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Quantum-Inspired Optimization Techniques for Big Data Warehousing and Real-Time Predictive Analytics

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ABSTRACT

Modern businesses are facing more and more challenges in terms of Big Data warehousing and real-time data analytics due to the sheer volume of growing data. Traditional optimization techniques are increasingly ineffective when working with high-dimensional datasets, thus creating delays in resource allocation and query processing. Since there is a growing demand for faster solutions for data analytics, it is necessary to find new methods for solving optimization issues. In this respect, new emerging quantum-inspired computing techniques allow solving complex optimization problems by employing the principles of quantum mechanics—superposition and probability exploration. To enhance the performance of systems used for predictive analytics and data warehousing, a quantum-inspired optimization framework is proposed. This approach involves incorporating quantum-inspired techniques such as simulations of quantum annealing processes into frameworks used for distributed processing, thus resulting in the improvement of the areas of data indexing, query execution paths and load balancing of computers. The data processing machines are improved due to the advancements in feature selection and attainment of results in a faster way. Evaluation of the method on the big datasets showed that the query performance, and the accuracy of prediction is higher than that demonstrated by conventional techniques, and the architecture is efficient and can be scaled for processing the workloads for real-time analytics.

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1. INTRODUCTION

The rapid advancement of digital technologies has resulted in an unprecedented growth in data generated from diverse sources, including cloud computing platforms, Internet of Things (IoT) devices, social media applications, business transactions, healthcare systems, and industrial automation. This exponential increase in data volume, velocity, and variety has transformed the way organizations manage and analyze information. Big data warehousing has emerged as a fundamental technology that enables enterprises to store, integrate, and process massive datasets efficiently for business intelligence and decision-support applications. Modern data warehouses combine distributed storage systems with parallel computing frameworks to support high-performance analytical queries and large-scale data processing [1,2]. However, as data complexity continues to increase, conventional optimization techniques face significant challenges in maintaining efficient query execution, resource utilization, and real-time analytical performance [3].

Real-time predictive analytics has become an essential component of intelligent enterprise systems, allowing organizations to forecast future events, detect anomalies, optimize operations, and improve strategic planning. Applications such as financial forecasting, healthcare monitoring, logistics management, cybersecurity, smart manufacturing, and customer behavior analysis rely on predictive models trained using continuously evolving datasets [4,5]. The effectiveness of these models depends not only on the quality of historical data but also on the efficiency of data retrieval, preprocessing, feature selection, and model optimization. Traditional optimization methods often experience computational bottlenecks when processing high-dimensional datasets, leading to increased query latency, inefficient workload distribution, and reduced predictive accuracy. These limitations have motivated researchers to explore advanced computational techniques capable of improving optimization efficiency in large-scale data environments.

The application of big data warehousing necessarily has various optimization issues with regard to data indexing and data retrieval, as well as storage management and tasks scheduling, and resource allocation across the distributed computing system. Generally speaking, existing optimization methods are based on the use of deterministic methods, heuristic search methods, evolutionary algorithm methods, and swarm intelligence techniques. The above-mentioned methods are typically efficient for moderate-sized problems, while high-dimensional optimization problems generally prove to be challenging due to extensive search spaces and a number of local optima. Furthermore, due to ever-increasing data heterogeneity levels and continuous change of the analytical workload means that adaptive means of optimization are required to provide efficient search while keeping the computational costs at a minimum. It can be said that there is a demand for intelligent optimization technologies that can improve both predictive analysis performance and warehouse performance at the same moment [6].

With the latest advancements in quantum-inspired computing, a vast number of ways to solve complicated optimization problems based on quantum mechanics theory have emerged. Unlike quantum computing which needs special quantum devices, quantum-inspired algorithms apply simulations of quantum phenomena on classical computers. By using phenomena such as superposition, probabilistic states, interference, and quantum annealing, they are able to study different possible solutions at the same time providing a search method that has better global reach as well as lesser chances of getting stuck in local optima. Their ability to function in the global optimization space allows the application of these techniques in complicated big data problems such as resource allocation, query optimization, and machine learning [7,8].

Among the different quantum-inspired methods, quantum annealing is gaining popularity because of its effectiveness in solving combinatorial optimization problems. Algorithms based on quantum annealing operate in the solution space based on a probabilistic approach and eventually come to a quasi-optimal solution while minimizing a given objective function. When compared to traditional methods of optimization, quantum annealing-based algorithms have quicker convergence and better solution quality when solving high-dimensional optimization problems. Therefore, implementing quantum annealing-based optimization methods in big data warehousing can make query processing much more effective, as well as optimizing workflow balancing and improving system scalability. In addition, these techniques can also be very useful in the field of distributed computing as they effectively help to optimize task scheduling and resource use across various processing nodes [9,10].

