Quantum Computing in Energy Systems

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Quantum computing is a rapidly expanding domain attracting researchers across various industries. One significant application is in the energy systems domain, which was the main focus of this paper. Energy systems contain different components that efficiently deliver electric energy to consumers. Some of these components can greatly benefit from the computational power and optimization capabilities of quantum computers, which can aid with advancing the efficiency of energy systems. This paper aimed to provide an overview of the milestones achieved in the literature regarding quantum computing algorithms in energy systems. The overview analyzed the intersection of quantum computing algorithms and energy systems, specifically in photovoltaic cells, wind turbines, and weather forecasting. The result was a comprehensive summary of innovative quantum algorithms applicable to solar and wind farms, along with an identification of gaps in the field.

Additional Key Words and Phrases: Quantum Computing, Algorithms, Energy Systems, Photovoltaic Cells, Wind Turbines, Weather Forecasting

1 INTRODUCTION

In recent years, the demand for sustainable and renewable energy sources has shifted the focus away from fossil fuels like crude oil and natural gas towards green energy sources such as solar and wind power. This shift has driven technological advancements aimed at better exploiting renewable sources to increase their energy production output. Quantum computing has distinguished itself from classical computing in terms of its computational power. According to [5], it is described as a disruptive technology that can lay the foundation for the next generation of energy systems by leveraging the unique properties of subatomic particles. The move towards more advanced energy systems increases the reliance on big data, bringing with it the challenges of computing and interpreting vast amounts of information. To address these challenges, algorithms and methods based on machine learning, artificial intelligence, and neural networks are essential for creating more efficient energy systems and have already proven their utility in other sectors.

This paper focused on quantum computing algorithms that enhance the potential of existing energy systems. Machine learning helps computers simulate a learning process by analyzing large quantities of data. The result is a computer that can take new actions according to what it previously learned from the data without being programmed to perform the respective task [32]. Artificial intelligence allows computers to find solutions to complex problems by mimicking the behaviour of humans [23]. Neural networks, a combination of both, are machine-learning models that simulate the neural networks of biological neurons in living bodies by transmitting information through their connections [23]. Throughout this paper, these technologies, in combination with quantum computing and their algorithms, were highlighted for their ability to enable computers to interpret large amounts of data and make independent decisions based on previous experiences. The aim was to recognize the milestones achieved using quantum computing in energy systems and to identify existing research gaps that future work in the domain can address.

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1.1 Quantum Computing

Quantum computing functions on the principles of quantum mechanics and operates at the subatomic particle level, allowing it to perform numerous tasks by simultaneously being in multiple states [5]. Unlike classical computers, which use bits that can exist in only one state at a time, either 1 or 0, quantum computing is based on qubits. Because of their superposition property, qubits can simultaneously be in the states of 1 and 0 [21]. This attribute is mathematically represented using Dirac notation as: $\alpha|0\rangle + \beta|1\rangle$, where "$\alpha$" and "$\beta$" are the probabilities for the qubit to be in each of the respective states.

1.2 Renewable Energy Systems and Quantum Computing

Energy systems, often called energy grids, provide end users with essential commodities such as electricity, heating, or water. This paper focused on renewable energy systems that supply electricity generated from solar and wind power, commonly known as solar and wind farms. These are complex structures designed to reliably deliver a consistent energy supply to consumers [4]. The domain of renewable energy is rapidly expanding and in dire need of advanced technologies, such as quantum computing, to innovate and address challenges like big data, as further discussed throughout this paper.

1.3 Applications of Quantum Computing in Energy Systems

The importance of quantum technology in addressing the challenges that smart sustainable cities and their power grids will face due to the rapid expansion of cities is highlighted by [21]. Challenges such as efficiency, optimization, security, and big data are real impediments in each of the development stages of the system: power generation, power control, and the energy dissipation stage [10].

This paper focused on the power generation and control stages, as photovoltaic cells and wind turbines are the primary green energy generators within a grid. Their performance can be improved with the help of quantum technology through optimization algorithms meant to find optimal parameters and solutions, as well as efficiency algorithms for processing big data rapidly, such as in weather forecasting. Methods like artificial intelligence, machine learning, and neural networks can improve data analysis, interpretation, and processing within a power grid. According to [21], the most beneficial output for optimizing the grid is the predictive capability of these methods, especially when handling big data where classical methods show limitations.

Quantum computing and deep learning neural networks form Quantum Neural Networks (QNN), with [5] discussing QNN applications ranging from optimization to weather forecasting and wind turbine design. [31] provides insights into how quantum computing and machine learning, known as Quantum Machine Learning (QML), and QNN can be used for the topology optimization of photovoltaic arrays, which essentially are multiple solar panels electrically connected to cover a larger surface and increase electrical power output. Section 2 addresses the problem statement, including the research questions and goals of this paper, while Section 3 presents the information-gathering methodology of this semi-systematic literature review. Sections 4 and 5 provide insights into quantum computing algorithms that have the potential to improve photovoltaic and wind-powered energy systems, respectively. Section 6 discusses the current progress of algorithms focusing strictly on weather forecasting in energy systems, while Section 7 offers a broader perspective on other innovations in quantum computing and renewable energy. The paper concludes with Sections 8 and 9, which summarize the results and future work, as well as the conclusions.

