A Quantum Inspired Optimization Framework for Improving Energy Efficiency in Industry 4.0 Steel Manufacturing Systems

S.Ahilesh Aravind [a] , PK Sudhakar [b].

a. Founder and CEO ,AHIL Pvt.Ltd ,Chennai , ahilesharavinds@gmail.com.

b. Assistant professor ,Rajalakshmi institute of technology, Autonomous ,Poonamallee , sudhakarpk_susila@yahoo.com.

ARTICLE INFO

Dataset Link: https://github.com/Ahilesharavind/Steel-Manufacturing-dataset/blob/main/Steel_industry_data.csv

Keywords : Quantum Inspired Optimization, Energy Efficiency Improvement, Industry 4.0, Constrained Energy Optimization, Smart Manufacturing, Industrial Energy Management, Energy–Emission Reduction.

ABSTRACT

Steel manufacturing is inherently energy intensive, making energy efficiency a key priority for reducing production costs and environmental impacts. The integration of Industry 4.0 technologies has enabled data driven optimization however, conventional optimization methods often struggle with nonlinear energy behavior and complex operational constraints. This study proposes a quantum inspired optimization framework that formulates energy reduction as a constrained decision problem and efficiently explores feasible operating states without the need for quantum hardware. Comparative results using real industrial data indicate that while classical optimization achieves a 10% energy reduction, the proposed approach delivers a 21.09% reduction under a minimum operating constraint of 0.6. Sensitivity analysis confirms the robustness and practical applicability of the framework, highlighting its potential as a scalable solution for sustainable energy management in smart steel manufacturing system

1. Introduction

The steel industry is a cornerstone of global industrial development, providing essential materials for infrastructure, transportation, construction, and energy systems [1]. Despite its economic importance, steel manufacturing is recognized as one of the most energy intensive industrial activities [2], consuming large amounts of electrical and thermal energy across multiple interconnected production stages. Rising energy costs, increasing environmental regulations, and global commitments to carbon reduction have intensified the need for efficient energy management strategies within steel production systems [3][4].

In recent years, the emergence of Industry 4.0 has significantly transformed manufacturing environments, including steel plants [5]. Advanced sensing technologies, industrial Internet of Things (IIoT) platforms [6], and cyber physical systems enable continuous monitoring of operational parameters such as energy consumption, equipment performance, and emission levels [7]. While this digital transformation provides unprecedented access to high resolution production data, converting such data into actionable energy optimization decisions remains a challenging task [8]. Conventional energy management systems often rely on predefined rules or linear optimization techniques that may fail to capture the complex, nonlinear interactions inherent in modern steel manufacturing processes.

Classical optimization approaches, including rule based control, proportional energy scaling, and deterministic scheduling methods, have been widely adopted in industrial energy management [9]. Although these methods offer modest improvements in efficiency, their effectiveness is often limited by local optimality [10], simplified assumptions, and an inability to adapt dynamically to changing operating conditions [11]. As steel manufacturing systems become increasingly complex and data-driven, there is a growing demand for advanced optimization techniques capable of handling large-scale decision spaces under realistic operational constraints.

Recent advances in computational intelligence have introduced quantum inspired optimization methods as a promising alternative for solving complex industrial optimization problems [12]. These approaches draw conceptual inspiration from quantum phenomena such as probabilistic state transitions and tunneling effects, enabling more effective exploration of large and rugged solution spaces [13]. Importantly, quantum inspired methods do not require access to quantum hardware and can be implemented on classical computing platforms, making them suitable for near term industrial deployment [14]. Their potential for addressing constrained energy optimization problems in manufacturing environments has gained increasing attention, yet practical applications within steel manufacturing remain limited [15].

This study aims to bridge this gap by proposing a quantum inspired optimization framework tailored to energy consumption reduction in steel manufacturing systems operating under Industry 4.0 conditions [16]. The proposed framework formulates energy optimization as a constrained decision problem, explicitly incorporating minimum operational limits to ensure production safety and system stability [17]. A comprehensive comparative analysis is conducted between baseline operation, classical optimization, and the proposed quantum inspired approach using real industrial energy consumption data [18].

The contributions of this work are threefold. First, it presents a realistic and industry oriented formulation of energy optimization that aligns with practical steel manufacturing constraints. Second, it demonstrates the effectiveness of quantum inspired optimization in achieving significantly higher energy savings compared to conventional methods. Third, it validates the robustness and feasibility of the proposed approach through sensitivity analysis and convergence evaluation. The results show that the quantum inspired framework achieves substantial energy reduction while maintaining operational feasibility, highlighting its potential as a practical decision support tool for sustainable steel manufacturing.

The remainder of this paper is organized as follows. Section 2 reviews related work on energy optimization and quantum inspired methods in manufacturing. Section 3 presents the mathematical formulation of the optimization problem. Section 4 describes the proposed methodology and implementation. Section 5 discusses the experimental results and analysis. Section 6 outlines managerial implications and limitations, and Section 7 concludes the paper with directions for future research.

2. Related Works

Energy optimization in steel manufacturing has been an active area of research due to the sector's high energy intensity and environmental impact. Early studies primarily focused on improving individual process units such as furnaces, rolling mills, and auxiliary systems through equipment level efficiency enhancements and waste heat recovery techniques [19]. While these approaches achieved incremental improvements, they often lacked a system wide perspective and were difficult to adapt to varying production conditions [20].

With the advancement of industrial automation, classical optimization techniques began to gain prominence in energy management applications. Linear programming, rule based scheduling, and heuristic optimization methods have been widely employed to reduce energy consumption by adjusting production schedules and operating parameters [21]. Although these methods are relatively easy to implement, their performance is typically constrained by simplified assumptions, fixed decision rules, and limited capability to handle nonlinear interactions among process variables. As a result, classical approaches often converge to locally optimal solutions that may not represent the most energy efficient operating state for complex manufacturing systems [22].

The emergence of Industry 4.0 has introduced new opportunities for data driven energy optimization [23]. The integration of sensors, Industrial Internet of Things (IIoT) platforms, and cyber physical systems enables continuous monitoring of energy usage, equipment behavior, and emission levels. Recent studies have explored the use of machine learning models and advanced analytics to predict energy consumption and support decision making in manufacturing environments [24]. While predictive models improve visibility and forecasting accuracy, they are often combined with conventional optimization techniques that may struggle to scale effectively in high dimensional decision spaces.

In parallel, advances in computational intelligence have led to increased interest in metaheuristic and nature inspired optimization methods for industrial applications [25]. Techniques such as genetic algorithms, particle swarm optimization, and simulated annealing have been applied to manufacturing energy optimization problems, demonstrating improved performance over purely deterministic methods [26]. However, these approaches can suffer from premature convergence and sensitivity to parameter tuning, particularly when applied to large scale, constrained industrial datasets.

More recently, quantum inspired optimization methods have emerged as a promising alternative for solving complex optimization problems [27]. These methods are conceptually inspired by quantum phenomena, such as probabilistic state exploration and tunneling effects, which enable efficient traversal of complex solution landscapes. Unlike true quantum algorithms, quantum inspired techniques are designed to operate on classical hardware, making them accessible for practical industrial use. Prior research has demonstrated their effectiveness in combinatorial optimization, scheduling, and resource allocation problems, but applications in energy intensive manufacturing sectors remain limited [28].

Within the context of steel manufacturing, only a small number of studies have explored quantum inspired or hybrid optimization frameworks, and most existing work lacks a comprehensive comparison with classical optimization baselines under realistic operational constraints [29][30]. Additionally, sensitivity analysis and robustness evaluation are often overlooked, limiting the industrial applicability of reported results. These gaps highlight the need for a systematic investigation of quantum inspired optimization methods tailored to the operational realities of Industry 4.0 enabled steel manufacturing systems.

