer-reviewed documents, including books, dissertations and theses

- × Papers not relating explicitly to the intersection of quantum computing with metaheuristic algorithm.
- × Insufficient details regarding methodology or results.
- × Short papers (less than 6 pages), unless important preliminary results are shown.
- × Duplicate studies or multiple publications of the same research.

We decided to include conference papers because it is likely that, in such a fast-moving area, important advances will first be published in leading international conferences before journals. We also did not exclude work in progress papers or preprints since the topic of metaheuristics using quantum computing is relatively young, and there is much to be learned from preliminary ideas of ongoing research.

2.3 Study Selection Results

As per PRISMA guidelines our selection process had four primary steps:

Stage1: Identification

The search string was run in Science Direct, Web of science, Springer nature link and Scopus database to retrieve the relevant publications, initially 1552 papers were received.

Stage 2: Screening

Before we did the screening step, we removed the duplicate papers, leaving us with 1033 unique studies. Application of our date range and language criteria made 835 records follow through for further consideration.

Stage 3: Eligibility

In this stage we undertook an initial screening of the papers, solely based on their titles and keywords. Papers which could not be excluded on these grounds were retained for further analysis. The output from initial screening was 484 potentially relevant papers. Further selection by reading abstracts resulted in 192 apparently relevant papers to our research topic.

For the 192 papers, we proceeded to read the introduction and conclusion in order to reach a final decision about their inclusion. For each rejected paper we recorded the reason for exclusion thus ascertaining transparency in the selection process. In this stage, irrelevant papers and those for which full texts were not available had to be removed.

In this systematic literature review on QIMAs, we have developed a research mechanism for comprehensive and unbiased coverage of the existing literature. In **Table 4**, clear and concise research questions and objectives established in an attempt to encompass all critical aspects of this prospective area of study were presented.

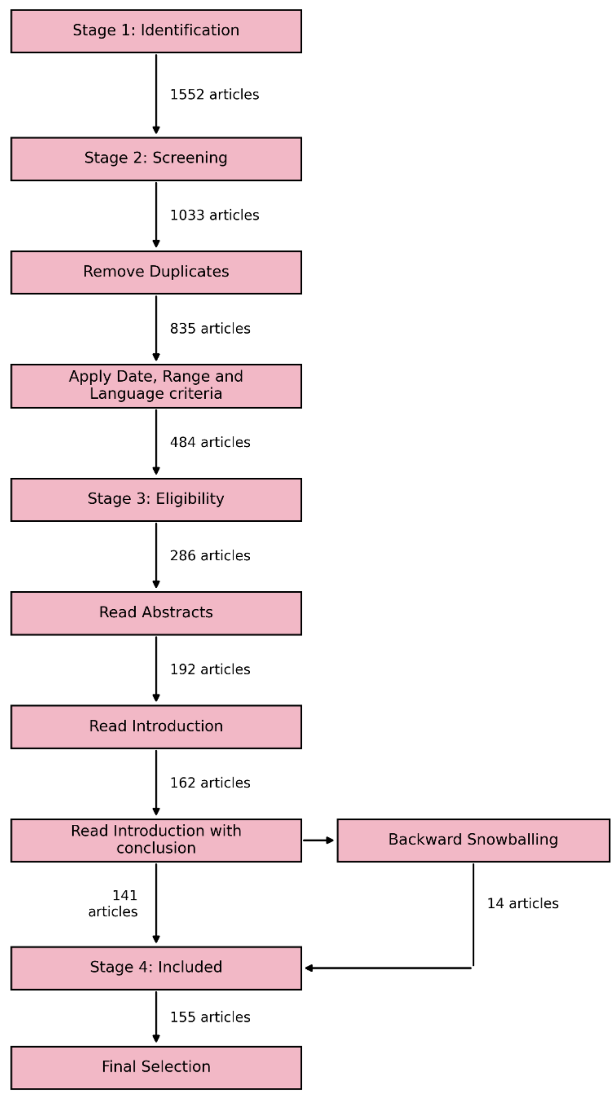

Figure 6. Prisma flowchart.

Table 4. Research questions.

Question no.	Research questions
Q1.	What are current advancements in Quantum-inspired metaheuristics?
Q2.	What are primary hurdles and constraints in integrating quantum computing with metaheuristic algorithms?
Q3.	What are latest innovative techniques and future directions in Quantum-inspired metaheuristics?

Our article selection method follows the PRISMA guidelines, as recommended by Kitchenham and Charters (2007), to address well-defined research questions and ensure the inclusion of the most relevant studies. The selection process is illustrated in the PRISMA flowchart shown in **Figure 6**.

3. Quantum-Inspired Metaheuristics (QIMAs)

For analysis purpose we have classified QIMAs into two broad categories namely Biologically-inspired quantum-based metaheuristics and Nature based Quantum-inspired metaheuristics. Biologically-inspired quantum-based metaheuristics further categories into three categories namely Quantum-inspired genetic algorithms (QIGA), Quantum-inspired evolutionary algorithms (QIEAs), Quantum-inspired swarm-based algorithms (QISBA) and Quantum-inspired human-based algorithms (QIHBA).

3.1 Biologically-Inspired Quantum-Based Metaheuristics

3.1.1(a) Quantum-Inspired Genetic Algorithms (QIGA)

These algorithms during operation are simply improved versions to that of the conventional genetic algorithms; instead of having a bi-numeric or symbolic types representation, QIGA uses qubit chromosomal representation. The qubit chromosomal representation provides every advantage of seeing the possible combinations of all state superposition's at the same time, against any classical representation. The algorithm initializes all qubits within the qubit chromosomes to $\frac{1}{\sqrt{2}}$ allowing for equal representation linear superposition of all states. Then, it generates binary candidate solutions by observing the chromosomal states of the qubits. After trying several of the candidates, the best is chosen and retained. Candidate solutions are finally updated via quantum chromosomes until the termination condition is satisfied. For the next generation, an upgrade will be done for quantum chromosomes using quantum gates.

The origin of this concept can be traced to the two researchers, Narayanan, Moore, who came up with the concept of QIEAs during 1990s as one of the solutions to the traveling salesman problem (Narayanan and Moore, 1996) by an interference theory-based crossover operation. The QIEA (Narayanan and Moore, 1996) is introduced, where quantum mechanics concepts and principles provide insights for developing efficient evolutionary computing methods for solving Traveling Salesperson Problems.

The potential advantages of parallelism from quantum computing applications could find use in evolutionary algorithms (Narayanan and Moore, 1996). Han and Kim (2000) plausibly offered a technique, which rekindled interest in QIEA (Narayanan and Moore, 1996). Han and Kim (2000) proposed a new evolutionary computing algorithm for a specific combinatorial optimization the knapsack problem, a system for discussing the performance of quantum genetic algorithms, where fundamental concepts of quantum computing like qubits and superposition of states were applied.

Han and Kim (2002) suggested parallel QIGA founded on quantum computing concepts. The authors demonstrated that the proposed parallel algorithm (Han and Kim, 2002) can explore and exploit simultaneously, thus making it superior to the previously proposed quantum genetic algorithm and classical genetic algorithms. This has now become a new area of research in evolutionary computation. QIEAs are therefore more similar to EAs in that they define an individual representation, fitness functions, and population dynamics, namely initial population size, selection, crossover, and mutation processes. QIEA uses qubits as units of information. A qubit individual is defined as a string of qubits. Any probabilistic representation of qubit provides more search diversification. Initially, while creating a population, QIEA put all qubits in the superposition state under equal probability. As the performance of the algorithm proceeded, the increased convergence of individuals to a single state intensified the search. QIEA balances exploration and exploitation. QIEA is certainly inspired by quantum computing; nevertheless, it is not a quantum algorithm but rather a new evolutionary algorithm targeted at classical computers.

3.1.1 (b) Other Biologically-Inspired Quantum-Based Metaheuristics

Patvardhan (2016), put forward an improved Parallel QIEA to solve the Quadratic Knapsack Problem. This is the advanced version of the algorithm proposed in 2002 by Han and Kim (2002). The structure and features have been provided in Patvardhan (2016) to enhance the ability of solutions to exploit competing ones. According to them QIEA may also be applicable to other similar or unrelated problems. The authors compare IQIEA-P against its sequential counterpart IQIEA and shows that the proposed parallelization speeded up the processing significantly and that the solutions can be obtained in a reasonable time by simply increasing the number of parallel threads from the software side and providing adequate hardware cores.

In real-time job scheduling, Konar et al. (2017) introduced a hybrid method that operates almost instantaneously by incorporating EDF (earliest deadline first) operations to supplement standard genetic ones. It was claimed by the authors of the proposed algorithm, HQIGA, that qubits were employed to ensure diversity in the mating pool for the enhancement of schedule generation, while the authors derived the efficiency of the proposed scheme by putting in values in the fitness function, in the same iteration number as that for its classical counterpart.

A novel real time task scheduling algorithm using multi objective QIGA has been developed by Konar et al. (2018). The proposed algorithm aims to minimize total completion time while reducing tardiness of real time tasks which serves as the main scheduling objective in multiprocessor systems. The system uses variable length chromosomes to show its ability to explore different solutions while quantum rotation gates function as schedule updating tools.

Alam and Raza (2018) presented a quantum genetic load balancing schedule which serves as their workflow scheduling solution. QGLBS works to achieve two main scheduling goals which are load imbalance (LIB) and load balancing cost ratio (LCR) through its design. The author used parallelism control for both job and sub-job execution to achieve better system throughput while completing work with dependent modules.