2 PROBLEM STATEMENT

Although the domain of quantum computing is still in the early days and its full utility is unknown, the potential it has in the development of the energy industry is clearly stated by literature [5, 10, 21, 31]. This paper aimed to provide a semi-systematic literature review of quantum computing algorithms and methodologies capable of improving current energy systems by answering the main research question and its respective secondary research questions as elaborated below.

2.1 Research Questions

The main research question was formulated as follows:

"What quantum computing algorithms and methods improve the performances of energy systems?"

Three Secondary Questions (SQ) arose when trying to answer the main question:

- SQ1: Which quantum computing algorithms can improve the performance of solar farms?
- SQ2: Which quantum computing algorithms can improve the performance of wind farms?
- SQ3: Which quantum computing algorithms can improve the weather forecasting accuracy for energy systems?

2.2 Goals

This paper's objective was to conduct a semi-systematic literature review analyzing how algorithms and methods enhanced by quantum computing can improve the performance of energy systems. The review focused on the photovoltaic and wind systems, as well as on the impact that weather forecasting has on them. The outcome provided a comprehensive overview of the algorithms and methods that can optimize and take energy systems to the next level.

3 METHODOLOGY

The first step of this semi-systematic literature review was to gather comprehensive information about the broad domains of the paper, quantum computing and energy systems, from veritable scientific databases such as IEEE, ResearchGate, Google Scholar, and ScienceDirect. The next step was to narrow down the search of papers for each research question.

For the SQ1, searches were performed using the keywords "quantum computing AND (solar panel OR photovoltaic OR solar energy OR solar cells)". This review focused on identifying these algorithms, their applications, and their mechanisms, as well as understanding what photovoltaic cells and arrays are, their usage, and how quantum computing algorithms can enhance their performance. A total of 27 relevant research papers were selected for further reading.

For the SQ2, the search was conducted using the keywords "quantum computing AND (wind OR wind turbine OR wind power OR wind energy)". The review concentrated on papers that detail how quantum computing algorithms can be used to improve the performances of wind turbines, thus optimizing them and increasing their efficiency. A total of 25 relevant research papers were selected for further reading.

For SQ3, the search used the keywords "quantum computing AND (weather OR weather forecast OR weather prediction)". This review selected papers that present applications of quantum computing algorithms in weather forecasts and how these can be leveraged to enhance the general efficiency of energy systems. A total of 10 relevant research papers were selected for further reading.

Ultimately, the goal was to answer the main research question by addressing each secondary research question and incorporating the findings into one comprehensive paper. Another objective was to identify gaps where innovation can occur and help advance energy systems with the aid of quantum computing. Numerous papers have been published on these topics. Therefore, the only filter applied was that all the papers must be written in English.

4 QUANTUM COMPUTING IN PHOTOVOLTAIC ENERGY SYSTEMS

The shift towards greener energy sources opens up opportunities for regenerative options with unlimited supply that can be exploited anywhere on the Earth's surface. As noted in [12], by the year 2030, an estimated 30 terawatts (TW) of energy will be necessary to sustain the consumption rate. This quantity can be extracted from clean energy sources, such as solar and wind power, with minimal environmental impact.

Solar power is extracted from the Sun through solar panels. The role of solar panels is to convert solar energy into electricity. There are numerous models of solar panels, each with different material advantages and disadvantages. The range of the light spectrum captured is crucial in determining the efficiency of a solar panel. Some panels can process wavelengths such as the infrared spectrum, while others can also process visible light [26]. High-performing solar panels are essential for effectively capturing and converting solar energy into electricity. Progress is being made towards a third generation of solar panels that aim to improve efficiency at a lower cost. Examples include the Perovskite solar cells [33] and the Quantum Dot solar cells [25, 26]. Solar panels have applications ranging from powering small households to supplying large grids. For smaller applications, solar panels can power an entire house and sometimes produce a surplus of electricity fed back into the electrical grid (prosumer).

Larger grids can contain hundreds or thousands of solar panels, providing power to cities or industrial areas.
Improvements can be made both at the material level and the algorithmic level. This paper focused on algorithms that can increase the efficiency of photovoltaic grids, aid scalability, and lower costs. Identifying points for improvement involved analyzing the main issues that photovoltaic grids face while in use. One challenge is forecasting energy production, given the unpredictable nature of regenerative energy sources [1]. Other challenges relate to scalability, such as handling large quantities of data collected from grid sensors measuring temperature, irradiance, or scanning for faults [30]. Cost reductions and optimizations are also essential for the efficient functioning of the grid, ranging from cable routing problems [35] to energy management frameworks [1].
Quantum computing is known for performing operations and finding optimal solutions faster than classical computers. Quantum computing can enhance machine learning algorithms, particularly neural network algorithms. The following subsections show that implementing these inside photovoltaic grids can increase overall efficiency. Several remarkable algorithms addressing these issues have been discussed and categorized into forecasting and optimization.