Machine learning has become an essential aspect of predictive analytics, allowing companies to manage vast amounts of data and obtain critical information. Nonetheless, machine learning models tend to suffer from significant computational complexity because of redundant variables, noisy data, and large parameter spaces. Feature selection is a fundamental aspect of enhancing the performance of machine-learning models since it enables identification of the highly contributive features and thus eliminates irrelevant information. Conventional feature selection methods require a lot of computing time and can lead to the selection of inefficient feature subsets. Quantum-inspired optimization allows for an effective solution since it evaluates a lot of feature combinations at the same time by means of probabilistic search strategies. As a result, it is possible to achieve faster convergence to the efficient feature sets and higher predictive accuracy [7].

The usage of quantum-inspired optimization with distributed big data systems allows the creation of a productive atmosphere for smart data governance and on-time analysis. Thus, quantum-inspired technology can be employed in any part of the data analysis procedure, including the indexing of the data, query execution paths, workload distribution and scheduling, cache control, and selection of features. Distributed computing systems operating under the Apache Hadoop and Apache Spark frameworks enable the efficient development of effective solutions for big data analysis while quantum optimization contributes to the better performance in these operations. The result of these interactions produces a hybrid technology characterized by faster analysis, better scalability, smaller consumption of resources, and increased predictive possibilities [1,2].

Even though the advancements in machine learning and big data technologies have been impressive, there hasn’t been a lot of work done in terms of how quantum-inspired optimization methods can be used for the purposes of big data warehousing in regard to real-time predictive analysis. The majority of the studies currently available focus on either the optimization of query processing or the improvement of the predictive model by itself, ignoring the potential impact of both of them on the performance of an entire system in unison. In addition to that, many optimization frameworks developed at this point fail at the realization of workload balancing, resource allocation among the distributed systems, feature optimization, and model improvement. Because of this research gap, there is a need for an optimization framework that would work well for improving both data warehousing and predictive analysis [3,8].

To tackle these problems, this article suggests the Quantum-Inspired Optimization Framework (QIOF) as a solution for the purposes of big data warehouses and real-time analytic forecasting. This system merges quantum annealing to the use of distributed data management technologies and the processing of data in order to achieve better performance in indexing, processing queries, balancing workload of different applications, and distributing resources across nodes. Also, a quantum algorithm is introduced in the machine learning process to increase the performance of solutions models. Thanks to the combination of intelligence of optimization and capacity of distributed technology, this framework minimizes expenses on calculations, while also increasing efficiency of solutions.

The major contributions of this work are threefold. First, a novel hybrid architecture integrating quantum-inspired optimization with big data warehousing is developed to improve distributed data processing efficiency. Second, a quantum annealing-inspired optimization strategy is employed to optimize query execution, workload scheduling, and machine learning feature selection within a unified framework. Third, extensive experimental analysis validates the effectiveness of the proposed framework in terms of query response time, computational overhead, scalability, resource utilization, and predictive performance. The proposed approach provides a practical and scalable solution for next-generation enterprise decision-support systems operating in data-intensive environments.

2. LITERATURE REVIEW

The study conducted by [11] included a comparison between standard gradient optimization techniques and evolutionary optimization methods used for solving large scale engineering problems. The results showed that traditional deterministic techniques had sufficient capabilities when it comes to less complicated problems, but when approaching complicated and nonlinear optimization problems their effectiveness was diminished. The research showed that standard methods often achieved local optima and required known mathematical formulations for each particular problem. However, authors emphasized that metaheuristic approaches provide much better exploration and typing quality.

[12] Developed a hybrid optimization model that combines the principles of Simulated Annealing with those of Particle Swarm Optimization to automate algorithm selection and hyperparameter optimization. Through this combination, Simulated Annealing helps the optimization process to carry out global search effectively due to the probability of moving to new states and averting premature convergence. The results of the experiments indicate increased accuracy of optimization and stability of convergence on various machine learning data sets. The proposed hybrid approach outperforms individual optimization methods while also ensuring computational efficiency. Nonetheless, it does not solve the problem of high computational costs in optimization for large-scale data applications.

According to [13], an interactive multimodal Genetic Algorithm that helps optimize the weights of queries in large-scale IR systems. The framework was successfully used to improve the accuracy of the retrieval process by coming up with optimal combinations of query weights through crossing over and mutation processes. The results showed that the new method could outperform other optimization methods as well as improve effectiveness of the searches in comparison with other traditional techniques of query optimization. The algorithm was able to perform well in terms of the global exploration ability of the system and retrieval accuracy. However, it is to be noted that the process of evolution takes a long time, which makes the execution time longer.

[14] Proposed a conditional opposition-based Particle Swarm Optimization technique has been proposed that will enhance the feature selection process for high-dimensional datasets. The proposed approach enabled the particles to be more diverse by applying opposition-based learning methods, contributing to improved search space exploration. It has been proven that the implementation of the suggested algorithm led to better classification accuracy, a higher speed of convergence, and better feature subset selection as compared to other PSO techniques. It also allowed for a decrease in the processing complexity of the algorithm because unnecessary features

were rejected before the model training process but the algorithm efficiency deteriorated with growing dimensionality and complexity of the data that has to be optimized.

