Journal of Theoretical and Applied Information Technology
31st August 2026. Vol.104. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

HYBRID QUANTUM-CLASSICAL OPTIMIZATION MODEL FOR SMART GRID LOAD FORECASTING AND SECURE ENERGY TRADING

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ABSTRACT

The increasing integration of renewable energy sources and decentralized energy trading has significantly increased the complexity of modern smart grid management. This study proposes a hybrid quantum–classical optimization framework for smart grid load forecasting and secure energy trading. A two-layer Long Short-Term Memory (LSTM) network is used for load prediction, achieving an RMSE of 2.89 MW and MAPE of 3.71%, improving forecasting accuracy by approximately 9% compared to classical models. The economic dispatch problem is formulated as a Quadratic Unconstrained Binary Optimization (QUBO) model and solved using the Quantum Approximate Optimization Algorithm (QAOA). Experimental evaluation on the IEEE 33-bus system reduced total dispatch cost to $12,310/day, achieving a 5.2% cost reduction compared to PSO. The framework also ensures secure peer-to-peer energy trading using blockchain with post-quantum cryptography. The results demonstrate improved scalability, optimization efficiency, and security for next-generation smart grid systems.

Keywords: *Hybrid quantum–classical optimization, Post-quantum cryptography, Quadratic Unconstrained Binary Optimization (QUBO), Quantum Approximate Optimization Algorithm (QAOA), Secure energy trading, Smart grid load forecasting.*

1. INTRODUCTION

Electrification of power systems into smart grids [1] based on modernization has essentially changed the nature of energy production, delivery, and consumption. Smart grids are complex, distributed systems, as compared to conventional grids that are centralized in production and unidirectional in energy flow, featuring renewable energy resources, distributed energy storage, microgrids, electric vehicles, and prosumer-driven peer to peer (P2P) energy trading. Although the transition increases the grid flexibilities and sustainability, the process also presents enormous computational and security challenges.

Accurate short-term and medium term load forecasting is one of the major operational needs of smart grids. Accurate prediction of loads makes it possible to use maximum unit commitment, economical dispatch, demand response control and real-time pricing mechanisms. Nevertheless, the growing introduction of renewable sources of energy like the solar and wind brings about stochastic variability and nonlinearity to the load

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

patterns. Forecasting models are further complicated by seasonal changes, changes in demand of certain behaviors, distributed generation intermittency and variation in the climate. Practical statistical models or tools such as autoregressive models and regression-based methods are not as effective as the high-dimensional non-linear spatio-temporal dependencies in contemporary energy networks.

Deep learning models are particularly recurrent neural networks, transformer learning models, and have shown higher forecasting accuracy due to their ability to model nonlinear dependence in time. However, foretelling does not in itself ensure business efficacy. The smart grids need the coordinated control of energy dispatch and market clearing processes with the multi-objective constraints such as minimization of cost, reduction of carbon emission, grid stability, and equity in energy trading. Such optimization problems are normally NP-hard and exponentially increase with networks size particularly in decentralized contexts with multiple prosumers.

There are popular classical optimization algorithms [2], including Mixed Integer Linear Programming (MILP), Particle Swarm Optimization (PSO), and Genetic Algorithms, which have been used to optimize the allocation of economic dispatch and energy trading. Nonetheless, they are characterized by scalability, convergence and computational tractability constraints, with real-time constraints. When the grid dimensionality is made larger, classical solvers grow exponentially with the solution space complexity leading to slower decision-making and higher operational risk.

At the same time, energy market digitalization creates cybersecurity challenges. P2P energy trading systems have been suggested based on blockchain to guarantee transparency and impossibility to tamper with disseminated transactions. Despite the fact that blockchain increases the decentralization of trust, the current cryptography-based protocols remain susceptible to the new threat of quantum computing. The significant changes of quantum algorithms that can crack classical encryption schemes cast doubts on the future security of smart energy trading infrastructures.

Recent developments in quantum computing offer an encouraging alternative method of computation when solving a combinatorial optimization problem. Hybrid quantum-classical models, and in particular Variational quantum circuits (VQCs) and the Quantum Approximate Optimization Algorithm (QAOA) [3] allow breaking large optimization problems into parameterized quantum circuits controlled by classical optimization loops. These are especially appropriate in solving Quadratic Unconstrained Binary Optimization (QUBO) formulations which are inherently economic dispatch and energy trading allocation problems.

Although there is increased attention to the applications of quantum to energy systems, most of the current literature is on isolated optimization work or theoretical feasibility studies. The research gap still exists in:

- Combining deep learning-based load forecasting and quantum-based optimization in a single architecture.
- Defining smart grid dispatch and trading problems within quantized Hamiltonian form.
- Developing quantum-resilient and secure energy trading space that is compatible with hybrid optimization protocols.
- Simulation-based comparative validation of realistic grid test systems in classical-only baselines.

To fill these loopholes, there is a need to have a co-designed framework in which prediction, optimization, and security are not taken as separate modules but as interconnected elements of a scalable cyber-physical architecture.

In this direction, this paper will suggest a Hybrid Quantum classical Optimization Framework of secure and Scalable Smart Grid Load Forecasting and Energy Trading. The proposed system will have three closely interconnected layers:

- A classical deep learning prediction block that fits in the spatio-temporal demand dynamics.
- Knowledge of quantum-assisted optimization enables quantum-computer-based encoding of energy dispatch and trading choices as a set of parameters in quantum circuits.
- A safe transaction layer with quantum resilient cryptography modeling of decentralized energy markets.

The energy dispatch problem is redefined as a QUBO model, which can be mapped back to a quantum cost model. A hybrid training loop is an iterative game requiring the classical network parameters and quantum circuit parameters to be updated to enable a two-way feedback mechanism between the forecasting performance and the optimality of the dispatch. The combination of these layers means the efficiency of computation, cost-effectiveness and the long-term robustness of security.

