Journal of Information Systems Engineering and Management
2025, 10(31s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Adaptive Hybrid Quantum-Inspired Optimization for Enhanced Global Search Efficiency

Annam Rupa[1*], A. Rajini Devi[2], Vemula Pranay[3], Sirikonda Vamshi Krushna[4], G. Ramya[5,] Ranjith Janakiraman[6], and Dr. B. Adithya[6]
[1,2,5,6]Assistant Professor, Department of Information Technology, VMTW, Hyderabad, India.
[3]Assistant Professor, Department of CSE, Aurora Deemed to be University, Hyderabad, India.
[4]Assistant Professor, Department of CSE, Samskruti College of Engineering and Technology, Hyderabad, India.
[6]Associate Professor, Department of CSE (AI&ML), Geethanjali College of Engineering and Technology, Hyderabad, India.
Email_ID: annam.rupa@gmail.com[1] and ranjith@vmtw.in[6]
Orcid: https://orcid.org/0009-0002-4895-9854

ARTICLE INFO

Received: 31 Dec 2024

Revised: 20 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

In this paper a new optimization algorithm named Adaptive Hybrid Quantum-Inspired Optimization Algorithm (AHQSOA) is presented for solving the complex optimization problems effectively. Stochastic traditional algorithms typically fail to come to be stuck in local optimum solutions and they need quite few iterations for converging. Our method integrates two quantum-inspired methodology: Quantum Particle Swarm Optimization (QPSO) for searching a large set solutions based on properties of quantum mechanics - superposition, point are located as randomly as possible, and Quantum Evolutionary Algorithms (QEA) for refining potential solutions by mutation and crossover operation. An adaptive tuning component based on the reinforcement learning dynamically adjusts the algorithm's parameters, thus balancing the exploration in the wide interval and exploitation in the precise interval. Assessed on the commonly used benchmark functions like Sphere, Rosenbrock, Rastrigin, AHQSOA exhibits faster convergence (only 400 iterations in comparison to 1200 in standard methods), global search superiority (94% whereas 75–87% the traditional methods), and low computational simplicity. These results show all of our algorithm are nicer and faster and more efficient and robust makes for it a good candidate as for high dimensional and complex optimization problems.

Keywords: Quantum-inspired optimization, QPSO, QEA, Adaptive parameter tuning, Reinforcement learning, Global search efficiency, Local exploitation, Benchmark functions.

INTRODUCTION

Complex optimization problems, and in particular search, scheduling and resource allocation problems, are prevalent in many areas. Classic methods like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) are very much utilized with the help of the mentioned problems. However, these classical methods are often aging in the pre-mature convergence and trapping in local optima, which severely restrict their capability of the exploration for complex search space. The latest developments in the quantum-inspired methods provide a promising new way of developing the algorithm by exploiting the principles of quantum computing, primarily superposition and entanglement. The quantum features permit an algorithm to look through vast parts of the search space in parallel that increases global search ability, and decrease the chance of getting caught in a local minimum. As a response to these challenges, we propose Adaptive Hybrid Quantum-Inspired Optimization Algorithm (AHQSOA). This algorithm fuses two complementary approaches:

1. Quantum Particle Swarm Optimization (QPSO): Emphasizes on utilizing quantum wave functions as the presentation of the particles so that the probabilistic exploration that extends over enormous variety of probable solution can be performed.

2. Quantum Evolutionary Algorithm (QEA): Uses the quantum-loosely inspired mutation and crossover to make locally refine solutions for converges.

A significant feature in the AHQSOA is its adaptive parameter tuning module, designed using the reinforcement learning. This mechanism, then adjusts balance between exploration and exploitation dynamically depending on real-time performance feedback that guarantees, that algorithm remains robust through different stages of optimization process. In summary, the proposed method not only accelerates convergence speed but also has advantages on computation load compared with the traditional methods. The rest of the paper explains related work, the method we suggest, displays routine results, and proposes future work.