Bian et al. (2019) presented an effective QIGA for optimizing FCS (Flight Control System) for wind disturbance abatement. The proposed method involves using a niching mechanism and a parallel archive system to examine all possible solutions. An adaptive search technique is used to gradually change the search domain, eventually reaching the local minima. The proposed technique optimizes FCS parameters based on a predefined cost function while also identifying suitable design solutions.

The authors, Dahi et al. (2016) introduced the first quantum information gateway authentication method to solve an NP-hard binary optimization problem which exists in modern cellular phone networks through their solution to the Accessible Person Profile problem. Researchers have performed multiple assessments to test the proposed methods which they applied to actual data and synthetic data and random data across different dimensional ranges. The proposed method evaluation demonstrates its three main characteristics of operational efficiency and system stability and ability to handle increased work.

In order to finely estimate segmentation threshold (Sabeti et al., 2020) presented a Quantum-inspired genetic algorithm. The suggested algorithm, along with GA, HSA, PSO, and QPSO, is applied to different datasets. For the two benchmarks, the most accurate results are obtained with QIGA and GA. The superiority suggested (Sabeti et al., 2020) QIGA gives greater diversity in producing new offspring, which encourages both exploration and exploitation of search qualities within the population.

Shi et al. (2019) presented a new multi-population assisted QIGA for predicting RNA secondary structure. The suggested technique updates several populations using separate quantum rotation operations. Operator transfer operations facilitate genetic exchanges among populations.

The traveling purchaser problem (TPP) for capacitated markets, which includes both original and substitute products, received a new formulation from Pradhan et al. (2020). The purchaser uses multiple vehicle types to achieve the goal of reducing unpredictable procurement expenses. The authors develop environmentally sustainable green procurement plans which include suitable penalty and credit systems. The proposed study uses a hub-and-spoke procurement planning framework which considers environmental factors and legal requirements and customer emotional responses. The researchers developed a QIGA system which uses IVF crossover and mutation operator to achieve faster execution speeds.

Furthermore, **Table 5** shows recent research that use a QIGA approach, along with its applications and improvements.

Table 5. Quantum-inspired genetic algorithms.

Applications	Year	Contribution /Innovation /Modification	References
Travelling salesman problem	2000	Interference crossover	Narayanan and Moore (1996)
The knapsack problem	2002	chromosomes are updated by quantum rotation gate	Han and Kim (2002)
Large size quadratic knapsack problem	2016	Parallel algorithm	Patvardhan et al. (2016)
Modified solid green travelling purchaser problem	2020	Vitro fertilization (IVF) crossover and mutation	Pradhan et al. (2020)
Real time task scheduling	2017	Association of evolution function using earliest deadline first heuristic	Konar et al. (2017)
Prediction RNA secondary structure	2019	Population updated by quantum rotation operator	Shi et al. (2019)
Multimodal optimization of flight control system	2019	Minimization of load imbalance and load balancing cost simultaneously	Bian et al. (2019)
Precedence constrained job scheduling	2018	Population updated by quantum rotation operator	Alam and Raza (2018)
Segmentation and optimization	2020	Threshold for segmenting digitized radiograph images	Sabeti et al. (2020)

3.1.2 Quantum-Inspired Evolutionary Algorithms (QIEAs)

Han and Kim (2000) proposed quantum-inspired evolutionary algorithms in which they presented in their work. The QIEA uses EAs to determine its three main components which are individual representation and fitness functions and population dynamics. The QIEA operates with its fundamental information unit which is contained in qubits. An individual's qubit consists of a sequence of qubits. The probabilistic representation enables enhanced search diversity through its multiple output paths. QIEA created diverse populations because it allowed qubits to exist in all possible states with equal probability during its initial operation.

The algorithm now proceeds forward while its users develop into one shared state which leads to greater exploration activities. The system maintains its search pattern throughout its duration by balancing between exploration activities and exploitation activities. QIEA functions as a new evolutionary algorithm which runs on classical computers while it operates according to the principles of quantum computing.

A QIEA with quantum rotation gate is proposed by Li et al. (2017) to solve Travelling salesman problem. This proposed algorithm conducts global search by updating the quantum chromosome using a dynamic H gate.

Gupta et al. (2017) developed two parallel QIEA methods, which they implemented on CUDA-enabled GPUs for community discovery purposes. bQIEAm-CD is a two-phase hierarchical bipartitioning quantum-inspired evolutionary algorithm designed for community detection (Gupta et al., 2017). The discrete QIEA system includes QIEAm-CD as a numeric version of the standard QIEA.

The researchers from da Silveira et al. (2017) introduced their innovative method which combines quantum-inspired computing with evolutionary computation to achieve order optimization.

The researchers used direct search methodology from Yang et al. (2018) to find dependable optimal solutions which solve electro-magnetic device design problems that involve interval uncertainty. The recommended direct search method from the study achieved identical final results with fewer total iterations according to numerical outcomes of two case studies.

Deng et al. (2021) developed quantum-inspired cooperative co-evolution which uses multiple methods for random rotation direction and hamming method to adapt its rotation angle according to its needs. The MSQCCEA system achieves improved global search performance through its implementation of cooperative co-evolution techniques. The random rotation direction method needs to implement two quantum rotation directions because it aims to help users escape from their current optimal position. The Hamming adaptive rotation angle technique enables users to modify their search step size based on their distance from target individuals which results in faster and more accurate convergence.

Wright and Jordanov (2017) examined two distinct Quantum Evolutionary approaches which they modified to solve practical problems across different environments. The author developed two quantum methodologies through his implementation of binary and real encoding methods which maintained the core principles of quantum computing.

The unique quantum-inspired evolutionary fuzzy c-Means algorithm which (Bharill et al., 2018) developed functions as a method for data clustering. The method uses quantum computing principles through Q-bit representation to define fuzziness factor (m) of the system. The fuzziness factor (m) undergoes five main stages of development during each generation. Through multiple generations of evolution, the authors obtain a vast search space which they use to find global optimum solutions that identify optimal values for m and c which produces the best fuzzy partition results.

According to Liu et al. (2017) research new employee work patterns create operational obstacles which require businesses to deal with their new challenges. The new jobs are those that replace the parts and components of the marketed goods with predictable arrival table 1times. It enables users to access real-time production information from subcontractors through its cloud-based system. The study established mathematical models which describe the subcontractor selection process and the project outsourcing procedure. The proposed models included three elements which were the primary scheduling objective and the transition from the first scheduling method to the second one and the subcontractor selection process which determined outsourcing expenses. The solution to the model used a QCGLOA as its proposed method. The research used chaotic mapping to create fresh random groups and utilized group leader optimization to enhance exploration results and implemented QIEA to boost population variety. The trial results demonstrated that the proposed algorithm produced excellent performance results.

The researchers, Kaveh et al. (2019) introduced a new method which enables more effective examination of unpredictable buckling stresses in their study about optimal design of hybrid symmetric laminated composites. The author presents a new advanced QIEA ranking system together with multiple QIEA and Genetic Algorithm (GA) variants in order to develop nested optimization systems. The Golden Section

Search (GSS) method uses an anti-optimization approach to find worst-case biaxial compressive loading conditions which lead to maximum buckling load capacity.

Rangoju et al. (2022) introduced the advanced quantum-inspired evolutionary optimization algorithm A-QEOA. The algorithm operates according to quantum computing principles. The QIEA system performs exploration through its improved observation method and uses quantum rotation gates for its exploitation process. The process of exploration helps to identify the search space which contains the parameter that requires optimization.

Table 6. Quantum-inspired evolutionary algorithms.

Applications	Year	Contribution /Innovation/Modification	References
Disruption management in cloud manufacturing	2017	QIEA with group leader optimization algorithm and chaotic mapping	Liu et al. (2017)
Ordering problems	2017	Using the QIEA solution to initialize a traditional order-based genetic algorithm population	da Silveira et al. (2017)
Travelling salesman problem	2017	Global search is performed by updating quantum chromosome with the dynamic He gate	Li et al. (2017)
Parallel implementations of community detection algorithm	2017	Single-population fine-grained approach	Gupta et al. (2017)
Hybrid laminated composite design	2019	Using rank-based dynamical version of QIEA	Kaveh et al. (2019)
Robust optimization problem	2019	Keeping only promising solutions for performance mechanism checking	Li and Li (2019), Li and Wang (2019)
Fuzzy controller design	2018	Simultaneously guarantees system stability and achieves optimal performances	Yu et al. (2018)
Optimal view selection	2018	Multidimensional lattice	Kumar and Kumar (2018)
Quadratic assignment problem	2018	Least absolute shrinkage and selection operator (LASSO)	Chmiel and Kwiecień (2018)
Constrained fuel loading pattern optimization	2018	Afford faster computation and more accurate solution	Oktavian et al. (2018)
Hand gesture recognition	2018	Applying minimum redundancy maximum relevance criteria to QIEA	Ryu et al. (2018)
Fuzzy clustering parameters optimization	2018	Integration with fuzzy c-means algorithm	Bharill et al. (2018)
Complex networks and community detection	2018	Use of conventional partitioning algorithm solution as a guiding quantum individual	Yuanyuan and Xiyu (2018)
Process planning and scheduling	2018	Integration with group leader optimization and chaotic mapping	Liu et al. (2018)
Complex systems optimization problems	2019	Modification of QIEA inspiration from colony evolution of Acromyrmex ants	Montiel et al. (2019)
Pitched roof frames design	2019	Using different quantum gate for exploitation improvement	Arzani et al. (2019)
Fuzzy cognitive maps	2019	Integration of QIEA with particle swarm optimization algorithm	Kolahdoozi et al. (2019)
Multi-objective fuzzy classifier	2019	Implementing QIEA with Categorical variables	Nunes et al. (2019)
Efficient data clustering	2019	Combination of QIEA with fuzzy c-means algorithm	Bharill et al. (2019)
Sensor placement optimization	2019	Development of a dynamic Version of QIEA	Kaveh and Eslamlou (2019)
Reactor loading design	2019	Using self-regulated learning	Hsieh and Wu (2019)
Multi-objective optimization	2020	Implementing parallelism to solve large scale problems	Cao et al. (2020)
Robot path planning	2020	Handling discretized environment	Gao et al. (2020)
Network resource optimization	2020	Using self-adaptive evolution mechanism	Qu et al. (2020)
Feature selection	2020	Utilizing chaotic maps	Ramos and Vellasco (2020)
Predictive management	2020	Applying biological coevolution for subpopulation evolution	Pereira et al. (2020)
Airport gate allocation	2021	Combination of cooperative co-evolution, random rotation direction and hamming adaptive rotation angle	Deng et al. (2021)
The disassembly lines balancing problem DLBP	2023	Multiple strategic observations of a single q-bit during the observation phase	Singh et al. (2023)
Minimum cost spanning tree problem	2023	New mutation and catastrophe operation	Kaur and Bansal (2023)
Multi-objective optimization problem	2024	Optimal crossover strategy	Deng et al. (2024)

