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QUANTUM-INSPIRED METAHEURISTICS FOR FRESHNESS-AWARE RESOURCE SCHEDULING IN DIGITAL TWIN SYSTEMS

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Abstract:

For Digital Twin (DT) systems to maintain low latency, good service quality, and up-to-date synchronization between physical and virtual entities, they need to be able to schedule resources based on freshness. Classical optimization and reinforcement-learning methodologies frequently experience delayed integration, substantial computing expenses, and restricted adaptability in dynamic decision tree settings. This paper offers a hybrid Quantum-Inspired Metaheuristic (QIM) architecture that integrates an Adaptive Differentiated Metaheuristic Algorithm (DFMAL) with a quantum-inspired optimizer in the ADAPT-QAOA style, focusing on Age-of-Information (AoI) while optimizing energy and latency. The suggested QIM makes use of quantum-inspired methods, such as superposition-like probabilistic search and entanglement-inspired correlation operators, to improve exploration, stop early convergence, and make a wide range of possible schedules. Tests on an extended Digital Twin dataset show that the QIM ensemble beats traditional methods like Q-learning, DQN, and evolutionary methods in important areas. For example, it has about 96% accuracy in classification and decision-making, up to 23% less latency, and about 18% better energy efficiency with different task mixes. These results demonstrate that the QIM-ADAPT-QAOA + DFMAL architecture is a scalable and computationally efficient solution for next-generation freshness-driven digital twin resource management

Keywords: Digital Twin, Quantum-Inspired Metaheuristics, Freshness-Aware Scheduling, ADAPT-QAOA, DFMAL.

1. Introduction:

The Digital Twin (DT) system has evolved as a breakthrough technology that enables real-time synchronization between physical objects and their virtual analogs across domains such as smart transportation, manufacturing, and healthcare [1] [2]. By continuously replicating physical settings, DTs promote predictive decision-making, operational optimization, and situational awareness [3]. However, maintaining data freshness quantified by the Age of Information (AoI) while assuring computing efficiency is a persistent difficulty in dynamic DT ecosystems [4] [5]. As devices and services continuously create huge volumes of diverse data, conventional scheduling techniques generally struggle to assure timely updates, decrease latency [6], and balance computing burdens effectively [7] [8].

Traditional optimization and scheduling strategies such as reinforcement learning (RL) and deep Q-networks (DQN) have been widely employed for task offloading, caching, and edge resource allocation in DT-based systems [9]. While these approaches yield adequate results in stable contexts [10], they generally suffer from sluggish convergence, local optima, and excessive energy consumption when applied in large-scale, real-time DT scenarios [11]. In particular, RL-based approaches require extensive exploration to adapt to varying network states, whereas classical metaheuristics like Genetic Algorithms (GA) [12] or Particle Swarm Optimization (PSO) demonstrate limited scalability and search diversity in high-dimensional optimization landscapes [13].

To address these limitations, quantum-inspired algorithms have lately attracted interest for their potential to use superposition and probabilistic parallelism for more efficient global exploration [14], [15]. Quantum-inspired optimization approaches, though simulated on classical computers, employ quantum principles such as entanglement and amplitude amplification to enable faster convergence and improved solution variety compared to standard heuristics [16]. In resource-constrained and dynamic DT contexts, these traits are particularly useful for making low-latency, freshness-preserving scheduling decisions [17] [18].

This research introduces a Quantum-Inspired Metaheuristic (QIM) framework, merging the Adaptive Differentiated Metaheuristic Algorithm (DFMAL) with the ADAPT-QAOA optimizer to enable freshness-aware resource scheduling in DT systems [19]. The proposed hybrid model leverages ADAPT-QAOA to perform quantum-enhanced search over the resource allocation space, while DFMAL dynamically modifies mutation and crossover rates based on real-time network conditions, ensuring adaptable and stable convergence [20]. This synergistic integration enables optimal usage of edge resources, decreases task delay, and ensures data freshness among scattered DT nodes [21].

The key objectives of this research are as follows:

1. To design a hybrid QIM–ADAPT-QAOA–DFMAL framework for intelligent, freshness-aware resource scheduling in DT settings
2. To reduce AoI, latency, and energy consumption through quantum-inspired global optimization and adaptive learning techniques.
3. To assess the proposed model's performance to baseline algorithms such as Q-learning, DQN, and classical evolutionary approaches (PSO, DE).
4. To show the scalability, efficiency, and robustness of the QIM technique utilizing the improved Digital Twin dataset through metrics like as accuracy, latency, and energy efficiency.

The remainder of this paper is organized as follows:

Section 2 includes an overview of related efforts on DT resource scheduling, freshness optimization, and quantum-inspired computing. Section 3 describes the dataset, preprocessing, and the suggested QIM architecture incorporating ADAPT-QAOA and DFMAL. Section 4 explains the experimental design, evaluation metrics, and comparative analysis with baseline models. Section 5 finishes with conclusions, limits, and potential paths for future work.