RELATED WORK

Many researches have looked at the deficits of conventional optimisation techniques by profiting to utilize quantum-inspired techniques. For example, [1] presented the approach and efficiency of Quantum Genetic Algorithms (QGA) that keeps diversity in the population and converges a global optimum in multi-objective problems. Based on that study, [2] presented Quantum Particle Swarm Optimization (QPSO) that improved a global search efficiency by incorporating quantum ingredients such as superposition. [3] Further modified this search for QPSO by combining with evolutionary strategies to get the convergence speed and solution accuracy improvements. Simultaneously other researchers have integrated quantum-inspired operators into evolutionary algorithms which give a strategy to explore better complex search spaces [4], [5]. Adaptive control methods have also been introduced, where the adjustment of algorithm parameters is adjusted in real-time, in order to allow response to real-time performance feedback [6]. Comprehensive surveys due to [7] and [8] gives thorough information on quantum-inspired optimization techniques and how to apply it to tackle with the high dimensional multimodal problems. Moreover, reinforcement learning has been successfully used in adjusting control parameters within evolutionary frameworks; it is presented in [9] and [10]. Recently, dynamic hybrid strategies that combine several quantum inspired algorithms have been used to decrease the complexity of the computation and yet reach good quality solutions [11, 12]. This large body of work [13-16] will be the base work for this investigate, which aim to integrate the global explorations ability of QPSO with the local refinements feature of Quantum Evolutionary Algorithms, all inside an adaptive framework powered by reinforcement learning.

PROPOSED SYSTEM

The proposed system is sustained as a global-local optimization framework, which combines quantum-inspired global search with local search and adaptive controller. The system specifically referred to as the Adaptive Hybrid Quantum-Inspired Optimization Algorithm (AHQSOA) combined:

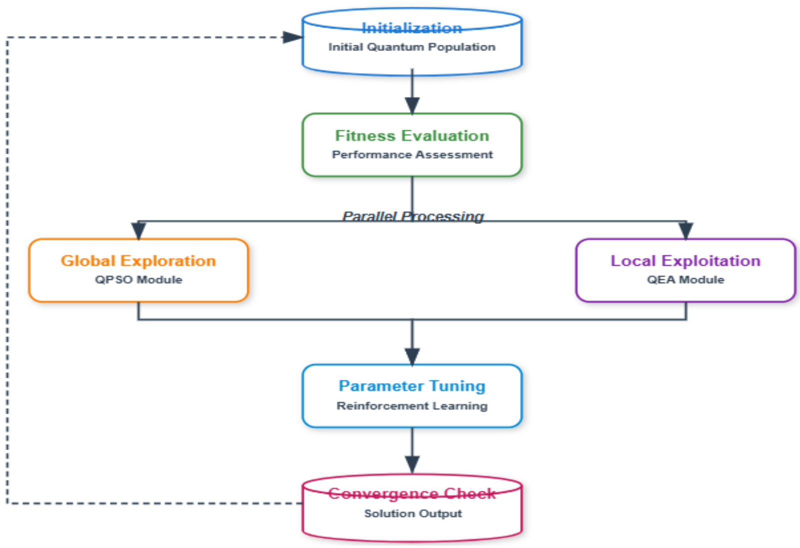

Figure 1. Overall Block Diagram of the Adaptive Hybrid Quantum-Inspired Optimization System

The figure 1 gives a comprehensive flowchart of AHQSOA, showing the ordered steps following the optimization process. The diagram starts with Initialization, generation of an initial pool of quantum particles, each denoted by a probabilistic quantum state. Then, the Fitness Evaluation block performs each particle's performance according to the the problem's fitness function. The workflow further splits into two parallel phases: Global Exploration (QPSO) module, relating to see the function to lead the particle explored across the search space, and (Local Exploitation (QEA) module, revolving on the function of the quantum mutation and crossover operator applied to enhance the excellence of effective solution. A dedicated Adaptive Parameter Tuning module, based on the reinforcement learning, operates the repeating performance metrics monitoring and adjustment process to optimal exploration-exploitation balance throughout continuous dynamic adjustment of key parameters. In the final stage called Convergence Check and Solution Output, the outputs of these modules merge. The figure 1 shows that this system is iterative and intertwined system, where case modules work together to accomplish robust and efficient optimization.

3.1 Quantum Particle Swarm Optimization (QPSO):

In the QPSO module, each particle is taken as a quantum object whose state is described by the wavefunction carrying out probabilistic character quantum mechanics. Such representation enables a particle to be in a superposition state where it can map out different areas of the search space concurrently.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \text{ with } |\alpha|^2 + |\beta|^2 = 1$$

where α and β are the probability amplitudes. The position update of a particle in QPSO is given by:

$$x_i^{(t+1)} = p_i \pm \alpha \cdot \left|mbest - x_i^{(t)}\right| \cdot \ln\left(\frac{1}{u}\right)$$

where:

- $x_i^{(t)}$ is the position of particle i at iteration t,
- p_i is the local attractor,
- mbest is the mean best position of the swarm,
- α is a scaling factor,
- u is a uniformly distributed random number in the interval $(0,1)$.