Vendrell and Kia (2022) developed a QIEA which solves COA through optimal service-matching coverage, according to their research. The studies demonstrated that quantum technology achieves better scalability while providing new capabilities which researchers can use to tackle diverse assignment problems that involve matching errors. **Table 6** outlines the use of QIEA in the past seven years, including upgrades and revisions.

3.1.3 Quantum-Inspired Swarm-Based Algorithms (QISBA)

Swarm-based optimization algorithms mimic the behavior of animal swarms. This strategy is known as swarm intelligence (Slowik, 2011). The introduction of the phrase "swarm intelligence" originated in 1993 by Beni and Wang (1993). Modified swarm-based methods improved by the quantum computing method in recent years.

The new particle swarm optimization algorithm developed through quantum individual-QPSO demonstrates its capability to solve discrete optimization problems according to the research (Yang et al., 2004). The proposed algorithm is simple and reliable, and it can achieve fast convergence through its intelligent quantum representation which establishes a new method for developing rapid and straightforward discrete PSO systems.

The enhanced-QPSO (e-QPSO) system presented by Agrawal et al. (2021) uses alpha parameter to manage a particle's personal and global impact throughout its operation. The system allows for initial exploration and subsequent exploitation through its variable gamma, which unites both research methods throughout its operational course. The system enables particles to break free from local optima by using the lowest performing population members to create new particles.

Weng et al. (2023) introduced a solution that efficiently solves a specific type of DRBDO (Dynamic reliability-based design optimization) problem which uses distributional random variable data as its design variables. The method assesses structural dynamic reliability through PDEM (probability density evolution method) while it solves optimization tasks using QPSO (Quantum Particle Swarm Optimization). The PDEM system uses the COM (change of probability measure) method to enable full access to all data which relates to the representative points.

Li et al. (2021) proposed a self-organizing quantum-inspired particle swarm optimization technique which solves MMOPs (Multi Model Multi-Objective optimization problems). The system can achieve both accurate PF (Pareto front) estimation and precise PS (different Pareto sets) retrieval. The core optimization method of the proposed MMO_SO_QPSO system operates through the QIPSO optimization technique. The offspring population of the system trains a self-organizing map to discover its important neighbor leader who will help the particle position update procedure. The population establishes the neuronal weight vectors in the self-organizing model, and the recommended progeny are designated as the training set.

Balicki (2022) developed a many-objective PSO technique that optimizes virtual machine placement in computing clouds using quantum gates. MQPSO solutions fulfill seven criteria which include host electric power requirements and cloud dependability standards and bottleneck host workload thresholds and critical node communication capacity limits and RAM utilization parameters and disc memory capacity needs and computer cost requirements. The suggested method uses Hadamard gates to create an initial population which exists in the quantum register through qubit superposition. Rotation gates enable users to change the current state of the quantum register which allows them to explore the area around the present particle location.

Kallioras et al. (2018) developed a new metaheuristic search method which the author named the pity beetle algorithm after studying the Pityogenes chalcographus beetle. The proposed technique outperforms local optimization for NP hard optimization problems and may search vast regions of potential solutions for an optimal global solution.

One-dimensional bin packing problems are important because they are widely used in loading, shipping, and industrial settings. This problem is classified as an NP-hard problem. Layeb and Boussalia (2012) introduced a new stochastic method that uses the quantum-inspired cuckoo search algorithm to solve this particular problem. The proposed method introduces a new hybrid measurement operation which combines the First Fit algorithm with standard measurement functions.

Mirjalili et al. (2014) introduced a new optimization method through their study of grey wolves because they used the animal's hunting behavior and their social structure as the basis for their "grey wolf optimizer" meta-heuristic method which they introduced in their work. The GWO algorithm demonstrated superior performance to established optimization methods according to the author who tested it on various benchmark functions and real-world engineering design challenges.

Researchers have conducted extensive studies on GWO because its implementation requires only basic parameters while the method successfully handles both exploration and exploitation needs. GWO provides excellent solution accuracy because it delivers precise results. GWO faces challenges with optimization problems that have multiple complex dependencies because it becomes stuck in local optimal solutions while its exploration capacity becomes limited. The study by Deshmukh et al. (2023) proposed using the quantum entanglement enhanced grey wolf optimizer (QEGWO) to replace traditional GWO. The authors established that quantum entanglement exists as a powerful tool to improve solutions for problems, which involve multiple solutions and highly interconnected dependency structures. The researchers employed a second method called local search to boost their search efforts.

The hybrid nature-inspired method HPSOGWO which combines Particle Swarm Optimization and Grey Wolf Optimizer was developed by Singh and Singh (2017) in their research. The author aims to enhance Particle Swarm Optimization by utilizing Grey Wolf Optimizer to boost its exploitation capabilities while testing two types of functions which include unimodal and multimodal functions.

The unit commitment problem gets solved through the binary grey wolf optimizer technique which (Srikanth et al., 2018) developed using quantum bits as its core operating element. The author demonstrated that his adapted quantum computing method achieved better solution results through its capacity to control search space exploration and access essential information with minimal operational resources. The research team demonstrated through their performance results that their proposed solution successfully addresses large-scale unit commitment problems according to their assessment of unit commitment performance.

El-ashry et al. (2020) introduced an improved version of the binary grey wolf optimizer which uses quantum techniques through their study. The article introduces an improved binary grey wolf optimizer which uses quantum mechanics to select features. The method used a quantum rotation gate to manage the update criteria which determined the optimization algorithm's progress through its various steps. The research demonstrates that using a quantum rotation gate to adjust grey wolf positions results in quicker weight updates which improve search area transitions and lead to better outcomes. The advanced system demonstrated significant improvements in both classification precision and ability to choose relevant features.

Liu et al. (2022) created a new clustering model which addresses the IWSN clustering needs for delay and energy consumption and system dependability through its pre-clustering operation and QEGWO-based clustering method which meets industrial production standards. The new evaluation function assesses three factors which include distance from the base station and distance between inter-cluster nodes and the remaining energy of the node. A new quantum operator exists which improves the chances of discovering the optimal clustering method. The QEGWO system employs its quantum probability amplitude updating method through quantum rotation gates to decrease processing demands at the base station.

A quantum-inspired differential evolution with a grey wolf optimizer (QDGWO) was proposed by Wang and Wang (2021). To solve 0-1 Knapsack problems. The test results which aimed to solve knapsack problems showed that QDGWO increased both diversity and convergence performance when used to solve 0-1 knapsack problems because it successfully found optimal solutions in high dimensional situations.

Deng et al. (2021) developed a new evolutionary algorithm which uses cooperative coevolution through divide-conquer principles and quantum computing features from quantum evolution algorithm to solve differential evolution algorithm problems related to inefficient searching and insufficient diversity during later search stages and slow solution finding and needs excessive time to reach its breaking point. The authors proposed their hybrid mutation method which uses local neighborhood mutation advantages as their new differential evolution algorithm called Improved differential evolution. The algorithm uses local mutation neighborhood which provides high search efficiency to boost its early-stage search performance. The SaNSDE algorithm introduces a new approach which enables search direction changes to help users escape from search stagnation. The researchers proved that SaNSDE together with QIEA creates better population diversity and faster convergence speed. The CCEA system uses its divide to conquer method to separate big populations into smaller groups which helps to boost their search performance for difficult real-world problems.

The development of cost-effective container port scheduling systems needs to be established as the primary method which will decrease expenses that follow the pandemic. Yang et al. (2024) developed an innovative scheduling approach for berth-tugboat-quay crane operations which uses quantum computing and chaos theory and SBO to handle unpredictable economic variables. The researchers conducted their simulation test research using two northern Chinese port simulation examples and discovered that through weight adjustment factor modification the E-BUQC model developed in this study achieved improved scheduling solutions which decreased container port time expenses and container truck additional freight distance expenses and tugboat operation expenses and quay crane operation expenses.

