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QUANTUM-INSPIRED NEURAL OPTIMIZATION FRAMEWORK FOR SUSTAINABLE ENERGY MANAGEMENT IN SMART GRID-CONNECTED RESIDENTIAL SYSTEMS

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SUMMARY

The incorporation of renewable energy sources and smart grids has resulted in the need for intelligent and adaptive energy management systems that are able to manage dynamic residential energy demands, uncertainties in renewable energy sources, and various constraints. Traditional optimization techniques and those based on artificial intelligence techniques have not been successful in addressing the issues of exploration and have been unable to offer a holistic solution for energy prediction, scheduling, energy management from batteries, and renewable energy integration. This study aims to introduce a new technique known as Quantum-Inspired Neural Optimization Framework for Sustainable Energy Management in Smart Grid-Connected Residential Systems (QINE-SGEM), which incorporates neural learning, quantum-inspired optimization, and adaptation techniques for efficient energy management in residential areas. The quantum-inspired neural optimization component carries out feature extraction, demand prediction, and decision-making for appliance scheduling, battery charging and discharging, grid energy distribution, and renewable energy integration. The performance of the framework is tested by using the Pecan Street Austin Smart Grid Energy dataset in a Python simulation environment. The results

show that the QINE-SGEM model consumes an average energy of 24.2 kWh/day, produces 26.2% energy savings, enhances the battery utilization efficiency up to 95.8%, and reaches prediction accuracies of 0.084, 0.126, and 3.2% for MAE, RMSE, and MAPE, respectively. The ablation study shows the role of quantum optimization and adaptive feedback components with 36.8% energy cost savings, 82.6% renewable energy utilization, and 28.7% carbon emission savings. The proposed approach represents a sustainable and adaptive solution for future energy management in smart grids.

Key words: quantum-inspired optimization, neural energy management, smart grid systems, renewable energy integration, battery energy storage, demand-side management, sustainable energy optimization.

INTRODUCTION

Modern intelligent energy management techniques have focused on quantum-inspired optimization, deep learning, and hybrid computing methodologies in order to increase the efficiency, sustainability, and adaptability of smart grid systems. Quantum-inspired reinforcement learning methods have been studied for the optimization of energy-aware decisions in microgrids by increasing the efficiency of resource management [1]. Quantum particle swarm optimization algorithms have proved to be very efficient in reducing energy expenses and CO₂ emissions in grid-connected microgrids by optimizing generation and demand management strategies [2]. Hybrid quantum-classical algorithms have increased the efficiency of microgrid energy management by considering behavioral and demand dynamics for adaptive energy scheduling in varying operating conditions [3]. Quantum-inspired optimization techniques have also been used in decentralized renewable energy grids for optimal use of solar energy and energy coordination in distributed renewable energy grids [4][5].

The quantum deep reinforcement learning algorithms have been adopted for dynamic frequency regulation and operation of microgrids based on renewable energy sources [6]. The quantum artificial intelligence has also been effective in increasing the reliability of energy storage and battery functioning through stabilization and operation improvement [7]. Quantum deep learning architectures like quantum gated recurrent neural network have been applied for precise forecasting of the photovoltaic power generation [8]. Power flow optimization in hybrid renewable energy systems has been facilitated through deep learning-based optimization solutions through prediction and operation improvement [9]. The comprehensive review of the optimization strategies for smart grids has stressed the need for computational intelligence, demand response, and adaptive optimization for energy optimization [10]. Though there have been studies that show how effective quantum optimization and intelligent learning can be, only take into account certain parameters like forecasting, frequency control, or microgrid optimization. Hence, an integrated framework that takes into consideration parameters such as neural learning, quantum-inspired optimization, renewable energy coordination, battery management, and adaptive decision-making must be devised to cater to the environment of a smart grid-enabled residence. The QINE-SGEM framework aims at filling this research gap and uses a combination of quantum-inspired search ability and neural prediction with continuous feedback-based optimization to provide efficient energy management of residences.

Research Challenges

There are many challenges that can be faced by the intelligent management of energy in a home grid-connected environment because of the dynamic behavior of energy consumption, the unpredictability of renewable energy sources, and other issues involved. The traditional optimization techniques have some deficiencies while dealing with large-scale and complex energy management problems, including nonlinearity and multiple objectives. It is difficult to make an efficient coordination among renewable energy generation, battery storage system, appliances, and grid connection because of constant changes in consumption patterns and the environment.

Research Motivation

The rising usage of renewable energy resources and intelligent grid technology requires the development of an intelligent and adaptive energy management system within residential settings. Optimal usage of renewable power generation, reduced cost of energy usage, improved efficiency of the battery, and

reduced dependence on the grid demand advanced techniques of optimization. The need for such an intelligent energy management technique arises due to the limitations of the existing classical and independent AI-based systems; therefore, the present study introduces a Quantum-Inspired Neural Optimization Framework for Sustainable Energy Management in Smart Grid-Connected Residential Systems (QINE-SGEM).

Key Contribution

- The integration of neural learning with quantum optimization algorithms has led to the development of an innovative framework to facilitate adaptive and efficient energy management for smart grid-enabled residential systems.
- The framework helps to optimize the operation of appliances, battery charging and discharging, usage of renewable energy sources, and power transactions with the grid to minimize the use of energy, costs, and emissions.
- An optimization mechanism based on feedback control is designed to adapt the energy management decision dynamically based on changes in residential loads, renewable sources, and grid operations.

The rest of this paper is structured as follows. In section I, the background of the research, its motivation, problems, and contributions are explained. Section II describes the relevant literature and the previous methodologies used along with their shortcomings and the research gap that this research attempts to address. Section III describes the methodology used in this research, including the architecture, functional modules, and optimization approach adopted to achieve sustainable performance. Section IV describes the experiment setup, which includes the dataset used, the simulation environment, methodology and criteria used for evaluation. Section V describes the experimental results and analysis performed in comparison with the existing methodologies. Section VI explained the main key summary of this research.