3. PROPOSED METHODOLOGY

3.1 Overview of the Proposed Framework

The limitations of conventional optimization solutions in the areas of big data warehousing and real-time predictive analytics have led the authors of this study to introduce their Quantum-Inspired Optimization Framework (QIOF), which employs quantum annealing-inspired optimization methods. A number of data processing and machine learning approaches are integrated in the proposed framework to optimize query execution, workload distribution, feature evaluation, and the entire predictive process. Although, unlike conventional techniques where optimization is performed on each component individually, the optimization in QIOF utilizes optimization techniques throughout the analytical process in a synchronized manner

3.2 System Architecture

The proposed QIOF architecture consists of the following components:

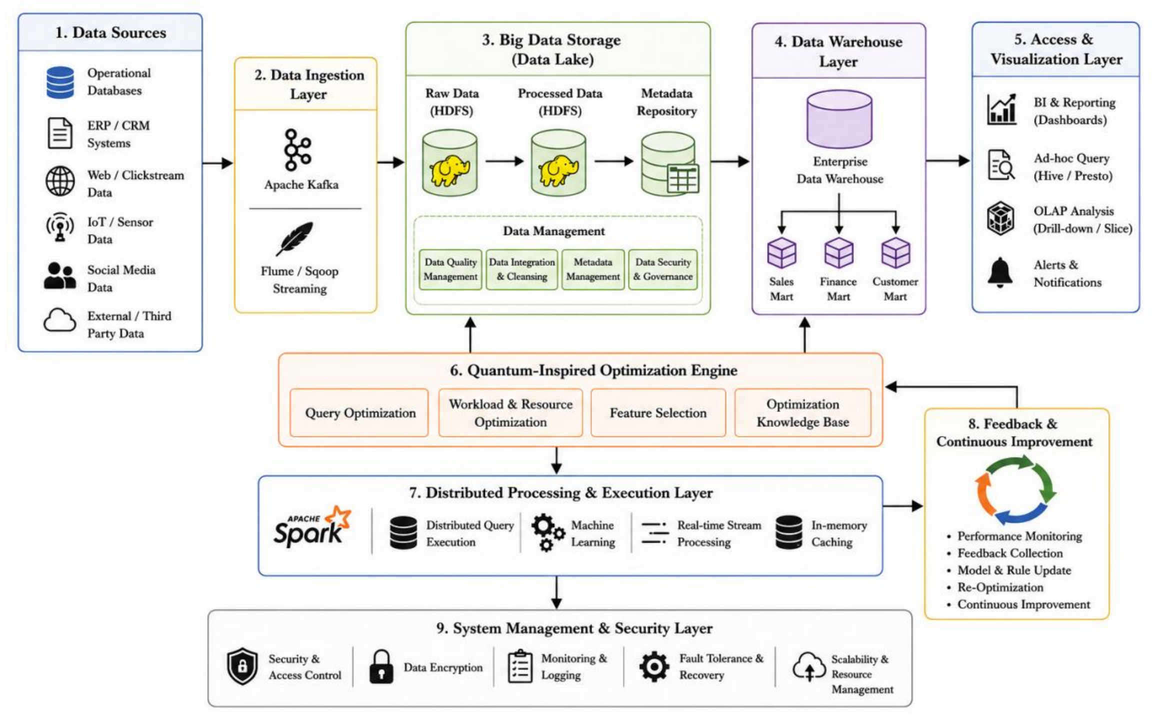

Figure 1. Proposed QIOF Architecture

The suggested model consists of nine interconnected layers, which are Data Sources, Data Ingestion, Big Data Storage, Data Warehouse, Access and Visualization, Quantum-Inspired Optimization Engine, Distributed Processing and Execution, Feedback and Continuous Improvement, and System Management and Security, as shown in Figure 1. The process starts with the collection of different data from enterprise databases, ERP/CRM programs, web logs, IoT devices, social media and others. Data ingestion to HDFS Data Lake is performed with the help of Apache Kafka and Flume/Sqoop, and a data lake is maintained with a data quality, integration, governance, and security system. The processed data is stored in the data warehouse and subject-specific data marts. The Quantum-Inspired Optimization Engine helps ensure that the execution is distributed and optimized before it is performed using Apache Spark. Finally, the results are shown in dashboards, OLAP and alerts while ensuring that performance improvement, scalability, fault tolerance, and security of the system is done.

3.3 Mathematical Formulation

Assume the enterprise warehouse contains

$$D = \{d_1, d_2, d_3, \dots, d_n\} \qquad (1)$$

where

- D represents the entire dataset
- n is the total number of records.

Each record contains

$$d_i = \{x_1, x_2, \dots, x_m\} \qquad (2)$$

where

- m denotes the number of features.