Bhattacharyya et al. (2018) developed a new method to categorize fat images through their application of quantum computing principles. The proposed method uses a quantum spider monkey optimization algorithm. The proposed QSMO method uses qubits to generate multiple solutions which it then uses to create an optimal cluster. The experimental results show that the proposed QMSO method outperforms traditional SMO because it achieves better fitness results and system accuracy and stability and convergence time and statistical correctness and statistical performance. Dey et al. (2020, 2024) developed three new quantum-inspired methods for automatic gray level picture grouping which use particle swarm optimization and spider monkey optimization and ageist spider monkey optimization as their primary methodologies.

Tawhid and Ali (2017) introduced their new hybrid grey wolf optimizer system which uses evolutionary algorithms to optimize energy functions of a basic molecular model. The authors named their proposed method hybrid grey wolf optimizer and genetic approach. The proposed method uses gray wolf optimizer to perform answer updates. The researchers use population partitioning method to simplify their molecular potential energy function calculations while using arithmetic crossover operator to enhance their search capabilities.

Jitkongchuen (2015) proposed a new optimization approach which combines differential evolution with grey wolf optimization to improve optimization results for continuous global optimization problems. The method uses evolutionary search to adapt control parameters while the grey wolf optimization algorithm performs crossover operations for improved solution discovery.

Komaki and Kayvanfar (2015) tackled the problem of two-stage assembly flow shop makespan reduction through their study. The solution requires three components which include dispatching rules and heuristic approaches and a lower bound (LB) estimation method. The researchers propose the GWO as their new MA.

Qiu et al. (2024) developed a new quantum ACO method that uses K-means clustering to solve problems. The system uses this method to solve discrete optimization problems that include the traveling salesman problem.

The QACMOR technique from Li et al. (2019b) uses quantum computing operations to enhance energy efficiency and speed up ACO routing system convergence. The study evaluated two performance metrics which operated steel casting production systems because of their industrial requirements. The simulation results demonstrated that the proposed method extended network operational time while achieving high convergence rates and supporting fast route selection. A steel manufacturing company implemented a WSN system which utilized the QACMOR algorithm for its MRO activities.

Mirjalili et al. (2017) developed two new optimization techniques which solve optimization problems that involve either one or multiple objectives through their Salp Swarm Algorithm and Multi-objective Salp Swarm Algorithm systems. The swarming patterns used by salps during their underwater movement and hunting activities serve as the primary basis for developing both SSA and MSSA systems. The researchers developed two mathematical models that track salps' movement patterns to enable position updates. The proposed models demonstrated their ability to track both stationary and moving food sources through simulations of swarm behavior in two-dimensional and three-dimensional environments.

Pathak et al. (2023) introduced CMSSO as a new version of SSA to solve actual optimization challenges and CEC2022 Benchmark tests. The four algorithms which CMSSO uses include Salp Swarm Algorithm (SSA) and Elite Opposition Learning-Based Salp Swarm Algorithm (EOSSA) and Elite Opposition Quantum-inspired Salp Swarm Algorithm (EQSSA) and Individual Dependent Approach for Differential Evolution (IDADE). The complete algorithm set from CMSSO enables users to solve both single objective numerical optimization tasks and multiobjective controller placement challenges.

Khan et al. (2021) introduced a new methodology which utilizes smart particles together with the convergence factor technique to solve the inverse problem tracking solution for electromagnetic devices through their electromagnetic device development.

According to study provided by Rizk-Allah et al. (2018), fractional optimization problems (FOPs) can be solved using the chaotic crow search algorithm (CCSA). The authors' team employs chaos theory to improve their system's capacity for global optimal point achievement through better exploration and exploitation methods. The addition of CT, which serves as a new adjustment mechanism, modifies the standard settings of the CSA system.

Jain et al. (2019) developed a new optimization method which uses squirrel behavior as its basis for solving unconstrained optimization tasks. This article examines and quantitatively simulates the foraging behavior of southern flying squirrels, accounting for every facet of their food hunt to attain the intended optimum. The proposed method undergoes evaluation through multiple traditional and contemporary benchmark functions which test its performance on unconstrained problems. It has been found in a statistical study that with better convergence performance, SSA provides the best global solutions when compared to other published optimizers.

Zhang et al. (2022b) created a new swarm optimization method which combines the native squirrel search algorithm with the quantum-behavior particle swarm optimization technique. The researchers developed their algorithm AM-QSSA which includes three search strategy enhancements that use population mutation and quantum state correlation location updates and an attractor method. The researchers studied the strengths and weaknesses of AM-QSSA to solve an image processing optimization problem. The analysis showed that AM-QSSA delivered high performance with precise results. The system successfully solved image processing optimization problems using AM-QSSA.

Kaur and Bansal (2023) introduced the QIEA which is an EA that uses quantum mechanics as its basis to solve the problem of finding minimum spanning trees in complete weighted undirected graphs. They also provided computational results that show the algorithm's efficacy. The authors developed a mutation and catastrophe operation which enables them to explore additional search space while preventing their system from reaching premature convergence.

The novel Krill Herd method which (Gandomi and Alavi, 2012) developed for optimization problems relies on krill herding motions. An individual's time-dependent position is determined by three main acts: random diffusion, foraging activity, and movement brought on the presence of other individuals. The first two actions possess two different types of optimizers which operate at global and local levels. The KH algorithm achieves superior efficiency because it combines two local techniques with two global techniques. The proposed method for random searching now includes the third action as an additional element. The bio-inspired approach needs to include adaptive evolutionary operators which consist of crossover and mutation techniques.

The research work Hybrid annealing krill herd and quantum-behaved particle swarm optimization (Wei and Wang, 2020) and Integrated Reactive Power Optimization Method for Active Distribution Networks are available as coevolutionary quantum krill herd algorithms that solve multi-objective optimization problems (Liu and Li, 2020). Two additional quantum-inspired swarm-based algorithms are built on a Quantum Krill Herd Algorithm (Li et al., 2019b).

Fathollahi-Fard et al. (2020) created the red deer algorithm through their investigation of Scottish red deer behavior. Our suggested method was primarily inspired by the mating behavior of RDs during the breading season. The male RD, who battled and yelled to gain authority over his harem of female deer, served as the model for the algorithm's fundamental elements.

The recommended algorithms for particular tasks consist of three firefly algorithms unified by multimodal optimization (Yang, 2009) and the global steered quantum-inspired firefly algorithm (Choudhury et al., 2022) and a cooperative hybrid quantum-inspired salp swarm and differential evolution (Pathak et al., 2023) and the quantum-inspired satin bowerbird algorithm with Bloch spherical search (Zhang et al., 2021).

Mirjalili and Lewis (2016) introduced a new optimization method based on swarm intelligence which they developed from studying humpback whale behavior. The proposed method used three operators which included searching for prey and encircling it and using a bubble net to imitate humpback whale foraging patterns. The researchers conducted a detailed assessment of 29 mathematical benchmark functions to test the algorithm's ability to explore and exploit and its effectiveness at finding optimal solutions and its speed of convergence. WOA proved to be an effective alternative to various modern meta-heuristic methods.

Agrawal et al. (2020) developed a quantum-based Whale Optimization Algorithm (QWOA) which improves both convergence and exploration capabilities of the standard whale optimization algorithm. The QWOA improves exploration capabilities because its quantum representation of whale positions allows for smaller population sizes while maintaining the chance of discovering new whale populations. The proposed QWOA implements whale shrinking and spiral movement through quantum-based exploration which uses modified mutation and crossover operators. Agrawal et al. (2020) technique uses quantum rotation gate operator to control the balance between exploration and exploitation through its implementation for research purposes.

Heidari et al. (2019) developed HHO which acts as an advanced optimization method that solves different types of optimization challenges. The HHO system functions through predators who work together to track their targets. The researchers employed multiple equations to simulate social behavior of Harris hawks and solve their social intelligence optimization challenges. The team evaluated HHO performance through testing on twenty-nine benchmark problems which lacked both restrictions and limitations. The researchers used three different problem types which included unimodal and multimodal and composition issues to evaluate HHO performance (Gölcük and Ozsoydan, 2021).

The Reptile Search Algorithm (RSA) which was developed through research by Abualigah et al. (2022) serves as a groundbreaking meta-heuristic that draws its inspiration from crocodile hunting methods. Crocodiles exhibit two fundamental behavioral patterns which include their hunting activities and their encircling behavior through high walking and belly walking. The researchers developed two mathematical models to update potential solution locations: one model describes an ideal search region while the other model describes a varied search area.

The quantum mutation reptile search algorithm (QMRSA) serves as an enhanced version of the reptile search algorithm (RSA) according to the work of Almodfer et al. (2022). The optimization method uses quantum mutation based search strategy to improve RSA performance through its application to various optimization problems. The method addresses two main challenges which affect the original RSA performance because it combines search operations with issues related to early convergence.

Zouache et al. (2024) presented their research report which contains both swarm intelligence methods and quantum-inspired research methods. The research study by Fang et al. (2016) introduced a decentralized quantum-inspired particle swarm optimization method which uses a cellular population structure. The researchers developed adaptive particle swarm optimization through their implementation of quantum-inspired quantum walking techniques (El-Latif and Abd-El-Atty, 2023). The researchers developed the quantum sperm motility algorithm (Hezam et al., 2022). The researchers developed a new quantum grasshopper optimization method (Wang et al., 2020).

The QISBA applications that have been introduced in the last ten years are listed in **Table 7** and QISBA concerning their source of inspiration are given in **Table 8**.

Table 7. Quantum-inspired swarm based algorithms (QISBA).