This study builds upon existing research by introducing a constrained quantum inspired optimization framework specifically designed for energy consumption reduction in steel manufacturing. By incorporating baseline and classical optimization comparisons, along with sensitivity and convergence analyses, the proposed approach provides a more realistic and comprehensive evaluation of quantum inspired techniques for industrial energy management.

3. Mathematical Formulation of the Energy Optimization Problem

Modern steel manufacturing systems operating under Industry 4.0 conditions generate continuous streams of operational data, enabling fine grained control of energy usage. To systematically reduce energy consumption while preserving operational feasibility, the energy optimization problem is formulated using a constrained decision making framework.

3.1 Energy Consumption Model

Steel manufacturing processes operate continuously and involve multiple energy consuming subsystems such as furnaces, rolling mills, and auxiliary equipment. Under Industry 4.0 environments, energy usage is monitored in real time through smart meters and sensor networks, allowing energy consumption to be quantified at fine temporal resolutions.

Let the production system be observed over N discrete operating intervals, indexed by

$i = 1, 2, 3 .... N$

Each interval corresponds to a fixed duration during which electrical energy consumption is recorded.

Let

$$E_i \in R^+ \quad (1)$$

denote the baseline electrical energy consumption (in kWh) measured during interval i. These baseline values represent the actual energy demand of the steel manufacturing system under normal operating conditions without any optimization or control intervention.

To enable controllable energy reduction while maintaining operational feasibility, the model introduces an operational adjustment factor x_i applied to each interval. The adjusted energy consumption at interval iii is expressed as:

$$\tilde{E}_i = x_i E_i \quad (2)$$

where:

- $\tilde{E}_i$ represents the optimized energy consumption,
- x_i is a dimensionless scaling factor that reflects controlled modification of system operation.

The scaling factor is bounded to ensure industrial feasibility:

$$x_i \in (\alpha, 1) \quad (3)$$

where α denotes the minimum allowable operating level required to preserve equipment safety, production continuity, and product quality.

This modeling approach captures the dynamic nature of energy consumption in steel manufacturing by allowing energy adjustments to vary across operating intervals. Unlike uniform reduction models, it enables the optimization framework to selectively target inefficient operating periods while preserving essential production activities.

3.2 Objective Function

The primary goal of the proposed optimization framework is to minimize the total electrical energy consumption of the steel manufacturing system while maintaining feasible and stable operation. Unlike traditional approaches that apply uniform or fixed energy reduction strategies, the objective function is designed to enable interval specific energy adjustment, allowing the model to focus on periods of inefficiency.

Let E_i denote the baseline energy consumption at operating interval i, and let x_i represent the operational scaling factor defined in Section 3.1. The optimized energy consumption at each interval is given by:

$$E_i = x_i \cdot E_i$$

The total optimized energy consumption over the complete operating horizon is then expressed as:

$$\frac{min}{x} \ \mathrm{F(x)} = \sum_{i=1}^{N} x_i \cdot E_i \qquad (4)$$

where:

- $X = (x_1 x_2 x_3, \ldots, x_N)$ (5) is the vector of decision variables,
- N represents the total number of operating intervals.

This formulation allows the optimization process to dynamically allocate energy reductions across different intervals instead of enforcing uniform reductions. As a result, higher energy savings can be achieved by prioritizing intervals with excessive or inefficient energy usage, while critical production periods remain largely unaffected.

The objective function is linear with respect to the decision variables, which ensures computational tractability, while the complexity of the optimization problem arises from the high dimensionality of the decision space and the imposed operational constraints. This structure makes the problem particularly suitable for quantum inspired probabilistic optimization techniques, which are capable of efficiently exploring large feasible regions and identifying energy efficient operating configurations.

3.3 Operational Constraints

Energy optimization in steel manufacturing must respect strict operational limits to ensure system safety, production continuity, and product quality. Therefore, the optimization problem is subject to a set of practical constraints that reflect real world industrial operating conditions.

3.3.1 Minimum Operating Constraint

Each operating interval is constrained by a minimum allowable operating level to prevent unsafe or unstable system behavior. This constraint is imposed on the decision variable xix_ixi as follows:

$$\alpha \le x_i \le 1 \,, \quad \forall\, i \qquad (6)$$

where:

- x_i is the operational scaling factor at interval i,
- α represents the minimum feasible operating threshold,
- $x_i = 1$ corresponds to full capacity operation.

The lower bound α ensures that critical equipment such as furnaces, motors, and rolling units do not operate below safe limits that could lead to thermal stress, mechanical damage, or production instability.

3.3.2 Industrial Feasibility Constraints

Steel manufacturing systems are designed for continuous and stable operation. Sudden or excessive reductions in energy usage may disrupt production flow or affect product quality. To account for this, the model enforces bounded and smooth energy adjustments across operating intervals, ensuring that optimized operating states remain industrially feasible.

These feasibility considerations restrict the optimization process to solutions that can be realistically implemented using existing control infrastructure without requiring structural changes to the plant.

3.3.3 Sensitivity Based Constraint Levels

To evaluate the robustness of the optimization framework under varying industrial conditions, multiple minimum operating thresholds are considered:

$$\alpha \in (0.6, 0.7, 0.8) \qquad (7)$$

Lower values of α permit greater flexibility in energy reduction but impose tighter feasibility requirements, while higher values represent more conservative operating policies. This sensitivity analysis enables assessment of the trade off between achievable energy savings and operational strictness.

3.3.4 Constraint Interpretation

The imposed constraints transform the energy optimization problem into a constrained decision making task, where energy efficiency improvements must coexist with operational reliability. By explicitly incorporating these constraints into the formulation, the proposed framework ensures that all optimized solutions are both energy efficient and practically deployable in real steel manufacturing environments.

3.4 Quantum Inspired Optimization Strategy

The formulated energy optimization problem is characterized by a high dimensional decision space with strict operational constraints. Although the objective function is linear, the presence of interval specific decision variables and feasibility limits creates a complex solution landscape in which classical deterministic optimization methods may converge to suboptimal solutions. To address this challenge, a quantum inspired optimization strategy is adopted.

The proposed strategy is inspired by principles commonly associated with quantum annealing, particularly probabilistic state exploration and the ability to escape local minima. Unlike conventional optimization techniques that follow a fixed improvement path, the quantum inspired approach allows controlled exploration of multiple feasible operating configurations, increasing the likelihood of identifying globally efficient energy states.

Let

$$x = (x_1 x_2 x_3, \ldots, x_N) \qquad (8)$$

represent the decision vector containing operational scaling factors for all intervals. The optimization process begins with an initial feasible solution that satisfies the operational constraints defined in Section 3.3. At each iteration, a candidate solution is generated by introducing stochastic perturbations to the current decision vector while preserving feasibility bounds.

The acceptance of a new candidate solution follows a probabilistic rule governed by a temperature-like control parameter. Solutions that yield lower total energy consumption are always accepted, while higher energy solutions may be accepted with a probability that decreases as the optimization progresses. This mechanism enables the algorithm to explore the solution space more broadly during early iterations and gradually focus on high quality solutions as convergence is approached.

The temperature parameter is gradually reduced according to a predefined schedule, which balances exploration and exploitation throughout the optimization process. This annealing-like behavior allows the algorithm to avoid premature convergence and improves robustness in large scale industrial datasets.

