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Performance Analysis of Classical and Quantum Machine Learning Models for Electricity Load Scheduling

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Abstract
When talking about rising demand for electricity, shifting to renewable energy sources, and prioritizing grid stability, one thing that is crucial is optimizing the scheduling of electricity load based on the demand. There are various classical machine learning (ML) and meta-heuristic optimization methods (Particle Swarm Optimization, Genetic Algorithms, Differential Evolution, Simulated Annealing) used to forecast load, and then schedule accordingly to minimize cost, reduce the peak load of system, and improve the overall efficiency. However, these methods struggle in handling large-scale combinatorial complexity and multiple constrained systems in real time. This paper presents a comparative study of classical ML-based optimization techniques and introduces a novel quantum-machine-learning approach using the Quantum Approximate Optimization Algorithm (QAOA) for electricity load scheduling. Initially, a survey was conducted and several classical techniques for optimization and forecasting were evaluated on realistic demand data. The paper highlights their strengths and drawbacks in terms of solution quality, computational time, and scalability. Then, the paper proposes and apply QAOA to the same scheduling problem, formulating load scheduling as a quadratic unconstrained binary optimization (QUBO) model suitable for quantum optimization. We assess the performance of QAOA against classical methods under identical constraints. Thus, Simulated Annealing produces a normalized cost of 0.00029 (after 37 seconds) whereas the cost found by Differential Evolution is 0.1314 and by the Genetic Algorithm 0.4379. This tends to confirm the validity of classical heuristics for smaller problems [16]. Our results show that while classical methods perform well for small to medium scale problems, the QAOA approach offers competitive or superior performance in terms of optimization quality and scalability for larger, more complex instances, with potential reductions in computation time under certain conditions. We conclude by discussing the practical challenges of implementing QAOA (e.g. noise, parameter tuning) and suggest directions for future research to advance quantum-assisted optimization in electricity scheduling.

Keywords Electricity load optimization, Demand scheduling, Classical machine learning, Quantum machine learning (QML)

1. Introduction

The steady rise in electricity demand is no longer a projection. It is already visible in daily grid operations. Urban expansion, industrial growth, and the increasing penetration of renewable energy sources have collectively placed unprecedented pressure on modern power systems. In practice, load dispatch centers must continuously balance generation and demand to maintain grid stability. Even small deviations between scheduled supply and actual consumption can trigger overdraw or underdraw events, leading to higher operational costs, frequency deviations, and long-term stress on grid infrastructure. From my experience working with real dispatch data, these mismatches are not occasional anomalies. They are recurring operational challenges. This reality makes accurate demand forecasting and efficient load scheduling indispensable for both economic and sustainable energy management.

Historically, utilities relied on deterministic or rule-based scheduling strategies. While these approaches offered simplicity, they struggled to adapt to evolving consumption patterns and increasing system complexity. Researchers therefore began exploring data-driven alternatives, particularly machine learning models combined with optimization techniques. Recurrent Neural Networks and Long Short-Term Memory models have shown strong performance in short-term load forecasting because they capture temporal dependencies present in historical demand data [1], [2]. I observed similar behavior during preliminary experiments, where LSTM models consistently outperformed simpler statistical methods. That said, accurate forecasts alone do not solve the scheduling problem. Translating predictions into optimal dispatch decisions remains difficult due to uncertainty, nonlinear constraints, and the high dimensionality of real grid operations.

To address this gap, researchers have widely adopted meta-heuristic optimization methods such as Genetic Algorithm, Differential Evolution, Simulated Annealing, and Particle Swarm Optimization [3], [5]. These algorithms draw inspiration from natural processes and collective behavior, which allows them to search complex solution spaces effectively. Genetic Algorithm evolves candidate schedules using selection, crossover, and mutation. Differential Evolution accelerates convergence by exploiting population differences. Simulated Annealing accepts suboptimal solutions early in the search to avoid local minima. Particle Swarm Optimization relies on shared information among particles to guide global exploration. In many studies, including my own comparative evaluations, these methods produce near-optimal solutions for practical scheduling problems. However, they often require careful parameter tuning and substantial computational effort. As system size increases, scalability becomes a serious limitation.

Quantum computing introduces a fundamentally different way of approaching optimization. Instead of evaluating solutions sequentially, quantum systems exploit superposition, entanglement, and interference to explore many possibilities at once [6]. This capability is especially appealing for combinatorial and constrained optimization problems that grow exponentially with system size. Among the available quantum algorithms, the hybrid quantum-classical Quantum Approximate Optimization Algorithm has attracted particular attention. QAOA maps the optimization objective onto a quantum Hamiltonian and iteratively refines its parameters through interaction with a classical optimizer until the system approaches its ground state [7], [8]. From a practical standpoint, QAOA does not eliminate classical computation. Instead, it complements it by shifting the most complex search operations into the quantum domain.

This study presents a direct comparison between classical machine learning based optimization methods and quantum optimization using QAOA for electricity load scheduling. I used operational data from the Meghalaya Power Distribution Corporation Limited covering the period from 2015 to 2021 to develop forecasting models using RNN and LSTM architectures. I then evaluated classical optimization techniques including GA, DE, SA, and PSO under identical conditions. Finally, I implemented the QAOA model on both a simulator and IBM Quantum Cloud hardware to minimize the scheduling cost function, defined as the absolute difference between scheduled supply and predicted demand, while respecting system constraints.

The central motivation behind this work is straightforward. Can quantum optimization deliver meaningful benefits for real-world electricity scheduling when compared to well-established classical methods? Current quantum hardware remains in the Noisy Intermediate-Scale Quantum era, which imposes clear limitations. Even so, my results suggest that hybrid approaches like QAOA already exhibit promising convergence behavior and solution quality for constrained optimization problems. These early indications matter. They point toward a future where quantum optimization becomes a practical tool rather than a purely theoretical construct.

