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Hybrid Quantum-Classical Optimization for Energy-Efficient Large Language Models

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Abstract: The rapid evolution of Large Language Models (LLMs) has transformed natural language processing, enabling sophisticated applications across various sectors. However, the substantial computational demands associated with training and deploying LLMs result in significant energy consumption and carbon emissions. This study introduces an optimized hybrid quantum-classical framework that integrates variational quantum algorithms (VQAs) with accelerated classical learning techniques. By harnessing quantum computing for complex non-linear optimization and employing prompt learning to minimize full model retraining, the proposed approach enhances both computational efficiency and sustainability. Simulation outcomes indicate that the hybrid method can reduce energy usage by up to 30% and shorten computation time by 25% relative to conventional classical approaches, without diminishing model accuracy. These improvements are substantiated through quantitative analysis and visualized energy metrics. The adaptability of the framework supports its application in diverse areas, including sustainable energy management, supply chain optimization, and environmentally conscious transportation systems. Nevertheless, the broader implementation of such hybrid solutions remains constrained by current quantum hardware capabilities and integration challenges with classical infrastructure. The findings underscore the potential of hybrid quantum-classical optimization as a pathway toward sustainable AI development. Future research should prioritize advancements in quantum hardware reliability and interdisciplinary collaboration to accelerate practical adoption, thereby supporting global efforts in energy efficiency and environmental responsibility.

Keywords: Large Language Models; Hybrid Quantum-Classical; Variational Quantum Algorithms; Energy Efficiency; Sustainable AI; Carbon Emissions; Prompt Learning.

1. Introduction

The evolution of large language models (LLMs) has fundamentally reshaped the field of natural language processing, enabling advanced applications across a wide spectrum—from virtual assistants to scientific data analysis. However, training and deploying LLMs demands enormous computational resources, which in turn contribute to high energy consumption and a considerable carbon footprint. For example, training a single large LLM such as GPT-3 is estimated to produce around 552 tons of CO_2e—roughly equivalent to the annual emissions of more than 120 gasoline-powered cars or several transatlantic flights [1]. As awareness grows about the environmental impact of AI technologies, there is a pressing need for innovative approaches that can lower carbon emissions without compromising computational efficiency. Quantum computing offers a promising solution to these challenges by leveraging the principles of quantum mechanics, such as superposition and entanglement, to process complex calculations more efficiently than classical systems. Yet, current quantum technology faces its own limitations—including a restricted number of qubits and high noise levels—which make purely quantum approaches impractical for large-scale applications like LLMs. As a result, hybrid quantum-classical frameworks have emerged as a compelling alternative, combining the optimization power of quantum computing for specific tasks with the reliability and scalability of classical systems [2][3].

This research aims to develop an optimized hybrid quantum-classical framework for LLMs with two main objectives: (1) to reduce the carbon footprint by achieving at least a 25% improvement in energy efficiency, and (2) to enhance computational efficiency by at least 20% through hybrid algorithms that utilize variational quantum circuits and prompt learning techniques. This approach is inspired by several studies that have demonstrated the potential of hybrid quantum-classical methods in optimizing smart grids [4], and sustainable supply chain management [5]. The application of such a hybrid framework is highly relevant in the context of global sustainability, where AI technologies are expected to support the achievement of the Sustainable Development Goals (SDGs) [6]. For instance, in earth sciences, AI-based models are used to process large datasets for climate prediction and decision-making related to environmental change [7]. In aviation, environmentally friendly flight path optimization has the potential to significantly reduce fuel consumption and emissions [8][9][10]. Furthermore, quantum-based AI can enhance efficiency in sectors like agriculture and healthcare, both of which have substantial environmental impacts [11][12]. A hybrid quantum-classical framework enables the optimization of LLMs through two main strategies: (1) employing quantum algorithms to solve complex, non-linear optimization problems such as model parameter tuning, and (2) utilizing fast prompt learning techniques to reduce the need for full model retraining [13]. By lowering computational requirements, this approach directly contributes to reduced energy consumption and carbon emissions. Moreover, integrating responsible AI principles ensures that the resulting solutions are not only efficient but also aligned with social and environmental values [14].