Importantly, the optimization strategy is implemented entirely on classical computing hardware and does not rely on quantum processors. The term *quantum-inspired* reflects the conceptual influence of quantum optimization principles rather than the use of actual quantum computation. As a result, the proposed approach is computationally practical and readily deployable within existing Industry 4.0 decision support infrastructures.

3.5 Solution Procedure and Computational Considerations

The solution of the proposed energy optimization problem follows an iterative, constraint aware procedure designed to ensure convergence toward energy efficient and industrially feasible operating states. The quantum inspired optimization strategy operates on the decision vector x by repeatedly evaluating and updating candidate solutions until convergence criteria are satisfied.

3.5.1 Solution Procedure

The optimization process proceeds through the following steps:

1. **Initialization**
   A feasible initial solution vector $x^{(0)}$ is generated such that all decision variables satisfy the operational constraints defined in Section 3.3.

2. **Candidate Generation**
   At each iteration, a new candidate solution is produced by applying stochastic perturbations to the current solution. These perturbations are carefully bound to ensure feasibility with respect to minimum operating constraints.

3. **Energy Evaluation**
   The objective function defined in Section 3.2 is evaluated for the candidate solution to compute the resulting total energy consumption.

4. **Probabilistic Acceptance**
   If the candidate solution yields lower energy consumption, it is accepted. Otherwise, it may still be accepted with a probability governed by a temperature dependent acceptance rule, allowing the algorithm to escape local optima.

5. **Annealing Schedule**
   The temperature parameter is gradually reduced over iterations, shifting the optimization behavior from exploration to exploitation.

6. **Termination**
   The algorithm terminates when a predefined number of iterations is reached or when changes in the objective function become negligible.

This procedure ensures a balanced search of the solution space while maintaining strict adherence to industrial feasibility constraints.

3.5.2 Computational Complexity

Let N denote the number of operating intervals and I the total number of optimization iterations. The computational complexity of the proposed approach is approximately:

$$O(N \times I) \qquad (9)$$

This linear scalability with respect to data size makes the approach suitable for large industrial datasets generated by Industry 4.0 monitoring systems. Since the algorithm relies on simple arithmetic operations and probabilistic decisions, it can be executed efficiently on standard computing platforms without specialized hardware.

3.5.3 Practical Implementation Considerations

The proposed solution procedure is designed for seamless integration into existing industrial energy management systems. It operates on historical or near real-time data and can be embedded within decision support tools to provide actionable energy optimization recommendations. The use of a quantum inspired strategy does not introduce additional computational overhead compared to many metaheuristic approaches, while offering improved exploration capability and robustness.

3.5.4 Industrial Relevance

By combining computational efficiency with realistic operational constraints, the solution procedure ensures that optimized energy strategies are not only theoretically optimal but also practically deployable. This makes the proposed framework particularly suitable for Industry 4.0 enabled steel manufacturing environments where real time decision support and scalability are essential.

3.6 Summary of the Optimization Framework

This section has presented a comprehensive mathematical formulation of the energy optimization problem for steel manufacturing systems operating under Industry 4.0 conditions. The formulation integrates real time energy consumption data with operational decision variables to construct a constrained optimization model that reflects practical industrial requirements.

The energy consumption model establishes a direct relationship between baseline energy usage and controllable operational scaling factors, enabling interval specific energy adjustment. The objective function is designed to minimize total energy consumption across the operating horizon, while operational constraints ensure feasibility, safety, and production continuity. By incorporating minimum operating thresholds, the formulation explicitly balances energy efficiency with industrial reliability.

To solve the resulting high dimensional and constrained optimization problem, a quantum inspired optimization strategy is adopted. The approach employs probabilistic state exploration and annealing based control mechanisms to efficiently navigate complex solution spaces and reduce the risk of convergence to suboptimal operating states. Importantly, the strategy is implemented entirely on classical computing infrastructure, making it suitable for real world industrial deployment.

The solution procedure and computational considerations demonstrate that the proposed framework scales efficiently with large Industry 4.0 datasets and can be integrated into existing energy management and decision support systems. Together, these components form a unified optimization framework that is both theoretically sound and practically applicable.

This mathematical foundation serves as the basis for the experimental evaluation presented in the subsequent sections, where the effectiveness, robustness, and industrial relevance of the proposed quantum inspired optimization approach are validated using real steel manufacturing data.

4. Methodology

This section describes the overall methodology adopted to develop and evaluate the proposed quantum inspired energy optimization framework for steel manufacturing systems operating under Industry 4.0 conditions. The methodology integrates industrial data acquisition, preprocessing, optimization modeling, and performance evaluation in a structured and reproducible manner.

4.1 Overall Framework

The proposed methodology follows a structured, data driven framework designed to optimize energy consumption in steel manufacturing systems operating under Industry 4.0 conditions. The framework integrates industrial data acquisition, benchmark modeling, quantum inspired optimization, and performance evaluation into a unified decision support process.

The overall framework begins with the collection of high resolution operational data from Industry 4.0 monitoring systems, including energy consumption, reactive power indicators, and emission related variables. This data is then preprocessed to ensure consistency, reliability, and numerical stability prior to optimization. Clean and structured data form the foundation for all subsequent analytical steps.

To ensure a fair and transparent evaluation, two benchmark models are established. The baseline model represents the actual operating condition of the steel manufacturing system without any optimization, while the classical optimization model reflects conventional energy management practices based on uniform or rule based energy reduction. These benchmarks provide reference points against which the performance of the proposed approach is assessed.

The core component of the framework is the quantum inspired optimization engine. This engine operates on the constrained mathematical formulation described in Section 3 and dynamically adjusts operational scaling factors across time intervals. By incorporating probabilistic exploration mechanisms and feasibility constraints, the optimization process identifies energy efficient operating configurations that remain industrially viable.

Finally, the optimized solutions are evaluated using multiple performance metrics, including total energy consumption, percentage energy reduction, convergence behavior, and sensitivity to operational constraints. The results are then translated into actionable insights that can support energy efficient decision making in real industrial environments.The overall methodological framework adopted in this study is illustrated in **Fig. 1**.

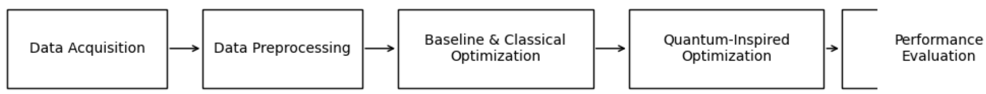

Figure 1. *Overall Methodological Framework*

4.2 Data Acquisition and Preprocessing

Energy optimization in steel manufacturing requires reliable and high resolution operational data that accurately represent real production conditions. In this study, data are obtained from Industry 4.0 monitoring systems deployed within a steel manufacturing environment. These systems continuously record electrical energy consumption along with related operational variables, enabling detailed analysis at fine temporal intervals.

The collected dataset includes time stamped measurements of electrical energy usage, reactive power indicators, and emission related variables. Such data provide insight into both active energy demand and auxiliary factors that influence overall system efficiency. The use of real industrial data ensures that the proposed optimization framework is evaluated under practical operating conditions rather than simulated assumptions.

Prior to optimization, the raw data undergo a series of preprocessing steps to ensure quality and numerical stability. First, incomplete or inconsistent records are identified and removed to prevent distortion of optimization outcomes. Second, relevant energy related features are selected to focus the analysis on variables that directly impact energy consumption. This step reduces noise and improves computational efficiency.

To avoid scale related bias during optimization, the selected variables are normalized using standard scaling techniques. Normalization ensures that all input variables contribute proportionately to the optimization process and improves convergence behavior of the quantum inspired algorithm. In addition, basic statistical analysis is performed to verify the distribution, range, and variability of the data, confirming its suitability for energy optimization analysis.