LITERATURE REVIEW

Some of the latest studies in the area of smart grid and microgrid energy management have involved intelligent optimization, integration of renewable energy sources, and adaptive control techniques. The use of swarm intelligence in the optimization of photovoltaic energy storage systems to optimize renewable energy usage and storage has been studied for dynamic energy environments [11]. Some of the recent studies have involved a review of advanced power management strategies for efficient energy distribution and control in microgrids [12]. Mathematical programming methods-based optimization decision models have been used for efficient renewable energy-based microgrid energy management in order to reduce operational cost and enhance energy scheduling [13]. The use of quantum-inspired optimization techniques for designing resilient and uncertainty-aware residential energy systems for better decision-making has been studied for vehicle-to-home energy management and dynamic energy management [14]. The intelligent prediction and optimization approach for energy integration using an artificial intelligence approach has been used in smart grids and smart homes [15].

Hybrid quantum-inspired optimization techniques have been designed for advanced microgrid control systems to enhance their stability, adaptive control, and energy efficiency under varying operation conditions [16]. Energy management systems with digital twins that are combined with quantum optimization have been studied for improved grid monitoring, predictive control, and frequency stability of smart grids [17]. Sustainable demand-side energy management models have been designed for grid-connected microgrids to manage loads, reduce energy costs, and improve the utilization of renewable energy sources. Such sustainable approaches support efficient resource management and long-term economic growth through optimized energy utilization strategies [23][18]. Quantum computing methods have become popular in decentralized management of microgrids owing to their enhanced computational power for solving optimization and energy management problems [19]. Trust-aware adaptive control systems have been explored for cyber-physical systems for security and energy efficiency purposes [20]. The effectiveness of data-driven decision-support techniques in smart

connected environments, supporting the use of intelligent data-driven approaches for optimizing energy management in smart grid-connected residential systems [22].

Despite showing remarkable enhancements in the integration of renewables, energy scheduling, and optimization performance, current techniques usually solve these problems independently. Hence, there is a need to have an intelligent technique which integrates neural learning, quantum inspired optimization techniques, coordination of renewables, battery management, and adaptive feedback loops in residential smart grid settings. The designed Quantum Inspired Neural Optimization Framework for Sustainable Energy Management in Smart Grid Connected Residential Systems (QINE-SGEM) seeks to solve this problem by providing an intelligent approach to residential energy management.

Research Gap

The current state-of-the-art energy management strategies for smart grids have succeeded in providing substantial improvements regarding energy scheduling, renewable energy use, and optimization. However, some important constraints still exist. Traditional optimization methods, like mathematical programming and heuristics, need a proper model of a system and are unable to cope with dynamical changes in residential energy consumption, uncertainties in the generation of renewables, and variations in grid environment. Although AI-based and DL-based approaches allow one to improve predictions and decision-making processes, still have no efficient exploration methods to solve the issue of multi-objective energy optimization. Quantum-inspired optimization approaches can provide better performance in terms of search but are typically focused on particular applications, like microgrid control, battery management, renewable scheduling, etc., without taking into account comprehensive residential energy management needs. Moreover, there is not enough literature devoted to the combination of energy demand prediction, appliance scheduling, coordination of battery charging/discharge, renewable energy usage, and the connection between the residential consumer and the grid into an adaptive framework. This paper therefore suggests the Quantum-inspired Neural Optimization Framework for Sustainable Energy Management in Smart Grid-enabled Residential Environments (QINE-SGEM), which address these limitations through intelligent, adaptable, and sustainable energy management within smart residential environments.

PROPOSED QUANTUM-INSPIRED NEURAL OPTIMIZATION FRAMEWORK

Overall Architecture for Proposed Methodology

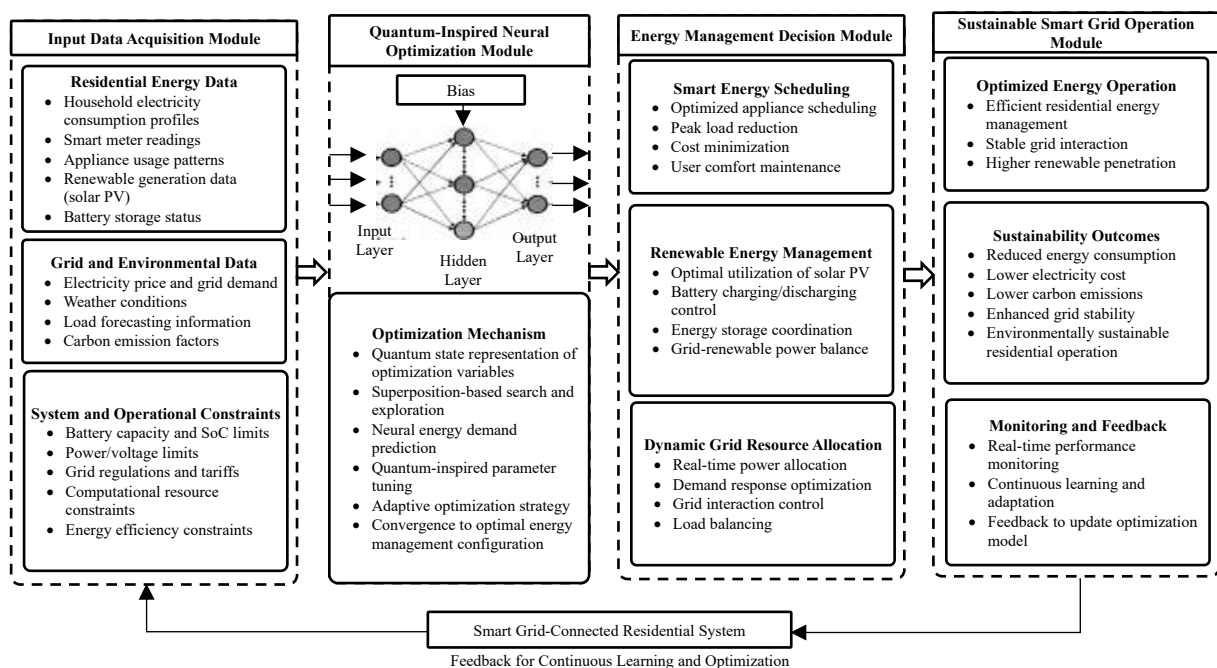


Figure 1. Overall architecture of proposed methodology

Input Data Acquisition Module

Input Data Acquisition Module is the first step in the proposed architecture of QINE-SGEM. In this module, diverse energy data are acquired and preprocessed for intelligent optimization. The input data are related to residents' consumption patterns, available renewable energy, grid conditions, and constraints. These inputs are processed into a common feature vector that is further fed to the Quantum-Inspired Neural Optimization Module for energy prediction and decision making, as shown in figure 1.