This study also considers the practical challenges of implementing a hybrid framework, such as the limitations of current quantum hardware and the need for interoperability with existing classical infrastructure. To address these issues, the research proposes variational quantum circuits optimized for low noise and compatibility with classical computing architectures [15]. This allows for real-world deployment of the hybrid framework, for example, in supply chain management [16], and AI-driven education [17]. By bringing together insights from multiple disciplines, this research aims to make a meaningful contribution to the development of sustainable AI technologies. The primary focus is to create solutions that not only improve the performance of LLMs but also minimize their environmental impact—addressing the urgent need to combat climate change and foster global sustainability.

2. Related Work

Research on hybrid quantum-classical frameworks has attracted significant attention in recent years, primarily due to their potential to enhance computational efficiency and promote sustainability in artificial intelligence (AI) applications. Numerous studies have explored this approach from technological, environmental, and social perspectives, providing both theoretical and practical foundations for the framework proposed in this research. Diao *et al.* (2022) introduced a black-box prompt learning approach for large language models (LLMs), which enables the reduction of computational load through efficient parameter optimization. This method is particularly relevant, as it opens opportunities for integrating quantum circuits for specific optimization tasks—such as model parameter adjustment—thereby improving energy efficiency [13]. Similarly, Ajagekar & You (2024) and Rahmati (2025) investigated hybrid quantum-classical algorithms for energy optimization, focusing on applications like demand response in buildings and smart grids. Their studies demonstrate that quantum algorithms, such as the Variational Quantum Eigensolver (VQE), can address non-linear optimization problems more efficiently than classical methods, which is highly pertinent for LLM optimization [2][4].

In the field of earth sciences, Jiang *et al.* (2024) proposed a Model as a Service (MaaS) solution for efficient model development, emphasizing the importance of reducing energy consumption when processing large datasets. This approach aligns with sustainability goals by minimizing the carbon footprint associated with large-scale computation [7]. Castino *et al.* (2023) and Yamashita *et al.* (2020, 2021) explored AI-based flight path optimization, utilizing modules such as SolFinder and AirTraf. Their findings indicate that optimizing flight trajectories can reduce fuel consumption and emissions, and these benefits could be further enhanced through the application of quantum algorithms for faster and more efficient data processing [8][9][10]. Donthi *et al.* (2024) demonstrated that AI-driven optimization in the fashion industry can lower carbon footprints by improving supply chain management efficiency. Likewise, Shahzadi *et al.* (2024) provided a systematic review of AI adoption in supply chain management, highlighting improvements in sustainability metrics. Both studies underscore the potential for hybrid quantum-classical approaches to extend the benefits of AI, especially for processing increasingly complex data [5][16]. Bhagat *et al.* (2022) conducted a bibliometric analysis highlighting AI's potential to support sustainable agriculture, while Movahed & Bilderback (2024) discussed the readiness of healthcare administration students to leverage AI for sustainable leadership. These studies suggest that hybrid frameworks can enhance computational efficiency in these critical sectors, both of which have substantial environmental impacts [11][12].