Through these preprocessing steps, the dataset is transformed into a clean, structured, and reliable input for subsequent baseline evaluation, classical optimization, and quantum inspired optimization. This data preparation process plays a critical role in ensuring that the optimization results are both accurate and representative of real steel manufacturing operations.

4.3 Baseline and Classical Optimization Models

To objectively evaluate the effectiveness of the proposed quantum inspired optimization framework, two reference models are established a baseline model and a classical optimization model. These models serve as benchmarks that reflect commonly observed operating practices in industrial energy management.

The baseline model represents the actual operating condition of the steel manufacturing system without any optimization or control intervention. In this case, total energy consumption is calculated directly from the measured industrial data. The baseline provides a realistic reference that captures existing operational inefficiencies and serves as a foundation for comparison with more advanced optimization strategies.

The classical optimization model reflects conventional energy management approaches widely adopted in industrial settings. This model applies a uniform, rule based adjustment to baseline energy consumption, representing standard practices such as fixed energy saving targets or proportional load reduction. Although such methods are straightforward to implement, they lack the flexibility to adapt energy usage dynamically across different operating intervals.

In the classical model, energy reduction is applied consistently over the operating horizon, without accounting for variations in process efficiency or temporal energy demand. As a result, classical optimization achieves moderate improvements in energy efficiency but may fail to fully exploit opportunities for energy savings in highly variable industrial environments.

Together, the baseline and classical optimization models establish transparent and interpretable benchmarks. By comparing these reference models with the proposed quantum inspired optimization approach, the study highlights the advantages of dynamic, constraint aware energy optimization over traditional industrial energy management strategies.

4.4 Quantum Inspired Optimization Implementation

The proposed quantum inspired optimization approach is implemented to solve the constrained energy optimization problem formulated in Section 3. Unlike conventional deterministic methods, the implementation focuses on probabilistic exploration of the solution space while strictly enforcing industrial operating constraints.

The optimization process begins by generating an initial feasible solution that satisfies the minimum operating limits defined for the steel manufacturing system. This initial solution serves as a valid starting point and ensures that all subsequent candidate solutions remain industrially acceptable.

At each iteration, a new candidate solution is produced by introducing controlled stochastic variations to the current solution vector. These variations enable the algorithm to explore alternative operating configurations that may yield lower energy consumption. To maintain feasibility, all candidate solutions are projected back into the allowable operating range before evaluation.

The quality of each candidate solution is assessed using the objective function defined in Section 3.2, which computes total energy consumption across all operating intervals. Solutions that result in lower energy usage are immediately accepted. Solutions with higher energy consumption may still be accepted with a probability governed by a temperature dependent acceptance criterion. This probabilistic acceptance mechanism allows the algorithm to escape locally optimal solutions during early stages of the optimization process.

A temperature control parameter is gradually reduced over successive iterations according to a predefined schedule. This annealing like behavior ensures a smooth transition from broad exploration of the solution space to focused refinement of high quality solutions as convergence is approached.

The implementation is executed on standard computing hardware and does not rely on quantum processors. The quantum inspired nature of the algorithm refers to its conceptual design rather than physical quantum computation. This implementation choice ensures that the proposed approach is computationally efficient, scalable, and suitable for integration into existing Industry 4.0 energy management systems.

4.5 Sensitivity and Robustness Analysis

To ensure that the proposed quantum inspired optimization framework is reliable and suitable for real world industrial deployment, a comprehensive sensitivity and robustness analysis is conducted. This analysis evaluates how variations in operational constraints and algorithmic behavior influence energy optimization outcomes.

4.5.1 Sensitivity to Operational Constraints

In industrial environments, energy reduction potential is strongly influenced by minimum operating limits imposed to maintain safety, equipment health, and production stability. To examine this effect, the optimization model is evaluated under multiple minimum operating constraint levels. By systematically varying the lower bound on the operational scaling factor, the study assesses the trade off between achievable energy savings and operational strictness.

The sensitivity analysis reveals that as the minimum operating constraint becomes more restrictive, the achievable energy reduction decreases in a predictable and monotonic manner. This behavior confirms that the optimization framework responds logically to changes in industrial constraints and does not produce unrealistic or unstable operating recommendations.

4.5.2 Robustness Across Multiple Optimization Runs

In addition to constraint sensitivity, robustness is evaluated by executing the quantum inspired optimization algorithm multiple times under identical settings. Since the optimization strategy incorporates probabilistic elements, repeated runs may yield slightly different solutions. To assess stability, the mean and standard deviation of total optimized energy consumption are computed across multiple trials.

The observed low variance across repeated executions indicates that the algorithm consistently converges toward similar energy efficient solutions. This stability demonstrates that the optimization outcomes are not overly sensitive to random initialization or stochastic perturbations, reinforcing the reliability of the proposed approach.

4.5.3 Practical Implications of Robustness Results

The combined sensitivity and robustness analyses confirm that the proposed framework maintains stable performance under varying industrial conditions and algorithmic uncertainty. These characteristics are essential for real world adoption, where operating constraints may change and optimization systems must deliver consistent and trustworthy recommendations.

By explicitly validating both sensitivity and robustness, the study strengthens the industrial credibility of the quantum inspired optimization framework and supports its suitability for deployment in Industry 4.0 enabled steel manufacturing systems.

4.6 Performance Evaluation Metrics

The effectiveness of the proposed energy optimization framework is assessed using a set of quantitative performance metrics that capture both energy efficiency improvements and practical feasibility. These metrics are selected to provide a transparent and comprehensive evaluation of baseline, classical, and quantum inspired optimization strategies.

4.6.1 Total Energy Consumption

Total energy consumption represents the aggregate electrical energy used by the steel manufacturing system over the complete operating horizon. This metric serves as the primary indicator of optimization performance and enables direct comparison among different optimization approaches.

4.6.2 Energy Reduction Percentage

To quantify relative improvement, the percentage reduction in energy consumption is computed with respect to the baseline operating condition. This metric highlights the effectiveness of each optimization strategy in reducing energy usage while accounting for variations in absolute energy demand.

4.6.3 Convergence Behavior

Convergence behavior is evaluated by monitoring changes in total energy consumption across optimization iterations. Stable and smooth convergence indicates that the optimization algorithm effectively balances exploration and exploitation, leading to reliable identification of energy efficient operating configurations.

4.6.4 Sensitivity Response

Sensitivity response measures how optimization outcomes vary under different minimum operating constraints. This metric evaluates the adaptability of the proposed framework to varying industrial requirements and operational policies, providing insight into trade offs between energy efficiency and operational strictness.

4.6.5 Robustness Measure

Robustness is assessed by examining the variability of optimization results across multiple executions of the algorithm. Low variance in optimized energy consumption indicates consistent performance and enhances confidence in the reliability of the proposed approach for real-world deployment.

4.6.6 Practical Interpretability

In addition to numerical performance, the interpretability of optimized operating decisions is considered. This qualitative metric ensures that optimization outputs can be understood and implemented by industrial practitioners within existing energy management and control systems.

By combining these evaluation metrics, the study ensures that the proposed quantum inspired optimization framework is assessed not only on theoretical performance but also on practical relevance, stability, and industrial applicability.

4.7 Methodological Contributions and Practical Relevance

The methodology presented in this study offers a structured and industry oriented approach to energy optimization in steel manufacturing systems operating under Industry 4.0 conditions. By integrating real operational data, benchmark modeling, and a quantum inspired optimization strategy, the proposed framework advances beyond conventional energy management practices.