The input feature vector can be represented as:

$$X(t) = \{X_R(t), X_G(t), X_C(t), X_{RE}(t)\} \quad (1)$$

Equation (1) describes the $X_R(t)$ represents residential energy parameters., $X_G(t)$ represents grid and environmental parameters. $X_C(t)$ represents operational constraint parameters. t denotes the time interval.

Residential Energy Data

Smart home energy information refers to the current as well as past energy consumption features of the smart homes. Such data allow the neural optimizer to learn about energy consumption patterns of the households.

The residential energy feature vector is defined as:

$$X_R(t) = \{P_H(t), M(t), A(t), PV(t), SOC(t)\} \quad (2)$$

Equation (2) describes $P_H(t)$ = household electricity consumption profile., $M(t)$ = smart meter measurement. $A(t)$ = appliance operation pattern. $PV(t)$ = solar photovoltaic generation. $SOC(t)$ = battery State of Charge.

Household Electricity Consumption Profiles

The total residential power demand is expressed as:

$$P_{load}(t) = \sum_{i=1}^N P_i(t) \quad (3)$$

Equation (3) describes the $P_i(t)$ is the power consumption of appliance i . N represents the number of connected appliances.

This information helps the optimizer determine peak times and schedule appliances during cheap power periods.

Smart Meter Measurements

The smart meter gives instantaneous readings on voltage, current, active power, and energy used.

The measured electrical power is calculated as:

$$P(t) = V(t)I(t) \cos(\phi) \quad (4)$$

Equation (4) describes the $V(t)$ represents voltage. $I(t)$ represents current. $\cos(\phi)$ represents the power factor. These numbers give an accurate response on energy consumption.

Appliance Operation Patterns

Operating behavior of appliances reveals information about the timing, length, and significance of appliance usage.

The appliance scheduling variable can be represented as:

$$S_i(t) \in \{0,1\} \quad (5)$$

Equation (5) describes the $S_i(t) = 1$ indicates appliance operation. $S_i(t) = 0$ indicates appliance inactivity. The optimizer uses this information to perform intelligent load shifting.

Solar PV Generation

The solar generation statistics depict the availability of renewable energy from PV sources.

The available renewable power is expressed as:

$$P_{PV}(t) = \eta AG(t) \quad (6)$$

Equation (6) describes η = PV conversion efficiency. A = solar panel area. $G(t)$ = solar irradiance.

This ensures that the system makes maximum use of renewable energy.

Battery State of Charge (SoC)

Battery condition is responsible for determining the stored energy in the battery.

The battery SoC is calculated as:

$$SOC(t) = SOC(t-1) + \frac{\eta_c P_c(t) - \frac{P_d(t)}{\eta_d}}{C_b} \quad (7)$$

Equation (7) describes the $P_c(t)$ = charging power. $P_d(t)$ = discharging power. η_c and η_d = charging/discharging efficiencies. C_b = battery capacity.

Input Data Acquisition module is responsible for providing the basis for the proposed QINE-SGEM solution, which combines residential consumers' behavior, renewable energy generation attributes, grid state, and constraints. The former type of information can be used for effective demand forecasting and scheduling of appliances' work, whereas the latter one can be used for cost-aware and sustainability-driven optimization. Constraints ensure that the energy management solutions generated by our system would be feasible and reliable. All this information is aggregated into a single vector and provided to the next module – Quantum-Inspired Neural Optimization Module.

Quantum Inspired Neural Optimization Module

Figure 2 depicts the designed Quantum-Inspired Neural Optimization Framework for Sustainable Energy Management in Smart Grid-Connected Residential Systems that incorporates data gathering, neural learning, quantum-inspired optimization, and decision-making in a holistic system. The framework starts with gathering heterogeneous input data from energy sources in residences, renewable generation systems, and grid conditions. The input feature vector is formulated as:

$$X(t) = \{X_R(t), X_{RE}(t), X_G(t), X_C(t)\} \quad (8)$$

Equation (8) where $X_R(t)$ represents residential energy characteristics, $X_{RE}(t)$ represents renewable energy parameters, $X_G(t)$ represents grid and environmental information, and $X_C(t)$ represents system

constraints. Residential energy data consists of profiles of electricity usage of households, smart meters, appliance usage patterns, solar PV production, and battery SoC data to give insight into the dynamics of energy demand and the resources available. The grid and environment data consisting of electricity tariffs, grid demand, weather data, renewable availability, and carbon emission factor make the optimization problem aware of the cost and sustainable. Constraints on battery storage limit, power limits, voltage limit, and energy efficiency keep the solutions feasible.