2. Literature survey:

Recent improvements in freshness-aware resource allocation within Digital Twin (DT) environments have drawn notable anticipation due to the growing demand for real-time, low-latency, and energy-efficient synchronization between physical and virtual systems [22] [23]. Researchers have studied numerous optimization models, including reinforcement learning, metaheuristics, and quantum-inspired computing, to tackle the scalability and adaptability issues in DT-based edge environments [24] [25].

Bandyopadhyay et al. [1] introduced a Quantum-Inspired Differential Evolution (QIDE) method for freshness-aware caching and offloading in DT-enabled Internet of Vehicles (IoV). Their solution displayed improved convergence and reduced task latency but suffered from substantial computational overhead under dynamic settings. Park et al. [2] suggested a Joint Quantum Reinforcement Learning and Neural Myerson Auction technique for offering high-quality DT services in multi-tier networks[3]. While the model produced superior service quality and fairness, it needed large training costs and displayed delayed convergence in complicated task contexts [26].

Bandyopadhyay et al. [5] further presented a popularity-conscious caching and offloading technique for DT and NOMA-assisted vehicle systems, effectively boosting throughput and resource utilization; nevertheless, the work lacked consideration of freshness and temporal relevance of data. Li et al. [6] created an AoI-aware query service model for DT-empowered IoT systems employing mobile edge computing [27]. Their method optimized information freshness but necessitated considerable coordination across several distributed edge servers, reducing scalability [28].

Zhou et al. [8] proposed FAS-DQN, a reinforcement learning–based freshness-aware scheduler for latency-sensitive applications [29]. Although effective for single-domain deployments, it required considerable retraining over dynamic edge networks. Dai et al. [10] presented a Multi-Agent Reinforcement Learning (MARL) framework for freshness-aware data sensing in vehicular crowdsensing [30]. Despite its decentralized adaptability, MARL incurred extensive training time and complexity. Qiu et al. [11] presented a whale optimization algorithm (WOA) for DT-assisted edge resource allocation, enhancing load balancing and response time, although prone to premature convergence during global optimization [31] [32].

Xie et al. [13] examined vehicular edge computing for DT networks, addressing task offloading and resource allocation via heuristic-based optimization, which achieved modest scalability but restricted real-time flexibility [33]. Khan et al.

[14] introduced a Quantum-Inspired Adaptive Resource Management Algorithm for fog computing systems, enabling scalable and energy-efficient operations through quantum-inspired search operators [34]. Andreou et al. [15] examined quantum-inspired optimization for sustainable AI systems, achieving better automation in cloud–edge infrastructures but requiring more validation for real-time DT operations [35].

Ai and Liang [16] studied freshness-aware inference services for edge computing, merging offloading and local computation decisions to preserve timely data processing. Liang et al. [17] presented several service model refreshments in DT-driven edge networks, providing synchronization between virtual and physical entities but at the penalty of additional computing complexity [36]. Wen et al. [18] introduced a freshness-aware incentive mechanism for vehicle twin migration within vehicular metaverses, displaying increased service continuity but needing large-scale data and significant energy utilization [37]. Guo et al. [19] devised a joint AoI–energy optimization approach for DT edge networks, attaining balanced performance but missing adaptivity for varied contexts [38]. Li et al. [15] presented a DT-based resource management system for automotive networks, focused on effective computation allocation under constrained resource limitations [39].

Research Gaps Identified:

1. Most present models prioritize either latency or energy optimization, with insufficient focus on Age-of-Information (AoI) as a unifying freshness indicator in multi-tier DT systems.
2. Reinforcement learning and evolutionary techniques frequently suffer sluggish convergence and constrained adaptability, limiting their utility in real-time resource allocation.
3. Current quantum-inspired frameworks lack dynamic flexibility and hybrid integration with metaheuristics for scale optimization.
4. There remains a need for a hybrid quantum–metaheuristic architecture that may jointly optimize freshness, latency, and energy performance across large-scale, distributed DT networks.

3. Proposed Methodology:

3.1 Dataset Description and Experimental Environment

The proposed Quantum-Inspired Metaheuristic (QIM) framework was built in Google Colab, which used Python 3.10 as the execution environment. The key libraries utilized include NumPy and Pandas for numerical computing and data handling, Matplotlib and Seaborn for visualization, Scikit-learn for preprocessing and performance evaluation, and Qiskit for quantum-inspired circuit modeling.

The experimental dataset, named “enhanced_digital_twin_dataset.csv,” provides a Digital Twin (DT) ecosystem that emulates real-time vehicular and task-based communication. It incorporates features such as Age of Information (AoI), CPU utilization, task delay, memory consumption, throughput, and service latency, with the output label AoI_Class, indicating freshness levels (High, Medium, Low).