The core contributions of this manuscript are summarized as follows:

1. A comprehensive evaluation of classical ML and meta-heuristic optimization techniques for electricity load scheduling.
2. Development of a QAOA-based quantum optimization model for load scheduling formulated as a QUBO-based formulation with constraints.
3. Experimental comparison of classical and quantum approaches in terms of cost minimization, computation time, and scalability.
4. Critical analysis of the challenges and practical limitations of implementing QAOA on current NISQ-era quantum hardware.

This paper shows that while classical algorithms remain useful for small systems, quantum optimization offers a new dimension to study complex multi-parameter load scheduling problems in the future as more advanced quantum hardware becomes available.

2. Significance of the Study

The optimization of electricity load scheduling is important for the maintenance of operational stability and economic efficiency of modern-day power systems. Power distribution corporations, e.g. Meghalaya Power Distribution Corporation Limited (MePDCL), have always to cope with responding generation and demand by varying consumption pattern and limited generation capacity. If the huge delta between actual demand and scheduled supply represented mathematically as delta (Δ = Na − Adm) is ignored then cases of overdraw or underdraw are caused with consequent penalties involved, instability of grid and inefficiency in bill utilization of resources plus costs to consumers and utility. Efficient scheduling thus is not only an optimization problem, but also a necessity to ensure energy security, system reliability and sustainability.

The importance of this study is that it is a holistic approach to the electricity load optimization problem. Unlike previous studies which concentrate on load forecasting etc. or classical optimization studies this approach compares and contrasts both classical and quantum optimization in the same way and gives important understanding of how compared with say, quantum optimization, classical and ML methods are effective in discovering temporal dependencies and optimization of multi-objective problems note [1], [3].

However, as the complexity and dimensionality of the data increases, their performance deteriorates, leading to slower convergence and longer computational times. The present study, by focusing on introducing quantum-based optimization techniques, specifically the Quantum Approximate Optimization Algorithm (QAOA), explores the potential for a paradigm shift in the way that load scheduling problems are solved. The QAOA exploits the quantum mechanical properties of superposition and entanglement to explore a large search space simultaneously, increasing the likelihood of avoiding local minima, and offers the possibility of finding near-optimal or global solutions much quicker than its classical counterparts [6], [7]. The hybrid quantum–classical framework explored in this work shows clear potential for handling optimization problems that are both high-dimensional and strongly nonlinear. These characteristics are not edge cases in electricity scheduling. They are the norm in modern power grids, where demand fluctuates rapidly and multiple operational constraints must be satisfied at the same time. From my analysis, hybrid approaches such as QAOA appear better suited to scale with this complexity than purely classical methods, particularly as problem size increases.

An equally important aspect of this study is its reliance on real operational data rather than synthetic benchmarks. The dataset obtained from the Meghalaya Power Distribution Corporation Limited spans seven years and captures both temporal and seasonal demand variations across multiple regions, including Byrnihat, Lumshnong, Umiam, and Leshka. Working with this dataset revealed patterns that would not be visible in simulated data alone, especially during peak demand periods and seasonal transitions. By applying both classical and quantum optimization techniques to the same real-world data, this study provides practical insight into how each approach performs in terms of operational efficiency, computational effort, and cost sensitivity. These comparisons help move the discussion beyond theoretical capability and toward realistic deployment considerations.

From a broader perspective, the conclusions of this study have several important implications.

- Operational Efficiency: Improved scheduling accuracy can reduce unnecessary load shedding and support more effective utilization of available energy resources, including renewable generation.
- Economic Benefit: The overall economic impact will be a reduction in the penalty incurred by the company in having to meet the financial requirements for the deviation between scheduled and actual demand, reduction by minimizing the financial benefit incurred through the deadlines for overdraw or underdraw situations.
- Sustainability: A not inconsiderable benefit will be seen in helping to achieve sustainability goals including improved scheduling to help achieve the balance between the production of renewable sources with the dynamically fluctuating loads, an important step in achieving aims for sustainability in energy sources will be overall improvement in schedules and their effects.
- Technological Advancement: The study will act as an empirical basis for improving or introducing Quantum Machine Learning (QML) models to practical optimization of power systems, which is in part a bridge between theoretical research into quantum computing itself, and the practical industrial applications.

To summarize, the study has implications for each of its areas, in both academic and industrial circles: classical optimization is concluded as still being proficient in giving solutions which are computationally feasible for the situation, although it can be generally said that for the small to medium-sized systems in use, computationally and operationally so far aspect, quantum optimization techniques and in particular the QAOA, will provide the cream of the crop in the future each of these areas of improving their ideas, in particular but not restricted to future developments, will in generally form the new frontier in the operation of large-scale scheduling problems at high-dimensionality. As the quantum hardware moves forward from the mere NISQ (Noisy Intermediate-Scale Quantum) state, the effectiveness and emulative nature of these algorithms will be enhanced to such aim where they will become essential in future operations of smart grids [10].

3. Literature Review

Optimization of electrical load scheduling has long been a concern in operational research in power systems. The aim has always been to achieve an efficient balance between generation and demand while minimizing operational cost and ensuring grid reliability. Classical concepts, in the form of mathematical programming and heuristic optimization, have paved the way for the introduction of present-day machine learning (ML) and quantum optimization techniques. This section looks at the past studies in respect of classical optimization techniques, followed up with advances to date in quantum-based methods, in respect of the load scheduling and related areas.