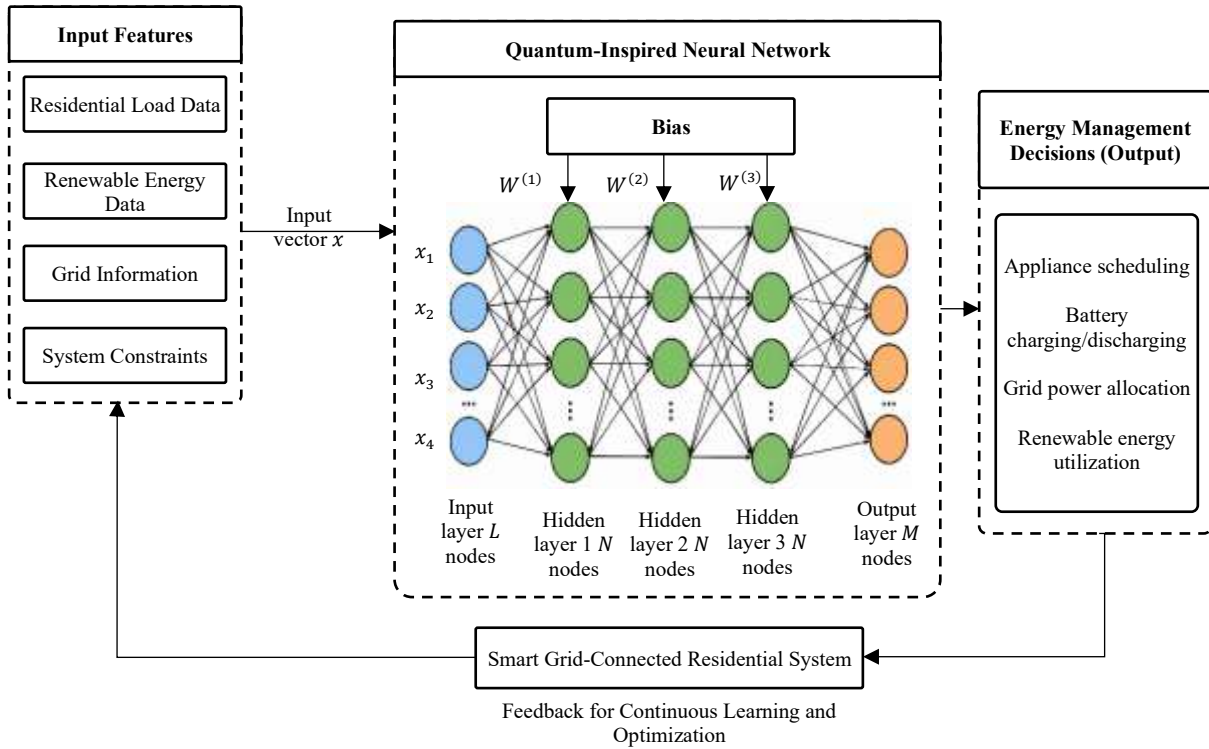


Figure 2. Overall architecture for quantum-inspired neural optimization module

The collected input features are transformed into a unified representation in equation (9)

$$X = [x_1, x_2, x_3, \dots, x_L] \quad (9)$$

and fed into the Quantum Inspired Neural Optimization Module, where the neural network extracts nonlinear features and predicts energy demand. The hidden layer calculations can be written as,

$$h_j^{(l)} = f\left(\sum_{i=1}^n W_{ij}^{(l)} x_i^{(l-1)} + b_j^{(l)}\right) \quad (10)$$

Equation (10) where $W_{ij}^{(l)}$ represents the connection weights, $b_j^{(l)}$ represents bias values, and $f(\cdot)$ denotes the activation function. Using several hidden layers, the neural network gains insights into the complicated relations between electricity usage behaviors, renewable power generation, and the grid operating environment.

To enhance the exploratory ability of the neural network, a quantum-inspired optimization technique is implemented in which the probable energy management configurations are expressed by means of quantum probability amplitudes.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (11)$$

Equations (11) and (12) describes the where α and β represent probabilities of various optimization states, where,

$$|\alpha|^2 + |\beta|^2 = 1 \quad (12)$$

This representation allows exploration of many different possible energy schedules simultaneously without falling into local minima. Optimization states are adaptively updated by applying the following quantum rotation.

From the optimized feature representation, the output layer makes smart decisions regarding energy management,

$$Y = f(W_o H + b_o) \quad (13)$$

Equation (13) where Y represents the final optimization outputs, W_o represents output weights, and H represents the extracted hidden-layer features. These decisions comprise scheduling for appliances, battery charging and discharging, grid power consumption, and renewable energy consumption. Optimization of appliance scheduling has been done through the use of binary control variables,

$$S_i(t) \in \{0,1\} \quad (14)$$

Equation (14) where $S_i(t) = 1$ indicates appliance activation and $S_i(t) = 0$ represents appliance deactivation. Battery management decisions are determined using:

$$P_B(t) = P_c(t) - P_d(t) \quad (15)$$

Equation (15) where $P_c(t)$ and $P_d(t)$ represent battery charging and discharging power, respectively. The grid power exchange is optimized as:

$$P_G(t) = P_L(t) - P_{PV}(t) - P_B(t) \quad (16)$$

Equation (16) where $P_L(t)$ represents residential load demand and $P_{PV}(t)$ represents solar PV generation. Furthermore, renewable energy utilization is evaluated using:

$$RU = \frac{E_{PV}}{E_{Total}} \times 100 \quad (17)$$

Equation (17) where E_{PV} denotes utilized renewable energy and E_{Total} represents total energy consumption.

The optimized solutions are implemented to the smart-grid connected residential system and the operational feedback is constantly provided back to the input module. The feedback updating process is depicted by,

$$X(t+1) = X(t) + \Delta X(t) \quad (18)$$

Equation (18) where $X(t+1)$ represents the updated system state and $\Delta X(t)$ represents variations due to changes in demand for energy, availability of renewables, and conditions within the grid network. Efficient appliance scheduling, effective integration of renewable energy resources, decreased electricity costs, reduced carbon emissions, and sustainability of energy management in smart grid-integrated environments are attained through this feedback-based optimization process.

Proposed Algorithm

Algorithm 1: Quantum

- Inspired Neural Optimization for Sustainable Energy Management (QINE
- SGEM)

Input: Residential energy data X_R , renewable energy data X_{RE} , grid information X_G ,

system constraints X_C .