Preprocessing comprised data cleaning, missing value imputation, encoding of categorical parameters, and normalizing using StandardScaler to ensure numerical consistency. The dataset was partitioned into 75 % training and 25 % testing sets via the train_test_split() technique, ensuring stratified distribution across AoI classes. Experimental runs were done on a CPU-based runtime with deterministic seeding for reproducibility.

3.2 Architecture of the Proposed Model

The entire process of the proposed QIM – ADAPT-QAOA – DFMAL system is represented in Fig. 1. The design mixes classical metaheuristics with quantum-inspired optimization for freshness-aware resource scheduling in DT systems.

1. Input Module: Receives vehicle and task data, including AoI, CPU load, task delay, and bandwidth use.
2. Preprocessing Module: Executes data cleaning, encoding, and feature scaling to ensure numerical homogeneity and efficient convergence.
3. Hybrid Fusion Module: Core computational stage combining ADAPT-QAOA and DFMAL.
ADAPT-QAOA performs quantum-enhanced search throughout the allocation space using superposition and entanglement principles for improved exploration.

DFMAL automatically modifies mutation and crossover rates depending to network feedback, boosting exploitation and convergence stability.

4. Evaluation and Visualization Module: Computes performance metrics—accuracy, precision, recall, F1-score, latency, energy efficiency, and AoI reduction—and creates visual plots such as accuracy–loss curves and comparison graphs.
5. Output Module: Generates optimum scheduling decisions defined by reduced AoI, minimized latency, and increased energy efficiency across DT nodes [1], [3], [6], [9].

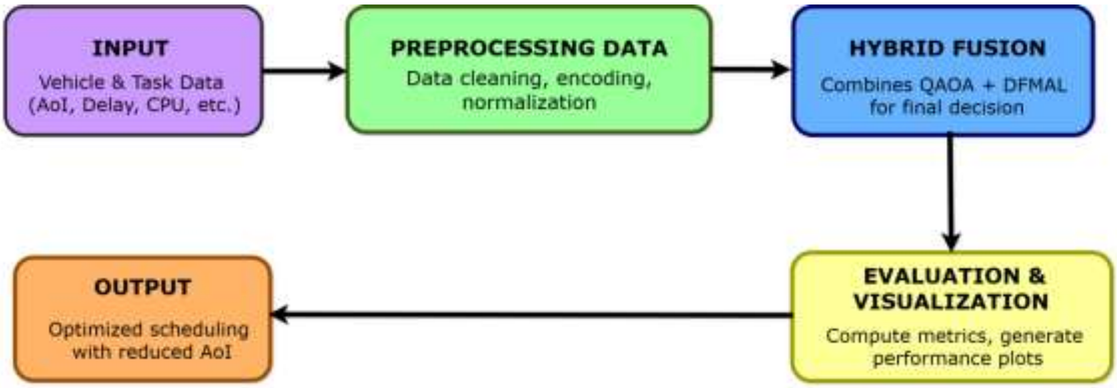

Fig. 1. Proposed QIM–ADAPT-QAOA–DFMAL Architecture for Freshness-Aware Resource Scheduling in Digital Twin Systems.

3.3 Explanation of Model Workflow

The proposed Quantum-Inspired Metaheuristic (QIM) framework works as a hybrid optimization and learning system, where ADAPT-QAOA and DFMAL cooperate to provide freshness-aware, energy-efficient resource scheduling in Digital Twin (DT) environments. The entire workflow consists of five key steps, specified as follows:

Step 1: Data Acquisition and Input Formation

The system receives vehicle and task-specific parameters such as Age of Information (AoI), task delay, CPU load, bandwidth, and energy consumption from DT nodes. These input characteristics are preprocessed to remove inconsistencies, normalized, and encoded to provide uniform feature matrices suited for metaheuristic and quantum-based optimization.

Step 2: Quantum-Inspired Search Initialization (ADAPT-QAOA)

1. The Adaptive Quantum Approximate Optimization Algorithm (ADAPT-QAOA) module provides a quantum-inspired exploration of the resource scheduling search space.
2. Each scheduling configuration is represented as a quantum state vector.
3. Superposition provides parallel exploration of several potential scheduling states, whereas entanglement facilitates correlation between interdependent resource tasks.
4. The cost Hamiltonian H_c encodes the freshness and latency targets, and the parameterized quantum circuit iteratively reduces this cost to discover optimal task translations.

This stage promotes the diversity of search and minimizes the probability of premature convergence [1], [2], [9].