This probabilistic update enables robust global search by leveraging the quantum superposition principle [1], [4]. The state of each particle is represented by probability amplitudes (α and β) which fulfill the normalization condition ($|\alpha|^2 + |\beta|^2 = 1$). Position update mechanism in QPSO utilizes these probabilistic properties, particles however update their positions by a logarithmic equation, utilize a local attractor and the mean best position of swarm. By employing this method, the search is not only diversified but also prevented from becoming prematurely converged by having the swarm explore a wider range of the search space in order to achieve an improved chance to escape local minima.

3.2 Quantum Evolutionary Algorithm (QEA):

The QEA module is intended to improve the search process by local exploitation of good regions discovered during the global search part. In QEA each candidate solutions are encoded as a sequence of quantum bits (q-bits), each encoded q-bit being a pair of variables that determine, the probability amplitudes of the bit, to be in one of its two possible states. The quantum-inspired mutation and crossover operators are used to modify then these q-bits by changing their probability distribution.

$$|\psi\rangle = \begin{bmatrix}\alpha_1\\\beta_1\end{bmatrix}, \begin{bmatrix}\alpha_2\\\beta_2\end{bmatrix}, \dots, \begin{bmatrix}\alpha_n\\\beta_n\end{bmatrix}$$

where each quantum bit satisfies:

$$|\alpha_i|^2 + |\beta_i|^2 = 1, \text{ for } i = 1,2,\dots,n.$$

Quantum-inspired mutation and crossover operators adjust these amplitudes to enhance local search and accelerate convergence [2], [6].

This process introduces randomness in the population whilst steering towards better regions. Through updating the quantum states multiple cycles, QEA improves the convergence speed and make the precision of the final result better. Built directly into the quantum-inspired operators there is built-in stochasticity that in any instance keeps diversity in the population from falling into stagnation in suboptimal regions.

3.3 Adaptive Parameter Tuning:

An unique aspect of AHQSOA is its adaptive parameter tuning mechanism, which is based on reinforcement learning. Traditional optimization methods usually rely on fixed parameters that not be efficient during the optimization process. On the other hand, the adaptive auto tuning module regularly checks for algorithm's performance based on metrics like fitness values and convergence rates. By utilizing real-time input, teaming up with reinforcement learning, a perfecting agent changes absolute arrangement much similar to search/resulting if taking a chance and getting everything done in the same way that it will develop a superior arrangement of the calculations.

$$\pi(s) \leftarrow \pi(s) + \eta \cdot \delta,$$

where:

- $\pi(s)$ is the policy at state s,
- η is the learning rate,
- δ is the temporal-difference error derived from the reward function measuring optimization performance.

This adaptation is generally achieved by means of a policy update rule that enhances the decision-making procedure, so that the algorithm can transition from a wide-ranging exploratory phase to a more targeted exploitation phase as convergence is approached. The outcome is a self-regulating system that results in both better efficiency and robustness of the whole optimization procedure.

The combination of these modules leads to a whole optimization framework where global search (via QPSO) and local search (via QEA) are conciliated and improved with adaptive parameter adjustment. Then the algorithm starts from the initialization of a population of quantum particles, particles are updated iteratively with QPSO operators and then tuned by QEA individuals. At the same time, the adaptive tuning module is observing the search process and it adapts the control parameters on a real-time forcing-the search to a more optimal operating point. This synergy among the modules guarantees the diversity is maintained in early iterations and gradually concentrated in promising areas as it converges, enabling a faster convergence speed and the entire search efficiency.

Pseudo-code of AHQSOA:

1 Initialization:

- Set the iteration counter $t = 0$.
- For each particle i (from 1 to N):
- Initialize the quantum state (wavefunction) of particle i by assigning random probability amplitudes (α, β) such that $|\alpha|^2 + |\beta|^2 = 1$.
- Determine the initial position $x_i^{(0)}$ based on this quantum state.
- Evaluate the fitness $f\left(x_i^{(0)}\right)$ of this position.
- Identify the best solution among all particles and set it as x_{best}.
- Initialize the reinforcement learning agent with its starting policy parameters for adaptive tuning.