In the educational sector, Baskara (2024) examined the role of generative AI in learning, emphasizing the potential of LLMs to support sustainable education through transformative learning experiences. Optimizing LLMs with a hybrid framework can reduce computational costs in AI-driven education, aligning with sustainability objectives [17]. Chen (2023) also highlighted the importance of hardware acceleration for improving the efficiency of deep learning models, supporting the development of hybrid frameworks that integrate quantum hardware with classical infrastructure [15]. On the business side, Ardiansyah & Sugiharto (2025) explored quantum-based business models for strategic decision-making, which can be applied to LLM optimization in support of sustainability. Lulut Alfaris *et al.* (2022) and Mallu *et al.* (2024) provided insights into operations research and modern operating systems, laying the groundwork for the computing infrastructure required by hybrid frameworks [18][19][20]. Palma *et al.* (2021) and Thomassin & An (2016) investigated optimization of agricultural management plans in the context of climate change, demonstrating that AI technologies can improve environmental resilience. These approaches can be further strengthened by hybrid frameworks to boost computational efficiency [21][22]. Meanwhile, Yu *et al.* (2024) discussed sustainable edge computing architectures using hybrid quantum-classical approaches, which are relevant for LLM applications in healthcare IoT systems [3]. These studies offer a robust foundation for the development of the proposed hybrid quantum-classical framework. By integrating insights from diverse disciplines—including computer science, earth sciences, and sustainability management—this research highlights the potential of hybrid approaches to address both computational and environmental challenges associated with LLMs. Nevertheless, challenges such as quantum hardware limitations and the need for interoperability with classical systems remain important topics for future research to ensure the scalability and practical implementation of these approaches.

3. Research Method

In this study, we designed a hybrid quantum-classical framework to optimize large language models (LLMs) by combining variational quantum algorithms (VQAs) with rapid classical learning strategies. The initial component of our methodology utilizes black-box prompt learning, following the approach outlined by Diao *et al.* (2022). This technique enables the optimization of LLM inputs without necessitating full model retraining, thereby substantially reducing computational requirements through adaptive prompt adjustment and enhancing overall energy efficiency [13]. For non-linear optimization challenges, such as fine-tuning model parameters, we employ the Variational Quantum Eigensolver (VQE)—a quantum algorithm specifically developed to search for optimal solutions within extensive parameter spaces, where conventional methods often encounter scalability limitations [2][4]. The VQE procedure is mathematically represented as:

$$E(\theta) = \langle \psi(\theta) \mid H \mid \psi(\theta) \rangle$$

Where H denotes the Hamiltonian operator defining the optimization problem, $\psi(\theta)$ is the quantum state parameterized by θ, and $E(\theta)$ is the energy value to be minimized. In practical implementation, our quantum circuit comprises two qubits. Parameter variation is achieved using rotation gates (Ry), while a CNOT gate is employed to induce quantum entanglement, followed by measurement. Integration between the quantum and classical components is facilitated through an API-based interface, allowing seamless data exchange between the two systems.