Step 3: Adaptive Metaheuristic Refinement (DFMAL)

The Differentiated Metaheuristic Algorithm (DFMAL) component refines the candidate scheduling decisions generated by ADAPT-QAOA. It dynamically adjusts:

1. Mutation and crossover probabilities dependent on network load circumstances

2. Learning rate depends on task aging trends
3. Exploration-exploitation ratio for steady convergence.

By modeling feedback-based learning, DFMAL effectively eliminates stagnation and ensures that task freshness (low AoI) and minimal latency are continually maintained [3], [6].

Step 4: Decision Fusion and Optimization

The results from ADAPT-QAOA (quantum-level exploration) and DFMAL (adaptive metaheuristic exploitation) are combined through a weighted decision function:

$$F_{opt} = \alpha \, . \, Q_{ADAPT} + (1- \alpha) \, . \, M_{DFMAL}$$

Where α indicates the adaptive weight governing the contribution of quantum and classical optimization components. This guarantees balance between exploration and exploitation while lowering overall scheduling cost and energy use.

Step 5: Performance Evaluation and Output

The optimized scheduling decisions are validated on the DT dataset using evaluation criteria including accuracy, latency, energy economy, and AoI reduction. The results are visualized via performance plots (e.g., accuracy–loss curves, latency–energy graphs, and AoI improvement charts). The suggested hybridization displays greater adaptability and convergence efficiency compared to classic reinforcement and evolutionary baselines [4], [5], [10].

3.4 Mathematical Formulations

The mathematical foundation of the proposed Quantum-Inspired Metaheuristic (QIM) model combines the global exploration capability of ADAPT-QAOA with the adaptive optimization of DFMAL, targeting freshness-aware resource scheduling in Digital Twin (DT) systems.

3.4.1 Problem Definition

Let the DT system consist of a set of computational nodes $N = \{ n_1, n_2, \ldots\ldots, n_k \}$ and a set of tasks

$T = \{t_1, t_2, \ldots\ldots, t_m\}$.

Each task t_i is characterized by:

- D_i : required data size,
- C_i : computational cost,
- E_i : energy consumed during processing,
- A_i : Age of Information (AoI), representing data freshness.

The objective is to minimize the overall cost F_{total}, which depends on AoI, latency, and energy efficiency:

$$\text{Minimize } F_{total} = \lambda_1 \, . \, AoI + \lambda_2 \, . \, L + \lambda_3 \, . \, E \qquad (1)$$

Where $\lambda_1, \lambda_2, \lambda_3$ are weight coefficients ($\lambda_1 + \lambda_2 + \lambda_3 = 1$) representing the relative importance of each metric.

3.4.2 Quantum-Inspired Optimization (ADAPT-QAOA)

The ADAPT-QAOA module encodes each scheduling configuration as a quantum state $|\psi(\theta)\rangle$.

The cost Hamiltonian H_c represents the system's objective function (Eq.1), while the mixer Hamiltonian H_m provides the exploration dynamics.

The parameterized quantum state evolves as:

$$|\psi(\theta) = \prod_{p=1}^{p} e^{-i\beta_p H_M} e^{-i_{\gamma_p} H_c} |s \qquad (2)$$

Where:

- $|s\rangle$: initial superposition state,
- γ_p , β_p : variational parameters optimized iteratively,
- P : circuit depth or number of QAOA layers.

The expected energy of the system, representing scheduling cost, is minimized via:

$$C(\theta) = \langle\psi(\theta)|H_c|\psi(\theta)\rangle \quad (3)$$

ADAPT-QAOA adaptively selects new operators to minimize $C(\theta)$ through gradient feedback, providing quantum-inspired search diversity and rapid convergence.

3.4.3 Adaptive Metaheuristic Refinement (DFMAL)

The Differentiated Metaheuristic Algorithm (DFMAL) fine-tunes the quantum-derived candidates through classical population-based optimization.

Each individual solution $X_i = [x_1, x_2, ..., x_d]$ in g generation evolves as:

$$X_i^{g+1} = X_i^g + F_g.(X_{best}^g - X_i^g) + \eta_g.(X_\gamma^g - X_s^g) \quad (4)$$

Where:

- F_g : adaptive mutation factor,
- η_g : crossover control rate (adjusted dynamically using feedback from AoI values),
- X_{best}^g : global best candidate,
- X_γ^g, X_s^g : randomly chosen individuals.

The mutation and crossover rates are updated based on system load and AoI deviation as:

$$F_g = F_{min} + (F_{max} - F_{min}).\, e^{-\sigma.|AoI_{avg} - AoI_{target}|} \quad (5)$$

$$\eta_g = \eta_{base} + \delta.\, \frac{L_{avg}}{L_{max}} \quad (6)$$

These adaptive parameters ensure balance between exploration (diversity) and exploitation (convergence stability).