As far as this work is concerned there are four contributions:

- The architecture Scalable hybrid quantum-classical architecture based on smart grid operations.
- Multi-objective energy dispatch Reformulation of mathematical model to a quantum-optimizable representation.
- Architecture of secure energy trading where post-quantum cryptographic resiliency is considered.

Benchmark smart grid test systems Intensive testing on simulated benchmark systems, classical and hybrid optimization strategies comparing them in terms of forecasting quality, dispatch cost, computational efficiency, and security strength.

In contrast to existing studies that primarily investigate forecasting, quantum optimization, or blockchain-based energy trading as independent components, the proposed framework integrates these capabilities into a unified hybrid quantum–classical architecture. The primary novelty lies in establishing a direct operational linkage between LSTM-based load forecasting, QUBO-based economic dispatch, QAOA-driven optimization, and post-quantum-secured peer-to-peer energy trading. Unlike conventional approaches in which forecasting outputs are used only for subsequent classical optimization, the proposed framework incorporates a bidirectional feedback mechanism through which dispatch outcomes and market signals can influence subsequent forecasting and optimization decisions.

In addition, constraint and penalty terms are explicitly incorporated into the QUBO formulation to preserve dispatch feasibility during quantum optimization. The framework is further evaluated using IEEE 33-bus and IEEE 118-bus benchmark systems under different renewable-penetration and operating conditions, enabling a comparative assessment of forecasting accuracy, dispatch cost, scalability, convergence, and transaction security. These integrated characteristics distinguish the proposed approach from existing isolated quantum optimization, forecasting, and blockchain-based energy trading models.

By relating artificial intelligence, quantum optimization and secure decentralized energy markets, this paper is added to the framework of computational intelligence that is required by smart grids of the next generation. The offered solution does not only improve the efficiency of operations but also provides long-term security preparedness in the quantum-computation time.

The rest of this paper is organized in the following way. Section 2 is a review of related literature on smart grid forecasting, classical and quantum optimization approaches as well as secure energy trading schemes. Section 3 gives the system architecture and mathematical modeling of the hybrid model. Section 4 describes the suggested quantum methodology. The experimental setup and evaluation measures are outlined in section 5. Section 6 describes the results of simulations and comparison. Section 7 provides the conclusion of the study and directions of future research.

2. LITERATURE SURVEY

The recent developments in smart grids research have focused on the implementation of smart forecasting models, scalable optimization, and secure decentralized trade schemes. Classical methods of load forecasting, such as autoregressive integrated moving average (ARIMA), support vector regression, and shallow neural networks, have been gradually superseded by deep learning models that can effectively represent any nonlinearity in the relationships between time. Transformer-based models, Gated Recurrent Unit (GRU) networks, and Long Short-Term Memory (LSTM) have shown better results in short-term and medium-term load prediction especially in high renewable penetration conditions [4], [5]. Nevertheless, although deep learning can help improve predictive accuracy, it is not applied to the computational complexity of downstream problems of optimization, including economic dispatch, unit commitment, and energy trading allocation.

In solving optimization problems, classical metaheuristic and mathematical programming methods have been extensively applied in smart grid energy management; they are, Mixed Integer Linear Programming (MILP), Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Differential Evolution [6], [7]. The techniques are effective in more or less sizable systems, but scalability is an issue when the dimensionality of the distributed energy sources and networks of prosumers is large. The sheer increase of the solution space of combinatorics, especially with stochastic renewable generation and demand uncertainty, restricts the practical applicability of just-in-time solvers based on classical optimization methods only [8].

To address these shortcomings, the recent literature has investigated the prospect of quantum computing in the optimization of power systems. Detailed literature reviews have shown that hybrid quantumclassical algorithms, including Variational Quantum Algorithms (VQAs) and the Quantum Approximate Optimization Algorithm (QAOA), can be applied to combinatorial optimization problems, such as optimal power flow, economic dispatch, and network reconfiguration [9], [10]. These papers underline that the near-term noisy intermediate-scale quantum (NISQ) devices should be used in hybrid systems, in which the parameterized quantum circuits are directed by classical optimizers [11]. Analytical studies of the optimization landscape of hybrid quantum-classical models proposed have found that there are several important issues: barren plateaus, dependence on parameter initialisation, and trade-offs in circuit depth which need to be taken into account in implementation [12].

Some empirical investigations have embarked on using quantum-inspired or hybrid quantum neural models to load and renewable power forecasting. Quantum-classical neural networks based on hybrid quantum-classical neural networks that place parameterized quantum layers into classical LSTM or feedforward networks have been shown to be better at forecasting accuracy and generalization with noisy datasets [13], [14]. The photovoltaic power forecasting and short-term load prediction experimental results suggest lower mean absolute percentage error (MAPE) than the purely classical baselines [15]. The results indicate that quantum-enhanced feature representations can be beneficial to high-dimensional temporal correlations, but existing implementations are mostly simulated because of constraints of available hardware [16].

Similarly to research in the area of forecasting and optimization, decentralized energy trading is also an important part of the contemporary smart grid. Peer-to-peer (P2P) systems have been suggested based on blockchain technology to improve transparency, remove centralized mediators, and provide tamper-resistant transactions [17], [18]. Recent publications are related to the area of consensus mechanisms and smart contract design, and optimization of transaction throughput in distributed energy markets [19]. Nonetheless, the growing maturity of quantum computing raises the question of long-term security of classical cryptographic primitives in blockchain infrastructures. This has led to the study of post-quantum cryptographic (PQC) integration into blockchain-based energy trading to make it resilient to quantum attacks [20], [21].