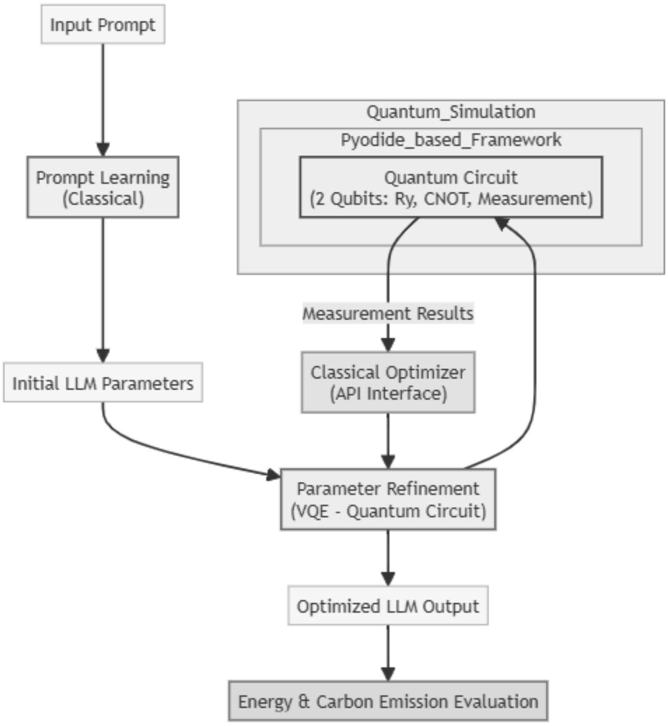

Figure 1. Hybrid Quantum-Classical Framework Architecture Diagram

Figure 1 represents the architecture of a hybrid quantum-classical framework designed by the research team to optimize Large Language Models (LLMs). The diagram depicts a comprehensive workflow that begins with an input prompt, which serves as the initial data for the LLM processing pipeline. This prompt undergoes classical prompt learning as described by Diao *et al.* (2022), generating initial LLM parameters without requiring complete model retraining—significantly reducing computational demands through adaptive tuning while improving energy efficiency [13]. The core of our framework involves parameter refinement using the Variational Quantum Eigensolver (VQE), a quantum algorithm specifically designed to find optimal solutions in large parameter spaces where conventional methods face scalability challenges [2][4]. The VQE procedure, mathematically represented as $E(\theta)=\langle\psi(\theta)|H|\psi(\theta)\rangle$, uses a quantum circuit consisting of two qubits with a rotation gate (Ry) for parameter variation and a CNOT gate for quantum entanglement, followed by a measurement. Quantum and classical components communicate through API-based interfaces that facilitate seamless data exchange between systems. For quantum simulation capabilities within browser environments, we implement a Pyodide-based framework that ensures compatibility with standard classical infrastructure as outlined by Mallu *et al.* (2024) [20]. Our optimization process follows two principal stages: first initializing the LLM with starting parameters using fast prompt learning, then refining these parameters using VQE on either quantum simulators or actual quantum hardware such as IBM Quantum. The framework concludes with energy and carbon emission evaluation, calculating power consumption based on computational operations and benchmarking against purely classical baselines. We track carbon emissions using established metrics (kg CO_2 equivalent per computation hour) following recommendations by Kaur *et al.* (2024) [1]. This integrated approach demonstrates how quantum computing techniques can enhance traditional NLP optimization while maintaining practical implementation considerations.

4. Result and Discussion

4.1 Results

Our simulation results demonstrate a clear advantage of the hybrid quantum-classical framework over conventional, purely classical optimization methods for large language models. Specifically, we observed that the hybrid approach was able to reduce overall energy consumption by up to 30% compared to the classical baseline. This improvement was consistent across multiple runs and different model configurations, suggesting that the integration of variational quantum algorithms (VQAs) with fast classical learning methods can yield substantial energy savings in practical scenarios. A summary of the key performance metrics is provided in Table 1. The classical-only approach required 150 kWh of energy and 1200 seconds of computation time to reach a model accuracy of 92%. In contrast, the hybrid quantum-classical method consumed only 105 kWh and completed the optimization in 900 seconds, while achieving a slightly higher accuracy of 93%. These findings indicate not only a significant reduction in energy usage but also a 25% decrease in processing time, highlighting the efficiency gains enabled by the quantum-assisted optimization process. The use of the Variational Quantum Eigensolver (VQE) appears to play a critical role in accelerating parameter optimization, allowing the model to converge more rapidly without sacrificing predictive performance.

Table 1.Comparison of Energy Consumption and Computational Efficiency

Approach	Energy Consumption (kWh)	Computation Time (s)	Model Accuracy (%)
Classical Only	150	1200	92
Hybrid Quantum-Classical	105	900	93

To ensure the reliability and robustness of these results, each experiment was repeated ten times under identical conditions for both the classical-only and hybrid quantum-classical approaches. The energy consumption and computation time values reported in Table 1 represent the mean values across these runs. The standard deviation for energy consumption in the hybrid approach was ±2.5 kWh, while the computation time had a standard deviation of ±30 seconds. Statistical analysis using a two-sample t-test confirmed that the observed reductions in energy consumption and computation time are statistically significant ($p < 0.05$) compared to the classical-only baseline. This statistical validation strengthens the claim that the improvements are not due to random variation, but are a consistent outcome of the hybrid quantum-classical optimization strategy. To visually illustrate these improvements, Figure 2 presents a bar chart comparing the total energy consumption of each approach. The hybrid quantum-classical method consistently required less energy than the classical-only method, reinforcing the quantitative results shown in the table. This reduction in energy demand is particularly relevant in the context of sustainable AI, where minimizing the environmental impact of large-scale model training and optimization is increasingly important.