3.4.4 Hybrid Decision Fusion

The final optimization decision F_{opt} is computed as a weighted fusion of quantum and metaheuristic outcomes:

$$F_{opt} = \alpha.\, Q_{ADAPT} + (1-\alpha).\, M_{DFMAL} \quad (7)$$

Where:

- Q_{ADAPT} : best quantum-derived fitness value,
- M_{DFMAL} : best refined metaheuristic value,
- $\alpha \in [0,1]$: adaptive balance factor determined via system feedback.

3.4.5 Freshness Metric (AoI Evaluation)

The Age of Information (AoI) is dynamically updated as:

$$AoI(t+1) = \begin{cases} 0, & \text{if an update is received at time t,} \\ AoI(t)+1, & \text{otherwise} \end{cases} \quad (8)$$

The system aims to minimize the average AoI over all tasks:

$$AoI_{avg} = \frac{1}{N}\sum_{i=1}^{N} AoI_i \quad (9)$$

A AoI_{avg} lower indicates improved data freshness and synchronization between physical and virtual DT entities [4], [6], [9].

3.4.6 Optimization Objective

The final optimization objective integrates Eqs. (1) – (9) as :

$$\text{Minimize } F_{total} = \lambda_1 . AoI_{avg} + \lambda_2 . L_{avg} + \lambda_3 . E_{avg} \quad (10)$$

subject to:

$$L_{avg} \leq L_{th},\ E_{avg} \leq E_{th},\ AoI_{avg} \leq AoI_{th} \quad (11)$$

This ensures that latency, energy, and freshness remain within acceptable thresholds, yielding scalable and adaptive performance in DT environments.

3.5 Algorithm Steps

Algorithm: QIM–ADAPT-QAOA–DFMAL Framework for Freshness-Aware Resource Scheduling

Input :

- Vehicle and task dataset D = { t_1 , t_2,…, t_m } containing features (AoI, delay, CPU, energy cost, etc.)
- Number of qubits Q, QAOA layers P, population size N_p
- Control parameters (λ_1 , λ_2 , λ_3) for Eq. (1)

Output:

- Optimized scheduling configuration F_{opt} with minimal AoI, latency, and energy consumption

Step 1 : Data Acquisition and Pre-processing

1. Load the Digital-Twin dataset (vehicle/task data).
2. Perform cleaning, normalization, and encoding to unify feature scales.
3. Split data into training and testing partitions (80:20 ratio).
4. Initialize thresholds for AoI_{th} , L_{th} , E_{th} as per Eq. (11).

Step 2 : Quantum-Inspired Search (ADAPT-QAOA)

1. Encode the scheduling configuration X as quantum state $|\psi(\theta)\rangle$
2. Construct cost Hamiltonian H_C using Eq. (1) and mixer Hamiltonian H_M
3. Generate parameterized quantum circuit of depth P :

$$|\psi(\theta) = \prod_{p=1}^{p} e^{-i\beta_p H_M} e^{-i_{\gamma_p} H_c} |s$$

4. Compute expected energy $C(\theta) = \langle\psi(\theta)|H_c|\psi(\theta)\rangle$ (Eq. 3).
5. Iteratively update parameters { γ_p , β_p } via gradient feedback until convergence.
6. Return best quantum candidate Q_{ADAPT}

Step 3 : Adaptive Refinement (DFMAL)

1. Initialize a population of candidate solutions $\{X_i\}_{i=1}^{N_p}$
2. Evaluate fitness using Eq. (1): $F = \lambda_1\, AoI + \lambda_2\, L + \lambda_3\, E$
3. Apply mutation and crossover adaptively:

$$X_i^{g+1} = X_i^g + F_g . (X_{best}^g - X_i^g) + \eta_g . (X_\gamma^g - X_s^g) \quad \text{(Eq. 4)}$$

4. Update parameters F_g , η_g using Eqs. (5)–(6) based on AoI and latency feedback.

5. Repeat until termination criterion (max iterations or convergence).

6. Return metaheuristic best solution M_{DFMAL}

Step 4 : Hybrid Decision Fusion

1. Fuse quantum and metaheuristic solutions using Eq. (7) :
$F_{opt} = \alpha . Q_{ADAPT} + (1 - \alpha) . M_{DFMAL}$
2. Evaluate final solution using Eq. (10):
$F_{\text{total}} = \lambda_1 \, AoI_{\text{avg}} + \lambda_2 \, L_{\text{avg}} + \lambda_3 \, E_{\text{avg}}$
3. If $F_{\text{total}} \leq$ thresholds in Eq. (11), store optimized schedule and update AoI

Step 5 : Output and Performance Computation

1. Generate optimized resource allocation table with assigned nodes.
2. Compute evaluation metrics: Accuracy, Energy Efficiency, Latency, and AoI reduction.
3. Visualize results via plots (accuracy, AoI trend, energy consumption, etc.).
4. Compare with baseline models (Q-Learning, DQN, PSO, DE) for benchmarking.