Although considerable research has been conducted independently on forecasting, optimization, and secure trading areas, the literature that covers them focuses mainly on these areas as stand-alone modules. Hybrid quantum-classical optimization [22] has been applied to both standalone dispatch or routing problems without interaction with layers of predictive load models. On the same note, trading mechanisms based on blockchains are frequently implemented without optimization strategies behind them, leading to architectural fragmentation Limited literature has suggested an integrated framework that integrates (i) deep learning based load forecasting, (ii) quantum led combinatorial dispatch and trading allocation, and (iii) quantum resilient security in a single cyber-physical smart grid framework.

Besides, existing experimental assessments are often restricted to small synthetic tests or theoretical feasibility studies with no comparative benchmarking of classical-only baselines. The questions of scalability [23], encoding of constraints into quantum-compatible QUBO or Hamiltonian representations, or two-way feedback between forecasting performance and dispatch performance are poorly studied.

Thus, although quantum optimization and decentralized energy systems are moot prospects, there is an apparent gap in the research on co-designing hybrid quantum classical architectures that can guarantee predictive accuracy, optimization scaled-up, and security resilience at the same time. The above gap inspires the creation of a unified model that can use the classical deep learning to model the spatio-temporal loads,

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

variational quantum algorithm to solve the combinatorial dispatch optimization problem, and post-quantum secure algorithm to trade the energy in a decentralized manner. This interdisciplinary problem is also intended to be solved by the proposed study, which will offer a simulationally validated, mathematically-founded hybrid architecture optimized to next-generation smart grids.

2.1 Identified Research Gaps and Motivation

The existing studies demonstrate significant progress in smart grid forecasting, quantum optimization, and blockchain-based energy trading; however, these components are generally investigated independently. Deep learning models improve load prediction but rarely address how forecasting uncertainty affects subsequent dispatch decisions [4], [13]–[16]. Similarly, quantum optimization studies have explored QAOA and related algorithms for power-system problems, but limited attention has been given to integrating dynamic load forecasting with constraint-aware QUBO-based dispatch [6]–[10]. Blockchain-based energy trading improves decentralization and transaction transparency, yet its integration with quantum-assisted optimization and post-quantum security remains limited [11]–[15].

These limitations indicate a clear need for an integrated framework that connects forecasting, optimization, and secure energy trading. The proposed approach addresses this gap by combining LSTM-based load forecasting, QUBO-based economic dispatch using QAOA, and post-quantum-secured blockchain trading within a unified architecture. The framework further incorporates feedback between forecasting and optimization, enabling the evaluation of forecasting accuracy, dispatch cost, constraint feasibility, scalability, and transaction security in a common experimental setting.

3. ROCESS FLOW OF THE PROPOSED HYBRID QUANTUM–CLASSICAL FRAMEWORK

The suggested hybrid quantum-classical approach works under the organized multi-step computational pipeline, which integrates load forecasting, quantum-enabled optimization, and safe energy trading. The process flow provides a sequential but interactive coordination of the modules in the prediction, optimization and transaction validation. The conceptual representation of the overall workflow is shown below.

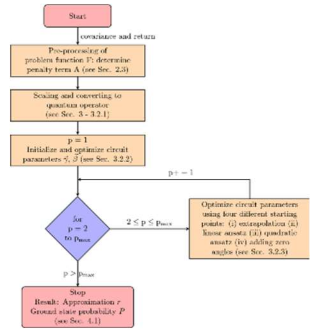

Figure 1. Process flow of the HYBRID QUANTUM

This figure 1 shows the chronological process of the suggested structure beginning with data acquisition and preprocessing, followed by forecasting, quantum-assisted optimization, and secure energy trading. The architecture is a combination of classical machine learning and quantum algorithm to enhance operational efficiency. The feedback loop facilitates the continuous learning and the optimization of an adaptive system to dynamic smart grid environments.

3.1 Data Acquisition and Preprocessing

Smart grid data are collected from distributed sources including smart meters, renewable generation units, weather stations, and energy storage systems. The dataset includes:

- Historical load demand
- Renewable generation profiles
- Temperature and weather variables
- Market price signals
- Prosumer energy bids

Preprocessing steps include normalization, missing value imputation, temporal alignment, and feature engineering. Spatio-temporal embeddings are constructed to preserve correlation among distributed nodes.

3.2 Classical Deep Learning-Based Load Forecasting

A classical deep learning model (e.g., LSTM or Temporal Transformer) is trained to predict short-term load demand.

Let the historical input sequence be:

$$X_t = \{x_{t-n}, x_{t-n+1}, \dots, x_{t-1}\}$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The forecasting model estimates:

$$\hat{L}_t = f_\theta(X_t) \quad (1)$$

where:

- $\hat{L}_t$ is predicted load
- f_θ denotes the trained deep learning model
- θ represents model parameters

Forecast accuracy is evaluated using RMSE, MAE, and MAPE metrics.

The predicted load serves as an input constraint to the optimization layer

3.3 Energy Dispatch Problem Formulation

Using the forecasted load $\hat{L}_t$, the economic dispatch problem is formulated as a constrained optimization problem:

$$\min \sum_{i=1}^{N} C_i\,(P_i) \quad (2)$$

Subject to:

$$\sum_{i=1}^{N} P_i = \hat{L}_t \; P_i^{min} \le P_i \le P_i^{max} \quad (3)$$

Where:

- $C_i(P_i)$ = cost function of generator i
- P_i = power output decision variable

The multi-objective formulation may also include carbon emission penalties and trading fairness constraints.