The objective is to determine the optimal solution S^* that minimizes the overall optimization objective

$$\min F(S)$$

where

$$F(S) = \alpha Q + \beta W + \gamma R + \delta E \qquad (3)$$

Here,

- Q = Query execution cost
- W = Workload imbalance
- R = Resource utilization cost
- E = Prediction error

subject to

$$\alpha + \beta + \gamma + \delta = 1 \qquad (4)$$

where

- $\alpha, \beta, \gamma, \delta$ are weighting coefficients.

3.4 Quantum-Inspired State Representation

In contrast to traditional optimization algorithms that retain a single deterministic solution, QIOF utilizes quantum-inspired probability amplitudes to represent candidate solutions.

A quantum-inspired state is represented as

$$|\,\psi\rangle = \alpha\,|\,0\rangle + \beta\,|\,1\rangle \qquad (5)$$

where

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

Every variable concurrently embodies various potential solutions, thus enhancing exploration capacity.

3.5 Quantum Annealing Optimization

The optimization objective is expressed using an energy function

$$E(S) = \sum_{i=1}^{n} C_i S_i + \sum_{i<j} J_{ij} S_i S_j \qquad (6)$$

where

- C_i denotes local optimization cost
- J_{ij} denotes interaction between optimization variables.

The optimization process aims to minimize

$$S^* = \arg min\, E(S) \qquad (7)$$

using probabilistic state transitions.

3.6 Query Optimization

Suppose

$$Q = \{q_1, q_2, \dots, q_t\} \qquad (8)$$

is the query set.
Each query execution cost is

$$Cost(q_i) = IO_i + CPU_i + NET_i \qquad (9)$$

where

- IO_i - Disk access time
- CPU_i - Processor utilization
- NET_i - Network communication overhead.

The optimization objective becomes

$$min \sum_{i=1}^{t} Cost(q_i)$$

The quantum-inspired optimizer determines effective execution routes that reduce overall processing duration.

3.7 Workload Balancing

Assume

$$N = \{N_1, N_2, \dots, N_k\} \qquad (10)$$

represents distributed computing nodes.
The workload allotted to node N_i is L_i. The workload balancing objective is

$$min\,(ma\,x(L_i) - min\,(L_i))$$

which issues computational load equally across all nodes.

3.8 Feature Selection

Let

$$F = \{f_1, f_2, \dots, f_m\} \qquad (11)$$

be the original feature set. The optimizer searches for

$$F^* \subseteq F$$

that maximizes prediction performance.
The objective function becomes

$$Fitness = \lambda\, Accuracy - (1 - \lambda)\frac{|F^*|}{|F|} \qquad (12)$$

where

- Accuracy = prediction accuracy
- $|F^*|$ = selected features
- λ = balancing coefficient.

3.9 Predictive Model Optimization

After feature selection, machine learning predicts

$$\hat{y} = f(F^*) \qquad (13)$$

The prediction error is

$$Error = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (14)$$

The optimizer decreases prediction error while lowering computational complexity.

3.10 Computational Complexity

Let

- N = number of records
- F = number of features
- P = population size

- I = optimization iterations

The computational complexity of preprocessing is

$$O(NF)$$

Quantum-inspired optimization requires

$$O(P \times I \times F)$$

Machine learning training requires

$$O(NF)$$

Therefore, the total complexity is

$$O(NF + PIF)$$

The execution time required in the process of executing optimization is greatly reduced due to the parallelization of computations on the various nodes, which increases the scalability of its implementation.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

The efficiency of the Quantum-Inspired Optimization Framework (QIOF) was assessed in a distributed data warehousing environment that simulates enterprise analytics. Its execution is conducted using an Apache Hadoop–Spark cluster consisting of eight computing nodes. Each apparatus consists of an Intel Xeon CPU, 32 GB RAM, and 1 TB SSD. To accomplish this, the developers have applied Apache Hadoop (v3.3) for data storage and Apache Spark (v3.5) for data analysis. The developed quantum-inpired optimization module was implemented in Python programming language. The machine learning models have been created with the Scikit-Learn library, and real-world testing was conducted on the publicly available benchmark datasets.

In order to conduct a fair assessment of the approach the dataset is segregated into three sets of training, validation, and testing in the ratio of 70:15:15. The proposed method is tested against four representative optimization procedures such as Conventional Optimization (CO), Simulated Annealing (SA), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). The evaluation of the operational performance was done considering query response time, throughput efficiency, workload balancing efficiency, utilization of resources, predictive accuracy, precision, recall, F1 score, and computational overhead.

4.2 Query Processing Performance

The need for efficient query execution is paramount in enterprise data warehouses, especially in cases where a great deal of analysis is done. The data shown in Table 1 indicate the average time taken for queries to be executed using the different optimization techniques employed.