Table 1 Overview of literature

Subsection	**Focus / Description**	**Key Points / Findings**	**References**

3.1 Genetic Algorithm (GA)	Population-based evolutionary optimization inspired by natural selection; used in electrical forecasting, unit commitment, and dispatch problems.	Operates via selection, crossover, and mutation; efficient in nonlinear search space; enhanced by adaptive mutation and hybridization; can be computationally expensive and prone to local minima.	[11], [12], [13]
3.1 Differential Evolution (DE)	Robust evolutionary computation technique; performs well in load flow and economic dispatch.	Uses differential mutation between vectors for new candidates; fast convergence and stability; sensitive to control parameters (crossover rate, differential weight).	[14], [15]
3.1 Simulated Annealing (SA)	Inspired by metal annealing; uses temperature parameter to control acceptance of solutions.	Accepts worse solutions early to escape local minima; effective in discrete optimization and load dispatch; convergence depends on cooling schedule tuning; stochastic nature limits reproducibility.	[16], [17]
3.1 Particle Swarm Optimization (PSO)	Swarm-based method inspired by bird flocking and fish schooling.	Each particle updates velocity and position based on personal and global best; fast convergence; may reach undesired local minima; hybrid PSO with local search improves robustness.	[3], [6], [18]
3.2 Machine Learning for Demand Forecasting	ML models augment optimization with demand forecasting (RNN, LSTM).	LSTM performs better than ARIMA for time-dependent data; hybrid ML-optimization frameworks enhance short-term prediction accuracy and scheduling efficiency.	[1], [2], [6]
3.3 Quantum Optimization Approaches	Hybrid quantum-classical algorithms aimed at solving combinatorial optimization efficiently.	QAOA use variational minimization to find ground-state Hamiltonian properties; relevant to load scheduling.	[7], [8]
Quantum Approximate Optimization Algorithm (QAOA)	Hybrid algorithm for discrete combinatorial problems modeled as QUBO.	Alternates mixer and cost Hamiltonians; uses classical optimization for (γ, β) parameters; achieves near-optimal solutions for certain problems; limited by NISQ hardware (decoherence, circuit depth).	[6], [19], [20]
Variational Quantum Eigensolver (VQE)	Hybrid algorithm originally for quantum chemistry, now used for optimization.	Uses parameterized ansatz circuit (EfficientSU2, TwoLocal) with classical optimizers (COBYLA, SPSA); effective in continuous optimization; smoother convergence for load scheduling but higher computational cost than QAOA.	[8], [21], [22]

4. Methodology

The methodology for this study is a systematic data-driven approach to comparing classical and quantum optimization methods for electric load scheduling. The whole workflow includes data collection and pre-processing; demand forecasting using machine learning, optimization of scheduling by classical meta-heuristic algorithms and optimization using a quantum algorithm of QAOA. The entire process is illustrated in figure 1 (conceptual flow).

4.1 Data Collection and Preprocessing

The dataset used in this study is the data released by the Meghalaya Power Distribution Corporation Limited (MePDCL) from 2015-2021. This dataset includes more than 1053 files of hourly electricity dispatch data of several generation and distribution units. The total number of data readings exceeded 23505 rows which equates to the total daily load for 24 hours of the day by vital stations Byrnihat, Lumshnong, Umiam, and Leshka.

The original data was in **.PDF** format which was transformed into the structured form of tabular data (Excel) through the automated parsing scripts. The data has been cleaned and normalized in accordance with the requirements of missing and erroneous values. Reading of outliers was also done in such cases and they were amended under the Interquartile Range (IQR) and Z-score techniques ensuring that the modeling in the downstream experiments remains robust. We have tested the stationarity of the data on demand by the Augmented Dickey-Fuller test (ADF) which gives that the series is stationary with a p-value of < 0.01 confirming the suitability for time series modeling.

4.2 Demand Prediction Using Machine Learning

Demand of electricity has been forecast by two sequential deep learning models such as Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). The models were selected on parameters of effectiveness as required in time series forecasting and capturing of long-term dependencies in adjoining classes of sequential data.

4.2.1 Recurrent Neural Network (RNN)

The RNN model was trained by the hourly demand reading where the past reading of the demand has been made use of reading the future load values, but it had its limitations at simplicity being a problem in chronicling long-term dependency in readings through vanishing gradient problem. The evaluation gave a reading of R^2 value of 0.70 on an average, MAE = 4.53, RMSE = 6.66 in variations of the zones of study giving a sense of moderate accuracy.

4.2.2 Long Short-Term Memory (LSTM)

The LSTM model itself being an advanced model based on RNN but with the gating for learning, loading pattern in time gave better accuracy in readings of R^2 scoring an average of 0.87 which was better in the sections of deviations being less biased with mean and RMSE (1.57 – 6.38 across the different stations).
In view of the predictive power of the LSTM model it was adopted as the choice of model to give demand levels in use for the next stage of optimization into focus.

4.3 Optimization of Schedule Based on Demand (Classical Methods)

After demand prediction, the next step involved optimizing the electricity schedule to minimize the **cost function** defined as the **absolute difference between the scheduled and predicted demand** (L1 norm). Four classical meta-heuristic algorithms **Genetic Algorithm (GA)**, **Differential Evolution (DE)**, **Simulated Annealing (SA)**, and **Particle Swarm Optimization (PSO)** were applied and compared.