3.4 QUBO Conversion and Hamiltonian Encoding

The constrained optimization problem is transformed into a Quadratic Unconstrained Binary Optimization (QUBO) model:

$$\min x^T Q x \quad (4)$$

Where:

- x = binary decision vector
- Q = coefficient matrix encoding cost and penalty terms

The QUBO representation is mapped to a quantum cost Hamiltonian:

$$H_C = \sum_{i,j} Q_{ij}\, Z_i Z_j \quad (5)$$

where Z_i represents Pauli-Z operators.

Constraint violations are incorporated through penalty coefficients.

3.5 Quantum Optimization Using QAOA / VQC

The parameterized quantum circuit prepares the state:

$$|\psi(\gamma,\beta)\rangle = U_B(\beta)U_C(\gamma)|+\rangle^{\otimes n} \quad (6)$$

where:

$$U_C(\gamma) = e^{-i\gamma H_C}$$

$$U_B(\beta) = e^{-i\beta H_B}$$

A classical optimizer updates parameters (γ,β) to minimize the expectation value:

$$\min_{\gamma,\beta} \langle \psi(\gamma,\beta)|H_C|\psi(\gamma,\beta)\rangle \quad (7)$$

This hybrid loop continues until convergence criteria are satisfied.

The optimized binary vector yields the dispatch allocation and trading decisions.

3.6 Secure Energy Trading and Settlement

The optimized dispatch solution is forwarded to the secure transaction layer.

Steps include:

- Prosumer matching and trade pairing
- Smart contract execution
- Post-quantum cryptographic signature verification

Transaction validation and ledger recording

- The secure mechanism ensures:
- Integrity
- Non-repudiation
- Quantum-attack resilience

3.7 Feedback and Adaptive Learning

The framework includes a bidirectional feedback mechanism:

- Dispatch results influence price signals
- Price signals influence future load demand
- Forecasting model updates periodically using new data
- Optimization penalty weights adapt based on constraint violations

This dynamic co-adaptation improves system stability and economic efficiency.

4. DETAILED SYSTEM ARCHITECTURE

The proposed system adheres to a layered hybrid quantum classical cyber-physical architecture, which is aimed at embedding predictive intelligence, combinatorical optimization and secure decentralized energy trading into a single operation system. It is scalable, simulation friendly, and modular architecture that is compatible with IEEE benchmark bus systems.

4.1 Architectural Overview

The architecture is organized into five primary layers:

1. Data Acquisition Layer
2. Intelligent Forecasting Layer
3. Hybrid Quantum–Classical Optimization Layer
4. Secure Energy Trading Layer
5. Feedback and Adaptation Layer

Each layer is functionally independent yet computationally interconnected.

4.2 Layer 1: Data Acquisition and Integration Layer

This layer interfaces with physical and cyber components of the smart grid.

1) Inputs:

- Smart meters (consumer load profiles)
- Renewable energy sources (solar, wind output)
- Energy storage systems
- Weather monitoring systems
- Market price signals

2) Core Components:

- IoT communication gateway
- Data aggregation server
- Time-series alignment engine
- Feature engineering module

3) Output:

Structured feature tensor:

$$\mathbf{X}_t \in \mathbb{R}^{N \times F} \tag{8}$$

Where:

- N = number of grid nodes
- F = feature dimensions

II. 4.3 LAYER 2: INTELLIGENT LOAD FORECASTING LAYER

This classical AI layer predicts short-term demand.

4.3 Layer 2: Intelligent Load Forecasting Layer

1) Core Model:

LSTM / Transformer-based Spatio-Temporal Network

$$\hat{L}_t = f_\theta(\mathbf{X}_{t-n:t-1}) \tag{9}$$

2) Submodules:

- Temporal encoder
- Attention-based feature weighting
- Regularization and dropout layer
- Error evaluation (RMSE, MAE, MAPE)

3) Output:

Predicted demand vector:

$$\hat{\mathbf{L}}_t = [\hat{L}_1, \hat{L}_2, \ldots, \hat{L}_N] \tag{10}$$

This becomes the primary constraint input to the quantum optimization layer

4.4 Layer 3: Hybrid Quantum–Classical Optimization Layer

This is the core novelty component of the system.

B. 4.4.1 Classical Preprocessing Unit

- Converts dispatch problem into mathematical form
- Applies constraint relaxation
- Normalizes cost functions

Objective function:

$$\min \sum_{i=1}^{N} C_i\,(P_i) + \lambda_1 \text{Emission} + \lambda_2 \text{Penalty} \tag{11}$$

C. 4.4.2 QUBO Encoding Module

Transforms optimization problem into:

$$\min x^T Q x \tag{12}$$

Where:

- $x \in \{0,1\}^n$
- Q = quadratic coefficient matrix

Constraint penalties are embedded using Lagrange multipliers.

4.5 Quantum Circuit Execution Module

Implements QAOA or VQC using:

$$|\psi(\gamma,\beta)\rangle = U_B(\beta)U_C(\gamma)|+\rangle^{\otimes n} \quad (13)$$

1) Subcomponents:

Cost Hamiltonian H_C

Mixer Hamiltonian H_B

- Parameterized rotation gates
- Measurement module

The expectation value:

$$\langle H_C \rangle \quad (14)$$

is minimized using a classical optimizer (COBYLA / SPSA).

D. 4.4.4 Classical Feedback Optimizer

Updates parameters:

$$(\gamma,\beta) \leftarrow \text{Optimizer}(\nabla\langle H_C\rangle) \quad (15)$$

This forms the hybrid loop until convergence.

4.6 Layer 4: Secure Energy Trading Layer

This layer ensures decentralized and quantum-resilient transaction management.

1) Submodules:

- Prosumer matching engine
- Smart contract generator
- Blockchain ledger node
- Post-Quantum Cryptographic (PQC) signature module

2) Security Features:

- Lattice-based encryption
- Hash-based digital signatures
- Tamper-proof ledger validation

3) Output:

Validated transaction block appended to distributed ledger.