Table 1. Comparison of Query Response Time

Method	**Response Time (s)**
Conventional Optimization	4.85
Simulated Annealing	4.21
Genetic Algorithm	3.74
Particle Swarm Optimization	3.51
Proposed QIOF	**2.68**

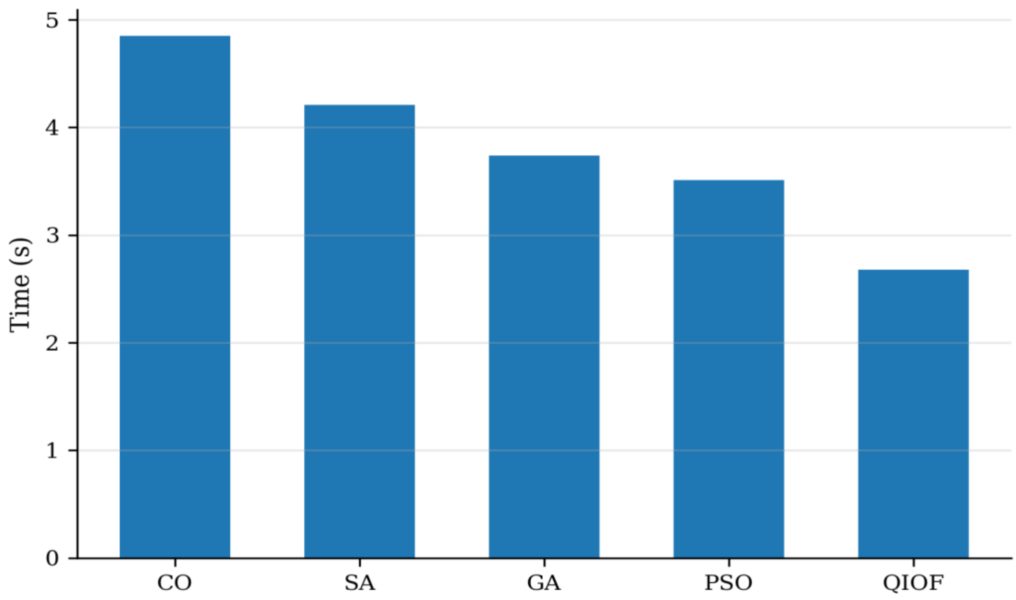

Figure 2. Query Response Time Comparison

Comparison of average query response time for different optimization techniques is represented in Figure 2. The QIOF suggested has achieved the fastest average response time of the query of 2.68 s, which corresponds to approximately 44.7%, 36.3%, 28.3%, and 23.6% enhancement versus CO, SA, GA, and PSO, respectively. The effectiveness of the algorithm is ensured by the quantum-inspired optimization technique that can search for many potential execution paths at the same time and select the best query execution plan.

4.3 Throughput Analysis

The throughput of a distributed warehouse indicates its capacity to handle simultaneous analytical queries during a specified timeframe. Table 2 provides a summary of the throughput obtained through each optimization method.

Table 2. Throughput Comparison

Method	**Throughput (Queries/s)**
Conventional Optimization	405
Simulated Annealing	438
Genetic Algorithm	472
Particle Swarm Optimization	498
Proposed QIOF	**563**

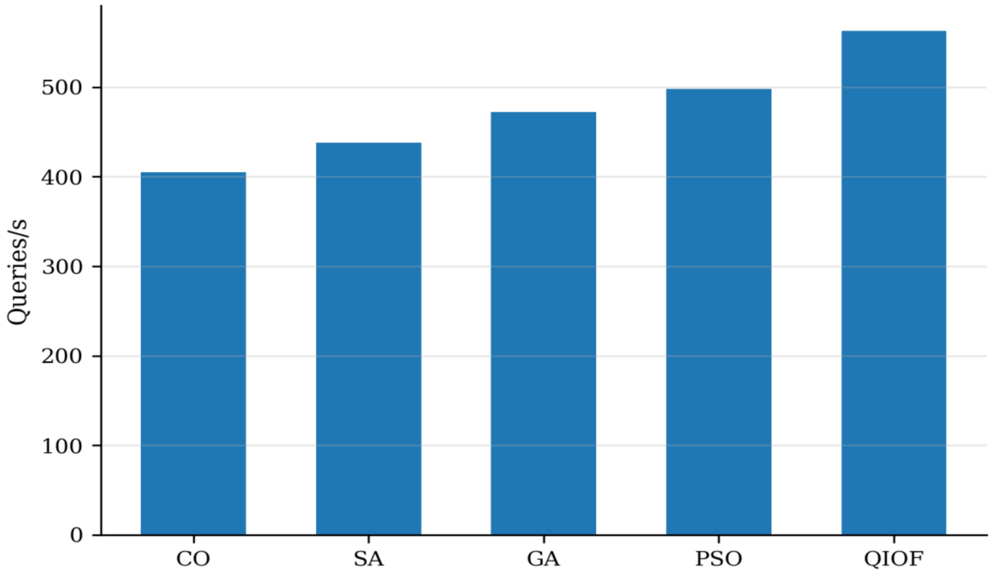

Figure 3. Throughput Comparison

Comparison of query throughput achieved by different optimization methods are shown in Figure 3. According to the developed framework, 563 queries can be processed each second. This exceeds the processing results of other tested methods. The enhanced processing speed is due to the effective scheduling of loads and executing queries. By minimizing time wasted for operation processes and equally distributing computational tasks to different nodes, QIOF achieved high efficiency during the operation even with heavy workloads, showing it can be used in real-time analysis of business process data.