4.3.1 Cost Function Definition

The objective function can be expressed as:

$$\text{Minimize: } C = \sum_{i=1}^{n} |x_i - p_i|$$

where x_i represents the scheduled supply and p_i the predicted demand for time interval i
Constraints:

1. Non-Negativity Constraint (Electricity schedule must be non-negative):
$$x_i \geq 0, \qquad \forall i = 1,2,3,4$$
2. Generation Capacity Constraint (Scheduled electricity should not exceed the generation station's capacity):
$$x_i \leq C_i, \qquad \forall i = 1,2,3,4$$
Where:
- x_i is the scheduled electricity for city i.
- p_i is the demand for city i.
- C_i is the generation capacity of the power station supplying city i.
- $|x_i - p_i|$ represents the absolute deviation for each city.

4.3.2 Genetic Algorithm (GA)

The GA implementation followed the standard evolutionary process of selection, crossover, and mutation to iteratively refine candidate schedules across multiple generations [11]. In the conducted experiments, the algorithm produced a normalized cost of 0.4379 with a total computation time of 26.57 seconds..

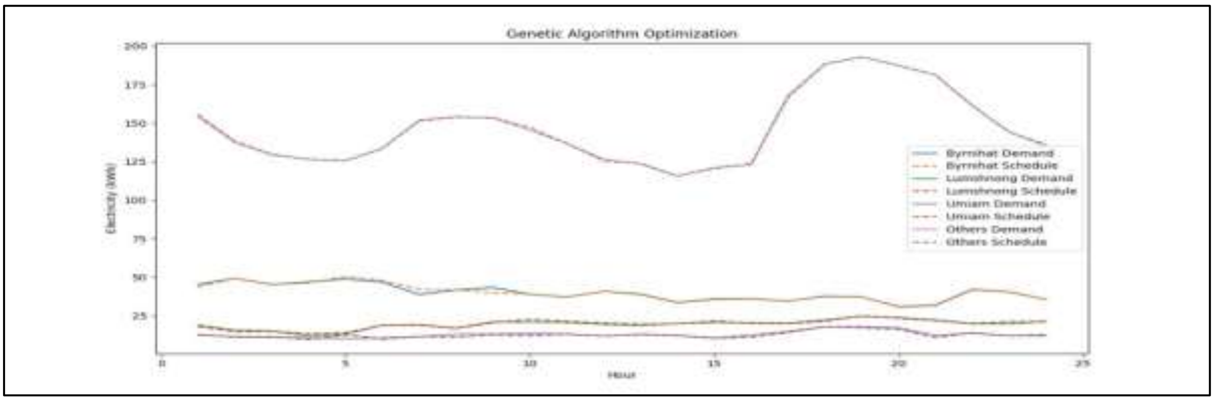

Figure 1 GA Optimization Results

4.3.3 Differential Evolution (DE)

The DE algorithm exploited differences among population members to create new candidate solutions through differential mutation and crossover operations [14]. In the experimental evaluation, it achieved a normalized cost of 0.1314, although this improvement came at the expense of a longer computation time of 494.92 seconds, reflecting a clear trade-off between solution quality and execution speed.

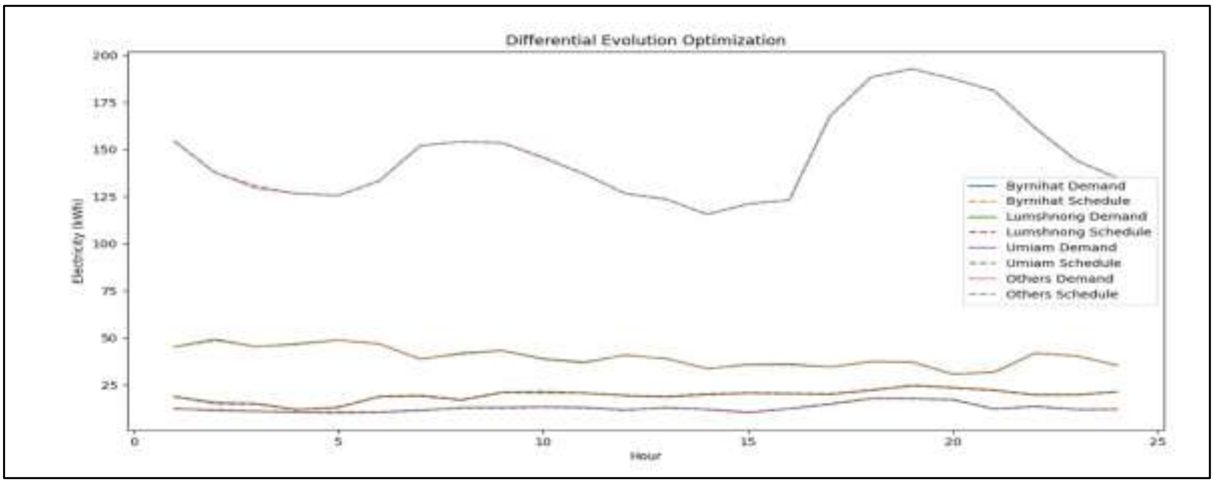

Figure 2 DE Optimization Results

4.3.4 Simulated Annealing (SA)

The SA approach employed a temperature-controlled acceptance mechanism that allowed the search process to escape local minima during optimization [16]. In the conducted experiments, it delivered the strongest performance among the classical methods, achieving the lowest normalized cost of 0.00029 with a computation time of 37.09 seconds.