4.1 Forecasting Photovoltaic Energy Production

4.1.1 *QRNN: Quantum-classical Recurrent Neural Network.*

The energy created by solar panels can be represented as a time series consisting of observations taken at regular intervals and containing parameters such as solar power production at specific timestamps.
Forecasting these parameters is important for managing a photovoltaic grid, providing insights into the short-term and long-term power output. However, such applications are challenging for classical computers due to the computational effort required to process large amounts of data to make accurate predictions.
Quantum computing technologies, combined with other methods used in computer science, can bridge the gap needed to achieve the desired accuracy. Quantum Machine Learning (QML), specifically Quantum Neural Networks (QNN) and Quantum-classical Recurrent Neural Network (QRNN) algorithms for time-series predictions, were proposed by [2] to address this challenge. Ceschini et al. [2] dived into a QRNN algorithm with multiple layers capable of forecasting photovoltaic energy production by considering intermittent factors such as weather and seasonal changes. The model consisted of four layers: two Long Short-Term Memory (LSTM) layers, one Variational Quantum (VQ) layer, and one Fully Connected (FC) layer. The advantages of using a QRNN with the layers proposed by [2] include leveraging the properties of quantum neural networks along those of LSTM, VQ, and FC layers. The experiment presented in [2] showed significant performance improvements compared to existing classical alternatives and opened future work possibilities, such as integrating a Random Forest (RF) regressor for accurate predictions in low light conditions.

4.1.2 *QLSTM: Quantum Long Short-Term Memory.*

A Long Short-Term Memory network, also known as an LSTM, is an algorithm widely covered by literature because of its ability to perform short-term predictions of photovoltaic power generation. These papers [2, 13, 18, 34] were selected to understand the importance of LSTM and how they placed this algorithm in the context of photovoltaic grids, highlighting its potential.
LSTM is a type of recurrent neural network architecture that excels in identifying patterns and dependencies in long time-series data, making it an excellent tool for learning from past experiences and adapting to new scenarios according to previous contexts [18]. Its applications within photovoltaic grids are vast, but the essential area where this algorithm can be used is in energy forecasting. Solar power is known for its irregular nature, creating difficulties in energy systems that aim to deliver a reliable flow of electricity. Predicting a day or even an hour in advance can enable the grid to make appropriate decisions regarding the delivery or storage of electricity. The output of solar panels is influenced mostly by natural causes, such as weather, which can obstruct parts of the solar panels and cause shadowing.
LSTM itself can be enhanced with quantum machine learning methods such that, if trained properly, it can extract the relevant information needed for making accurate predictions more efficiently. [34] proposed a Quantum LSTM (QLSTM) that incorporated a Variational Quantum Circuit (VQC) into the LSTM instead of its classical neural network. A VQC is a quantum circuit that first encodes data into qubit quantum states, then forms entanglement operations using quantum gates, and in the end, measures the quantum state to determine the output, forwarding it to the LSTM for processing. The experiment's goal in [34] was to predict solar irradiance for the following hour by using data from the past 24 hours. The training was based on 3 years of data collected from five cities in China, showing remarkable results with the proposed QLSTM method in annual, seasonal, and month-specific prediction performances compared to classic LSTM and other classical algorithms.

4.1.3 *QGAN: Quantum Generative Adversarial Network.*

The intermittent nature of solar power led to a need for scenario generation that reduces uncertainty, a topic discussed in [29]. Scenarios mimic real life and contain numerous parameters that can be altered to replicate potential future situations. This aids in decision-making and forecasting processes, allowing stakeholders to assess situations and formulate strategies for future development.
Tang et al. [29] proposed a quantum alternative to existing scenario generation algorithms based on a Generative Adversarial Network (GAN). A GAN system consists of two neural networks, one serving as the generator and the other as the discriminator. The generator creates false scenarios, which the discriminator analyzes and attempts to differentiate from real scenarios. Nash equilibrium is achieved when the discriminator can no longer distinguish between false and real scenarios. The heavy computation required for this process can be enhanced by quantum computing, resulting in a quantum GAN (QGAN). In QGAN, both the generator and discriminator are replaced by quantum components.
[29] took QGAN two steps forward by introducing Multi-QGAN and Correlation-based Multi-QGAN (CMulti-QGAN). Multi-QGAN consists of multiple QGAN systems operating in parallel, with each generator paired to its assigned discriminator. CMulti-QGAN has a similar structure but also accounts for the correlations between neighbouring data points. The experiments conducted by Tang et al.

[29] showed promising results in generating scenarios for solar power with Multi-QGAN and CMulti-QGAN, potentially improving the efficiency of solar power prediction.

4.2 Optimizations in Photovoltaic Energy Systems

4.2.1 QAOA: Quantum Approximate Optimization Algorithms.

Optimization problems are inevitable when dealing with large photovoltaic grids and big data. These issues are of significant concern to researchers in the field, and the following papers were selected for the topic of grid optimization [6, 18]. These papers explored the idea of Quantum Approximate Optimization Algorithms (QAOA).