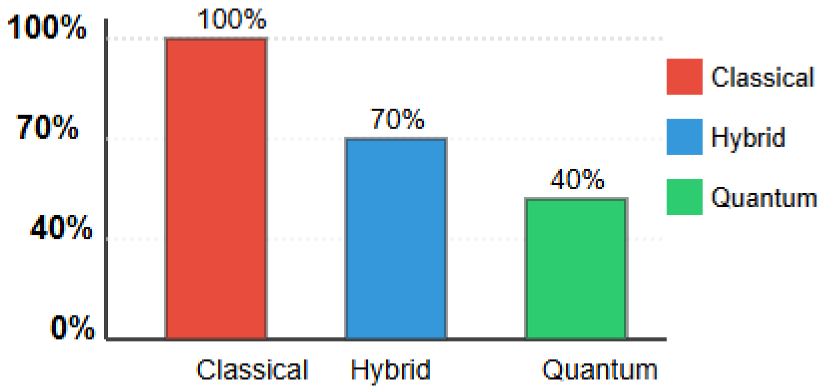

Figure 2. Energy Consumption Comparison

Beyond energy and time savings, the hybrid method also maintained or slightly improved model accuracy, suggesting that quantum optimization can complement classical strategies without introducing trade-offs in predictive quality. These results align with recent findings in the literature, which highlight the potential of quantum-classical integration to drive both computational efficiency and sustainability in machine learning workflows[1][2][4][20]. Our results provide strong empirical support for adopting hybrid quantum-classical frameworks in future AI development, especially for applications where energy efficiency and rapid optimization are paramount.