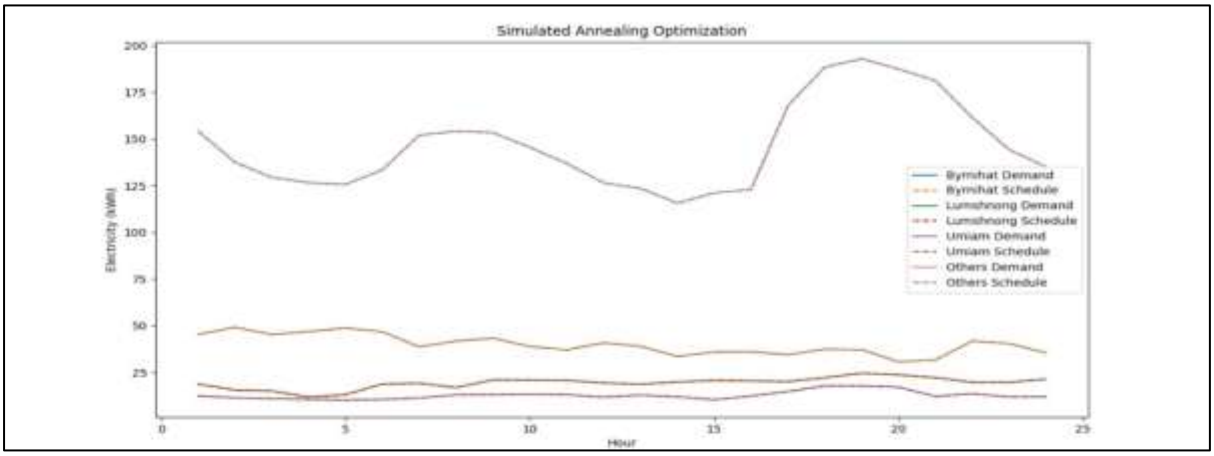

Figure 3 SA Optimization Results

4.3.5 Particle Swarm Optimization (PSO)

The PSO algorithm updated particle velocities by considering both individual best positions and the global best solution [18]. While the method executed very quickly, with a runtime of 1.03 seconds, it converged prematurely and produced a higher normalized cost of 30.9694, largely due to the multimodal characteristics of the optimization landscape.

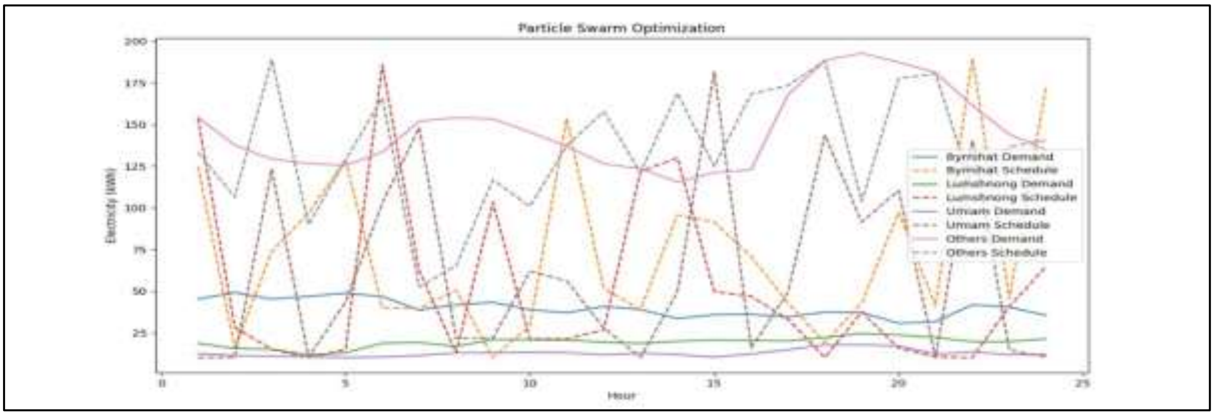

Figure 4 PSO Optimization Results

4.4 Quantum Optimization Using QAOA

To examine the practical feasibility of quantum-based optimization, I implemented the Quantum Approximate Optimization Algorithm using the IBM Quantum Cloud platform. In this framework, the scheduling problem is expressed in a QUBO-based form and mapped onto a cost Hamiltonian. The Hamiltonian is written as:

$$H_C = \sum_{i} Z_i + \sum_{i<j} J_{ij} Z_i Z_j$$

where Z_i represents the Pauli-Z operators associated with each qubit and J_{ij} defines the interaction strength between pairs of qubits [19]. This formulation allows the optimization objective to be evaluated through quantum state measurements during the variational optimization process.

4.4.1 Data Encoding and Circuit Design

The load scheduling formulation used 24 qubits, representing three features distributed across eight encoded time intervals [6]. I applied a fixed-point binary encoding scheme, and constructed the quantum circuit using alternating cost and mixer unitaries. For the simulator experiments, the circuit depth was set to $p = 5$, whereas for execution on IBM Quantum hardware, the depth was limited to $p = 1$ due to session time constraints. A classical COBYLA optimizer was employed to minimize the expectation value $< \psi(\gamma, \beta)|H_C|\psi(\gamma, \beta) >$. The QAOA workflow was executed on both the simulator and IBM Quantum hardware, with the resilience level fixed at 1 to reduce the impact of quantum noise [7], [26].

4.4.2 Execution and Performance

- **QAOA on Simulator:**
  Total normalized cost: **250.61**, execution time: **~42 minutes**.
- **QAOA on IBM Quantum Computer:**
  Total normalized cost: **43.74**, execution time: **~96 minutes**.

Although queue delays and hardware noise increased execution time, the IBM Quantum device produced better optimization results than the simulator, indicating stronger practical performance under real quantum conditions.