Output: Optimal energy management strategy Y^*

Algorithm QINE – SGEM

1: Initialize neural network weights W , bias b , quantum states $|\psi\rangle$

2: Collect energy inputs:

$$X(t) = \{X_R(t), X_{RE}(t), X_G(t), X_C(t)\}$$

3: Preprocess and normalize input features

4: For each optimization iteration do

5: Extract energy features using neural network:

$$H = f(WX + b)$$

6: Generate quantum – inspired states:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

7: Generate candidate energy management solutions

8: Evaluate solutions using objective function:

$$F = w_1 \text{Cost} + w_2 \text{PeakLoad} + w_3 \text{CO}_2 + w_4 \text{GridDependency}$$

9: Select optimal solution:

$$Y^* = \arg \min(F)$$

10: Update quantum states and neural parameters

11: Until convergence condition is satisfied

12: Generate optimal decisions:

– Appliance scheduling

– Battery charging/discharging

– Grid power allocation

– Renewable energy utilization

13: Apply decisions to smart grid – connected residential system

14: Update model using feedback information

15: Return optimal energy management strategy Y^*

End Algorithm

Algorithm Explanation

The QINE-SGEM algorithm offers a dynamic solution to optimize residential energy management connected to the smart grid system. Algorithm 1 combines neural learning and quantum-inspired optimization methods to analyze energy data, develop optimal decisions, and make wise decisions. The QINE-SGEM algorithm optimizes the schedule of appliances, battery management, renewable energy sources, and power supply from the grid through continuous feedback-based learning.

EXPERIMENTAL SETUP

Dataset Description

The Pecan Street Austin Smart Grid Energy Dataset is used for evaluating the performance of the Quantum-Inspired Neural Optimization Framework for Sustainable Energy Management in Smart Grid-Connected Residential Systems (QINE-SGEM). The Pecan Street Austin Smart Grid Energy Dataset comprises energy consumption data along with renewable energy data collected from smart grids of the residents in Austin, Texas. The dataset comprises real-life household electricity consumption along with the solar photovoltaic (PV) generation, which is done through the high-resolution time-series measurements of the household electricity consumption as well as the renewable energy generation [21]. Such energy parameters as the household load profile, smart meter measurements, appliance consumption, and renewable energy generation are essential in order to develop the intelligent energy management strategy for the residential sector. The collected data serve as input features in the QINE-SGEM, including the residential energy parameters (X_R) and the renewable energy parameters (X_{RE}). Data on residential energy usage are useful for predicting energy demand and scheduling appliances. On the other hand, solar energy production data help in maximizing energy use from renewables and minimizing dependency on the grid. Hence, Pecan Street Austin Smart Grid Energy Dataset can be used as an appropriate real-world benchmark to test the effectiveness of QINE-SGEM in energy scheduling.

Simulation Environment

Table 1. Simulation parameters of QINE-SGEM framework

Parameter	Configuration
Programming Language	Python 3.10
Deep Learning Framework	TensorFlow 2.13 / Keras
Data Processing Libraries	NumPy, Pandas, Scikit-learn
Optimization Implementation	Custom Quantum-Inspired Optimization Module
Dataset	Pecan Street Austin Smart Grid Energy Dataset
Data Type	Residential energy consumption and renewable generation time-series data
Simulation Platform	Jupyter Notebook / Google Colab
Hardware Processor	Intel Core i7 CPU
RAM Capacity	32 GB
GPU Accelerator	NVIDIA RTX 3060
Neural Network Type	Quantum-Inspired Neural Network
Optimizer	Adam
Learning Rate	0.001
Batch Size	64
Training Epochs	100
Training Data Split	70% Training, 15% Validation, 15% Testing
Activation Function	ReLU
Output Activation	Sigmoid
Number of Optimization Iterations	500
Battery Capacity	10 kWh
PV Generation Capacity	5 kW
Simulation Time Resolution	15 minutes
Optimization Objectives	Energy cost reduction, peak load reduction, renewable utilization, carbon emission reduction

The developed quantum inspired neural optimization framework for sustainable energy management (QINE-SGEM) was implemented and tested in a simulation environment utilizing a software system. This software contains modules that perform data pre-processing, neural network training, quantum inspired optimization, and energy scheduling to simulate real residential energy operating environments. The tests were performed in computational frameworks utilizing Python and related deep learning and optimization packages. The proposed model was built using Python 3.10 as the programming platform. The neural prediction and optimization modules were built with TensorFlow 2.13 and Keras, respectively, whereas the numerical calculations and data processing tasks were done with NumPy, Pandas, and Scikit-learn modules. The quantum-inspired optimization module was built through custom Python functions to update quantum states, probability amplitudes, and optimization parameters. All experiments were conducted on a workstation with an Intel Core i7 CPU, 32 GB RAM, and NVIDIA RTX 3060 GPU to speed up the neural network training and optimization process. The simulation was carried out for a smart residential setting with household loads, roof-mounted PV generation, battery energy storage system, and grid. The simulation settings for evaluating the performance of QINE-SGEM are listed in table 1.

Metric Evaluation

Energy Consumption Reduction (ECR)

Reduction in energy consumption measures the capability of QINE-SGEM in minimizing unnecessary energy consumption by the household through proper load scheduling.

$$ECR(\%) = \frac{E_{\text{base}} - E_{\text{opt}}}{E_{\text{base}}} \times 100 \quad (19)$$

Equation (19) describes the E_{base} represents the energy consumption before optimization. E_{opt} is the optimal energy consumption after using QINE-SGEM. A higher value of ECR implies better energy efficiency.

Battery Energy Storage Efficiency (BSE)

The efficiency of a battery can be determined by assessing its charge and discharge efficiency.

$$BSE(\%) = \frac{E_{\text{out}}}{E_{\text{in}}} \times 100 \quad (20)$$

Equation (20) describes the E_{out} represents discharged energy. E_{in} represents charged energy. This metric determines the effectiveness of battery energy management.

Prediction Performance Metrics

The neural network element of QINE-SGEM is used to forecast residential energy consumption. Prediction performances are assessed by MAE, RMSE, and MAPE, in accordance with the prediction analysis part.

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (21)$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (22)$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (23)$$

Equations (21), (22) and (23), the y_i represents actual energy demand. $\hat{y}_i$ represents predicted energy demand. N represents the number of samples. Lower MAE, RMSE, and MAPE values indicate better prediction accuracy.

RESULTS AND DISCUSSION

Energy Consumption Optimization Analysis

The optimization analysis of energy consumption considers the efficiency of QINE-SGEM in reducing electricity demand of households through scheduling and energy load balancing of appliances. The suggested approach compared with other energy management systems based on average daily energy consumption and peak load balancing.