Optimizations occur at various levels, from cost and material optimizations aimed at reducing expenses and material waste to scheduling optimizations that create more efficient schedules for delivering or storing energy. Optimization is carried out with scalability in mind. As the world progresses towards regenerative energy sources like solar power, photovoltaic grids will expand, and data collection will increase accordingly.

The experiment in [18] compared quantum computing approaches to classical optimization algorithms such as Linear Programming (LP) and Genetic Algorithms (GA) in the context of renewable energy systems. The experiment's goal was to reduce the cost of producing energy by optimizing grids of different sizes. QAOA proved to be approximately 18.92% more efficient than linear programming and 10.71% more efficient than the genetic algorithm, taking roughly a third and, respectively, a fifth of the computing time.

Federer et al. [6] investigated the application of QAOA in an airport's energy system, where it was employed to create schedules for electrically powered vehicles considering constraints from external factors such as the power output of the solar panels or the flight schedule. Although the experiment showed promising results, a decisive factor was the current state of quantum hardware, which was too sensitive to the choice of penalties and impacted the quality of the solution. The experiment obtained similar results between the quantum and classical approaches, noting promising results with increases in qubits. This identifies a gap between the existing accessible hardware and the hardware needed to obtain the desired results, which can be filled with more stable quantum hardware that can better handle error correction.

4.2.2 QUBO: Quadratic Unconstrained Binary Optimization.

Increases in the number of solar panels that constitute photovoltaic grids create complex cable routing problems. Cables are an essential part of an energy system, with considerable lengths needed to connect each solar panel to the rest of the grid.

Zhao et al. [35] discussed the usage of a quantum-based algorithm to solve the cable routing problem. Quadratic Unconstrained Binary Optimization (QUBO) was proposed for its ability to find efficient solutions. The goal was to reduce cable waste by finding the shortest routes and decreasing costs by requiring minimal cable lengths to connect the grid. The experiments in [35] demonstrated that QUBO is an effective method for addressing cable routing problems of various sizes in photovoltaic grids. The advantages lie in computation speed and scalability, achieving similar results to classical computers but with greater efficiency. These benefits are crucial for large-scale photovoltaic grids, where speed, cable waste, and cost reduction are critically important.

4.2.3 QCBOA: Quantum Chaotic Butterfly Optimization Algorithm.

Optimization algorithms can be utilized at almost every step of a process. Some of these algorithms' provenience and inspiration come from nature, such as the butterfly feeding behaviour, which was the topic of [15].

The Butterfly Optimization Algorithm (BOA) is one of the algorithms inspired by nature that involves a process with two phases, one for exploration and the other for exploitation. The exploration phase examines the entire search space, while the exploitation phase focuses on a smaller area, trying to find a globally optimal solution. The way BOA utilizes numerous constant parameters and performs the exploration and exploitation phases is a limitation that can be surpassed by using a Quantum Chaotic BOA (QCBOA).

The QCBOA proposed by [15] used chaotic maps to calculate the parameters better, quantum waves to improve the exploration, and a ranking strategy for the probability switch. With these changes presented in the experiments of [15], QCBOA was able to outperform BOA, including in the case of photovoltaic parameter optimization. In the context of photovoltaic systems, these parameters refer to irradiance, temperature, and other natural factors that influence the system's ability to optimize and predict power output.

4.2.4 Other algorithms.

While numerous quantum computing algorithms have been created to innovate the domain of photovoltaic systems, the abovementioned algorithms address some of the major issues. Additional credits can be offered to other papers such as [3, 14, 17]. Raghav et al. [17] discussed Quantum Teaching Learning Based Optimization (QTLBO), which aimed to solve energy management problems in solar power applications. [3] proposed a Fuzzy Logic-based Quantum Evolutionary Algorithm (FLQEA) designed to achieve an optimal economic strategy for photovoltaic grids. Additionally, [14] highlighted the importance of using Post-Quantum Cryptography (PQC) to protect energy systems from potential future quantum attacks.

5 QUANTUM COMPUTING IN WIND-POWERED ENERGY SYSTEMS

Besides photovoltaic panels, wind power is another regenerative energy source that has gained popularity compared to fossil-based fuel alternatives. According to [9], the power production capacity of wind farms around the world is projected to reach approximately 841 gigawatts (GW). This makes wind energy a crucial factor in meeting the estimated 30 terawatts needed by the year 2030, as noted by [12].

Wind power is extracted from wind through large turbines placed on land or water in areas with abundant air currents. The role of the wind turbine is to convert wind energy passing through its blades into electricity. Numerous factors impact the performance of a wind farm, from the positioning of the turbines to various optimizations in different segments of the system, all of which can be enhanced through quantum computing.

Wind power is an intermittent energy source due to uncontrollable factors such as wind variability and seasonality [8]. This sporadic nature creates difficulties in accurate prediction and opens opportunities for new optimization and forecasting algorithms that utilize quantum computing technology. Some well-known issues that wind farms encounter and can be addressed with quantum computing include Wind Farm Layout Optimization, numerical anomaly detection, the Unit Commitment Problem, and day-ahead wind speed forecasting. Quantum computing is known for its capability to tackle these challenges, showing many similarities to its applications in the domain of photovoltaic energy systems.