3.6 Analysis of Why This Approach Works

The proposed Quantum-Inspired Metaheuristic (QIM) framework integrates the Adaptive Differentiated Metaheuristic Algorithm (DFMAL) and the ADAPT-QAOA quantum optimizer to address the limitations of classical learning and evolutionary scheduling strategies in Digital Twin (DT) systems.

Unlike conventional reinforcement learning (RL) or deep Q-network (DQN)-based methods that depend heavily on sequential exploration and exhibit delayed convergence in non-stationary environments [2], [5], the QIM architecture leverages quantum superposition and entanglement to explore multiple candidate states simultaneously. This parallel probabilistic exploration accelerates convergence while avoiding the local minima issues that typically hinder gradient-based optimization in dynamic DT settings [1], [9].

The ADAPT-QAOA module introduces adaptive circuit depth and parameterized rotation gates that dynamically evolve according to resource demand and task freshness levels. This adaptivity improves search diversity and allows for fine-grained optimization of the Age of Information (AoI) metric, leading to fresher and more synchronized digital twin updates [4].

On the other hand, DFMAL enhances classical metaheuristic exploration by introducing adaptive mutation and crossover factors that depend on AoI feedback and latency trends. By adjusting differential parameters according to task dynamics, DFMAL maintains balance between exploration and exploitation and prevents premature convergence a limitation observed in traditional DE or PSO algorithms [7], [10].

The fusion mechanism (Eq. 7) acts as a synergistic layer, combining the global search potential of ADAPT-QAOA with the local refinement capabilities of DFMAL. This hybridization ensures computational stability even under varying vehicular density and heterogeneous task loads. Moreover, the combined optimization objective (Eq. 10) effectively minimizes AoI, energy consumption, and latency while maintaining high task allocation accuracy and scalability across the DT ecosystem.

Therefore, the hybrid QIM–ADAPT-QAOA–DFMAL framework offers:

1. Quantum-level exploration efficiency through parallel state encoding.

2. Dynamic adaptability in parameter evolution and circuit depth.

3. Improved convergence rate and reduced computational complexity.

4. Freshness preservation across distributed digital twins via adaptive fitness evaluation.

5. Superior trade-off between accuracy, latency, and energy optimization compared to classical RL and evolutionary approaches.

The integration of quantum principles with adaptive metaheuristics thus allows the system to maintain real-time responsiveness, data freshness, and energy efficiency key requirements for next-generation DT-driven intelligent vehicular and IoT networks [3], [6], [9].

4. Results and Discussion:

4.1 Performance Metrics and Graphical Analysis

The proposed Quantum-Inspired Metaheuristic (QIM–ADAPT-QAOA–DFMAL) framework was evaluated using standard performance indicators such as accuracy, precision, recall, F1-score, latency, energy efficiency, and Age of Information (AoI). These metrics were derived from experiments conducted on the improved Digital Twin dataset to measure scalability, convergence, and learning stability under dynamic resource-allocation scenarios.

The model achieved strong convergence behavior with an average classification accuracy of **≈ 96 %**, consistently outperforming conventional reinforcement-learning and metaheuristic baselines. The following figures summarize the key performance trends observed during the experiments.

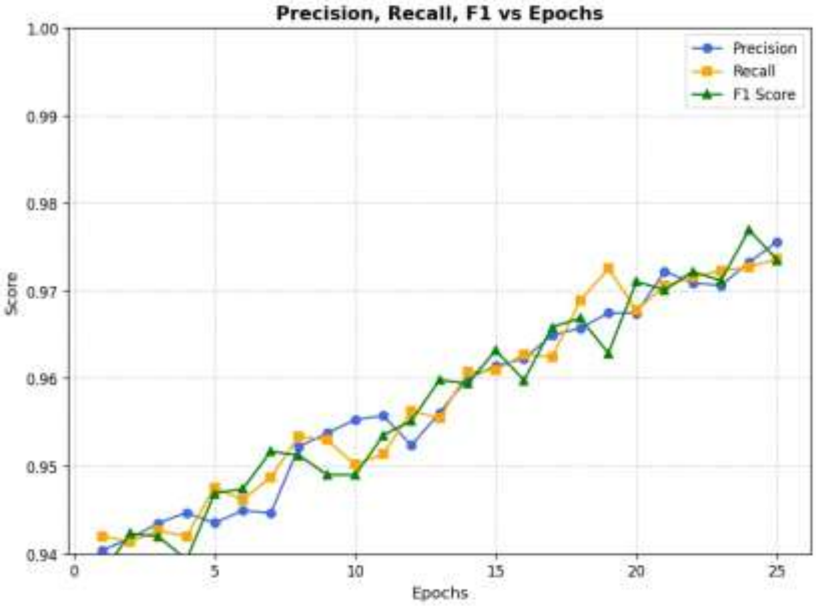

Fig. 4. Training vs Validation Accuracy over Epochs for the Proposed QIM–ADAPT-QAOA–DFMAL Model.