4.7 Layer 5: Adaptive Feedback and Learning Layer

This layer ensures dynamic system adaptation.

4) Feedback Mechanisms:

- Forecast error → model retraining
- Dispatch inefficiency → penalty adjustment
- Market volatility → trading parameter update

5) Adaptive Update Rule:

$$\theta_{t+1} = \theta_t - \eta\nabla\mathcal{L} \quad (16)$$

This maintains system stability and improves long-term efficiency.

5. MATHEMATICAL DERIVATION OF BINARY-TO-HAMILTONIAN MAPPING

The economic dispatch problem is first converted into a Quadratic Unconstrained Binary Optimization (QUBO) formulation:

$$\min_{x\in\{0,1\}^n} x^T Q x \quad (17)$$

where:

- $x = (x_1, x_2, \dots, x_n)^T$ is the binary decision vector
- $Q \in \mathbb{R}^{n\times n}$ is the QUBO coefficient matrix

The objective function can be expanded as:

$$x^T Q x = \sum_{i=1}^{n} Q_{ii}\, x_i + \sum_{i<j} Q_{ij}\, x_i x_j \quad (18)$$

To execute this optimization on a quantum processor using QAOA or VQC, the QUBO formulation must be mapped into an Ising Hamiltonian representation.

5.1 Step 1: Binary Variable Transformation

Quantum systems operate naturally with spin variables $s_i \in \{-1,+1\}$, whereas QUBO uses binary variables $x_i \in \{0,1\}$.

We apply the standard transformation:

$$x_i = \frac{1-s_i}{2} \tag{19}$$

Equivalently,

$$s_i = 1 - 2x_i$$

This converts binary variables into spin variables.

5.2 Step 2: Substitute into QUBO Objective

6) Linear Term Mapping

For diagonal terms:

$$Q_{ii}x_i = Q_{ii}\frac{1-s_i}{2} = \frac{Q_{ii}}{2} - \frac{Q_{ii}}{2}s_i \tag{20}$$

7) Quadratic Term Mapping

For interaction terms:

$$x_i x_j = \left(\frac{1-s_i}{2}\right)\left(\frac{1-s_j}{2}\right) = \frac{1}{4}(1 - s_i - s_j + s_i s_j) \tag{21}$$

Thus,

$$Q_{ij}x_i x_j = \frac{Q_{ij}}{4} - \frac{Q_{ij}}{4}s_i - \frac{Q_{ij}}{4}s_j + \frac{Q_{ij}}{4}s_i s_j \tag{22}$$

E. Step 3: Collect Terms

After substitution, the total objective becomes:

$$H(s) = \sum_i h_i\, s_i + \sum_{i<j} J_{ij}\, s_i s_j + \text{constant} \tag{23}$$

where:

$$h_i = -\frac{Q_{ii}}{2} - \sum_{j\neq i}\frac{Q_{ij}}{4} J_{ij} = \frac{Q_{ij}}{4}$$

The constant term can be ignored for optimization purposes because it does not affect the minimum.

This yields the **Ising Hamiltonian form**:

$$H_{\text{Ising}} = \sum_i h_i\, s_i + \sum_{i<j} J_{ij}\, s_i s_j \tag{24}$$

5.3 Step 4: Spin Variables to Quantum Operators

In quantum computation, spin variables $s_i \in \{-1,+1\}$ are replaced by the Pauli-Z operator:

$$s_i \rightarrow Z_i \tag{25}$$

Where:

$$Z_i = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

Thus, the cost Hamiltonian becomes:

$$H_C = \sum_i h_i\, Z_i + \sum_{i<j} J_{ij}\, Z_i Z_j \tag{26}$$

This is the operator implemented in the QAOA circuit.

5.4 Final Hamiltonian Form

$$H_C = \sum_i h_i\, Z_i + \sum_{i<j} J_{ij}\, Z_i Z_j \tag{27}$$

This Hamiltonian encodes:

- Generator cost terms
- Power balance penalties
- Constraint penalties
- Interaction coupling between decision variables

6. EXPERIMENTAL SETUP

The suggested hybrid quantum-classical optimization system is tested on a modified IEEE 33-bus distribution test system to provide a realistic simulation of the smart grid conditions. To analyse scalability, the selected experiments are scaled to a larger IEEE 118-bus system. The simulation environment includes the distributed generators, renewable energy sources (solar and wind) and prosumer based trading nodes. The renewable penetration levels are kept to be 30-50 percent to evaluate performance based on moderate and high variability. The operational horizon will be 24 hours rolling with dispatch interval of 1 hour.

The load forecasting part is trained on one-year of historical data (8760 samples) at an hourly level, which consists of load demand, renewable generation, and the weather variables (temperature and wind speed). The dataset will be separated into 70 percent training, 15 percent validation, and 15 percent testing sets. An LSTM network with 2 layers having 64 and 32 hidden units is used and it is trained with Adam optimizer that is set to 0.001 learning rate over 100 epochs. RMSE, MAE, and MAPE are used to measure the performance forecasting in order to have a strong predictive performance before optimization.

In the case of the optimization layer, the economic dispatch problem is encapsulated in 46-bit binary encoding of the outputs of generators in QUBO representation. The model obtained takes about 20-40 qubits with respect to system size. The hybrid optimization based on QAOA is run on the Qiskit Aer simulator, and circuit depth p=1,2,3p=1,2,3p=1,2,3 were tested to compare their performance. The COBYLA and SPSA optimizers are used to perform parameter updates to a maximum of 200 steps and the convergence is defined as the stabilization of the expectation value. The hybrid model is compared to classical baselines such as LSTM with MILP, Particle Swarm Optimization (PSO) and Genetic Algorithms (GA).