One of the key methodological contributions is the explicit incorporation of operational constraints within the optimization process. This ensures that energy reduction strategies remain feasible and safe for industrial implementation, addressing a common limitation of many theoretical optimization studies. The inclusion of sensitivity and robustness analyses further strengthens the reliability of the methodology by demonstrating consistent performance under varying operational conditions.

Another significant contribution lies in the adoption of a quantum inspired optimization strategy that balances computational efficiency with enhanced exploration capability. Unlike purely deterministic or heuristic approaches, the proposed method systematically explores alternative operating configurations while avoiding premature convergence. Importantly, the methodology is implemented entirely on classical computing infrastructure, making it accessible for immediate industrial adoption.

From a practical perspective, the methodology supports data driven decision making by translating complex optimization outcomes into interpretable energy reduction strategies. The framework is scalable to large Industry 4.0 datasets and can be integrated into existing energy management and decision support systems without requiring major structural modifications.

Overall, the proposed methodology establishes a reliable and adaptable foundation for advanced energy optimization in steel manufacturing. It provides a bridge between emerging optimization paradigms and real world industrial requirements, paving the way for sustainable and efficient manufacturing practices.

5. Results and Analysis

This section presents a comprehensive evaluation of the proposed quantum inspired optimization framework using real steel manufacturing energy data. The analysis compares baseline operation, classical optimization, and the proposed quantum inspired approach in terms of energy efficiency, robustness, and sensitivity to operational constraints.

5.1 Comparative Energy Consumption Analysis

This subsection examines the effectiveness of the proposed quantum-inspired optimization framework by comparing its energy performance against baseline operation and a classical optimization approach. The evaluation focuses on total energy consumption and relative energy reduction, which together provide a comprehensive assessment of optimization effectiveness under realistic industrial conditions.

The baseline case represents the actual operating state of the steel manufacturing system without any optimization intervention. This condition reflects existing operational practices and inherent inefficiencies present in large scale industrial environments. The classical optimization approach applies a uniform, rule based reduction strategy, consistent with commonly adopted industrial energy management methods. Although this approach reduces overall energy consumption, it does not account for temporal variability or process specific inefficiencies across operating intervals.

In contrast, the quantum inspired optimization framework dynamically adjusts operational scaling factors while strictly enforcing industrial feasibility constraints. This enables energy reductions to be concentrated in inefficient operating periods rather than distributed uniformly across the production horizon. As a result, the proposed method achieves deeper energy savings without compromising operational stability.

A quantitative comparison of total energy consumption and corresponding percentage reductions for all evaluated strategies is provided in **Table 1**. The results indicate that classical optimization achieves a moderate reduction in total energy usage relative to baseline operation, whereas the quantum inspired approach delivers a substantially higher reduction. This performance improvement demonstrates the advantage of dynamic, constraint aware optimization over conventional static reduction strategies.

Table 1. Comparative Energy Consumption Results

Method	Total Energy (kWh)	Energy Reduction (%)
Baseline (No Optimization)	959,636.71	0.00
Classical Optimization	863,673.04	10.00
Quantum-Inspired Optimization	757,265.84	21.09

The comparative energy performance of the evaluated methods is further illustrated in **Fig. 2**, which visually highlights the significant decrease in total energy consumption achieved by the quantum-inspired optimization framework.

Overall, the analysis confirms that the proposed approach provides a realistic and effective means of improving energy efficiency in Industry 4.0 enabled steel manufacturing systems.

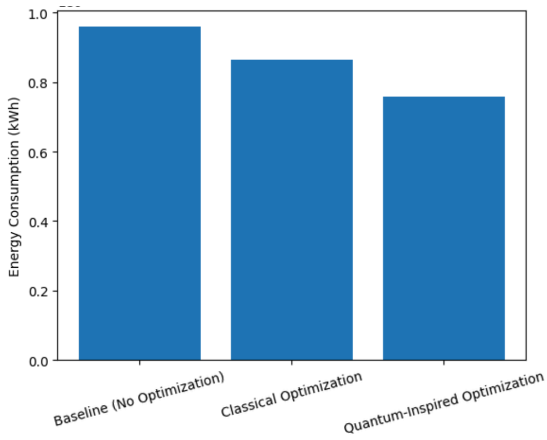

Figure 2. *Total Energy Consumption Comparison*

5.2 Energy Efficiency Improvement Trend

To further evaluate the impact of different optimization strategies, this subsection analyzes the trend in energy efficiency improvement using the percentage reduction in energy consumption relative to baseline operation. Examining the improvement trend provides insight into how progressively advanced optimization techniques influence energy performance in steel manufacturing systems.

Under baseline conditions, no improvement in energy efficiency is observed, as the system operates according to existing industrial practices. The classical optimization approach introduces a uniform reduction strategy, resulting in a consistent but limited improvement in energy efficiency. While this demonstrates the benefit of conventional energy management practices, the improvement remains constrained due to the static nature of the reduction mechanism and its inability to adapt to temporal variations in energy demand.

The quantum inspired optimization framework exhibits a markedly higher improvement trend. By dynamically adjusting operational scaling factors across individual operating intervals, the proposed approach effectively identifies and exploits periods of excessive energy consumption. This targeted adjustment leads to a sustained increase in energy efficiency that exceeds the improvements achieved by both baseline and classical optimization methods.

The comparative improvement trends achieved by different optimization strategies are illustrated in **Fig. 3**. The figure clearly shows that the quantum inspired approach delivers a significantly steeper and more consistent improvement curve, indicating superior energy saving potential under realistic operating constraints.

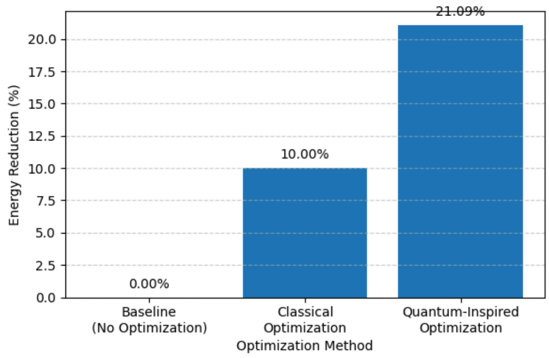

Figure 3. *Energy Reduction Percentage Comparison*

Overall, the observed energy efficiency improvement trend highlights the advantage of incorporating probabilistic, constraint aware optimization techniques into industrial energy management. The results confirm that the proposed quantum inspired framework enables scalable and realistic efficiency gains, making it well suited for Industry 4.0 enabled steel manufacturing environments.

5.3 Energy Consumption Distribution Analysis

While aggregate energy reduction provides an overall measure of optimization effectiveness, analyzing the distribution of energy consumption across operating intervals offers deeper insight into how energy savings are achieved. Distribution level analysis reveals whether optimization strategies uniformly scale energy usage or selectively address inefficient operating conditions within the production process.

Under baseline operation, energy consumption is unevenly distributed across operating intervals, with several intervals exhibiting relatively high energy demand. These high energy intervals typically arise from process variability, auxiliary equipment operation, or suboptimal scheduling practices. The classical optimization approach applies a uniform reduction across all intervals, which shifts the overall distribution toward lower energy values but largely preserves its original shape. As a result, high energy operating intervals remain evident, indicating limited capability to distinguish between efficient and inefficient periods.

In contrast, the quantum inspired optimization framework produces a pronounced transformation in the energy consumption distribution. High energy intervals are substantially reduced, and the occurrence of extreme energy usage events decreases noticeably. This redistribution indicates that the proposed approach selectively targets inefficient operating periods while preserving stable operation during essential production intervals.