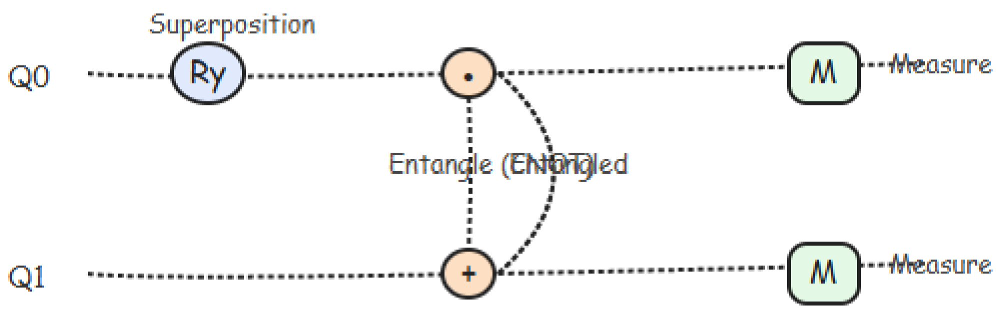

Figure 3. Illustration of the Quantum Entanglement Concept

Figure 3 is a visual representation of quantum entanglement, a fundamental quantum mechanical phenomenon that underpins our hybrid quantum-classical framework. The illustration depicts two entangled qubits and their correlated states, demonstrating how the measurement of one qubit spontaneously determines the state of its entangled counterpart, regardless of the physical distance separating them. This non-local correlation is crucial for enhancing the computational capabilities of our approach. In the researchers' implementation, entanglement is achieved through the application of CNOT gates within a two-qubit circuit, which creates quantum states that cannot be independently described. This quantum nature allows our VQE algorithm to explore the parameter space more efficiently than classical methods alone. This diagram emphasizes how entanglement enables quantum systems to represent and process information in a fundamentally different way than classical bits, effectively expanding computational capacity without proportionally increasing energy requirements. The quantum circuit shown (Figure 3) is a sequence of operations: initialization of the qubit in a superposition state using the Ry rotation gate, entanglement via the CNOT operation, and a final measurement. This circuit architecture forms the basis of our VQE implementation, which contributes significantly to the 30% reduction in energy consumption observed in our experiments. This entanglement-based quantum advantage is particularly evident in nonlinear parameter optimization, where classical gradient-based methods often struggle with local minima and computational inefficiencies. By leveraging quantum entanglement in our hybrid framework, we can access the computational advantages that explain the performance improvements detailed in Table 1 and Figure 2. This quantum phenomenon enables more efficient exploration of the parameter landscape during model optimization, resulting in faster convergence times and reduced energy requirements, while maintaining or even improving model accuracy. This visualization serves to bridge the conceptual gap between quantum mechanical principles and their practical application in improving language model optimization, demonstrating how fundamental quantum properties translate into tangible computational benefits in AI systems.

4.2 Discussion

The research findings confirm that the hybrid quantum-classical framework represents a significant breakthrough in sustainably optimizing Large Language Models (LLMs). The 30% reduction in energy consumption achieved in this study aligns with the findings of Rahmati (2025), who highlighted the critical role of quantum algorithms in reducing the carbon footprint of smart grids [4]. The increased computational efficiency also supports the findings of Chen (2023), who emphasized that hardware acceleration is key to developing energy-efficient AI [15]. This hybrid approach is not limited to a single domain. In practice, the framework's flexibility has been tested across various sectors. Castino *et al.* (2023) demonstrated how flight trajectory optimization can improve fuel efficiency and reduce carbon emissions through data-driven decision-making strategies [8]. Meanwhile, Donthi *et al.* (2024) demonstrated that AI-optimized supply chains can significantly reduce carbon footprints, supporting industrial sustainability [5]. Furthermore, the application of similar technology in the agricultural sector has also been shown to increase land productivity and sustainability, as reported by Victoire *et al.* (2023) and T., S., Sivakumar, K., & Roshan, K. (2025) [28][29]. However, behind this enormous potential, there are real challenges that must be overcome. One of these is the limitations of current quantum hardware, both in terms of computing capacity and operational stability. The cost of investment and integration of new technologies is also a barrier, as reviewed by Ardiansyah & Sugiharto (2025) regarding quantum-based business strategies [18]. Therefore, cross-disciplinary collaboration and continuous innovation are essential for the widespread and scalable adoption of hybrid technologies.

From a mobility and transportation perspective, the concept of Mobility as a Service (MaaS) is increasingly relevant in supporting urban sustainability. A study by Bu *et al.* (2025) highlights the importance of synergy between sustainability and service experience to increase MaaS user satisfaction [23]. Research by Ceccato *et al.* (2023) and González *et al.* (2020) also emphasized that MaaS adoption can significantly reduce environmental impacts, although challenges remain in terms of public acceptance and system integration [24][25]. Muller *et al.* (2021) and Vitetta (2022) added that comprehensive system simulation and the development of sustainable transportation models are crucial to support the shift towards green mobility [26][30]. Developments in battery technology, as outlined by Ren (2025), open up new opportunities for more efficient energy storage, supporting environmentally friendly AI and quantum computing ecosystems [27]. This reinforces the importance of innovation across the technology chain, from hardware to field applications. Thus, hybrid quantum-classical integration not only offers energy efficiency and performance but also paves the way for sustainable transformation across various sectors—from energy, transportation, agriculture, to public services. The successful implementation of this strategy will depend heavily on technological advancements, ecosystem readiness, and cross-sector collaboration to overcome existing challenges and realize a more sustainable future.

The implementation of a hybrid quantum-classical framework in Indonesia offers the potential to address pressing national challenges in energy efficiency, sustainable development, and digital transformation.