5.1 Wind Farm Layout Optimization Problem in Wind Farms

5.1.1 QCOP: Quadratic-Constrained Optimization Problem and QUBO: Quadratic Unconstrained Binary Optimization.

One of the optimization problems encountered in wind grids is the Wind Farm Layout Optimization (WFLO), which [22] aimed to solve. WFLO challenges arise due to wind patterns and wind turbine placement. The goal was to achieve the highest energy potential while considering proximity restrictions and wake-based interferences between turbines. Current solutions are often slow in providing optimal results. [22] proposed a Quadratic Unconstrained Binary Optimization (QUBO) model that can find solutions in seconds and a Quadratic-Constrained Optimization Problem (QCOP) model that finds optimal solutions over a longer period.

As mentioned in Section 4.2.2, the computational power of quantum computing algorithms can be used to solve complex optimization problems, such as QUBO for cable routing in photovoltaic energy systems. This computational power is equally beneficial in wind turbine applications.

Wind turbines are large, and grids can contain hundreds of them spread across large areas. Multiple factors determine the distance between each turbine, such as blade length and interference effects known as "wakes". This phenomenon occurs when nearby turbines receive less wind energy due to interferences with each other. Wind passing through the blades of front-standing turbines loses speed and creates turbulences that are caught by the rear-standing turbines, reducing efficiency in power generation. Optimization algorithms, such as those proposed in [22], are designed to solve this problem.

Senderovich et al. [22] proposed a combination of QUBO and QCOP algorithms that together achieved more efficient solutions than existing alternatives, which either focus on fast sub-optimal solutions or slow optimal solutions. These algorithms consider domain-specific parameters such as wind turbine height and blade size, wind direction and speed, terrain size, and configuration. They aim to find an optimal solution quickly, addressing the two main issues of turbine placement and wake effects.

The proposed QUBO and QCOP solutions were compared to Integer Linear Programming and a Quadratic Approximation Approach across 12 wind farm layout optimization frameworks. The results of the experiment in [22] showed that QCOP is highly efficient at solving WFLO problems optimally, QUBO can quickly find approximate solutions, and both QCOP and QUBO outperform existing alternatives in the majority of testing instances.

5.2 Numerical Anomalies Problem in Wind Farms

5.2.1 QPSO: Quantum Rotation Gate Particle Swarm Optimization.

Neural network architecture models play a crucial role in solving complex optimization problems through advanced optimization algorithms, such as the one presented in [7], which focused on parameter selection in numerical anomaly detection. He et al. [7] proposed a quantum-based Particle Swarm Optimization (PSO) algorithm under the name of Quantum Rotation Gate Particle Swarm Optimization (QPSO). This algorithm addresses the limitations of traditional PSO, which include slow convergence, premature convergence, and low performance in searching high-dimensional spaces. He et al. [7] emphasized the importance of automated parameter optimization for neural networks, as manual parameter selection is time-consuming. An automated process can enhance optimization algorithms, including those used for swarm intelligence.

Swarm intelligence algorithms, such as PSO, are nature-inspired and mimic the behaviour observed in groups of animals. This is similar to how the Quantum Chaotic Butterfly Optimization Algorithm (QCBOA) discussed in Section 4.2.3 replicates butterfly feeding behaviour. The fundamental principle of swarm intelligence algorithms is that particles move through the search space and learn from neighbouring particles to determine the optimal position.

QPSO leverages quantum rotation gates to optimize parameters. Quantum gates manipulate the quantum states of qubits and are essential in quantum circuits. In the experiments conducted by [7], QPSO was used to optimize the parameters of a neural network to improve numerical anomaly detection. The experiment compared QPSO against classical algorithms on a test dataset from an aerodynamic wind tunnel. The results demonstrated that QPSO outperformed established algorithms such as the Local Outlier Factor (LOF), Support Vector Machine (SVM), Isolation Forest (FOREST), and also the algorithm it is based on, the PSO.

5.3 Unit Commitment Problem in Wind Farms

5.3.1 MABRQIEA: Multipartite Adaptive Binary and Real coded Quantum-inspired Evolutionary Algorithm.

Combining various energy sources with various emission rates and power outputs can lead to improved overall performance. An example of such a combination is the integration of a thermal source with a wind source, as shown in the experiment of [24]. This experiment sought to lower both costs and emissions by using a thermal unit alongside a wind farm.

The primary focus of the experiment was to address the Unit Commitment Problem (UCP), which involves creating optimal schedules for powering on or off the grid to meet demand and cost requirements. Traditional approaches to UCP often rely on Evolutionary Algorithms, which inherently have some limitations with premature convergence, slow convergence, and the challenge of tuning parameters. To overcome these limitations and effectively solve the UCP, Singh et al. [24] proposed a Multipartite Adaptive Binary and Real coded Quantum-inspired Evolutionary Algorithm (MABRQIEA).