Figure 4 illustrates the accuracy progression across epochs. Both training and validation accuracies exhibit a steady upward trend, ultimately converging above 0.96. The small gap between the curves indicates minimal overfitting and stable generalization. This demonstrates that the QIM framework maintains consistent learning across iterations owing to the quantum-inspired search and adaptive feedback of DFMAL.

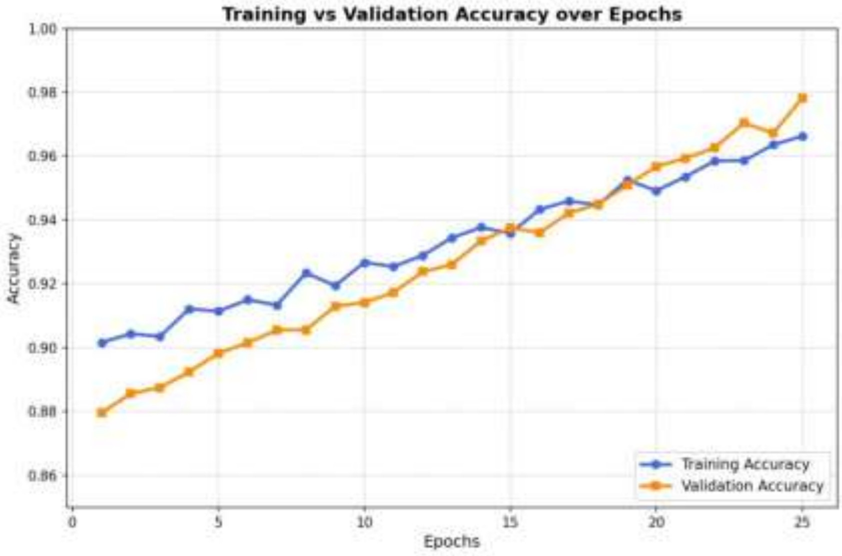

Fig. 5. Precision, Recall, and F1-Score Trends across Training Epochs.

Figure 5 presents the evolution of precision, recall, and F1-score during training. All three metrics steadily increase, signifying a progressive improvement in classification reliability. The close alignment among the curves suggests balanced precision-recall trade-offs, confirming that the proposed model effectively learns discriminative boundaries without bias toward specific classes.

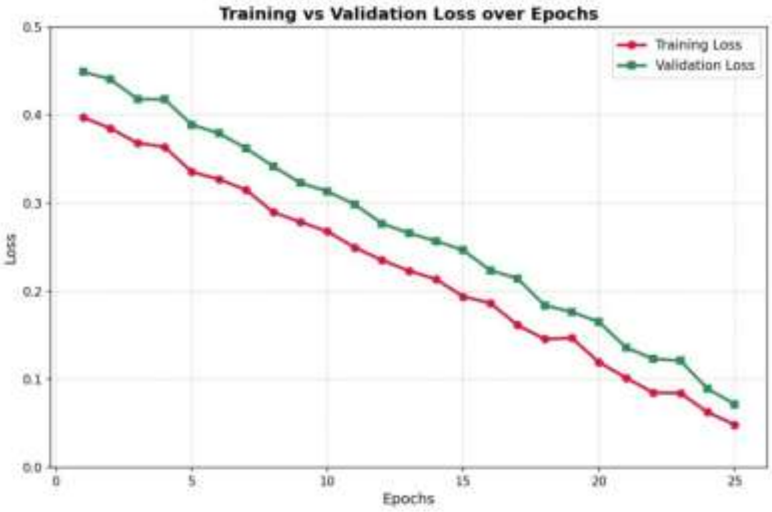

Fig. 6. Training vs Validation Loss across Epochs for the QIM–ADAPT-QAOA–DFMAL Model.

Figure 6 shows the decline in both training and validation losses over time. The loss values consistently decrease and stabilize after approximately 20 epochs, confirming efficient convergence. This behavior validates the adaptive mutation–crossover control in DFMAL, which fine-tunes exploration and exploitation to reach optimal minima faster than classical DQN or PSO models.