Applications	Year	Contribution /Innovation /Modification	References
Image security	2023	Integration of PSO with quantum walks for image encryption	El-Latif and Abd-El-Atty (2023)
Dynamic reliability based optimization problem	2023	The change of probability measure	Weng et al. (2023)
High dependence and complex optimization problems	2023	Quantum entanglement and local search	Deshmukh et al. (2023)
Multi-criteria optimization problems	2022	Hadamard gates and rotation gates	Balicki (2022)
Industrial wireless sensor networks	2022	New evaluation function of clustering scheme	Liu et al. (2022)
Multimodal optimization problems	2021	Self-organizing map (SOM)	Li et al. (2021)
Feature selection	2020	Supervised machine learning	El-Ashry et al. (2020)
Unit commitment problem	2018	Updates using quantum gate variation operators	Srikanth et al. (2018)
To improve ability of exploration in PSO	2017	Using the ability of exploration in grey wolf optimizer	Singh and Singh (2017)
Minimizing potential energy function	2017	Dimensionality reduction and population partitioning	Tawhid and Ali (2017)
Continuous global optimization problems	2015	Control parameters are self-adapted using evolutionary search	Jitkongchuen (2015)
Two-stage assembly flow shop	2015	Local search	Komaki and Kayvanfar (2015)

Table 8. Quantum-inspired Swarm based algorithms (QISBA) concerning their source of inspiration.

Source of inspiration	Year	Application	References
Spider monkey optimization (SMO)	2020	Grey level image clustering	Dey et al. (2020)
Ant colony optimization (ACO)	2019	Multi-objective routing in WSN	Li et al. (2019a)
Salp swarm algorithm (SSA)	2019	Multiobjective controller placement problem	Pathak et al. (2023)
Krill herd optimization algorithm (KH)	2020	Multi-objective optimization problems	Wei and Wang (2020)
Whale optimization algorithm (WOA)	2020	Wrapper feature selection clustering	Agrawal et al. (2020)
Grey wolf optimizer (GWO)	2021	0-1 knapsack problems	Wang and Wang (2021)
Firefly algorithm (FA)	2021	Segmentation of hippocampus images	Choudhury et al. (2022)
Satin bowerbird optimization (SBO)	2021	Constrained structural optimization	Zhang et al. (2021)
Squirrel search algorithm (SSA)	2021	Unimodal and multimodal problems	Zhang et al. (2021)
Reptile search algorithm (RSA)	2022	Global optimization and data clustering	Almodfer et al. (2022)
Sperm motility algorithm (SMA)	2022	Global optimization problems	Hezam et al. (2022)

3.1.4 Quantum-Inspired Human-Based Algorithms (QIHBA)

The development of human-based metaheuristic algorithms stemmed from studies of human behavior. The human-based metaheuristic algorithms which people know best include (Glover, 1989; Layeb, 2013; Taillard, 2016; Kuo and Chou, 2017; Chou et al., 2019; Chou et al., 2021; Hesar et al., 2021; Liang et al., 2022; Hesar and Houshmand, 2024). Harmony Search develops its better harmony through artist improvisation. The two main parts of Tabu Search define Moves as either prohibited or "tabu" while "strategic forgetfulness" lets people break their restrictions. Recent research produced several innovative QIHBA designs about these topics (**Table 9**).

Table 9. Quantum-inspired human based algorithms.

Algorithm	Year	Application	References
Harmony search (HS)	2014	0-1 optimization	Layeb (2013)
	2021	Multi-objective optimization problems	Hesar et al. (2021)
	2022	Global optimization problems	Liang et al. (2022)
Tabu search (TS)	2017	Combinatorial and numerical optimization problems	Kuo and Chou (2017)
	2019	Portfolio optimization	Chou et al. (2019)
	2024	Global optimization problems	Hesar and Houshmand (2024)

3.2 Nature Based Quantum-Inspired Metaheuristics Algorithms (NBQIMA)

Nature has always been a source of inspiration for humans. The characteristic appears in both of these metaheuristic methods. Nature-based metaheuristics use essential scientific knowledge from physical and chemical principles together with actual natural phenomenon occurrences. The research papers (Mirjalili et al., 2012; Kaveh and Mahdavi, 2014; Barani et al., 2017; Singh and Raza, 2017; Kaveh et al., 2020; Mirhosseini et al., 2021) describe Colliding Bodies Optimization (CBO) while the research papers (Kaveh and Talatahari, 2010; Talatahari et al., 2022) describe Charged System Search (CSS). GSA uses gravitational forces as its foundation while CBO and CSS use mechanical systems and electrostatic forces as their respective bases. The public was first exposed to quantum-inspired algorithms in 2018 with the Multi-scale Quantum Harmonic Oscillator Algorithm (MQHOA) (Wang et al., 2018; Mu., 2019; Mu et al., 2020).

Table 10 summarizes quantum versions of nature-inspired metaheuristic algorithms from 2015-2024.

Table 10. Nature based quantum-inspired metaheuristics algorithms (NBQIMA).

Source of inspiration	Year	Application	References
Gravitation search algorithm (GSA)	2012	Neural networks	Mirjalili et al. (2012)
	2017	Feature subset selection	Barani et al. (2017)
	2017	Job Scheduling	Singh and Raza (2017)
	2021	Wireless sensor networks	Mirhosseini et al. (2021)
Colliding bodies optimization (CBO)	2020	Numerical optimization	Kaveh et al. (2020)
Multi-scale quantum harmonic oscillator algorithm (MQHOA)	2018	Global numerical optimization	Wang et al. (2018)
	2019	Ground state convergence	Li et al. (2019a)
	2020	Numerical optimization	Mu et al. (2020)
Charged system search (CSS)	2022	Large-scale structure design	Talatahari et al. (2022)

3.3 Recent Metaheuristics Without Quantum Version

The section presents different common metaheuristic methods together with their particular applications. Our research shows that no existing work has tested the combination of these algorithms with quantum mechanical concepts. Quantum mechanics will serve as the inspiration for upcoming technological advancements.

The Arithmetic Optimization Algorithm (AOA) provides a common solution approach which relies on arithmetic operations for problem-solving (Abualigah et al., 2021a; Fang et al., 2022; Zhang et al., 2022a). The Aquila Optimizer (AO) (Abualigah et al., 2021b; Xing et al., 2022; Reddy et al., 2022; Ekinci et al., 2023) serves as a leading metaheuristic which researchers developed through their study of aquila hunting techniques. Researchers developed the Equilibrium Optimizer (EO) A physics-based optimization method through its application of the volume-mass balance equation. The Social Engineering Optimizer (SEO) (Fathollahi-Fard et al., 2018; Goodarzian et al., 2022) uses human social behavior as its main inspiration. The Red Deer Algorithm (RDA) models Scottish red deer mating behavior according to Fathollahi-Fard et al. (2020). The Keshtel Algorithm (Hajiaghaei-Keshteli and Aminnayeri, 2014; Mosallanezhad et al., 2021; Mousavi et al., 2021; Hamdi-Asl et al., 2021; Zahedi et al., 2021) applied in various domains including the supply chain.

The African Vultures Optimizer (AVO) (Abdollahzadeh et al., 2021; Balakrishnan et al., 2022; Hu et al., 2022) represents a new metaheuristic method which simulates the foraging and navigation patterns of African vultures. The Wild Horse Optimizer (WHO) (Narue and Keynia, 2022; Li et al., 2022; Zheng et al., 2022) introduces a new metaheuristic system which derives its principles from the social patterns of wild horses. The second version (Zheng et al., 2022) introduces a waterhole competition system which encourages players to search for resources while using a random movement method to achieve both exploration and resource discovery. The complete presentation of these algorithms appears in **Table 11.**

Table 11. Metaheuristics without quantum version.

Algorithm	Year	Application	References
Red deer algorithm (RDA)	2020	Multi-objective optimization problems	Fathollahi-Fard et al. (2020)
Keshtel algorithm (KA)	2021	Shrimp closed loop supply chain	Mosallanezhad et al. (2021)
	2021	Supply chain network design for blood decomposition	Mousavi et al. (2021)
	2021	Agricultural supply chain network design	Hamdi-Asl et al. (2021)
African vultures optimizer (AVO)	2021	Global optimization problem	Abdollahzadeh et al. (2021)
	2022	Skin cancer detection	Hu et al. (2022)
	2022	Feature selection	Balakrishnan et al. (2022)
Arithmetic optimization algorithm (AOA)	2021	Tension/compression spring design problem	Abualigah et al. (2021a)
	2022	To determine parameters of support vector machine	Fang et al. (2022)
	2022	Engineering optimization problem	Zhang et al. (2022a)
Social engineering optimizer (SEO)	2022	Engineering applications	Goodarzian et al. (2022)
Aquila optimizer (AO)	2021	Numerical and engineering optimization problems	Abualigah et al. (2021b)
	2022	Numerical weather prediction	Xing et al. (2022)
	2022	Hyperspectral image classification	Reddy et al. (2022)
	2023	Automatic voltage regulator	Ekinci et al. (2023)
Equilibrium optimizer (EO)	2020	Engineering optimization problem	Faramarzi et al. (2020)
	2023	Global optimization and the optimal power flow problems.	Houssein et al. (2023)

When it comes to exploration capability, convergence behavior, the whole computing complexity thing, and even where you can apply it, it looks like a comparison of the main QIMA families shows pretty clear upsides and downsides.