MABRQIEA operates on two entangled qubits for each solution vector, allowing it to balance the exploration and exploitation phases more efficiently. The experiment demonstrated that MABRQIEA effectively reduces costs and lowers emissions across multiple test scenarios. These scenarios include optimizing for costs only, emissions only, and a combination of both costs and emissions.

5.3.2 QI-ADP: Quantum-Inspired Approximate Dynamic Programming.

Qin and Wei [16] also attempted to solve the Unit Commitment Problem with a Quantum-Inspired Approximate Dynamic Programming algorithm (QI-ADP) in the context of wind power. The existing alternatives consist of scenario generation algorithms that are limited by reduced performances when multiple wind farms are simulated. The proposed algorithm in [16] presented a solution using Approximate Dynamic Programming (ADP). ADP is used to optimize complex problems but also suffers from limitations in balancing the exploitation and exploration phases. Therefore, the addition of quantum computing aims to overcome this aspect. The result of the paper was the QI-ADP algorithm, which can find sub-optimal solutions to large wind farms' unit commitment problems by optimizing the costs of running the energy system in a feasible time.

The experiments made by Qin and Wei [16] showed a relatively consistent reduction in costs of approximately 9% with almost linear increases in computing time relative to the increases in the system's scale.

5.4 Day-ahead Wind Speed Forecasting in Wind Farms

5.4.1 QRLSTMPSOWSF: Quantum Residual-LSTM PSO Wind Speed Forecast.

The ability to predict wind speed and power can greatly impact the strategy taken inside an electricity system to obtain improved efficiency, as described previously in Section 4 for solar farms. Hong and Santos [9] saw the opportunity to combine multiple methods previously mentioned in this paper to achieve accurate forecasting. The outcome was a quantum residual-LSTM that benefits from PSO optimization to forecast wind speeds 24 hours in advance. Hong and Santos [9] did not provide an abbreviation for their novelty. Therefore, we will refer to it throughout this paper as QRLSTMPSOWSF. Each prediction model has certain limitations that [9] tried to overcome with the QRLSTMPSOWSF. These limitations range from overfitting and computation cost to lost accuracy in long-term predictions and insufficient historical data. In the experiment, the data was initially collected from wind farms in multiple locations around Taiwan, China, South Korea, and the Philippines. PSO (Section 5.2.1) was used to optimize the parameters and the number of layers the residual-LSTM uses. The resulting configuration was forwarded to a QNN based on QAOA, where the proposed model was implemented, and the result was expected to forecast the next 24 hours of data accurately.

The algorithm was tested against traditional performance metrics such as R-squared (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Although the computational time was much higher than the alternatives, the proposed algorithm obtained promising results compared to classical options.

5.4.2 LSTM-QNN: Long Short-Term Memory - Quantum Neural Networks.

LSTM (Section 4.1.2) and QNN (Section 4.1.1) are two topics often discussed throughout this paper. Hong et al. [8] combined these topics to obtain an algorithm that can offer a 24-hour prediction similar to the QRLSTMPSOWSF mentioned above in Section 5.4.1. The LSTM is again used for its capability to find dependencies in long-term time series, and QNN is used for the advantages in computational speed by accessing quantum features such as superposition and entanglement.

By combining them, Hong et al. [8] aimed to overcome the limitations of the existing forecasting alternatives, such as computation complexity, unreliability on long-term predictions, and the need for large historical data. The proposed LSTM-QNN model works by using LSTM to obtain the results and forward those results to QNN for future learning. The data used in this experiment was collected similarly to [9] from wind farms in Taiwan, the Philippines, South Korea, and China, spanning approximately one year of data collection. The experiment in [8] was again similar to [9] in the comparison made against three performance metrics, namely R-squared (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The model seemed to output optimal results compared to classical alternatives against datasets that span the entire year and include factors such as the seasonality impact on wind speed.

6 QUANTUM COMPUTING IN WEATHER FORECAST FOR ENERGY SYSTEMS

Weather enormously impacts renewable energy sources such as solar and wind power. Its unpredictable nature depends on numerous atmospheric factors, making it hard to predict in advance to support energy systems with accurate data. The computational power that quantum computing has can be used to analyze big data and interpret it to offer precise weather forecasts that later can be utilized to improve and optimize processes in renewable energy systems such as solar and power farms [28]. Big data is essential in obtaining accurate predictions in numerous domains, such as energy, where the data can offer patterns and trends that help companies grow [11]. Such an effort to collect weather data and forecast for the benefit of energy systems comes with problems in processing and interpreting vast amounts of data.

To the best of the author's knowledge, and after extensive reviews of the available literature, there appear to be no relevant studies that tackle the general subject of the weather forecast in energy systems. As seen in the previous sections of this paper, algorithms such as LSTM exist to predict solar and wind power, which are factors that, among others, such as temperature, constitute weather. This indicates a noteworthy gap in the existing literature and requires further research into algorithms that use quantum computing to predict the weather in energy systems as a whole and not only in individual segments of the system.