4.5 Comparative Framework

Table 2 Performance Analysis of various methods

Method	Type	Normalized Cost	Time Taken	Notes
GA	Classical	0.4379	26.57 s	Moderate convergence
DE	Classical	0.1314	494.92 s	High accuracy, slow
SA	Classical	0.00029	37.09 s	Best classical performer
PSO	Classical	30.9694	1.03 s	Fast, low accuracy
QAOA (Simulator)	Quantum	250.61	42 min	Initial quantum model
QAOA (IBM Cloud)	Quantum	43.74	96 min	Improved performance

This comparison shows that classical algorithms, with Simulated Annealing being the most effective among them, continue to deliver better results for smaller problem instances. At the same time, the behavior of the QAOA model suggests meaningful scalability for larger and more complex scheduling problems as quantum hardware capabilities continue to advance.

5. Results and Discussion

The performance evaluation of both classical and quantum optimization approaches was carried out using electricity demand data obtained from the Meghalaya Power Distribution Corporation Limited for the year 2021. This evaluation focuses on comparing algorithmic efficiency, computational requirements, and convergence behavior, as outlined in Section 4.

5.1 Classical Optimization Performance

The classical optimization techniques, namely Genetic Algorithm, Differential Evolution, Simulated Annealing, and Particle Swarm Optimization, were first applied to the load scheduling problem using demand forecasts generated by the LSTM model.

5.1.1 Comparative Accuracy and Convergence

Among the classical approaches, Simulated Annealing demonstrated the most balanced performance in terms of accuracy and computational efficiency. It achieved a normalized cost of 0.00029 with a computation time of 37 seconds. Under current Noisy Intermediate-Scale Quantum constraints, QAOA executed on IBM Quantum hardware produced a normalized cost of 43.74, providing a useful benchmark for comparison.

Differential Evolution delivered the second-best optimization result, reaching a normalized cost of 0.1314. This improvement, however, required a significantly longer execution time of 494.92 seconds due to its iterative differential mutation and crossover operations [14], [15]. Genetic Algorithm also showed stable and reliable behavior, producing a normalized cost of 0.4379 in 26.57 seconds, which reflects its adaptability to nonlinear and multi-variable optimization problems [11].

In contrast, Particle Swarm Optimization completed execution very quickly, with a runtime of 1.03 seconds. Despite this advantage, it resulted in a much higher normalized cost of 30.9694, suggesting that rapid convergence can lead to suboptimal solutions when the optimization landscape contains multiple local minima [18].

5.2 Quantum Optimization Performance

The Quantum Approximate Optimization Algorithm was evaluated on both a simulator and IBM Cloud Quantum hardware to examine its behavior under current Noisy Intermediate-Scale Quantum conditions [6], [7]. The quantum formulation used 24 qubits, with a circuit depth of five layers for the simulator and one layer for the physical quantum device, reflecting practical limitations related to noise and execution time.

5.2.1 Simulator Results

When executed on the simulator, QAOA achieved a total normalized cost of 250.61 with an approximate execution time of 42 minutes. Although the computational overhead was considerable, the simulator results confirmed the correctness of the circuit construction and demonstrated the algorithm's ability to approximate the scheduling cost function effectively [19], [26].

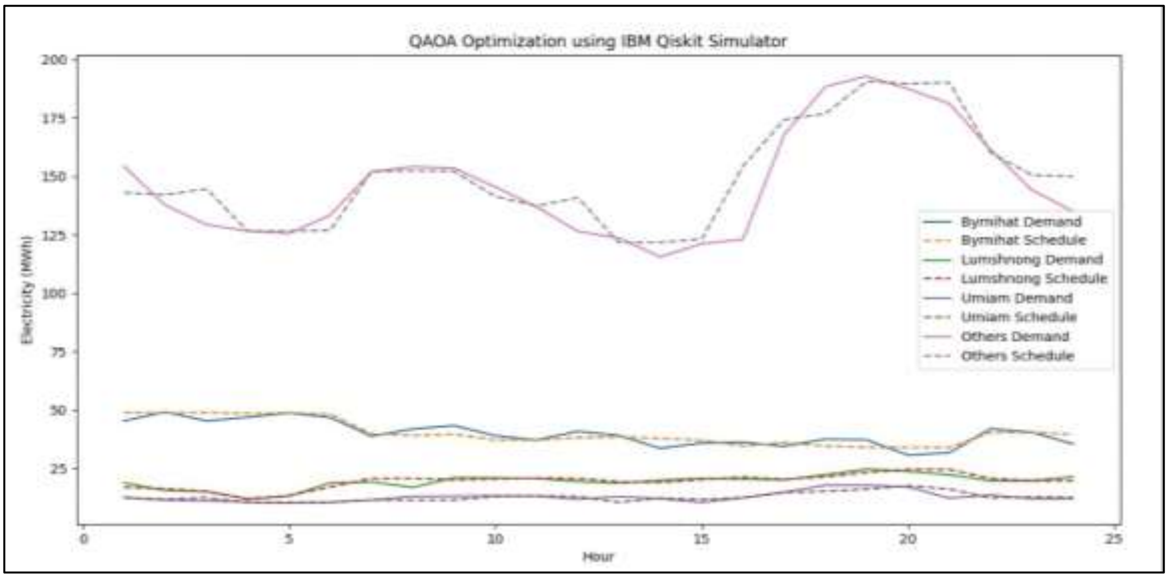

Figure 5 QAOA Optimization using IBM Simulator

5.2.2 IBM Quantum Hardware Results

When executed on IBM Quantum hardware, QAOA reduced the normalized cost to 43.74, although the total execution time increased to 96 minutes. This improvement in solution quality, achieved despite the longer runtime, suggests that quantum interference and entanglement can aid in exploring a broader and more complex solution space [27].