So, to preserve population variability, Quantum-Inspired Genetic Algorithms (QIGAs) use quantum rotation gates, and qubit-based chromosome representations. In a sense, their probabilistic representation reduces the chance of premature convergence, while still improving global exploration, sort of. But then again, because chromosomal updates involve extra computing overhead, convergence speed can end up being slower, for large-scale optimization problems, and that's the tradeoff people notice.

Quantum-Inspired Evolutionary Algorithms, also known as QIEAs, can sort of juggle exploration with exploitation by using a probabilistic way of encoding a state. You get pretty strong global search, plus a flexible form of objective fit across several optimization areas, which is demonstrated in the algorithms themselves. Still, the computational burden tends to rise as the population size grows, and also when the problem dimensionality climbs. On top of that, the final results may become somewhat dependent on how parameters are chosen, which can be a bit wobbly.

Quantum-Inspired Swarm-Based Algorithms, often called QISBAs, mix swarm intelligence techniques such as Particle Swarm Optimization, Grey Wolf Optimization, and Ant Colony Optimization with quantum ideas. Typically, these approaches can deliver improved search efficiency and faster convergence, even if the mechanism feels a bit indirect. Still, if diversity preservation measures are not handled well, they may end up suffering from premature convergence, like the swarm sort of collapses early, and then the exploration gets stuck.

QIHBAs, or Quantum-inspired human based algorithms, are a pretty fresh kind of research area, like it just showed up recently. These algorithms use human style learning and decision-making tricks, and they seem to give decent outcomes on nasty optimization problems. But unlike other QIMA families, the theory behind them, and how they converge, hasn't really been looked at too much, at least not in the same way.

Most of the time, QISBAs focus on fast convergence and doing the exploiting part efficiently, while QIGAs, plus QIEAs tend to lean more toward exploration and keeping diversity around, sort of like that. And the whole thing about which QIMA family is "best" really depends on the optimization situation itself. for example, dimensionality, how tangled the constraints are, and how heavy the computational needs get.

Table 12 establishes a comparative framework that reveals the distinct methodological differences between current quantum-inspired optimization algorithms. The table presents essential information about multiple algorithms through its demonstration of basic inspiration and solution representation and exploration mechanisms and computational complexity and typical application domains. The comparison demonstrates that the exploration abilities and algorithm performance across various optimization tasks depend on the specific quantum-inspired representation and update methods used by the algorithms.

Table 12. Comparison of representative quantum-inspired metaheuristic algorithms in terms of inspiration, solution representation, exploration mechanism, computational complexity, and applications.

Algorithm	Solution representation	Exploration mechanism	Computational complexity	Typical applications
Quantum-inspired Genetic algorithm (Han and Kim, 2002)	Linear superposition and Q-bits	Rotation gates	$O(10^7)$	Combinatorial optimization problem
Quantum-inspired Harmony Search algorithm (Layeb, 2013)	Linear superposition and Q-bits	Rotation gates and quantum mutation	$O(3 \times 10^7)$	High dimensional knapsack problems
Quantum-inspired Differential Evolution (Wang and Wang, 2021)	Angle encoding	Rotation gates	$O(3 \times 10^7)$	High dimensional knapsack problems
Quantum-inspired Squirrel Search Algorithm (Zhang et al., 2022b)	Linear superposition and Q-bits	Wave function	$O(5 \times 10^6)$	Engineering design optimization
Entanglement enhanced Grey Wolf Optimizer (Deshmukh et al., 2023)	Binary encoding	Entanglement and Local search	$O(3 \times 10^5)$	High dependency Problems

Quantum-inspired metaheuristic algorithms (QIMAs) solve complex optimization problems effectively because they represent solutions with qubits and use quantum superposition principles for their probabilistic solution representation (**Table 13**). The algorithms use these mechanisms to perform simultaneous searches across different search space sections, which leads to better global search results and helps prevent premature solution narrowing. QIMAs demonstrate better results than classical metaheuristics when solving problems that feature extensive search areas and multiple nonlinear relationships.

The benefits that QIMAs deliver to performance do not apply to every situation. Classical metaheuristic algorithms deliver better results than modern algorithms for basic optimization tasks that involve few dimensions because these traditional methods require less processing power and use easy-to-understand updating methods. Some quantum-inspired algorithms show operating problems because their parameters need tight control and their rotation updates need consistency and their process needs active control between searching and confirming results.

Scalability represents a key element that needs assessment. QIMAs handle medium-sized optimization tasks successfully until their computational requirements increase with both problem dimensions and population count. Researchers need to create new update methods together with hybrid systems because this area represents a crucial research pathway for improving the scalability and robustness of quantum-inspired optimization algorithms.

Table 13. Comparative analysis of quantum-inspired optimization techniques using quantum mechanisms, representation, performance and restrictions.

Algorithm	**References**	**Quantum representation**	**Quantum mechanism**	**Problem domain**	**Performance summary**	**Advantages**	**Limitations**
Aquantum-inspired genetic algorithm for solving the antenna positioning problem	Dahi et al. (2016)	Linear superposition	Quantum crossover, mutation, interference	Advanced cellular phone networks. (The Antenna Positioning Problem) (APP)	QIGA is the fastest to reach high fitness	Fastest convergence, Strong balance between exploration and exploitation	High computational complexity
Entanglement-enhanced quantum-inspired tabu search algorithm for function optimization	Kuo and Chou (2017)	Binary encoding	Entanglement and local search	Classic benchmark functions.	Entanglement-QTS achieves the best solution quality, entanglement-QTS requires far fewer function evaluations	Performance remains stable as dimension increases, superior scalability	Limited benchmark set, performance on real applications not verified
A hybrid quantum-inspired harmony search algorithm for 0-1 optimization problems	Layeb (2013)	Linear superposition and Q-bits	Quantum mutation, quantum interference	Knapsack problem (mknapcb1, mknapcb4)	Exhibits competitive performance and superior robustness	Better solution quality than PSO and BCS	Does not always reach the best-known optimum
Quantum-inspired differential evolution	Wang and Wang (2021)	Angle encoding	Rotation gates	High dimensional knapsack problems	QDGWO achieved superior success rate, better solution quality and good scalability	Produces solution closer to global optimum	Performance declines with problem size, limited comparative study
Quantum-inspired particle swarm optimization with guided exploration for function optimization	Agarwal et al. (2021)	Binary encoding	Probability distribution	High dimensional unimodal and multimodal problems	e-QPSO achieved best performance amongst most benchmark functions	High solution accuracy, robustness across problem types	Algorithmic complexity, parameter sensitivity
Quantum-inspired squirrel search algorithm	Zhang et al. (2022b)	Linear superposition and Q-bits	Wave function	Unimodal and multimodal problems	AM-QSSA shows the best overall performance	High accuracy, strong convergence capability	Not best on every function
Quantum-inspired ant colony optimization	Ghosh et al. (2022)	Quantum path encoding	NOT, CNOT gates	Vehicle network routing	A 4-qubit QACO generates 16 paths, large variation in path costs	Compact representation, enhanced exploration	Small demonstration problem, No comparative results
Quantum entanglement inspired grey wolf optimization algorithm and its application	Deshmukh et al. (2023)	Binary encoding	Quantum entanglement and local search	High dependence and complex optimization problems	QEGWO outperforms GWO in CEC-2019,2020 benchmark functions	Entanglement and local search help to prevent local optima	High computational complexity

RQ1: Current Advancements in Quantum-Inspired Metaheuristics

The selected works shows some notable progress in making metaheuristic methods inspired by quantum theory, not fully but enough. In general, well known approaches for tackling tough optimization tasks include the Quantum-inspired Evolutionary Algorithm (QIEA), Quantum Particle Swarm Optimization (QPSO), and also Quantum Genetic Algorithm (QGA). Instead of only using usual evolutionary operators, the methods rely on quantum rotation gates plus a qubit representation, so they can expand their exploring potential, and push the optimal solution rate, a bit faster.

RQ2: Hurdles and Constraints in Integrating Quantum Computing with Metaheuristics

Because quantum mechanical ideas like superposition, entanglement, and quantum tunneling might boost search efficiency and help with better solution quality, people have shown serious scientific interest in quantum computing approaches for optimization issues. Still, there are a few problems that make it hard for these quantum optimization techniques to be used broadly and actually put into practice.

The scarcity of truly scalable quantum hardware is one of the largest hurdles. The Noisy Intermediate-Scale Quantum (NISQ) era for present day quantum computers is marked by a limited count of qubits with short coherence windows. When optimization problems start to grow bigger, and then get a lot more complicated, deployment at scale becomes hard, because we suddenly need far more trustworthy qubits, like reliable, dependable ones, not just a few.

Quantum decoherence is, like, another big hurdle. Over time, it's basically the case that quantum information goes away, not because of some simple reason but because quantum states are extremely touchy about interactions with their surroundings. This decoherence can really mess with the efficiency of quantum algorithms and can also pull-down computational accuracy. It's especially noticeable for optimization problems, when there is need of high circuit depths and these longer calculation times.

Another big issue with today's quantum devices is noise, because errors can show up in qubit operations, in quantum gates, and even in measurements too. These kinds of disturbances can stack up as the calculation goes on and end up with wrong or skewed solutions and the whole dependability of optimization results drops off. And quantum error correction approaches have been suggested, but they require a lot of extra hardware, which we don't really have available right now.