Table 2. Energy consumption optimization performance

Method	Average Energy Consumption (kWh/day)	Peak Load (kW)	Energy Reduction (%)
MILP-Based EMS	29.6	5.8	9.7
ANN-Based EMS	27.9	5.4	14.9
DRL-Based EMS	26.8	5.1	18.3
QINE-SGEM	24.2	4.5	26.2

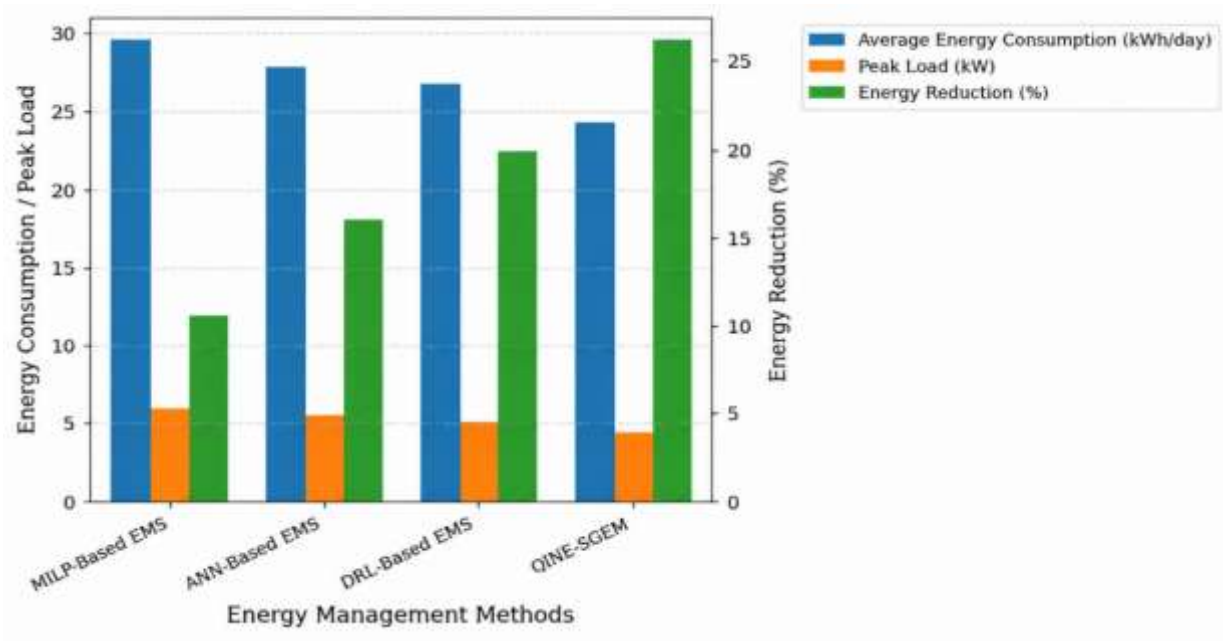


Figure 3. Battery energy storage optimization

The comparative energy optimization performance of various energy management techniques such as MILP-Based EMS, ANN-Based EMS, DRL-Based EMS, and the proposed technique (QINE-SGEM) is illustrated in table 2 and figure 3. According to the results obtained, QINE-SGEM technique is more efficient in terms of energy optimization due to decreasing the average energy consumption to 24.2 kWh/day and peak load to 4.5 kW, which are lower compared to 29.6 kWh/day and 5.8 kW, 27.9 kWh/day and 5.4 kW, and 26.8 kWh/day and 5.1 kW of the traditional methods, such as MILP-Based EMS, ANN-Based EMS, and DRL-Based EMS. Moreover, the QINE-SGEM technique achieves an energy reduction of 26.2%, outperforming MILP-Based EMS, ANN-Based EMS, and DRL-Based EMS by 16.5, 11.3, and 7.9 percentage points, respectively. These enhancements demonstrate that combining quantum-inspired optimization with neural learning yields superior load scheduling and minimizes energy waste.

Battery Energy Storage Management Analysis

Battery management system analysis assesses the battery charging and discharging control of the proposed system while ensuring battery stability and effective renewable resource usage.

Table 3. Battery energy storage optimization

Method	Battery Efficiency (%)	SoC Stability (%)	Charging/Discharging Loss (%)
Conventional Control	82.4	78.5	17.6
MILP Optimization	87.2	84.6	12.8
DRL-Based Control	91.5	90.2	8.5
QINE-SGEM	95.8	94.7	4.2

The comparative performance evaluation of the various battery energy storage optimization schemes with respect to battery efficiency, state-of-charge (SoC) stability, and charging/discharge loss is presented in table 3. As seen from the results, the proposed QINE-SGEM scheme has been able to attain a maximum battery efficiency of 95.8% and SoC stability of 94.7%, and minimize the charging/discharge losses to 4.2%. The QINE-SGEM method increased battery efficiency by 13.4%, 8.6%, and 4.3% compared with Conventional Control, MILP Optimization, and DRL-Based Control, respectively. Also, the SoC stability has been improved to 16.2%, 10.1%, and 4.5% as compared with the Conventional Control, MILP Optimization, and DRL-Based Control approaches, respectively. The losses related to charging and discharging have been minimized by 17.6%, 12.8%, and 8.5% with respect to the existing methods to 4.2%.

Prediction Performance Analysis

Prediction analysis studies the neural aspect of QINE-SGEM for predicting residential energy demand accurately.