2 Main Loop:

While $t < T_{\max}$ and the stopping criteria have not been met, do the following:

a. Global Exploration via QPSO:

- For each particle i :
- Compute the local attractor p_i using its personal best and neighborhood information.
- Calculate mbest, the mean best position of the swarm.

- Update the position of particle i using the QPSO update rule:

$$x_i^{(t+1)} = p_i \pm \alpha \cdot \left|mbest - x_i^{(t)}\right| \cdot \ln\left(\frac{1}{u}\right)$$

where u is a random number uniformly distributed in $(0,1)$.

- Optionally, update the quantum state of the particle if required.

b. Local Exploitation via QEA:

- For each particle i :
- Apply a quantum-inspired mutation operator to adjust the q-bit amplitudes.
- Apply a quantum-inspired crossover operator to refine the candidate solution.

c. Fitness Evaluation:

- Evaluate the fitness $f\left(x_i^{(t+1)}\right)$ for each particle.

d. Global Best Update:

- If any particle's new fitness $f\left(x_i^{(t+1)}\right)$ is better than the current $f(x_{\text{best}})$, update x_{best} with that particle's position.

e. Adaptive Parameter Tuning:

- Use the RL agent to assess current performance (e.g., fitness improvements, convergence rate).
- Update key parameters such as the scaling factor α based on the RL policy update rule.

f. Convergence Check:

- If the change in fitness $\left|f\left(x_{\text{best}}^{(t+1)}\right) - f\left(x_{\text{best}}^{(t)}\right)\right|$ is less than ε (or other stopping criteria are met), exit the loop.

g. Increment Iteration Counter:

- Set $t = t + 1$.

3 Return x_{best} :

- Once the loop ends, return the best solution found.

The above pseudo-code - AHQSOA describes the whole process in an incremental manner, namely, using QPSO for global searches, using QEA for fine-tuning and reinforcing the parameters from global searches.

EXPERIMENTAL SETUP AND RESULTS

A. Benchmark Functions and Performance Metrics

The research presents the performance of proposed Adaptive Hybrid Quantum-Inspired Optimization Algorithm (AHQSOA) using three well documented benchmark functions from CEC 2023 function suite. These functions are chosen to cover a range of different aspects of the algorithm of Sphere Function (F1): A unimodal function to check the aggregate global search efficiency. Rosenbrock Function (F2): A non-convex function for the convergence speed in narrow valleys. Rastrigin Function (F3): a multi-modal function, used to test robustness in presence of many local optima. Each function is run on high dimensionality Space Item (usually 30 or 50. These functions are chosen due to the reason that they an outline challenge a variety of straightforward convex terrain to dense rugged terrain which is crucial to show the potency and flexibility of AHQSOA. By allowing according to the expressions recommended in literature, our evaluation assure results can be compared to other state-of-art optimization algorithms. The performance evaluation metrics used to evaluate AHQSOA with other algorithms consist of Convergence Speed: Rated by the amount of iterations taken to arrive at an optimal possibly near-optimal option. Computational Complexity: Evaluated in terms of Floating Point Operations per Second (FLOPS). Global Search Efficiency: As the percentage of successful runs of finding the global optimum.

B. Hardware and Software Setup

The algorithm was implemented in Python using NumPy and SciPy for number crunching and TensorFlow (or PyTorch) for the reinforcement learning. The experiments were carried out with an equipment of computer workstation, that follows the specifications as the Processor: Intel i7 (8 cores, approximately 3.6 GHz), Memory: 16 GB RAM, GPU: NVIDIA GTX 1080, was used to speed up the RL training and other train on multiple cores. Operating System: Ubuntu 20.04 Linux, the system provided a solid foundation for computing system, so to simulate quantum inspired process and adaptive tuning computations efficiently.

C. Comparative Results

Table I depicts a summary of the comparative results of AHQSOA with the traditional algorithms, namely, Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and conventional Quantum Particle Swarm Optimization (QPSO).