On the other hand, without actually requiring real quantum hardware, quantum-inspired metaheuristic algorithms, or QIMAs, try to mimic quantum principles on standard computers. Instead of being stuck by physical constraints they can still lean on notions such as qubit style representation, probabilistic state evolution, and quantum-inspired search methods. That said, a careful assessment of QIMAs remains necessary to verify how well they truly match the advantages of authentic quantum computation, especially regarding computational efficiency, scaling, convergence tempo, the ability to explore, and the overall quality of the solutions they produce.

There are still a number of methodological constraints on top of the hardware and implementation issues. It is kind of hard to judge how effective quantum, and also quantum-inspired optimization algorithms are across many problem areas in a very objective way, mainly because there is no standardized benchmarking framework, sort of like a common yardstick. Also, it becomes tricky to anticipate the behavior of many quantum-inspired algorithms when you move toward large-scale optimization problems, because they often do not have strong theoretical convergence promises. Even if some methods look great on benchmark functions, they might not keep the same tempo and performance when you take them to high dimensional, limited, or more real world optimization cases, so scalability is still a problem. Lastly there are more practical difficulties in weaving quantum optimization methods into today's classical computer infrastructures, particularly in large-scale and industrial computational environments.

RQ3: Innovative Techniques and Future Directions

Recent studies indicate growing interest in hybrid optimization frameworks that combine quantum-inspired algorithms with classical metaheuristics and machine learning techniques. The new methods developed by researchers work to enhance both solution quality and the computational performance of large-scale optimization challenges.

4. Bibliometric Analysis

The bibliometric analysis highlights research developments from 2015 to 2024, using data sourced from the SCOPUS database. We have attempted a query based on the themes quantum-inspired genetic algorithm, quantum-inspired evolutionary algorithm, and quantum-inspired swarm-based algorithms. This is to know about the authors who have been working in the area of quantum computational intelligence for about the last decade. The outcomes of this particular query are shown in **Figure 7**. **Figure 8** indicates that the number of QIMAs related articles developed so far is increasing steadily.

Subject wise publication analysis and document type distribution of publications have been shown in the **Figures 9** and **10** respectively.

The bibliometric analysis establishes quantitative measurements of publication patterns and citation behaviors and research partnerships which exist in quantum-inspired metaheuristic algorithm research. The complete thematic structure and research methods used in the literature cannot be discovered through bibliometric analysis. The research mapping study establishes research directions and algorithmic categories and application domains through its systematic mapping study. The selected studies undergo classification and analysis according to established mapping criteria which are presented in this section.

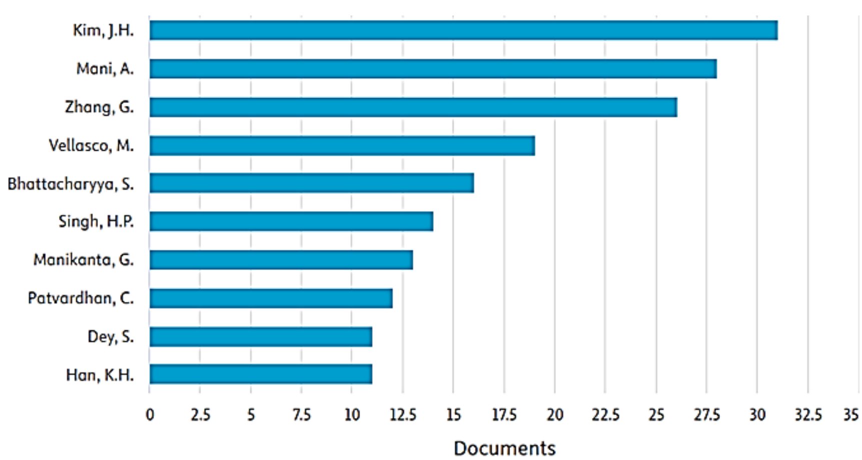

Figure 7. Top contributing authors in quantum-inspired metaheuristics research (source: analysis based on data retrieved from the Scopus database).

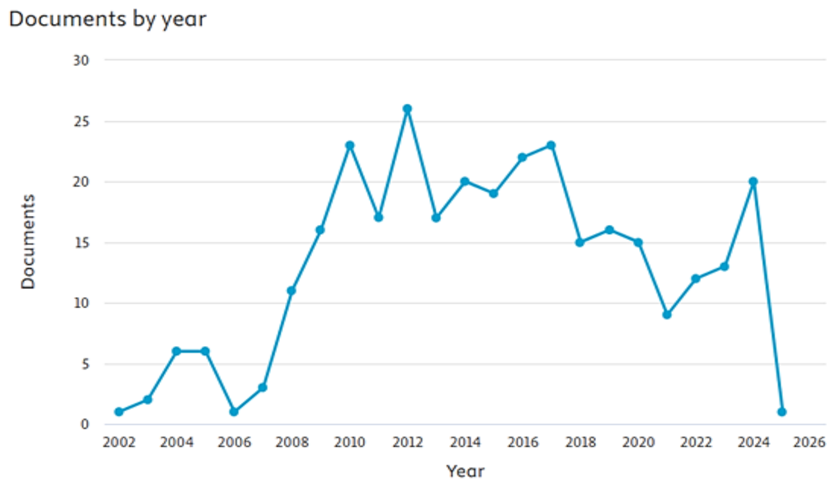

Figure 8. Documents by year for quantum-inspired metaheuristics research based on records retrieved from the Scopus database.

Additionally, the method used for the further visualization of the "Quantum-inspired metaheuristics" networks and relationships was the VOS viewer program by Perianes-Rodriguez et al. (2016). A search in the Scopus database helped to identify the network, relations, and clusters pertaining to the topic 'Quantum-inspired evolutionary algorithms'. A total of 141 connected articles were detected based on title, abstract, and keyword. The data from Scopus were further analysed using VOS viewer for the mapping of results. The very first step was to create a map using bibliographic data from Scopus. The data were inputted in csv format. The analysis used was Co-occurrence, full counting. The keywords with at least two occurrences were considered for this study. A total of 1515 keywords were gathered, and 261 of them met the criteria. The second step was to assign the total strength of co-occurrence links to every one of the 261 keywords.

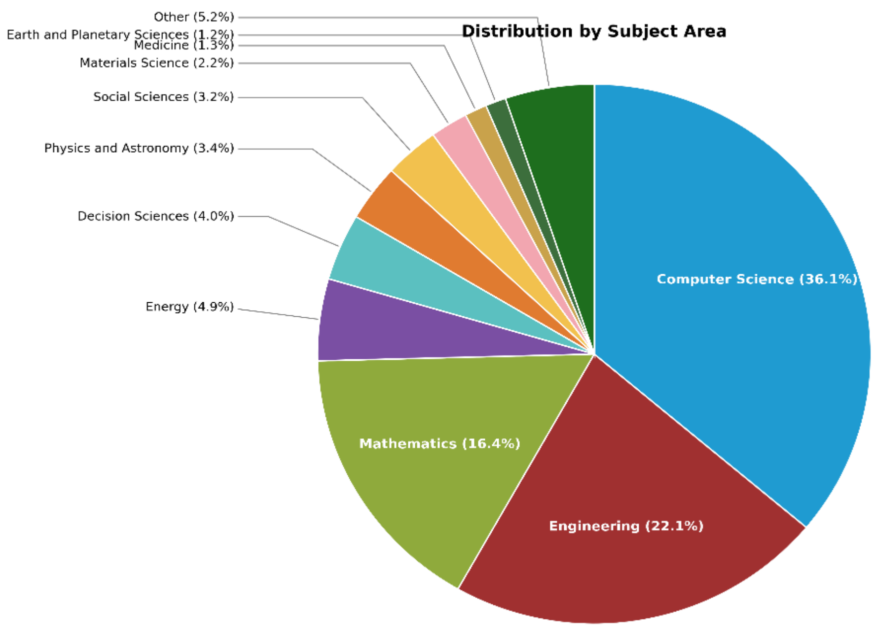

Figure 9. Percentage distribution of publications by subject area in the Scopus dataset.

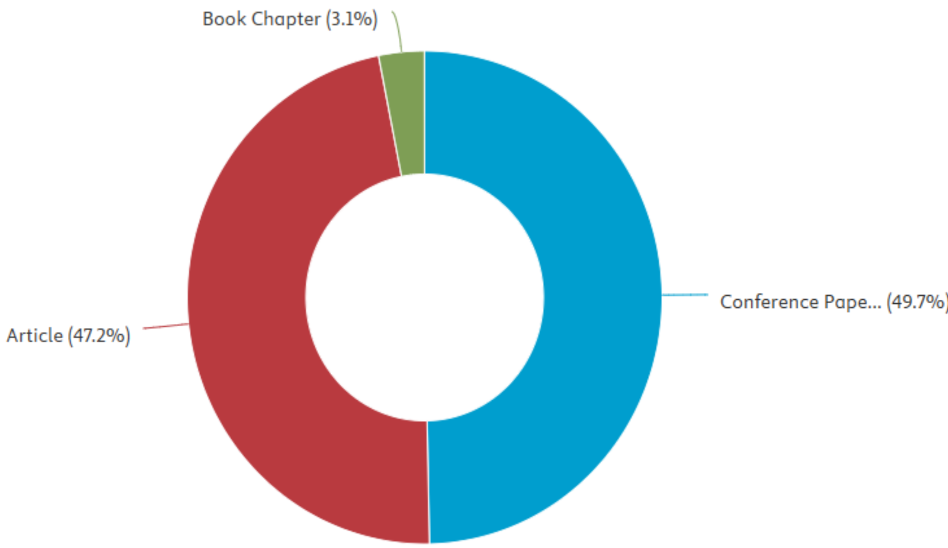

Figure 10. Percentage distribution of document types in the Scopus dataset used for the study.