Table 4. Energy demand prediction performance

Model	MAE	RMSE	MAPE (%)
ANN	0.182	0.264	8.6
LSTM	0.146	0.219	6.4
GRU	0.131	0.198	5.8
Transformer	0.118	0.176	4.9
QINE-SGEM	0.084	0.126	3.2

Table 4 depicts the energy demand prediction accuracy comparison of various deep learning models employed within the QINE-SGEM framework. The comparison is based on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) criteria, whereby lower values imply better forecast accuracy. It is apparent from the proposed QINE-SGEM model has produced the lowest prediction errors with an MAE of 0.084, RMSE of 0.126, and MAPE of 3.2%, outperforming ANN, LSTM, GRU, and Transformer-based models. In addition, compared with

the best conventional model, i.e., Transformer, QINE-SGEM has shown a reduction of 28.8% in MAE, 28.4% in RMSE, and 34.7% in MAPE. Likewise, compared with ANN, LSTM, and GRU models, QINE-SGEM has shown reduced prediction errors, implying a better ability to capture residential energy consumption patterns. Such improvements are possible due to the quantum-inspired optimization process that allows effective feature learning and prediction of energy demand changes.

Ablation Study Analysis

The ablation study tests the effect of each component of QINE-SGEM through the omission of its quantum optimization and adaptive learning capabilities.

Table 5. Ablation study of the proposed QINE-SGEM framework

Model Variant	Energy Cost Reduction (%)	Peak Load Reduction (%)	Renewable Utilization (%)	Prediction RMSE	Convergence Iterations	Carbon Emission Reduction (%)
ANN Only	18.6	14.8	61.2	0.182	760	13.5
Quantum Optimizer Only	23.4	18.9	66.8	0.164	680	17.2
QINE without Feedback	29.7	23.6	75.4	0.121	590	22.8
QINE without Quantum Optimization	31.2	24.8	77.1	0.109	560	24.1
Proposed QINE-SGEM	36.8	29.5	82.6	0.084	500	28.7

Table 5 shows the ablation study for the proposed QINE-SGEM framework to study the contributions of different components such as the neural prediction module, quantum optimizer, feedback mechanism, and quantum optimization approach. Results indicate that the entire QINE-SGEM framework outperforms all the others and has the maximum energy cost reduction, peak load reduction, renewable energy utilization, and carbon emission reduction, in addition to the minimum prediction RMSE with just 500 convergence iterations. Comparing QINE-SGEM with the ANN-based model shows that the energy cost reduction and renewable utilization increase by 18.2% and 21.4%, respectively, and the carbon emission reduction increases by 15.2%, which reflects the efficiency of the quantum-inspired optimization approach in combination with adaptive learning. When the quantum optimizer is removed, the optimization process becomes less efficient, and the RMSE increased to 0.109, and energy cost reduction decreased to 31.2%, proving the significance of using the quantum optimization method. In addition, the exclusion of the feedback mechanism has shown that the prediction accuracy decreased along with reduced renewable utilization.

Discussion

The results show the successful application of the QINE-SGEM framework that effectively enhances the residential energy management process with the help of neural prediction, quantum-inspired optimization, and adaptive feedback mechanisms. Significant energy savings and a reduction in peak load can be obtained through intelligent appliance scheduling, integration of renewable energy sources, and efficient interaction with the smart grid. The efficiency of energy storage is evidenced by improved battery efficiency and stability of the state of charge, while the decreased charging/discharging losses are an indicator of the ability of QINE-SGEM to ensure reliable energy utilization. Moreover, the better accuracy of predictions with the lower values of MAE, RMSE, and MAPE confirms the high effectiveness of the neural optimization component. The results of the ablation analysis also prove the contribution of the quantum optimization and adaptive feedback components to the improvement of energy cost savings, renewable energy use, and carbon emissions reduction. In summary, the

QINE-SGEM offers an adaptive approach to residential energy management that is connected to a smart grid infrastructure, which eliminates the shortcomings in conventional optimization approaches and independent AI systems. Nevertheless, further research should be conducted in regard to the application of the model in real-time and at a larger scale of residential buildings.

CONCLUSION

The objectives of this study were to propose an intelligent and adaptive energy management system framework for the residential energy system that is connected to a smart grid in order to overcome the drawbacks of traditional optimization techniques and the standalone use of artificial intelligence. The proposed framework, named Quantum-Inspired Neural Optimization Framework for Sustainable Energy Management in Smart Grid-Connected Residential Systems (QINE-SGEM), integrates neural learning, quantum-inspired optimization, and feedback-based adaptation in order to facilitate effective energy scheduling, renewable energy coordination, battery management, and grid connection. The uniqueness of the proposed framework lies in the unified optimization framework, which uses the capability of quantum-inspired search along with the neural learning mechanism. Experimentation with the Pecan Street Austin Smart Grid Energy Dataset proves the efficacy of the developed approach, obtaining an average energy consumption of 24.2 kWh/day, 26.2% energy savings, 95.8% battery efficiency, and prediction accuracy with MAE of 0.084, RMSE of 0.126, and MAPE of 3.2%. Moreover, the ablation study proves the effect of quantum optimization and adaptive feedback schemes by obtaining 36.8% energy cost savings, 82.6% utilization of renewable energy sources, and 28.7% carbon emission savings. It is concluded that QINE-SGEM offers a scalable and adaptive solution for future energy management at homes. Future work includes the hardware implementation of the scheme in real time, its application to large-scale residential communities, and incorporation into modern smart grid frameworks.