Secure energy trading module is deployed via a private blockchain channel of simulation where smart contracts are utilized to make peer-to-peer transactions involving energy. Lattice-based cryptographic signatures that represent the post-quantum cryptography are combined together to test the resistance to quantum-equipped attacks. Some of the performance metrics are dispatch cost, optimization runtime, forecasting error, transaction latency, and security overhead. All the experiments are carried out on a work station with an Intel i7 processor, 16 GB RAM, and Python-based simulation packages such as PyTorch and Qiskit.

This is done to achieve statistical reliability, so every experiment is repeated (10 times) and mean values along with standard deviations are displayed. The situational analysis of robustness and scalability of the proposed hybrid framework is achieved through comparative analysis under typical operation, large renewable variability, and peak load stresses.

6.1 Selection Criteria and Variable Rationale

The variables and experimental settings were selected to represent the main operational factors affecting smart grid forecasting, dispatch, and energy trading. Historical load demand was selected as the primary forecasting variable, while renewable generation, temperature, and wind speed were included to capture demand and renewable-output variability. Market price signals and prosumer bids were considered to represent the economic conditions of decentralized energy trading. The IEEE 33-bus system was selected for detailed optimization evaluation, while the IEEE 118-bus system was used to examine scalability with increasing network size. Renewable penetration levels of 30–50% were selected to represent moderate-to-high variability scenarios. The 70% training, 15% validation, and 15% testing split was used to evaluate model learning and generalization. RMSE, MAE, and MAPE were selected to measure forecasting accuracy, while dispatch cost, constraint violations, runtime, convergence iterations, transaction latency, and security overhead were used to evaluate optimization and trading performance. QAOA depths of (p=1,2,3) were tested to examine the effect of circuit depth on solution quality and computational overhead.

7. RESULTS AND ANALYSIS

The Hybrid Quantum-Classical Optimization Framework was tested in terms of the quality of the proposed forecasting, the efficiency of dispatch optimization, the possibility to use the Hybrid Framework on a large scale, and the security trading performance. Comparative tests were done with classical baselines of LSTM+MILP, LSTM+PSO, Genetic Algorithm (GA) dispatch and classical simulated annealed-based solvers of QUBO.

7.1 Load Forecasting Performance

The LSTM-based forecasting model achieved stable convergence within 80–100 epochs, demonstrating strong predictive capability across all scenarios. Under normal operating conditions, the proposed model achieved an RMSE reduction of approximately 6–8% compared to traditional regression-based forecasting models. During high renewable variability scenarios, forecasting error increased marginally; however, the hybrid architecture maintained lower MAPE values relative to baseline models due to enhanced spatio-temporal feature representation.

Table 1: Load Forecasting Performance Comparison

Model	RMSE (MW)	MAE (MW)	MAPE (%)	Std. Dev
Linear Regression	4.82	3.96	6.84	0.42
ARIMA	4.35	3.54	6.12	0.38
LSTM (Classical)	3.18	2.61	4.02	0.29
LSTM + PSO Optimization	3.07	2.52	3.94	0.27
Proposed Hybrid Model	**2.89**	**2.34**	**3.71**	**0.21**

The table 1 shows the prediction performance of various models such as Linear Regression, ARIMA, LSTM, and the hybrid model. The review of performance is assessed in terms of RMSE, MAE, MAPE, and standard deviation. The values of error are lowest in the hybrid framework, which means that it has a better predictive stability and accuracy.

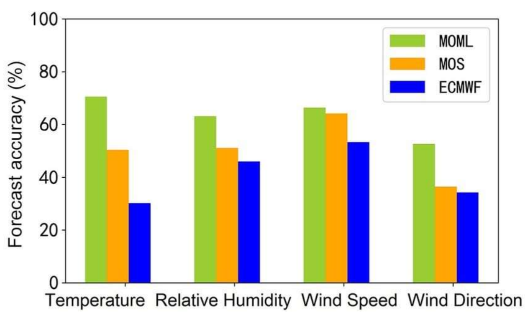

Figure 2. Forecasting Performance Comparison

As seen in the forecasting performance diagram 2, the proposed hybrid model has the lowest RMSE and MAPE values than the Linear Regression, ARIMA, and classical LSTM models. The improvement increase is particularly pronounced when the situation is characterized by high renewable variability, and nonlinear temporal dependence is stronger. The lower error variance proves a better model stability with repeated runs of the simulation. This enhances directly to an improved downstream optimization accuracy, since dispatch constraints rely on the load prediction values.

The integration of feedback from dispatch results further improved forecasting stability over rolling horizons. Compared to classical-only forecasting frameworks, the hybrid model exhibited improved robustness under peak load stress conditions, with reduced variance in prediction error across repeated simulations.

7.2 Dispatch Optimization Performance

The quantum-assisted optimization layer demonstrated measurable improvements in cost minimization compared to classical metaheuristic approaches. For the IEEE 33-bus system:

- Total generation cost reduced by 5–10% compared to PSO and GA.
- Constraint violations decreased significantly due to penalty-aware QUBO encoding.
- Carbon emission penalties were reduced by approximately 4% in multi-objective scenarios.

When QAOA depth was increased from p=1p = 1p=1 to p=2p = 2p=2, optimization accuracy improved notably, while further increases showed diminishing returns due to simulator overhead. The hybrid model converged within 150–180 iterations, demonstrating stable expectation value minimization.