The keywords with the highest total link strength were selected. The final results is based on 261 keywords. **Figure 11** depicts the network, relations, clusters, and linkages in a graph of this query from the Scopus data. The density of Quantum-inspired evolutionary algorithms identify research hotspots, trends, and areas of high activity or influence in a dataset is depicted in **Figure 12**.

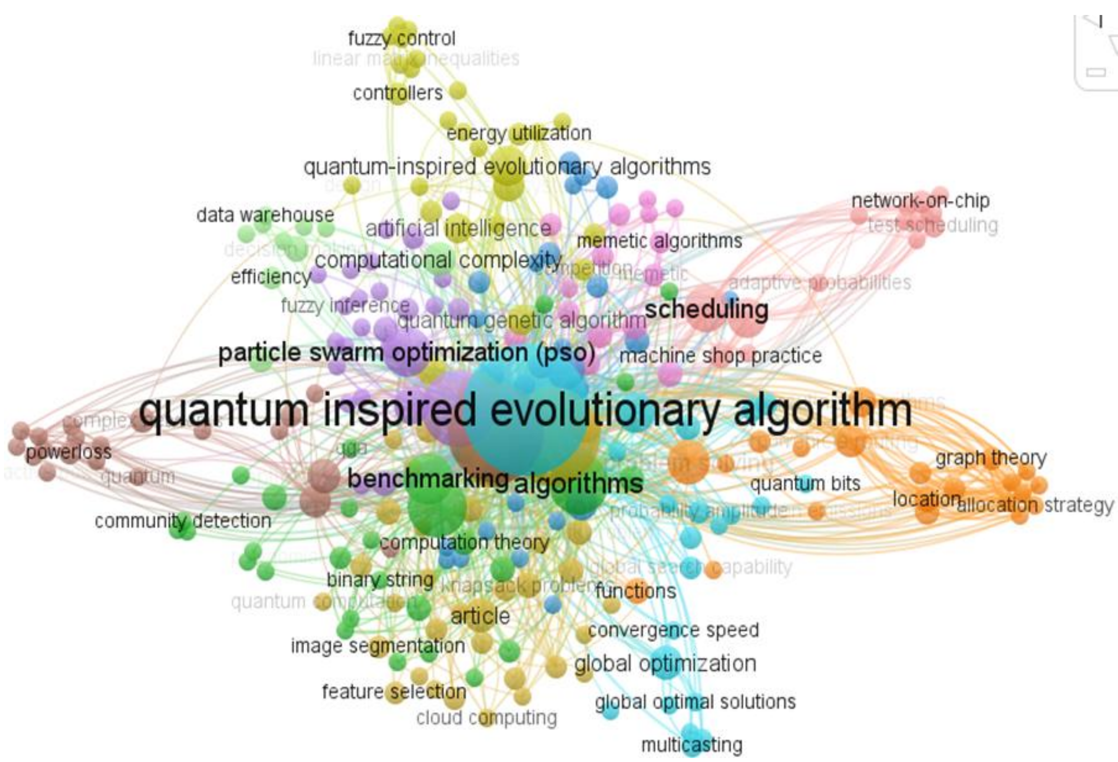

Figure 11. Network with the topic quantum-inspired evolutionary algorithm.

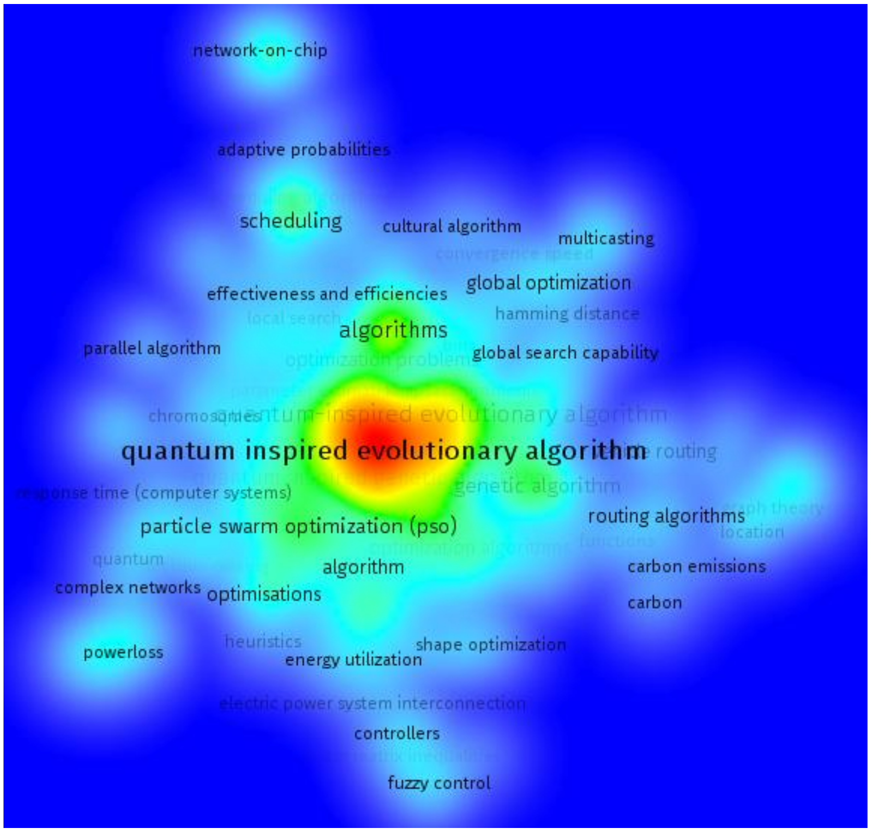

Figure 12. Density map of quantum-inspired evolutionary algorithms.

5. Findings, Challenges and Future Directions

Quantum-inspired algorithms differ from classical metaheuristics because they use probabilistic qubit representation to explore multiple solution states simultaneously. The algorithms QIEA and QPSO achieve faster convergence rates than their classical counterparts because they possess better exploration abilities. The computational complexity of the system increases when the qubit representation and population size grow. The majority of quantum-inspired metaheuristics fail to provide solid theoretical evidence for their convergence, and their performance varies depending on the specific problem. The process of choosing the right algorithms for particular optimization problems requires a thorough analysis of both algorithm structures and performance attributes.

1) The analysis shows that the efficiency of metaheuristic algorithms can be improved by weaving in operators like quantum bit encoding, quantum gate, and quantum rotation gate. When it comes to shrinking the population size, avoiding premature convergence, keeping a kind of balance between exploitation and exploration, maintaining acceptable closeness as well as diversity, and needing less execution iterations, QIMAs also do better than standard metaheuristic algorithms.
2) As the target functions scale increases, the coding matrix's dimensions rise, requiring more time to solve and update iteratively.
3) This applies to binary-coded algorithms, but real-coded algorithms provide a more difficult situation. As a result, there is an increasing need for real-world quantum computer implementations of quantum-inspired metaheuristics.

4) As far as we are aware, quite a few metaheuristic algorithms have not yet been integrated with those ideas from quantum mechanics. So, because of this, future iterations of these routines might get their inspiration from quantum mechanics, in a sort of indirect way that feels less immediate but still related.
5) Most reported practical implementations compared QIMAs to their classical equivalents. However, studying the strengths and limitations of various QIMAs in relation to one another remains an open topic of research.
6) Design of scalable parallel QIMAs for massive data and distributed system design may be done in future.
7) Understanding which algorithms prefer specific search areas opens new potential for hybridization based on this knowledge. Researchers can combine many algorithms to explore the search space more thoroughly.
8) The analysis stresses the untapped potential of QIMAs, thus suggesting the opportunity for a radical change through their incorporation and utilization in optimization. In this sense, exploring and exploiting the capacities of different QIMAs may lead to huge breakthroughs and radical changes in optimization.

6. Conclusion

Quantum-inspired metaheuristic approaches constitute a significant advancement in the field of optimization. These approaches, inspired by quantum computing concepts, bring a plethora of new possibilities, including parallel exploration, increased diversity, and the capacity to more efficiently escape local optima. Quantum-inspired algorithms, which include principles such as quantum superposition, entanglement, and interference into conventional optimization processes, give up new options for tackling complicated, high-dimensional, and multimodal issues that standard methods cannot address.

While the theoretical foundations and practical applications of these techniques are still evolving, they have already showed extraordinary effectiveness in a wide range of domains, including engineering and scheduling, machine learning, and artificial intelligence. The combination of quantum-inspired algorithms and classical optimization approaches holds enormous potential for building powerful, adaptable solutions to real-world difficulties with speed and precision.

However, as promising as they are, quantum-inspired systems still face the problems, particularly in terms of computational efficiency, scalability, and the need for additional research into hybrid models. As quantum computing advances, we expect more breakthroughs that will refine and improve the practical application of these algorithms, ultimately propelling the industry into new paradigms of optimization.

To conclude, quantum-inspired metaheuristics are at the forefront of optimization research, bridging the gap between quantum computers and traditional algorithmic approaches. These approaches have enormous potential to revolutionize optimization across multiple domains, making them an intriguing area of research with limitless future possibilities. Continued innovation and exploration in this subject will surely result in more efficient, adaptable, and robust solutions to some of the most difficult problems of our day.

Conflicts of Interest
The authors confirm that there is no conflict of interest to declare for this publication.

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AI Disclosure
The author(s) declare that no assistance is taken from generative AI to write this article.

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