A step in the direction of a general perspective of the importance of quantum computing in weather forecasting for energy systems was offered by [20, 21]. Safari and Ghavifekr [20, 21] expressed the importance of weather in the efficient production of energy in smart grids; therefore, being able to predict accurately can help create an optimal strategy for running the grid, although without an exact algorithm or method being mentioned besides QNN. In current energy production facilities, numerous methods of predicting meteorological factors such as temperature, wind, or precipitation exist,

and classical computers and algorithms are utilized to perform this analysis. The big data obtained from collecting the information to predict the weather keeps growing and requires more computing power to be able to make accurate forecasts. This requires quantum computing, in combination with other methods, such as machine learning, to create algorithms that can interpret and find useful patterns inside big data.
Another acknowledgement goes to [27], which proposed a framework that utilizes quantum computing methods to solve the complexity of forecasting weather. The strategy is to use algorithms such as QML, QNN, Quantum Support Vector Machines (QSVM), and Quantum Clustering (QC) in the existing system to improve the accuracy of the prediction and surpass the limitations of classical alternatives. The framework then continues with a data preprocessing phase and a quantum simulation of weather models. Although this paper did not contain an experiment and requires further study, it has the potential to represent a foundation for the development of new algorithms that can use this framework to guide their process, from data collection to weather prediction.

7 OTHER INNOVATIONS IN QUANTUM COMPUTING AND ENERGY SYSTEMS

Research has been conducted in the past for photovoltaic cells, wind turbines, and weather forecasting, often under the context of Smart Electrical Grids. In the field of photovoltaic cells, [25, 26] highlighted the ability of quantum dots to enhance solar energy conversion efficiency by capturing both visible light and infrared spectrum waves. This can potentially double the current conversion rate of solar panels and take the next step toward the third generation of photovoltaic cells.
Topology optimization in photovoltaic arrays using quantum machine learning algorithms was presented in [31]. This is essential for large grids with thousands of interconnected solar panels encountering shading issues, which reduces their power output [19]. [31] compared a classical neural network algorithm and a quantum neural network algorithm using different numbers of qubits to solve the topology reconfiguration problem. The results showed 95% accuracy for the classical neural network and 85% accuracy for the quantum neural network in the most accurate scenario using 4 qubits. Despite the lower accuracy, the research suggested that the quantum neural network could achieve results comparable to the classical neural network with proper adjustments.
In the segment of wind turbines, the computation power of quantum computers compared to classical computers was discussed by [5, 21] and deemed a million times faster and more efficient. Therefore, quantum computers can aid in designing new generations of wind turbines by utilizing quantum-based computational fluid dynamics calculations to enhance turbine performance in real-life scenarios. As described by [5, 20, 21], forecasting is a vital domain in energy systems, particularly in Weather Forecasting. Various algorithms developed for domains such as financial systems or genetic algorithms can be used to address this challenge. Improving prediction accuracy can be achieved with the help of neural networks, which, when combined with the properties of quantum computing, can analyze large amounts of data more quickly.

8 RESULTS SUMMARY AND FUTURE WORK

This paper aimed to conduct a semi-systematic literature review of algorithms and methods enhanced by quantum computing that can improve the performance of energy systems. The primary research question focused on identifying these algorithms and was broken down into three secondary questions in Section 2.1.
In Section 4, the answer to SQ1 was provided with a comprehensive list of algorithms addressing challenges such as solar energy forecasting, scenario generation, cable routing, and grid parameter optimization. The domain of quantum computing in photovoltaic systems appears to be the most extensively researched compared to wind-powered systems and weather forecasting. Although significant focus is on physical advancements and cost reduction for solar panels, numerous quantum computing algorithms demonstrate remarkable potential. However, gaps exist due to limited access to real quantum hardware, indicating the need for further research in this area. While energy forecasting, both short-term and long-term, is well-studied, more specific problems like scenario generation, cable routing, or solar array placements have received less attention, highlighting the need for more research and comparative algorithm testing.
In Section 5, the answer to SQ2 included another extensive list of algorithms that tackle challenges such as Wind Farm Layout Optimization (WFLO), Unit Commitment Problems (UCP), numerical anomaly detection, and day-ahead wind speed forecasting. Overlaps between solar and wind power algorithms were noted due to similarities in the intermittent nature of both energy sources. Quantum computing in wind turbine systems is less researched than in photovoltaic systems and more researched than weather forecasting. The focus remains on mechanical advancements and cost reductions for wind turbines. Despite the lower interest, many quantum computing algorithms show exceptional results. Gaps are observable due to limited access to real quantum hardware and a lack of real-life scenario testing. Future work should focus on developing algorithms specific to wind-powered systems to leverage their unique properties and address specific challenges, such as WFLO or UCP, from multiple perspectives for comparative algorithm testing.
Section 6 addressed SQ3, where a research gap was identified. Despite the importance of weather forecasting in optimizing both solar and wind farms, there is a lack of general research on this topic. Algorithms in Sections 4 and 5 use weather-specific elements like temperature, solar irradiance, and wind speed, but future research should focus on developing algorithms with a general view on weather forecasting, considering multiple factors that compose weather such as cloud coverage or precipitation, to benefit other industries.
Table 1 provides a summary of all three secondary questions that answer the main question. The table offers an overview of all the quantum computing algorithms and methods discussed in the paper, highlighting their abbreviations, usage, advantages, and limitations for a general view of the results.
Figure 1 presents a tree diagram of all the algorithms discussed in the paper, showing overlaps between domains. The diagram illustrates the shared elements among algorithms, such as QUBO being used in both solar and wind power, LSTM-QNN sharing elements