REFERENCES

- [1] Shili M, Hammedi S, Chaoui H, Nouri K. Energy-aware swarm robotics in smart microgrids using quantum-inspired reinforcement learning. *Electronics*. 2025 Oct 28;14(21):4210. <https://doi.org/10.3390/electronics14214210>
- [2] Paul K, Jyothi B, Kumar RS, Singh AR, Bajaj M, Hemanth Kumar B, Zaitsev I. Optimizing sustainable energy management in grid connected microgrids using quantum particle swarm optimization for cost and emission reduction. *Scientific Reports*. 2025 Feb 18;15(1):5843. <https://doi.org/10.1038/s41598-025-90040-0>
- [3] Minghong L, Gaoshan F, Pengchao W, Xin Y, Qing L, Hou T, Shuo Z. Behavior-aware energy management in microgrids using quantum-classical hybrid algorithms under social and demand dynamics. *Scientific Reports*. 2025 Jul 1;15(1):21326. <https://doi.org/10.1038/s41598-025-06199-z>
- [4] Naresh P, Kumar KH, Kulkarni P. Adaptive Solar Power Optimization via SolGenX: Quantum-Inspired Techniques for Decentralized Renewable Energy Networks. In: 2026 6th International Conference on Trends in Material Science and Inventive Materials (ICTMIM) 2026 Apr 8 (pp. 714-720). IEEE. <https://doi.org/10.1109/ICTMIM68190.2026.11506980>
- [5] Khatiri A, Mousavi SY, Golestan S. Quantum neural networks for optimal energy management in renewable based microgrids with plug-in electric vehicles and battery energy storages. *Journal of Energy Storage*. 2025 Sep 1;129:117304. <https://doi.org/10.1016/j.est.2025.117304>
- [6] Shen X, Tang J, Pan F, Qian B, Zhao Y. Quantum-inspired deep reinforcement learning for adaptive frequency control of low carbon park island microgrid considering renewable energy sources. *Frontiers in Energy Research*. 2024 May 3;12:1366009. <https://doi.org/10.3389/fenrg.2024.1366009>
- [7] Nidamanuri SK, Netibottu MB, Kasipogula BR, Syed Masood JA, Kolandaisamy R, Veerappan KN. Quantum-artificial intelligence framework for suppressing dendrites and enhancing interface stability in lithium-metal solid-state batteries. *Energy Exploration & Exploitation*. 2026 Jul;44(4):2015-51. <https://doi.org/10.1177/01445987251414740>
- [8] Jeong SG, Do QV, Hwang WJ. Short-term photovoltaic power forecasting based on hybrid quantum gated recurrent unit. *Ict Express*. 2024 Jun 1;10(3):608-13. <https://doi.org/10.1016/j.ict.2023.12.005>
- [9] Gurumoorthi G, Senthilkumar S, Karthikeyan G, Alsaf F. A hybrid deep learning approach to solve optimal power flow problem in hybrid renewable energy systems. *Scientific Reports*. 2024 Aug 21;14(1):19377. <https://doi.org/10.1038/s41598-024-69483-4>
- [10] Assad U, Hassan MA, Farooq U, Kabir A, Khan MZ, Bukhari SS, Jaffri ZU, Olah J, Popp J. Smart grid, demand response and optimization: A critical review of computational methods. *Energies*. 2022 Mar 9;15(6):2003. <https://doi.org/10.3390/en15062003>

- [11] Wang S, Yue Y, Cai S, Li X, Chen C, Zhao H, Li T. A comprehensive survey of the application of swarm intelligent optimization algorithm in photovoltaic energy storage systems. *Scientific Reports*. 2024 Aug 2;14(1):17958. <https://doi.org/10.1038/s41598-024-68964-w>
- [12] Rangu SK, Lolla PR, Dhenuvakonda KR, Singh AR. Recent trends in power management strategies for optimal operation of distributed energy resources in microgrids: A comprehensive review. *International Journal of Energy Research*. 2020 Oct 25;44(13):9889-911. <https://doi.org/10.1002/er.5649>
- [13] Bio Gassi K, Baysal M. Analysis of a linear programming-based decision-making model for microgrid energy management systems with renewable sources. *International journal of energy research*. 2022 May;46(6):7495-518. <https://doi.org/10.1002/er.7656>
- [14] Huynh DC, Nguyen PT, Ho LD, Barbalata C, Dunnigan MW. Resilience-and Uncertainty-Aware Optimization Framework for Vehicle-to-Home-Enabled Smart Residential Energy Systems Using a Quantum-Inspired Gradient-Based Optimizer. *IEEE Access*. 2026 Aug 10. <https://doi.org/10.1109/ACCESS.2026.3722216>
- [15] Olagundoye OO, Bamisile O, Joseph Ejayi C, Bamisile O, Ni T, Onyango V. A Review of Artificial Intelligence Techniques for Low-Carbon Energy Integration and Optimization in Smart Grids and Smart Homes. *Processes*. 2026 Jan 28;14(3):464. <https://doi.org/10.3390/pr14030464>
- [16] Kumar D, Rai JN, Nagarajan ST. An Adaptive Hybrid Quantum-Inspired Optimization Approach for Advanced VSG Control Strategy in Inverter-Based Microgrid. *Journal of Electrical Engineering & Technology*. 2026 Jul 24;1-6. <https://doi.org/10.1007/s42835-026-02851-4>
- [17] Kaleeswari M, Sivakumar P, Aswini A. Digital twin assisted of frequency stability enhancement in Indian smart grids with EV charging infrastructure along with quantum optimization. *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy*. 2026 Apr 18:09576509261444821. <https://doi.org/10.1177/09576509261444821>
- [18] Ojo KE, Saha AK, Srivastava VM. A Sustainable Optimization Framework for Demand-Side Energy Scheduling in Grid-Connected Microgrid Management System. *Sustainability*. 2026 Mar 12;18(6):2763. <https://doi.org/10.3390/su18062763>
- [19] Liu M, Liao M, Zhang R, Yuan X, Zhu Z, Wu Z. Quantum computing as a catalyst for microgrid management: Enhancing decentralized energy systems through innovative computational techniques. *Sustainability*. 2025 Apr 18;17(8):3662. <https://doi.org/10.3390/su17083662>
- [20] Rimada Y, KL Mrinh C. Trust-Aware Adaptive Control Architecture for Secure and Energy-Efficient Cyber-Physical Systems under Dynamic Operating Conditions. *Journal of Reconfigurable Hardware Architectures and Embedded Systems*. 2026 Sep 3:25-32.
- [21] Pecan Street Austin Smart Grid Energy Data. *Kaggle*; 2026 Oct 1. <https://www.kaggle.com/datasets/bassaml65/pecan-street-austin-smart-grid-energy-data>
- [22] Balasm Z, Shavkidinova D, Rajesh D, Prabakaran N, Kadirov I, Nayak A. Data-driven decision support in smart ubiquitous agriculture. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*. 2025 Jun;16(2):647-56. <https://doi.org/10.58346/JOWUA.2025.12.039>
- [23] Iyer R, Sharma A. Sustainable finance and its role in promoting long-term economic growth. *Global Perspectives in Management*. 2026;4(2):90-99.