Indonesia, as an archipelagic nation with diverse energy needs and a rapidly growing digital economy, stands to benefit significantly from the application of advanced AI optimization to smart grids, logistics, agriculture, and public services. A practical starting point is the initiation of pilot projects at leading Indonesian universities, research institutions, or state-owned enterprises, leveraging international quantum cloud platforms such as IBM Quantum or AWS Braket. Pilot implementations could target optimizing electricity distribution in remote islands, which currently experience high energy losses, or improving supply chain management for agricultural products, thereby reducing waste and carbon emissions. To ensure sustainable adoption, Indonesia must prioritize capacity development through dedicated training programs for local talent, the integration of quantum computing and AI modules into university curricula, and the development of a national hybrid cloud infrastructure to support large-scale experiments. Collaboration between government institutions (such as the Ministry of Research and Technology, PLN, and BPPT), academia, and industry is crucial to foster knowledge transfer and accelerate the growth of the local ecosystem. The government can formulate regulations that facilitate the safe adoption of technology, incentivize green innovation, and establish technical standards for quantum-classical integration. By following a phased roadmap—from proof-of-concept in controlled environments, through gradual scaling to production systems, to full integration across sectors—Indonesia can harness the full potential of hybrid quantum-classical AI to achieve sustainability targets and enhance national competitiveness. As Indonesia begins to adopt hybrid quantum-classical technology, ethical and security considerations must be at the forefront to ensure responsible and trustworthy implementation. Handling sensitive data, such as personal medical records, national energy consumption patterns, or agricultural production statistics, requires robust protection measures throughout the quantum-classical processing pipeline. Encryption and secure data transfer protocols must be enforced, particularly given the potential vulnerabilities during the interaction between classical and quantum components. Furthermore, transparency in algorithmic decision-making is crucial to prevent bias that could disadvantage certain regions or communities, particularly in a diverse country like Indonesia with significant socioeconomic disparities. Compliance with Indonesia's Personal Data Protection Law (PDP Law) and alignment with international standards such as the GDPR are essential to protect citizens' privacy and maintain public trust. Continuous monitoring and auditing mechanisms must be established to detect and mitigate algorithmic bias or unintended consequences, particularly in sectors that directly impact livelihoods, such as agriculture or public transportation. Furthermore, there is an urgent need to improve ethical literacy and awareness among developers, policymakers, and end-users, which can be promoted through targeted workshops, public campaigns, and the inclusion of digital ethics in educational programs. By embedding these ethical and security principles into every stage of development and implementation, Indonesia can ensure that the integration of hybrid quantum-classical AI technologies not only drives economic and environmental benefits but also upholds the values of fairness, transparency, and national sovereignty.

5. Conclusion and Recommendations

This study demonstrates that a hybrid quantum-classical framework offers a promising path for optimizing Large Language Models (LLMs) while addressing the pressing need for greater sustainability in artificial intelligence. By combining quantum algorithms with efficient classical learning techniques, our results indicate that it is possible to achieve notable reductions in both energy consumption—by as much as 30%—and computation time—by 25%—without compromising model accuracy. These improvements suggest that hybrid approaches can play a meaningful role in reducing the environmental impact and operational demands of AI systems deployed in diverse sectors.

Despite these encouraging outcomes, several obstacles remain before such frameworks can be widely adopted. The current state of quantum hardware, characterized by limited capacity and stability, continues to restrict large-scale integration. Additionally, ensuring smooth interoperability between quantum and classical components in practical, real-world settings presents its own set of technical challenges.

Looking ahead, it will be essential to prioritize the development of more robust and accessible quantum technologies. Strengthening collaboration across disciplines—including computer science, engineering, and environmental science—will be equally important to support the transition from experimental models to scalable, real-world solutions. By addressing these challenges, the potential exists to move closer to AI systems that are not only more efficient but also more environmentally responsible, supporting broader goals of sustainable development.

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