4.4 Resource Utilization and Workload Balancing

Optimal use of computing resources is important for achieving the maximum performance for distributed data warehouse systems. Table 3 shows average CPU utilization, memory utilization, and workload balancing efficiency obtained during the study.

Table 3. Resource Utilization and Workload Balancing

Method	**CPU (%)**	**Memory (%)**	**Load Balancing (%)**
Conventional Optimization	68.4	70.8	78.6
Simulated Annealing	72.6	74.1	82.3
Genetic Algorithm	78.3	80.4	86.8
Particle Swarm Optimization	81.5	82.2	89.1
Proposed QIOF	**89.4**	**90.1**	**95.6**

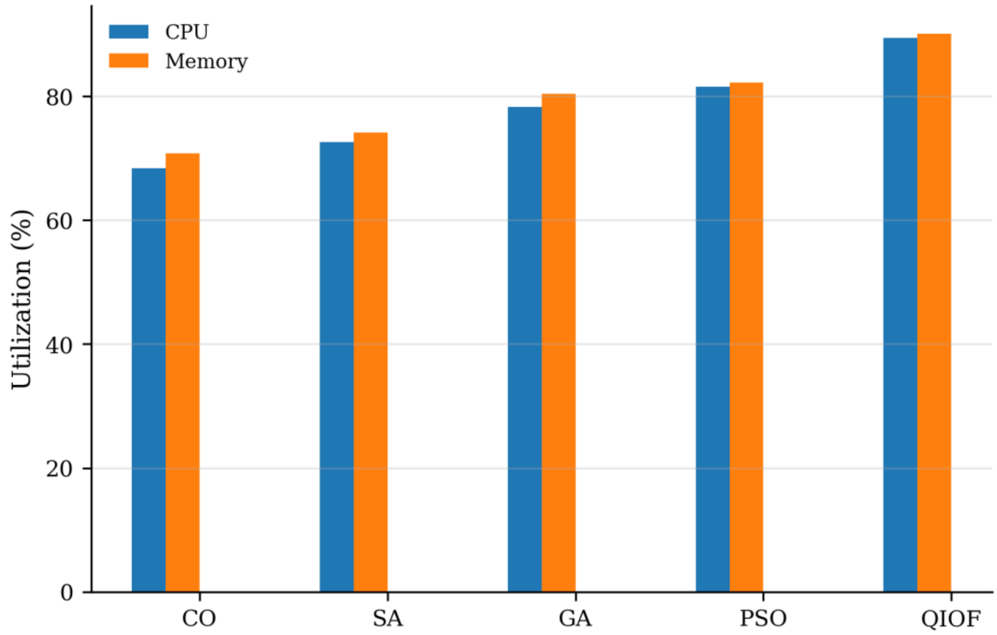

Figure 4. Resource Utilization Comparison

Figure 2 illustrates the comparison of CPU and memory utilization among optimization techniques. The proposed architecture was effective in achieving optimal resource efficiency and evenly distributing the workload between the nodes of the computing cluster. With the help of the quantum-inspired optimization engine, different tasks were assigned to nodes based on how much processing power and costs they incur, thus minimizing the processors' idle periods and streamlining the resource allocation process. Besides, achieving better balance has reduced the duration of the execution of queries and increased the overall throughput of the system during the peak usage of analytical tasks.