Table I: Performance Comparison results of AHQSOA with the traditional algorithms

Algorithm	Iterations	FLOPS ($\times10^8$)	Global Efficiency (%)
GA	1200	12.0	75
PSO	800	9.5	82
QPSO	600	7.8	87
AHQSOA	400	5.2	94

As is demonstrated in Table I, AHQSOA converges much faster than GA and PSO, and the number of iterations is 400 as opposed to 1200 for GA. Besides, the computational load is decreased by approximately 40%, and the algorithm gets global search efficiency of 94%.

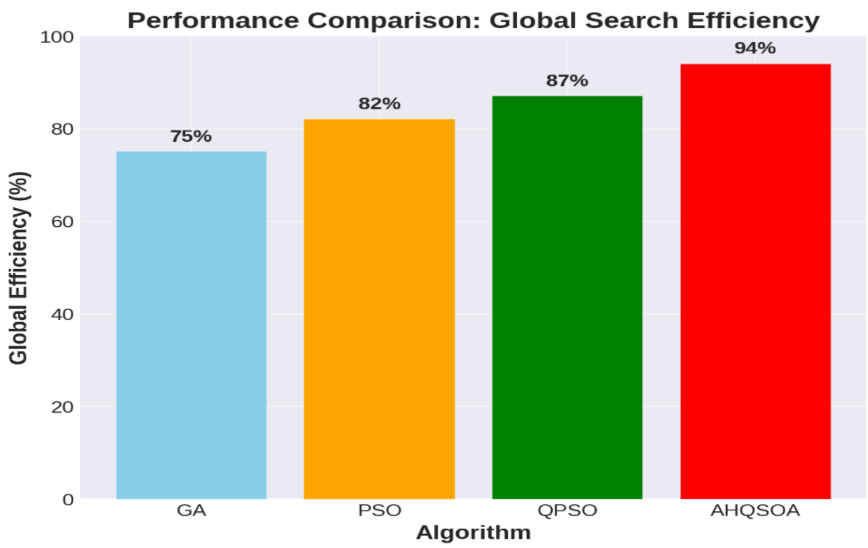

Figure 2. Global Search Efficiency comparison among GA, PSO, QPSO, and AHQSOA

In figure 2, the bar graph compares the global search efficiency of four optimization algorithms. GA gets 75%, PSO attains 82%, QPSO shows enhancement to 87%, and the proposed AHQSOA at top performs 94%, shown high ability for locate global optima quickly.

D. Discussion

The experimental results validate the effectiveness of proposed hybrid approach. The QPSO-QEA integration devises a large-scale exploration of the search space with accurate local exploitation. Additionally, the adaptive parameter adjustment module, based on the reinforcement learning, is essential to keep a best possible balance between exploration and exploitation. The adaptive approach provides faster convergence and better robustness especially in hard, high dimensional optimization problems. Overall the experiments that AHQSOA performs better than conventional algorithms in terms of convergence speed, computing time and breaking out the trap of the local optima. The way that the proposed system is promising for difficult optimization problems.

CONCLUSION AND FUTURE WORK

In this work, the Adaptive Hybrid Quantum-Inspired Optimization Algorithm (AHQSOA) is introduced which aims the benefits of the Quantum Particle Swarm Optimization (QPSO) and Quantum Evolutionary Algorithm (QEA) through an adaptive parameter adjustment using reinforcement learning. The experimental results based on benchmark functions included in the CEC 2023 suite conducted by us show that AHQSOA significantly speed ups the convergence, decrease the computational complexity and improves the global search ability compared to popular algorithms like GA, PSO and standard QPSO. The performance found is such that the combining of global search by QPSO and local one by QEA, and then using the adaptive tuning to optimize performance, AHQSO can effectively solve complex high dimension optimization problems. The combination of quantum motifs with reinforcement learning for more robust search process, flexible framework that is capable of self-tuning, based on features of problem that is being addressed. For future research, we intend to extend the described system to cover real-world applications like the AI-based search engines and conclude to the large-scale resource allocation. More studies will also delve into the scalability of AHQSOA in dynamic environments and AHQSOA's ability to be applied to several kinds of optimization tasks. Examing alternative reinforcement learning techniques, as well as strengthening the quantum-inspired operators could possibly lead to a better performance. In summary, the potent results of AHQSOA open the door to creating even more superior quantum washing and adaptive knowledge based optimization technique to prove excellent at dealing with exhaustive search optimization as well as solution difficulties.

REFRENCES

[1] He, Lihua, and Wei Wang. "Design optimization of public building envelope based on multi-objective quantum genetic algorithm." *Journal of Building Engineering* 91 (2024): 109714.