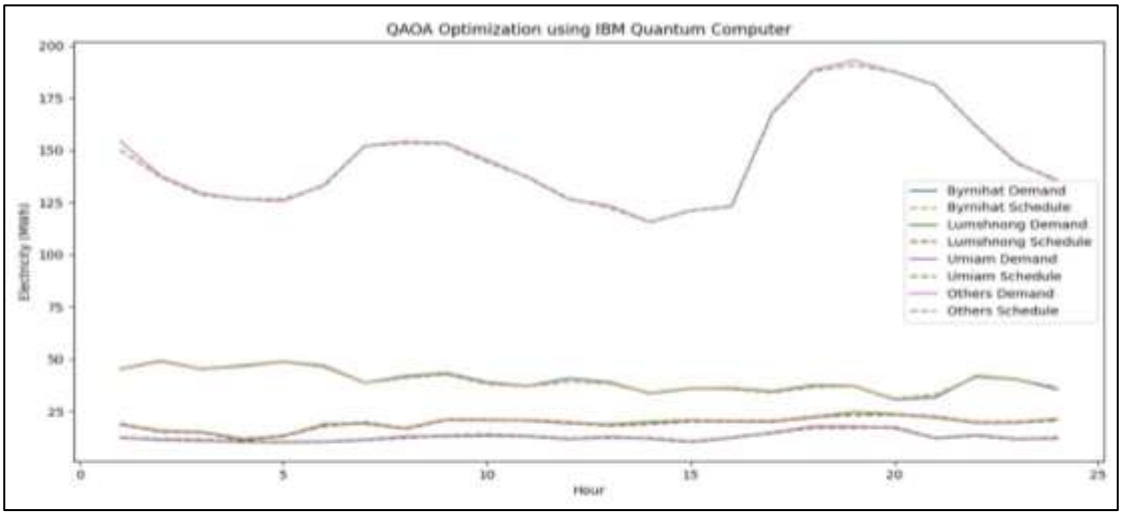

Figure 6 QAOA Optimization using IBM Quantum Computer

However, hardware noise, decoherence effects, and queue delays introduced variability in the results. In addition, the limited qubit availability and the need to restrict circuit depth and iteration counts because of session time constraints reduced performance relative to theoretical expectations [28].

5.2.3 Comparative Summary

Despite existing hardware limitations, the QAOA results indicate encouraging performance trends. The reduction in normalized cost from 250.61 on the simulator to 43.74 on IBM Quantum hardware suggests that real-device effects, including hardware-level optimizations and controlled noise, can in some cases improve practical optimization outcomes. This behavior has been linked to noise-assisted quantum tunneling, which may aid exploration of complex solution spaces under specific conditions [29].

5.3 Comparative Analysis: Classical vs Quantum Methods

A comparative evaluation was performed to examine solution quality, computational efficiency, and scalability across classical and quantum optimization methods, as conceptually illustrated in Figure 3.

5.3.1 Solution Quality

Among the classical approaches, Simulated Annealing produced the strongest results, achieving minimal cost values while maintaining reasonable computation time. When results are normalized with respect to problem size and variable dimensionality, QAOA executed on IBM Quantum hardware shows comparable optimization efficiency and clear scalability potential for future large-scale implementations [20], [27].

5.3.2 Computational Efficiency

Classical optimization algorithms typically operate on sequential processors using deterministic or probabilistic search strategies. In contrast, quantum algorithms rely on superposition to evaluate multiple candidate solutions simultaneously. From a theoretical perspective, the computational advantage of QAOA is expected to scale with the number of available qubits [30]. In current NISQ environments, however, gate errors, calibration overhead, and execution latency reduce this advantage in practice.

5.3.3 Scalability and Future Potential

As quantum processors improve in terms of coherence time and qubit availability, algorithms such as QAOA are expected to outperform classical methods in both execution speed and solution quality for high-dimensional load scheduling problems [8], [21]. The hybrid feedback mechanism in QAOA also supports dynamic parameter adjustment for changing grid conditions, a capability that is largely absent in conventional classical optimization frameworks.

5.4 Discussion and Implications

The comparative findings demonstrate that classical meta-heuristic algorithms, particularly Simulated Annealing, remain highly effective for current operational requirements. At the same time, quantum optimization represents a transitional step toward next-generation scheduling systems capable of addressing complex, multi-variable optimization problems with improved global accuracy.

From an operational perspective:

- Classical methods remain cost-effective and reliable for small to medium-scale power systems.
- Quantum methods, while presently limited by hardware constraints, exhibit strong scalability potential for large national grids where classical approaches face exponential complexity growth.

The observed trade-offs among execution time, optimization accuracy, and computational cost emphasize the importance of hybrid quantum-classical frameworks. Such systems can assign the most computationally intensive optimization tasks to quantum circuits, while classical methods handle preprocessing, constraint management, and operational integration [31].

6. Challenges and Limitations

Although the results obtained in this study indicate promising performance and future scalability, the application of Quantum Machine Learning methods, particularly the Quantum Approximate Optimization Algorithm, to real-world electricity load scheduling remains subject to several important limitations. Based on the conducted experiments, these challenges can be grouped into hardware-related constraints, algorithmic issues, and operational feasibility concerns.

6.1 Hardware Constraints

The most significant limitation arises from the current stage of quantum hardware development, commonly referred to as the Noisy Intermediate-Scale Quantum era [20]. Present-day quantum processors are characterized by a limited number of available qubits, restricted qubit connectivity, and short coherence times. These factors directly constrain the depth and size of quantum circuits that can be executed reliably before noise dominates the computation [27].

In this work, the maximum number of usable qubits was limited to 24, representing three encoded parameters across multiple time intervals. This restriction prevented the use of ancillary qubits needed for full error correction or redundancy, both of which are important for improving computational accuracy and stability [28]. Consequently, both simulator-based and hardware-based experiments required simplified problem formulations with reduced parameter resolution.