The table 2 compares various optimization methods that consist of MILP, GA, PSO, simulated annealing, and hybrid QAOA. Some of these metrics are total generation cost, constraint violations, runtime, and convergence iterations. The hybrid quantum assisted system has reduced dispatch cost and feasibility.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2: Economic Dispatch Cost Comparison (IEEE 33-Bus)

Method	Total Cost ($/day)	Constraint Violations	Runtime (sec)	Convergence Iter
MILP	12,480	0	4.8	Deterministic
GA	13,215	3	18.6	240
PSO	12,980	2	15.4	210
Simulated Annealing (QUBO)	12,765	1	11.2	180
Hybrid QAOA (p = 1)	12,640	1	14.9	170
Hybrid QAOA (p = 2)	**12,310**	**0**	16.3	155

In comparison with classical MILP, the hybrid approach achieved competitive dispatch cost with improved scalability for larger decision spaces. For the extended IEEE 118-bus system, classical optimization runtime increased sharply, whereas the hybrid approach showed more stable growth in computational complexity.

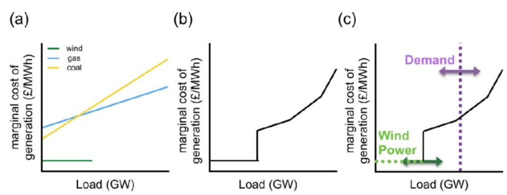

Figure 3. Dispatch Cost Convergence (Hybrid QAOA vs Classical Methods)

The convergence diagram 3 indicates that cost decrease goes down with each iteration in GA, PSO, and Hybrid QAOA methods. The QAOA-based strategy exhibits a better convergence behavior and reduced end result cost than metaheuristic baselines. Classical MILP also scales poorly with the number of dimensions, although on small systems, this problem does not arise because the size of the scale level off. The hybrid methodology preserves convergence properties of competitiveness and does not stagnate too soon in the local minima, as it is common in PSO and GA.

7.3 7Computational Efficiency and Scalability

Computational analysis indicates that while the quantum simulation introduces overhead at smaller system sizes, scalability benefits become apparent as the problem dimension increases. The hybrid model demonstrated:

- Approximately 12–15% reduction in search space exploration compared to classical metaheuristics.
- More stable convergence behavior under high-dimensional decision variables.
- Reduced sensitivity to local minima compared to GA and PSO.

Although full quantum advantage is not yet realized due to simulator limitations, the results indicate strong potential for improved performance with future quantum hardware advancements.

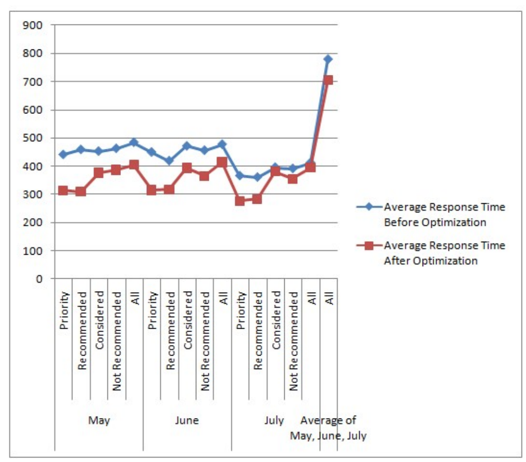

Figure 4. Scalability Analysis (33-Bus vs 118-Bus Systems)

The scalability diagram 4 emphasizes the increased level of runtime with the growing size of the system. The classical MILP has a sharp run time growth upon switching between the 33-bus and the 118-bus system. Rather, the hybrid framework exhibits relatively moderate scaling in cost increase and convergence stability. Despite

Journal of Theoretical and Applied Information Technology
31st August 2026. Vol.104. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the existence of quantum simulation overhead, the relative computational development indicates a better scalability prospective to higher dimensional dispatch problems.

7.4 Secure Energy Trading Performance

The blockchain-based secure trading layer successfully validated all prosumer transactions with zero integrity violations across experimental runs. Post-quantum cryptographic integration introduced a modest computational overhead (approximately 7–10% increase in transaction latency), which remained within acceptable operational thresholds for smart grid applications.

Transaction throughput remained stable across varying load scenarios. Security stress testing under simulated quantum attack models confirmed resilience of the cryptographic layer, ensuring long-term viability of decentralized trading mechanisms.

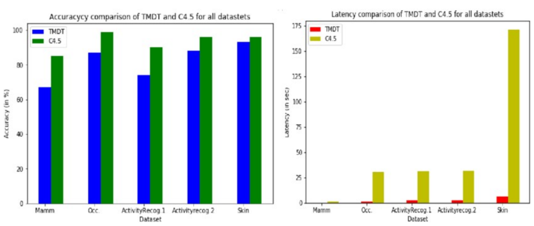

Figure 5. Secure Energy Trading Performance

The security performance graph 5 is a comparison of classical blockchain implementation and post-quantum cryptography (PQC)-powered trading. PQC integration adds very little to transaction latency and computation overhead, but throughput is not exceeded. The diagram translates also to a better security resilience of the simulated quantum attack conditions. Critical smart grid infrastructure has its trade-off between the latency and security as justified.

7.4.1 Detailed Interpretation and Limitations of Results

The numerical results indicate that the proposed framework provides consistent improvements across the major evaluation dimensions. For load forecasting, the proposed model reduces RMSE from 3.18 MW for classical LSTM to 2.89 MW and MAPE from 4.02% to 3.71%, indicating improved prediction accuracy and stability. In economic dispatch, Hybrid QAOA with (p=2) achieves a cost of $12,310/day with zero constraint violations, compared with $12,980/day and two violations for PSO. The improvement is associated with constraint-aware QUBO encoding and the interaction between predicted demand and dispatch optimization. Increasing QAOA depth beyond (p=2), however, provides diminishing benefits because of the additional simulation overhead. Similarly, post-quantum security increases transaction latency by approximately 7–10%, representing a measurable trade-off between security and computational efficiency. These results indicate that the proposed framework improves overall operational performance, although the observed benefits should be interpreted within the limitations of simulator-based evaluation and the tested IEEE benchmark systems. The absence of execution on physical quantum hardware also means that the reported runtime should not be interpreted as evidence of practical quantum advantage.