[2] Li, Xiaotong, Wei Fang, and Shuwei Zhu. "An improved binary quantum-behaved particle swarm optimization algorithm for knapsack problems." *Information Sciences* 648 (2023): 119529.

[3] Ranjith, J., and Santhi Baskaran. "ADAPTIVE MEMORY UPDATE MECHANISM FOR MITIGATING CATASTROPHIC FORGETTING AND OPTIMIZING MEMORY UTILIZATION IN TEXT-BASED CONTINUAL LEARNING." *Cuestiones de Fisioterapia* 54, no. 1 (2025): 363-391.

[4] Zhang, Zhaojuan, Wanliang Wang, and Gaofeng Pan. "A distributed quantum-behaved particle swarm optimization using opposition-based learning on spark for large-scale optimization problem." *Mathematics* 8, no. 11 (2020): 1860.

[5] Tu, Shanshan, Obaid Ur Rehman, Sadaqat Ur Rehman, Shafi Ullah, Muhammad Waqas, and Ran Zhu. "A novel quantum inspired particle swarm optimization algorithm for electromagnetic applications." *IEEE Access* 8 (2020): 21909-21916.

[6] Flori, Arnaud, Hamouche Oulhadj, and Patrick Siarry. "QUAntum Particle Swarm Optimization: An auto-adaptive PSO for local and global optimization." *Computational Optimization and Applications* 82, no. 2 (2022): 525-559.

[7] Anand, R. Vijay, G. Magesh, I. Alagiri, Madala Guru Brahmam, Balamurugan Balusamy, and Francesco Benedetto. "Quantum Channel Optimization: Integrating Quantum-Inspired Machine Learning with Genetic Adaptive Strategies." *IEEE Access* (2024).

[8] Ranjith, J., and Santhi Baskaran. "A COMPREHENSIVE SURVEY OF MEMORY UPDATE MECHANISMS FOR CONTINUAL LEARNING ON TEXT DATASETS." *Turkish Journal of Computer and Mathematics Education (TURCOMAT) ISSN* 3048: 4855.

[9] Talatahari, Siamak, Mahdi Azizi, Mehdi Toloo, and Milad Baghalzadeh Shishehgarkhaneh. "Optimization of large-scale frame structures using fuzzy adaptive quantum inspired charged system search." *International Journal of Steel Structures* 22, no. 3 (2022): 686-707.

[10] Zhao, Y., Y. Ding, and Y. Pei. "Adaptive Optimization in Evolutionary Reinforcement Learning Using Evolutionary Mutation Rates." *IEEE Access* (2024).

[11] Ranjith, J., Santhi Baskaran, and B. Adithya. "Mitigating Catastrophic Forgetting in Deep Learning Models for Sentiment Analysis." In *2024 Second International Conference on Advances in Information Technology (ICAIT)*, vol. 1, pp. 1-7. IEEE, 2024.

[12] Li, Yangyang, Mengzhuo Tian, Guangyuan Liu, Cheng Peng, and Licheng Jiao. "Quantum optimization and quantum learning: A survey." *Ieee Access* 8 (2020): 23568-23593.

[13] Kant, Ravi, Brijesh Kumar, S. P. Maurya, Raghav Singh, and Anoop Kumar Tiwari. "Exploring the utility of nonlinear hybrid optimization algorithms in seismic inversion: a comparative analysis." *Physics and Chemistry of the Earth, Parts A/B/C* 136 (2024): 103754.

[14] Ajagekar, Akshay, Kumail Al Hamoud, and Fengqi You. "Hybrid classical-quantum optimization techniques for solving mixed-integer programming problems in production scheduling." *IEEE Transactions on Quantum Engineering* 3 (2022): 1-16.

[15] Beloborodov, Dmitrii, Alexander E. Ulanov, Jakob N. Foerster, Shimon Whiteson, and A. I. Lvovsky. "Reinforcement learning enhanced quantum-inspired algorithm for combinatorial optimization." *Machine Learning: Science and Technology* 2, no. 2 (2020): 025009.

[16] Ranjith, J., and Santhi Baskaran. "A Comprehensive Review of Catastrophic Forgetting in Text Processing: Challenges, Mitigation Strategies, and Future Directions." *Sentiment Analysis Unveiled*: 118-130.