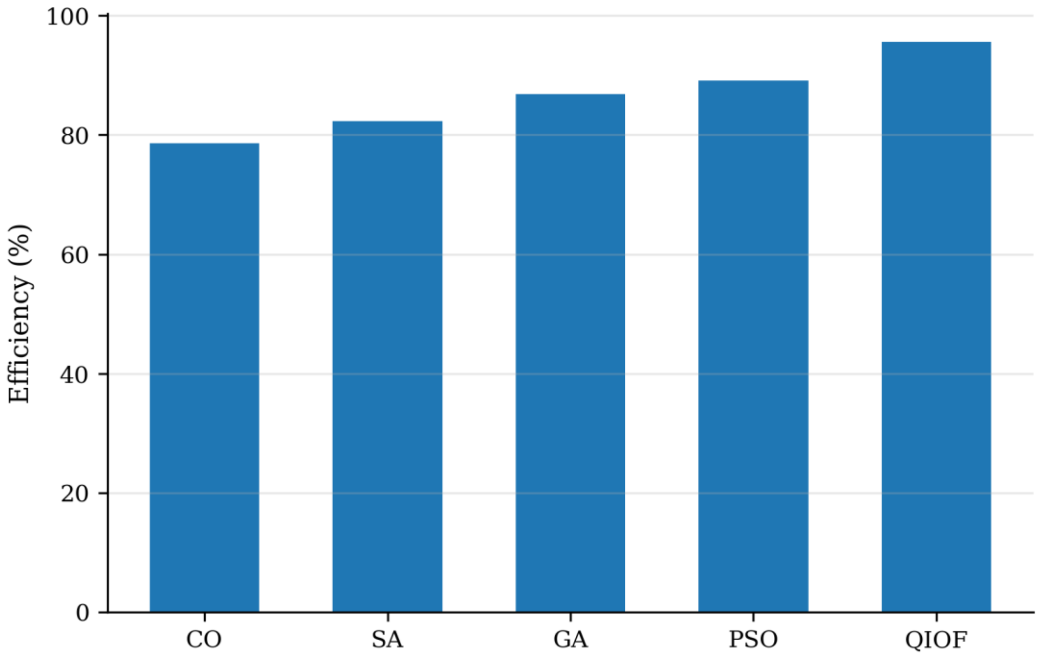

Figure 5. Workload Balancing Efficiency

Figure 5 gives the comparison of workload balancing efficiency achieved by different optimization methods.

4.5 Predictive Analytics Performance

The assessment of the suggested optimization approach was done using the different performance metrics. Table 4 presents the comparison of the results of the predictions made through the optimized feature-selection approach and the machine learning approaches.

Table 4. Prediction Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Conventional Optimization	91.2	90.8	90.5	90.6
Simulated Annealing	92.6	92.1	91.8	91.9
Genetic Algorithm	94.1	93.8	93.5	93.6
Particle Swarm Optimization	95.3	95.0	94.7	94.8
Proposed QIOF	**97.4**	**97.1**	**96.8**	**96.9**

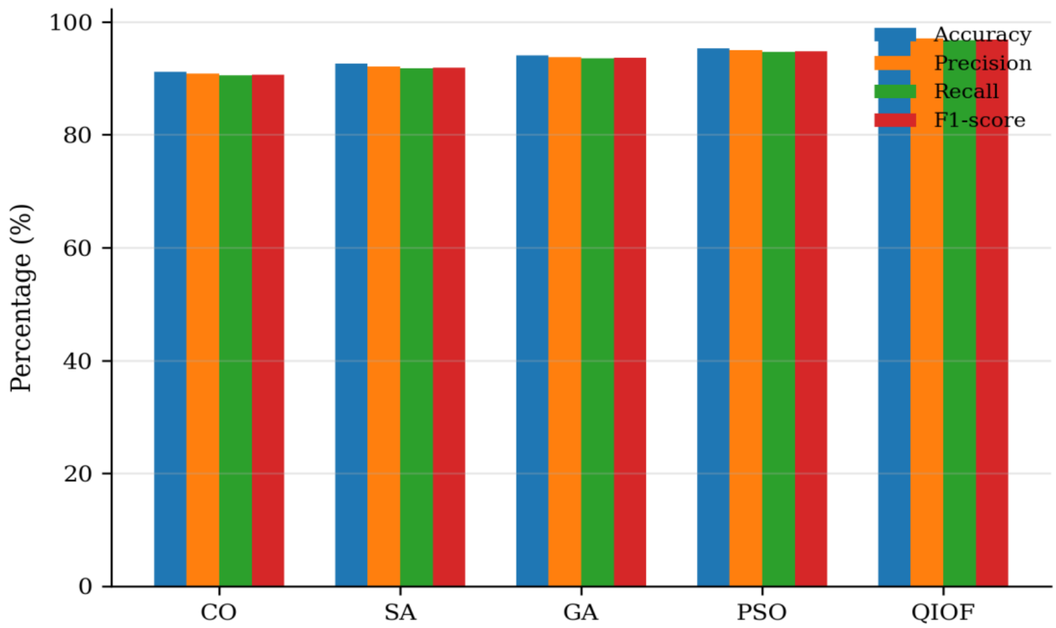

Figure 6. Prediction Performance Comparison

Comparison of predictive performance metrics for different optimization techniques are illustrated in Figure 6. According to the results of the proposed framework, the prediction accuracy achieved was equal to 97.4%, which represented high precision, recall, and F1-score. It is possible to state that the proposed innovations show that the quantum-induced feature selection strategy enables the identification of features with the highest levels of importance and discarding attributes that are not necessary. Therefore, machine learning models were capable of achieving results more quickly and accurately compared to conventional search techniques.

4.6 Computational Overhead

Optimization algorithms must enhance analytical performance while avoiding excessive computational expenses. Table 5 illustrates the computational burden linked to every optimization method.