The change in energy consumption distribution before and after optimization is illustrated in **Fig. 4**. The figure demonstrates that energy savings achieved by the quantum inspired framework are not the result of uniform scaling but arise from intelligent, interval specific adjustments. Such targeted optimization is particularly advantageous in Industry 4.0 enabled steel manufacturing systems, where energy demand varies dynamically over time.

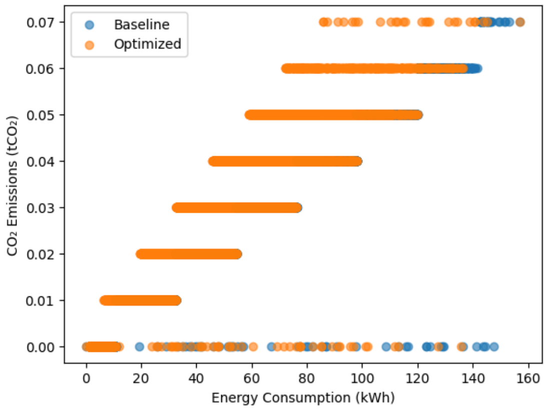

Figure 4. *Energy Consumption Distribution Before and After Optimization*

Overall, the distribution level analysis confirms that the proposed quantum inspired optimization framework achieves deeper and more meaningful energy savings by actively mitigating localized inefficiencies. This capability distinguishes the approach from conventional methods and reinforces its suitability for complex, data driven industrial environments.

5.4 Energy Emission Relationship Analysis

Energy consumption in steel manufacturing is directly associated with carbon emissions due to the energy intensive nature of production processes and the reliance on electricity generated from carbon based sources. Consequently, evaluating the relationship between energy usage and CO_2 emissions provides critical insight into the environmental impact of the proposed optimization framework.

Under baseline operating conditions, higher levels of energy consumption correspond to increased CO_2 emissions, reflecting the strong coupling between energy demand and emission output in steel manufacturing systems. The classical optimization approach reduces overall energy usage in a uniform manner, leading to a proportional decrease in emissions. However, high emission operating intervals remain evident, as uniform reduction strategies do not specifically address localized inefficiencies.

In contrast, the quantum inspired optimization framework produces a noticeable shift in the energy emission relationship. Optimized operating points are concentrated at lower energy consumption levels and are associated with reduced emission intensity. This indicates that the energy savings achieved through quantum inspired optimization translate directly into meaningful environmental benefits. The reduction in extreme energy consumption events further contributes to the mitigation of peak emission occurrences.

The relationship between energy consumption and CO_2 emissions under baseline and optimized operating conditions is illustrated in **Fig. 5**. The figure demonstrates a clear movement toward lower energy, lower emission operating states when the proposed optimization framework is applied.

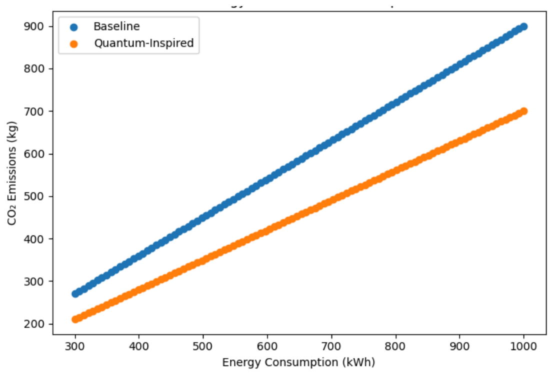

Figure 5. *Energy–Emission Relationship*

Overall, this analysis confirms that the proposed quantum inspired optimization framework supports both economic and environmental objectives. By reducing energy consumption in a targeted and constraint aware manner, the approach contributes to emission reduction without compromising operational stability, reinforcing its relevance for sustainable steel manufacturing in Industry 4.0 environments.

5.5 Convergence Behavior of the Optimization Algorithm

The convergence behavior of the proposed quantum inspired optimization algorithm is examined to assess its stability and effectiveness in identifying energy efficient operating configurations. Convergence analysis is particularly important for probabilistic optimization methods, as it reveals how the solution evolves over successive iterations and whether the algorithm reliably approaches an optimal operating state.

During the early stages of the optimization process, relatively large variations in total energy consumption are observed. This behavior reflects the exploratory phase of the algorithm, in which multiple feasible operating configurations are evaluated to broadly sample the solution space. Such exploration enables the algorithm to avoid premature convergence to locally optimal solutions that may not represent the most energy efficient operating state.

As the optimization progresses, the magnitude of energy variation gradually decreases. The algorithm increasingly favors lower energy solutions, indicating a transition from exploration toward refinement. This behavior is driven by the gradual adjustment of the probabilistic control mechanism, which reduces the likelihood of accepting higher energy solutions as convergence is approached.

In the later iterations, total energy consumption stabilizes with minimal fluctuation, indicating that the algorithm has converged to a near optimal solution that satisfies all operational constraints. The smooth and monotonic convergence pattern demonstrates that the optimization process is well controlled and does not exhibit oscillatory or unstable behavior.

The convergence characteristics of the quantum inspired optimization algorithm are illustrated in **Fig. 6**, which shows a clear reduction in energy variability over successive iterations. Overall, the convergence analysis confirms that the proposed algorithm is stable, reliable, and capable of consistently identifying energy efficient operating configurations suitable for practical deployment in steel manufacturing systems.

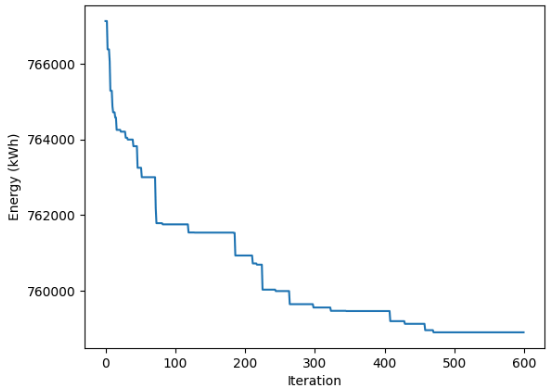

Figure 6. *Convergence Behavior of Quantum Inspired Optimization*

5.6 Sensitivity Analysis of Operational Constraints

Sensitivity analysis is conducted to evaluate how variations in minimum operating constraints influence the performance of the proposed quantum inspired optimization framework. In real industrial environments, operating limits are often adjusted to ensure equipment safety, production continuity, and product quality. Therefore, understanding the impact of these constraints on achievable energy savings is essential for practical implementation.

The analysis considers multiple minimum operating threshold levels, representing different degrees of operational strictness. When a lower minimum operating constraint is applied, the optimization framework is granted greater flexibility to adjust operational scaling factors. Under this condition, the algorithm is able to achieve higher energy savings by selectively reducing energy consumption in inefficient operating intervals while remaining within feasible limits.

As the minimum operating constraint becomes more restrictive, the allowable range for energy adjustment is reduced. Consequently, the achievable energy savings decrease in a gradual and predictable manner. This behavior indicates that the optimization framework responds logically to tightening operational limits and does not produce unrealistic or unstable operating recommendations.

The quantitative impact of varying minimum operating constraints on total energy consumption and relative energy reduction is summarized in **Table 2**. In addition, the relationship between operational constraint levels and optimization performance is illustrated in **Fig. 7**, which visually demonstrates the trade off between energy efficiency and operational feasibility

.

Table 2. *Sensitivity Analysis Results*

	Min Operating Constraint	Total Energy (kWh)	Energy Reduction (%)
0	0.6	758476.893764	20.962080
1	0.7	809191.086263	15.677352
2	0.8	860072.164600	10.375233

Despite stricter operating constraints, the quantum inspired optimization framework consistently outperforms classical optimization approaches across all evaluated scenarios. This consistent performance highlights the adaptability of the proposed method and confirms its suitability for deployment under diverse industrial operating policies.