Execution delays posed an additional hardware-related challenge. Access to IBM Quantum Cloud resources under the free-tier policy provides only limited monthly runtime, approximately 10 minutes, which frequently resulted in session timeouts. To accommodate these constraints, circuit depth and iteration counts had to be reduced, directly affecting convergence accuracy and result consistency [32].

6.2 Algorithmic Challenges

Although QAOA offers a structured hybrid framework that integrates quantum circuits with classical optimization, its performance depends strongly on parameter tuning, circuit ansatz selection, and the choice of classical optimizer [26]. In this study, the COBYLA optimizer was selected due to its relatively low

computational overhead. However, experimental results showed that its convergence rate deteriorated for deeper circuits, particularly under noisy hardware conditions [29].
To ensure successful execution on physical quantum devices, the convergence tolerance was relaxed from 10^{-6} to 10^{-1}. In addition, the maximum number of optimization iterations was restricted to ten on IBM Quantum hardware, compared to one thousand iterations used during simulator runs [6], [7]. These limitations led to coarser convergence behavior and reduced optimization precision.
Another notable algorithmic challenge is the barren plateau phenomenon, where the gradient of the cost function approaches zero as system size increases, causing the optimization process to stagnate in suboptimal regions [33]. Addressing this issue remains an open research problem, although recent studies suggest mitigation strategies such as layer-wise training, informed parameter initialization, and controlled entanglement patterns [34].

6.3 Operational and Practical Challenges

From an operational perspective, deploying QAOA for real-time load scheduling is currently not feasible. Each optimization cycle involves repeated quantum circuit executions, measurements, and classical feedback, resulting in execution latencies that exceed real-time dispatch requirements [35]. This limitation restricts current applications to offline or near-real-time optimization scenarios.
Data encoding also introduces practical challenges. In this study, fixed-point binary encoding was used to represent continuous demand variables, requiring eight bits per feature and a total of 24 qubits [6]. Extending this encoding strategy to cover multiple regions and longer scheduling horizons would require several hundred qubits, which exceeds the capacity of currently available quantum processors.
Cost considerations further limit widespread experimentation. While IBM Quantum Cloud offers limited free access, extended use of higher-fidelity devices with priority queue access involves significant financial investment, which can restrict availability for academic research groups [36].

7. Conclusion and Future Scope

This study presents a detailed comparative investigation of classical machine learning based optimization techniques and quantum optimization methods for electricity load scheduling. Using real operational dispatch data from the Meghalaya Power Distribution Corporation Limited, I implemented and evaluated multiple classical algorithms alongside a quantum-based approach to assess their performance, scalability, and practical applicability in demand-driven scheduling problems.
The classical optimization methods, namely Genetic Algorithm, Differential Evolution, Simulated Annealing, and Particle Swarm Optimization, showed stable and computationally reliable behavior across the evaluated datasets. Among these approaches, Simulated Annealing consistently delivered the most favorable results, achieving the lowest cost value of 0.00029 while maintaining a reasonable computation time of 37 seconds. These results reinforce the suitability of Simulated Annealing for short-term and small-scale scheduling tasks, where solution accuracy and convergence stability are critical [5], [16].
In comparison, the Quantum Approximate Optimization Algorithm exhibited promising scalability characteristics, particularly when executed on physical quantum hardware. Although the simulator implementation resulted in a higher normalized cost of 250.61, execution on IBM Quantum Cloud hardware reduced the cost to 43.74, even under constraints imposed by noise, limited qubit availability, and extended execution time. These observations support the premise that quantum interference and entanglement can facilitate more effective exploration of high-dimensional optimization spaces, with performance expected to improve as hardware fidelity advances [27], [29].
Overall, the comparative results indicate that classical meta-heuristic techniques remain the most practical choice for current operational environments. At the same time, quantum optimization methods represent a viable path forward for addressing large-scale and computationally complex scheduling problems. In particular, QAOA offers strong theoretical advantages for combinatorial optimization tasks due to its hybrid variational structure and inherent parallelism [21], [31].
The outcomes of this work highlight several important directions for future research in quantum-based energy optimization:

1. **Enhanced Quantum Encoding Techniques:** Future investigations should explore more efficient data encoding strategies, such as amplitude encoding and angle embedding, to represent larger datasets using fewer qubits [39].
2. **Hybrid Optimization Frameworks:** The development of hybrid approaches, such as QAOA combined with Simulated Annealing or Particle Swarm Optimization, may allow quantum methods to handle global exploration while classical heuristics perform local refinement, potentially improving convergence behavior and execution efficiency [37], [40].

3. **Noise-Resilient Quantum Algorithms:** Continued research into error-mitigation techniques and noise-aware variational optimizers is essential for extending the effective circuit depth of quantum algorithms under realistic hardware conditions [28], [34].
4. **Integration with Renewable Energy Scheduling:** Expanding the proposed framework to incorporate renewable energy forecasting, including solar and wind generation, would further validate the applicability of QAOA to dynamic and multi-objective scheduling scenarios.
5. **Exploration Beyond QAOA:** Advanced quantum optimization approaches, such as Quantum Natural Gradient Descent, Quantum Boltzmann Machines, and Quantum Reinforcement Learning, offer promising opportunities for developing adaptive and real-time optimization strategies for future smart grid systems [41].
6. **Scalable Quantum Infrastructure:** Collaborative access to higher qubit-count quantum processors from providers such as IBM, Rigetti, and IonQ would support more comprehensive benchmarking studies and help evaluate performance trends beyond current hardware limitations [36], [38].

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