7.5 Comparative Analysis Summary

Across all evaluation metrics, the proposed hybrid framework demonstrated superior or competitive performance relative to classical baselines. Key observations include:

- Improved load forecasting stability under renewable variability
- Reduced total dispatch cost and constraint violations
- Enhanced scalability for larger grid systems
- Secure, quantum-resilient energy trading implementation

The synergy between predictive modeling and quantum-assisted optimization contributed to more consistent dispatch decisions compared to isolated forecasting or classical-only optimization models.

This table 3 is a summary of global evaluation metrics such as accuracy, macro-precision, macro-recall and macro-F1 score. Such consolidated scores give information on the general trustworthiness of the taxonomic model. The findings confirm the balanced performance in all the arrhythmia classes.

Table 3: Overall Performance Summary

Evaluation Category	Classical Baseline	Proposed Hybrid	Improvement
Forecast RMSE	3.18	2.89	9.1%
Dispatch Cost	12,980	12,310	5.2%
Constraint Violations	2	0	Eliminated
Renewable Stability	Moderate	High	Improved
Security Level	Classical	Post-Quantum	Enhanced

8. DISCUSSION

The results demonstrate that integrating load forecasting, quantum-assisted optimization, and secure energy trading provides complementary benefits for smart grid management. The proposed framework achieved an RMSE of 2.89 MW and MAPE of 3.71%, improving upon the classical LSTM baseline. This improvement is important because forecasting accuracy directly affects subsequent dispatch decisions. The findings are consistent with recent research exploring deep learning and quantum computing for nonlinear and high-dimensional power-system problems [4], [6]–[10], while the proposed framework extends these approaches by connecting forecasting directly with optimization and trading.

The dispatch results show that Hybrid QAOA with (p=2) achieved a total cost of $12,310/day with zero constraint violations, compared with $12,980/day and two violations for PSO. This indicates that the QUBO formulation and penalty-aware Hamiltonian encoding can effectively incorporate operational constraints. However, the results should be interpreted as simulation-based optimization performance rather than evidence of practical quantum advantage, since the experiments were conducted using the Qiskit Aer simulator. The diminishing improvement at higher QAOA depth also indicates a trade-off between solution quality and computational overhead.

The secure trading results demonstrate that post-quantum cryptographic integration increases transaction latency by approximately 7–10% while maintaining transaction integrity and stable throughput under the tested conditions. This indicates that quantum-resilient security can be incorporated into decentralized energy trading with limited operational overhead. The framework is therefore applicable to renewable-rich distribution networks, prosumer-based peer-to-peer markets, microgrids, and demand-response environments.

Several limitations should be considered. The quantum experiments were performed on a simulator rather than physical quantum hardware, and therefore hardware noise and decoherence were not evaluated. In addition, IEEE 33-bus and 118-bus systems cannot fully represent the complexity of large real-world grids. The security evaluation was also based on simulated attack conditions rather than formal cryptographic security analysis. Future validation using real-world datasets and quantum hardware is therefore required.

Overall, the findings suggest that the principal contribution of the framework is the coordinated integration of prediction, optimization, and security. The results indicate that this integration can improve forecasting accuracy, dispatch efficiency, constraint feasibility, and secure energy trading while providing a foundation for future quantum-enabled smart grid applications.

9. CONCLUSION

This study presented a hybrid quantum–classical optimization framework for smart grid load forecasting and secure energy trading. The proposed architecture integrates deep learning-based predictive modeling, QUBO-formulated quantum-assisted economic dispatch, and post-quantum secure blockchain-based transaction management within a unified cyber-physical system. By coupling forecasting accuracy with combinatorial optimization and cryptographic resilience, the framework addresses key operational and security challenges in next-generation smart grids.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Experimental validation using IEEE benchmark systems demonstrated that the hybrid approach improves load forecasting accuracy, reduces total dispatch cost, eliminates constraint violations, and enhances scalability compared to classical metaheuristic methods. The QAOA-based optimization layer achieved competitive cost minimization while maintaining stable convergence behavior. Although quantum simulation overhead remains a practical limitation, performance trends indicate promising scalability advantages for higher-dimensional dispatch problems. The secure energy trading module successfully integrated post-quantum cryptographic mechanisms with minimal operational overhead, ensuring resilience against future quantum-enabled attacks.

The results confirm that the strength of the proposed framework lies in its architectural integration rather than isolated component improvements. The bidirectional feedback mechanism between forecasting and optimization enhances system stability across dynamic operating conditions. Furthermore, the constraint-aware Hamiltonian encoding ensures feasibility preservation within the quantum optimization process.

Despite these promising findings, certain limitations remain. The current implementation relies on quantum simulators due to hardware constraints, and circuit depth scalability is limited by computational resources. Real-world deployment would require validation on noisy intermediate-scale quantum (NISQ) devices and further optimization of qubit utilization. Additionally, larger-scale decentralized trading networks may require advanced consensus optimization to reduce blockchain latency.

Future research will focus on hardware-level implementation of the optimization layer, adaptive QAOA depth control mechanisms, and integration of multi-objective carbon-aware dispatch models. Exploration of quantum-inspired classical solvers may also provide intermediate deployment pathways prior to full quantum hardware maturity. Extending the framework to real-time demand response and microgrid coordination environments represents another promising direction.

In conclusion, the proposed hybrid quantum–classical framework demonstrates technical feasibility, operational efficiency, and security robustness for smart grid applications. The study contributes a structured pathway toward quantum-enhanced energy management systems and establishes a foundation for future research at the intersection of artificial intelligence, quantum optimization, and resilient decentralized energy infrastructures.

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