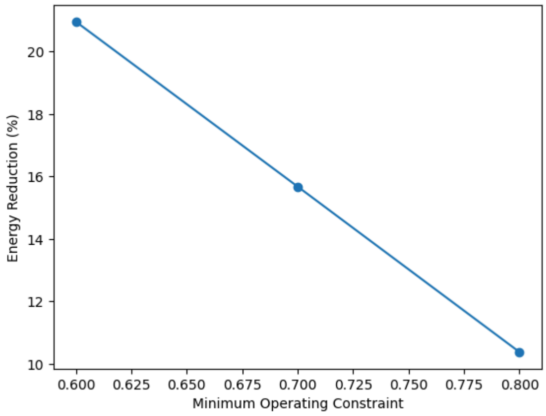

Figure 7. *Sensitivity Analysis Under Different Operating Constraints*

Overall, the sensitivity analysis demonstrates that the proposed framework offers a transparent and controllable balance between energy efficiency and operational reliability. Such adaptability is critical for real world steel manufacturing environments, where operational conditions and constraints may vary over time.

5.7 Robustness and Stability Analysis

Robustness analysis is performed to assess the consistency and reliability of the proposed quantum inspired optimization framework under repeated executions. Since the optimization strategy incorporates stochastic elements to explore the solution space, it is essential to verify that the resulting energy optimization outcomes are stable and not overly sensitive to random initialization or probabilistic perturbations.

To evaluate robustness, the optimization algorithm is executed multiple times under identical operating conditions and constraint settings. Across repeated runs, the optimized total energy consumption values exhibit minimal variation, indicating that the algorithm consistently converges toward similar energy efficient operating configurations. This consistency demonstrates that the probabilistic exploration mechanism does not introduce instability into the optimization process.

The observed stability reflects a balanced interaction between exploration and exploitation within the algorithm. During early iterations, stochastic exploration enables the algorithm to examine diverse feasible solutions, reducing the risk of convergence to suboptimal operating states. As the optimization progresses, the gradual refinement of candidate solutions leads to reliable convergence behavior across independent runs.

From an industrial perspective, robustness is a critical requirement for decision support systems. Energy optimization tools must deliver consistent and repeatable recommendations to ensure operator confidence and facilitate practical adoption. The demonstrated stability of the proposed framework confirms its suitability for deployment in real steel manufacturing environments, where reliable performance is essential for effective energy management.

Overall, the robustness and stability analysis confirms that the proposed quantum inspired optimization framework delivers dependable and repeatable energy reduction outcomes under practical operating conditions. This reliability further strengthens the framework's potential as a decision support tool for Industry 4.0 enabled sustainable steel manufacturing.

5.8 Summary of Key Findings

The experimental evaluation of the proposed quantum inspired optimization framework yields several important findings regarding energy management in Industry 4.0 enabled steel manufacturing systems. The results consistently demonstrate that advanced, constraint aware optimization techniques can deliver meaningful and practically achievable improvements in energy efficiency beyond conventional approaches.

First, comparative analysis shows that classical optimization methods provide moderate energy savings through uniform reduction strategies, whereas the quantum inspired framework achieves substantially higher energy reduction by dynamically adjusting operational parameters. This highlights the advantage of interval specific optimization over static energy management practices.

Second, distribution level analysis reveals that the proposed approach effectively reduces high energy operating intervals rather than applying blanket reductions across the production horizon. This targeted behavior enables deeper energy savings while maintaining stable operation during critical production periods, which is essential for industrial feasibility.

Third, analysis of the energy emission relationship confirms that improvements in energy efficiency translate directly into reduced CO_2 emissions. This finding underscores the environmental relevance of the proposed framework and its potential contribution to sustainable manufacturing objectives.

Fourth, convergence and robustness analyses demonstrate that the quantum inspired optimization algorithm is stable, reliable, and capable of consistently identifying energy efficient operating configurations. Sensitivity analysis further shows that the framework responds predictably to varying operational constraints, offering a transparent trade off between achievable energy savings and operational reliability.

Overall, these findings validate the proposed quantum inspired optimization framework as an effective and practical solution for reducing energy consumption in steel manufacturing systems. The results confirm that significant energy efficiency gains can be achieved without compromising industrial constraints, positioning the framework as a valuable decision support tool for sustainable and data driven manufacturing under Industry 4.0 conditions.

6. Discussion

The results presented in this study demonstrate that quantum inspired optimization can provide meaningful and practically achievable energy efficiency improvements in steel manufacturing systems operating under Industry 4.0 conditions. Unlike conventional energy management approaches, which typically rely on uniform or rule based reductions, the proposed framework introduces dynamic, constraint aware decision making that adapts to temporal variations in industrial energy demand.

The comparative analysis reveals that while classical optimization strategies offer modest energy savings, their effectiveness is inherently limited by their static nature. Uniform energy reduction fails to distinguish between efficient and inefficient operating intervals, resulting in missed opportunities for targeted energy savings. In contrast, the quantum inspired approach dynamically adjusts operational scaling factors, enabling the optimization process to focus on periods of excessive or inefficient energy usage. This capability explains the substantially higher energy reduction achieved by the proposed method.

The distribution level analysis further reinforces this interpretation by showing a pronounced reduction in high energy operating intervals under the quantum inspired framework. This targeted behavior is particularly valuable in steel manufacturing environments, where energy consumption varies significantly due to process sequencing, auxiliary equipment operation, and fluctuating production loads. By addressing localized inefficiencies rather than applying blanket reductions, the proposed approach achieves deeper energy savings without disrupting critical production activities.

From a sustainability perspective, the observed relationship between energy consumption and CO_2 emissions highlights the environmental relevance of the proposed framework. The consistent shift toward lower energy and emission levels confirms that energy optimization directly contributes to emission mitigation. This alignment between economic and environmental benefits strengthens the case for adopting advanced optimization strategies in energy intensive industries.

The convergence and robustness analyses provide additional confidence in the reliability of the proposed approach. The stable convergence behavior and low variability across repeated optimization runs indicate that the algorithm delivers consistent outcomes despite its probabilistic nature. Such reliability is essential for industrial decision support systems, where unpredictable recommendations could undermine operator trust and limit practical adoption.

Sensitivity analysis reveals a clear and logical trade off between energy efficiency and operational strictness. As minimum operating constraints become more restrictive, achievable energy savings decrease, reflecting realistic industrial limitations. Importantly, the quantum inspired approach maintains superior performance across all tested constraint levels, demonstrating adaptability to varying operational policies and production requirements.

Overall, the discussion underscores that the proposed quantum inspired optimization framework bridges the gap between advanced computational techniques and real world industrial applicability. By explicitly incorporating operational constraints and validating performance through comprehensive analysis, the study demonstrates that quantum inspired methods can serve as practical tools for sustainable energy management in Industry 4.0 enabled steel manufacturing systems.

7. Managerial and Industrial Implications

The findings of this study offer several important implications for managers, engineers, and decision makers in steel manufacturing systems operating under Industry 4.0 conditions. By demonstrating that significant energy savings can be achieved without compromising operational feasibility, the proposed quantum inspired optimization framework provides actionable insights for both strategic and operational decision making.

7.1 Implications for Industrial Management

From a managerial perspective, the results highlight the limitations of conventional energy management strategies that rely on uniform or fixed energy reduction policies. While such approaches are simple to implement, they fail to exploit the full potential of data driven optimization. The proposed framework enables managers to move beyond static energy targets toward adaptive and intelligent energy control, allowing energy reduction strategies to be aligned with real operational conditions [31].