Table 1. Quantum Computing Algorithms in Energy Systems Summary

Algorithm	Usage	Advantages	Limitations
		Photovoltaic Systems	
QRNN	Forecasting solar energy production.	Better performance and faster convergence compared to classical methods.	Limited scalability due to fault-tolerant quantum hardware.
QLSTM	Short-term prediction of photovoltaic power generation.	Improved short-term and long-term forecasting performance.	Scalability challenges due to quantum hardware noise and errors.
QGAN	Scenario generation for regenerative power grids.	Advanced scenario generation with customizable parameters.	Limited scalability due to quantum circuit complexity and constraints.
QAOA	Optimization of regenerative energy systems.	Quantum principles outperform classical methods.	Sensitivity to quantum hardware affecting solution quality.
QUBO	Optimization of cable routing in photovoltaic arrays.	Fast optimal solutions for large grids compared to classical alternatives.	Scalability limited by the qubit number in quantum hardware.
QCBOA	Photovoltaic parameter optimization.	Outperforms classical methods in achieving global optima.	Mixed performance in certain benchmarks compared to classical methods.
		Wind Turbines Systems	
QCOP	Solves Wind Farm Layout Optimization (WFLO).	Finds optimal solutions under high runtime limits.	Performance affected by optimization software.
QUBO	Solves Wind Farm Layout Optimization (WFLO).	Finds optimal solutions quickly.	Mixed performance in certain benchmarks compared to classical methods.
QPSO	Neural network optimization for numerical anomaly detection.	Better than classical alternatives, including PSO.	Not extensively tested in complex scenarios or real-life applications.
MABRQIEA	Optimizes Unit Commitment Problem in Energy Systems.	Overcomes limitations of existing algorithms.	Limited testing in real-life environments.
QI-ADP	Solves Unit Commitment Problems in Energy Systems.	Finds sub-optimal solutions in large-scale applications.	Requires testing on real quantum hardware.
QRLSTMPSOWSF	Day-ahead wind speed forecasting.	Overcomes limitations of classical methods.	Requires longer testing time than alternatives.
LSTM-QNN	Day-ahead wind speed forecasting.	Overcomes limitations of classical methods.	Needs testing on quantum hardware with noise effects.

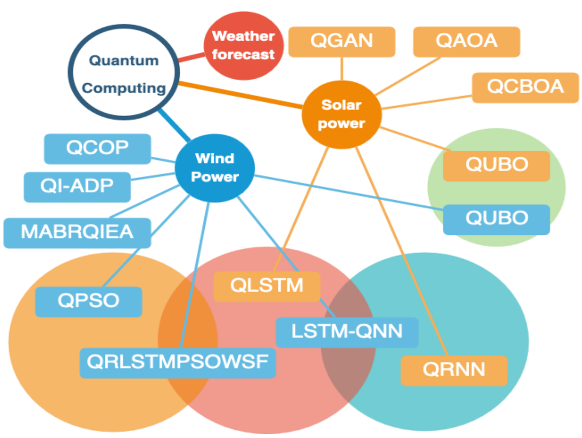

Fig. 1. Tree diagram visualization of the mentioned algorithms

with QRNN and QLSTM, and QRLSTMPSOWSF sharing elements with QLSTM and QPSO.

9 CONCLUSION

In conclusion, this paper has extensively researched the role of quantum computing in advancing energy systems, specifically photovoltaic and wind power technologies, and its influence on weather forecasting. The semi-systematic literature review highlighted remarkable advancements in quantum computing algorithms such as QUBO, QLSTM, QPSO, and QRNN. While this paper demonstrated that quantum algorithms generally outperform classical alternatives, it reveals challenges related to scalability and limitations in current quantum hardware. The domain of photovoltaic systems appeared to be the most extensively researched, with developments in energy forecasting, parameter optimization, scenario generation and cable routing. Wind power showed promising results despite being less researched, with advancements in solving challenges such as WFLO and UCP. A research gap was identified in the field of general weather forecasting, which is essential not only for optimizing solar and wind farms but also for other industries that are influenced by meteorological factors. Future research should focus on developing algorithms that provide a general perspective on weather forecasting, considering multiple factors such as precipitation and cloud coverage.

Ultimately, quantum computing has the potential to significantly impact the next generation of energy systems by enhancing efficiency, optimization, and revolutionizing power grids. Future research should aim to perform testing in real-life scenarios so that these algorithms can completely show their potential.

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A APPENDIX

During the preparation of this work, the author used Overleaf to format the paper, Draw.io for Figure 1, Grammarly and ChatGPT for grammar checking and text rephrasing. The prompts provided to Grammarly and ChatGPT and their contents were made by the author, the output representing only a grammatically correct, rephrased interpretation of the author's words. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.