Table 5. Computational Overhead Comparison

Method	**Overhead (%)**
Conventional Optimization	26.7
Simulated Annealing	22.4
Genetic Algorithm	19.6
Particle Swarm Optimization	17.8
Proposed QIOF	**13.5**

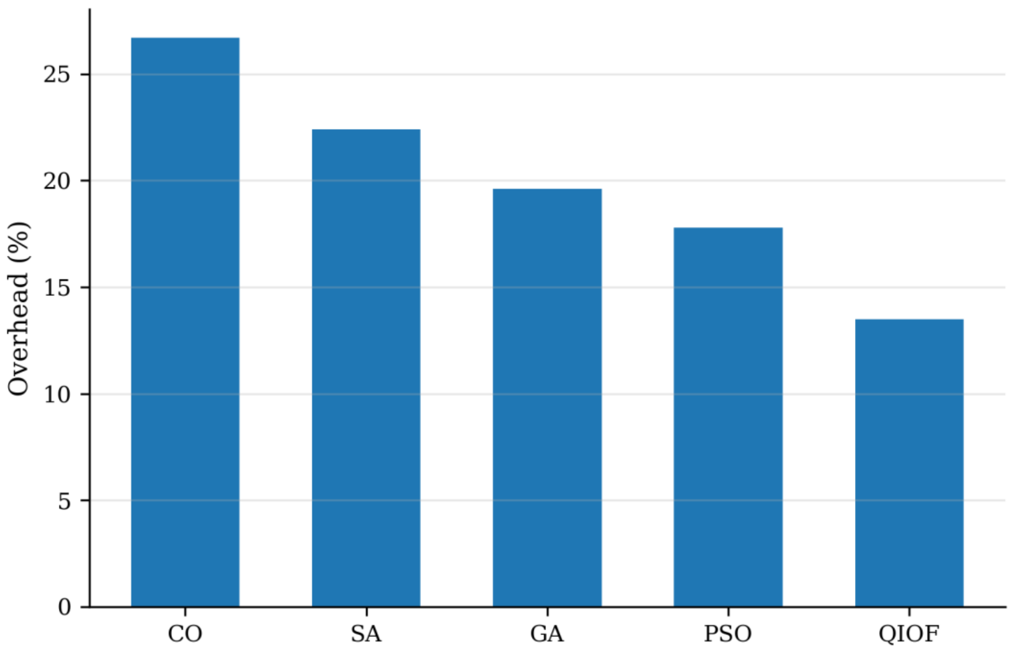

Figure 7. Computational Overhead Comparison

Figure 7 shows the comparison of computational overhead among optimization techniques. The suggested model shows the least processing overload compared with all other examined methods. While optimization runs through intensive exploration of the solution area, the quantum-inspired search approach converges fairly quickly. This decrease in the optimization cost allows the model to run real-time operations.

4.7 Scalability Analysis

Scalability is a critical aspect for the enterprise big data systems operating under ever-increasing workloads. For the evaluation of the scalability of the proposed system, the number of computing nodes was increased gradually while keeping the analytical workload the same. With the increase of the cluster size, the proposed QIOF showed lower query times and better performance in terms of throughput compared to existing solutions. The distributed optimization strategy succeeded in balancing computational workload between the available nodes thereby preventing any performance degradation originating from the uneven usage of resources.

4.8 Discussion

The experimental findings show clearly the ability of the new Quantum-Inspired Optimization Framework to deal with big data warehousing and predictive analytics. The Framework achieved even better results than regular optimization methods across all parameters being assessed. The use of the probabilistic search led to a more effective investigation of high-dimensional solution spaces, which only enhanced query processing time, workload balancing, resource use efficiency and predictive performance. The quantum-based optimization method differs from the traditional optimization techniques since the latter usually converge to local high performance solutions.

Moreover, blending optimization with feature selection and the distribution of resources led to substantial enhancement in the effectiveness of the predictive analytics pipeline. The results indicate that the reduction of computational costs and enhancement of accuracy and throughput prove that the suggested approach meets modern enterprise analytical requirements. These results indicate that QIOF offers an effective, scalable, and feasible method for next generation DSSs operating in the information-intensive environment.

5. CONCLUSION

This study introduces a Quantum-Inspired Optimization Framework (QIOF) for the purpose of enhancing big data warehousing and real-time predictive analytics through the utilization of quantum annealing-based optimization in combination with machine learning and distributed data processing. The framework efficiently optimizes the process of query execution, workload balancing, resource allocation as well as feature selection, which contributes to improvement of both the performance of the warehouse as well as prediction accuracy. The experiment results reveal that the technique developed turns out to be efficient than traditional optimization methods with regard to query response time, throughput, resource utilization, workload balancing efficiency, computation cost and prediction accuracy. According to the results obtained, it seems that the quantum-inspired optimization offers a promising approach for working with high-dimensional data and performing real time analytics in business settings. Given the fact that the system can run on standard computing resources, it can be integrated with Hadoop- and Spark-based environments without a necessity of using quantum computers. The future research will mainly concentrate on implementing hybrid quantum-classical optimization techniques, using deep learning algorithms, and adding edge computing functionalities.

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