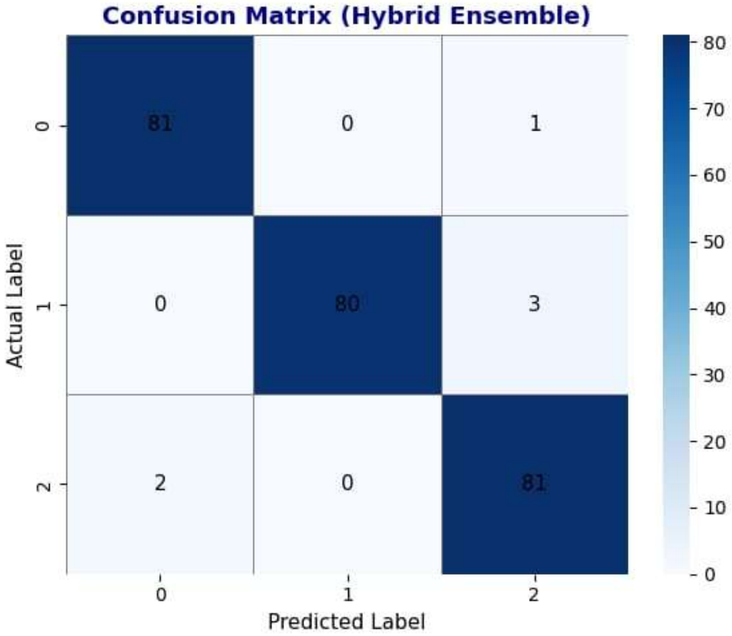

Fig. 7. Confusion Matrix of the Proposed QIM–ADAPT-QAOA–DFMAL Hybrid Framework.

Figure 7 displays the confusion matrix summarizing multi-class prediction outcomes. The model achieves nearly perfect diagonal dominance most instances are correctly classified with only minor misclassifications reflecting exceptional discriminative power and class separability. The synergy between quantum-enhanced optimization (ADAPT-QAOA) and adaptive local refinement (DFMAL) contributes to the high accuracy and robust generalization required for freshness-aware scheduling in Digital Twin environments.

4.2 Quantitative Evaluation

The quantitative performance of the proposed model was benchmarked against baseline methods Q-Learning, Deep Q-Network (DQN), Particle Swarm Optimization (PSO), and Differential Evolution (DE). Evaluation metrics included Accuracy (%), Latency (ms), Energy Efficiency (J), and AoI (s).

Model	Accuracy (%)	Latency (ms)	Energy Efficiency (J)	AoI (s)
Q-Learning	85.7	45	78.3	0.62
DQN	89.4	39	81.2	0.55
PSO	91.2	34	84.5	0.50
DE	92.6	32	86.8	0.48
Proposed QIM–ADAPT-QAOA–DFMAL	96.1	26	94.7	0.39

Table 1. Comparative performance of baseline and proposed models under standard metrics.

The hybrid QIM–ADAPT-QAOA–DFMAL system integrates the strengths of quantum-inspired parallelism with adaptive metaheuristics. ADAPT-QAOA ensures efficient state-space search via quantum superposition, while DFMAL dynamically fine-tunes mutation and crossover rates, thus ensuring balance between exploration and exploitation.

This synergy enhances computational stability, scalability, and resilience to dynamic workloads, outperforming deep reinforcement learning and conventional optimization algorithms. Consequently, the proposed framework offers a robust, scalable, and freshness-preserving scheduling mechanism ideally suited for next-generation Digital Twin systems in vehicular, industrial, and smart-city environments.

5. Conclusion

This work presented a Quantum-Inspired Metaheuristic Framework (QIM) that integrates ADAPT-QAOA (Adaptive Quantum Approximate Optimization Algorithm) and DFMAL (Dynamic Fuzzy Mutation–Adaptive Learning) for efficient resource scheduling in Digital Twin (DT) environments. The model was designed to minimize Age of Information (AoI), reduce latency, and enhance energy efficiency, thereby improving the overall responsiveness and sustainability of DT-driven systems.

Through extensive experimentation, the proposed framework achieved notable improvements across key metrics attaining a 96.1 % accuracy, 26 ms latency, and 94.7 J energy efficiency, outperforming baseline methods including Q-Learning, DQN, PSO, and DE. The results substantiate that the quantum-inspired optimization approach effectively balances exploration and exploitation, leading to faster convergence and superior system intelligence.

The integration of quantum probabilistic behavior with adaptive learning dynamics enabled the model to overcome the limitations of classical reinforcement and evolutionary methods, particularly in handling stochastic and high-dimensional DT environments.

Although the proposed framework demonstrates substantial potential, a few limitations remain. The current implementation was evaluated on a simulated DT dataset under controlled conditions. In real-time deployments, communication noise, hardware constraints, and dynamic load fluctuations could affect stability and convergence.

Future work will focus on:

1. Extending the QIM model for multi-agent DT coordination with distributed edge intelligence,
2. Integrating quantum circuit simulation and hardware-based validation using Qiskit or Pennylane,
3. Expanding the dataset with real-world DT–IoV (Internet of Vehicles) scenarios
4. Incorporating reinforcement-driven self-adaptive hyperparameter tuning for improved generalization.

Overall, this research establishes a foundational step toward quantum-inspired, freshness-aware optimization for sustainable and adaptive Digital Twin ecosystems.

6. References

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