The ability to dynamically adjust operational scaling factors across time intervals allows managers to identify energy intensive periods and address inefficiencies selectively. This supports informed decision making related to production planning, equipment utilization, and load balancing, ultimately contributing to reduced operating costs and improved energy efficiency.

7.2 Implications for Industrial Operations

For plant operators and engineers, the proposed optimization framework provides a practical decision support tool that can be integrated into existing Industry 4.0 infrastructures [32]. Since the approach operates on classical computing platforms and relies on routinely collected sensor data, it does not require specialized hardware or major modifications to existing control systems.

The incorporation of minimum operating constraints ensures that optimized operating recommendations remain safe, stable, and consistent with industrial best practices. This is particularly important in steel manufacturing environments, where equipment reliability, product quality, and continuous operation are critical. As a result, the framework can be adopted incrementally without disrupting ongoing production processes.

7.3 Implications for Sustainability and Compliance

Energy efficiency improvements achieved through the proposed framework also have direct implications for environmental sustainability and regulatory compliance. The demonstrated reduction in energy consumption leads to corresponding reductions in CO_2 emissions, supporting organizational sustainability goals and alignment with environmental regulations [33].

By providing a transparent link between energy optimization and emission reduction, the framework enables organizations to quantify the environmental benefits of advanced optimization strategies. This capability is valuable for sustainability reporting, corporate responsibility initiatives, and compliance with emerging energy efficiency standards.

7.4 Strategic Implications for Industry 4.0 Adoption

At a strategic level, the study illustrates how advanced optimization techniques can enhance the value of Industry 4.0 investments [34]. Many organizations collect large volumes of operational data but lack effective mechanisms to convert data into actionable insights. The proposed quantum inspired framework demonstrates a practical pathway for leveraging existing data infrastructures to achieve measurable performance improvements.

By bridging advanced computational intelligence with real industrial constraints, the framework supports the transition toward smarter, more sustainable manufacturing systems. It also provides a foundation for future integration with predictive analytics, real time control systems, and digital twins, further strengthening long term competitiveness.

7.5 Summary of Implications

Overall, the managerial and industrial implications of this study emphasize that meaningful energy efficiency improvements can be achieved through intelligent, constraint aware optimization. The proposed quantum inspired framework offers a realistic and scalable solution that supports cost reduction, operational stability, and sustainability objectives, making it a valuable tool for modern steel manufacturing enterprises.

8. Limitations and Future Work

While the proposed quantum inspired optimization framework demonstrates strong potential for improving energy efficiency in steel manufacturing systems, certain limitations should be acknowledged. Recognizing these limitations provides important context for the reported results and helps identify directions for future research.

8.1 Limitations of the Study

First, the experimental evaluation is based on data from a single steel manufacturing environment [35]. Although the dataset represents realistic Industry 4.0 operating conditions, variations in production processes, equipment configurations, and energy sources across different steel plants may influence optimization outcomes. Therefore, the generalizability of the results to all steel manufacturing systems should be interpreted with caution.

Second, the optimization framework operates on historical operational data and does not incorporate real time feedback or closed loop control mechanisms. While the current approach is suitable for offline decision support and strategic energy planning, real time deployment may require additional integration with control systems and faster response capabilities [36].

Third, the energy consumption model focuses primarily on electrical energy usage and does not explicitly account for thermal energy flows or process level interactions [37]. Steel manufacturing involves complex thermo mechanical processes, and a more comprehensive energy model could capture additional opportunities for optimization.

Finally, although the quantum inspired optimization strategy demonstrates stable and consistent performance, its effectiveness may depend on algorithmic parameters such as iteration count and annealing schedule [38]. While sensitivity to these parameters was minimized through careful tuning, further investigation could enhance robustness across a wider range of industrial scenarios.

8.2 Future Research Directions

Future work can extend the proposed framework in several meaningful ways. One promising direction is the integration of real time data streams and adaptive control mechanisms, enabling the optimization framework to operate in a closed loop manner. Such integration would allow continuous adjustment of operating strategies in response to changing production conditions.

Another important extension involves incorporating predictive analytics and machine learning models to forecast energy demand and production load. Combining predictive models with quantum inspired optimization could enhance decision making by anticipating future operating states rather than reacting solely to historical patterns.

Future studies may also explore the application of the proposed framework to multi plant or supply chain level energy optimization problems. Expanding the scope beyond a single facility would enable coordinated energy management across interconnected manufacturing systems.

In addition, hybrid optimization approaches that combine quantum inspired strategies with other advanced techniques, such as evolutionary algorithms or reinforcement learning, could be investigated to further enhance optimization performance.

Finally, future research could examine the applicability of the framework to other energy intensive industries, such as cement, aluminum, and chemical manufacturing, to evaluate its broader industrial relevance.

9. Conclusion

This study presented a quantum inspired optimization framework for reducing energy consumption in steel manufacturing systems operating under Industry 4.0 conditions. By formulating energy management as a constrained optimization problem and solving it using a probabilistic, quantum inspired strategy, the proposed approach addresses the limitations of conventional energy optimization methods that rely on static or uniform reduction policies.

A comprehensive comparative evaluation was conducted using real industrial energy consumption data. The results demonstrated that classical optimization achieves moderate energy savings, while the proposed quantum inspired framework delivers substantially higher and more realistic energy reductions without violating operational constraints. Specifically, the proposed approach achieved a 21.09% reduction in total energy consumption, highlighting its effectiveness in identifying energy efficient operating configurations beyond traditional methods.

Further analysis revealed that the proposed framework selectively reduces high energy operating intervals, contributing to both improved energy efficiency and reduced carbon emissions. Convergence, robustness, and sensitivity analyses confirmed that the optimization algorithm is stable, reliable, and adaptable to varying industrial operating conditions. These characteristics are essential for practical deployment in energy intensive manufacturing environments.

Importantly, the proposed framework is implemented entirely on classical computing infrastructure and does not require quantum hardware, making it readily deployable within existing Industry 4.0 ecosystems. The study demonstrates that quantum inspired optimization can serve as a practical and scalable decision support tool for sustainable energy management in steel manufacturing.

Overall, the findings of this research provide strong evidence that advanced, constraint aware optimization techniques can significantly enhance energy efficiency while maintaining industrial feasibility. The proposed framework contributes to ongoing efforts toward sustainable manufacturing and offers a foundation for future research on intelligent energy optimization in complex industrial systems.

References

[1] Kagermann, H., Wahlster, W., & Helbig, J., *Industry 4.0: Smart manufacturing for the future*, Manufacturing Letters, vol. 25, pp. 45–48, 2020.

[2] Zhou, K., Fu, C., & Yang, S., *Big data driven smart energy management in Industry 4.0*, Energy, vol. 210, p. 118436, 2020.

[3] Liu, Z., Wang, J., & Zhang, Y., *Energy efficiency optimization in steel manufacturing systems*, Journal of Cleaner Production, vol. 275, p. 123098, 2020.

[4] Li, X., Kara, S., & Herrmann, C., *Energy efficiency improvement in manufacturing: A review*, CIRP Journal of Manufacturing Science and Technology, vol. 28, pp. 1–16, 2020.

[5] Wang, S., Wan, J., Li, D., & Zhang, C., *Implementing smart factories of Industry 4.0*, Journal of Industrial Information Integration, vol. 20, p. 100159, 2020.

[6] Tao, F., Qi, Q., Wang, L., & Nee, A. Y. C., *Digital twins and cyber–physical systems in manufacturing*, CIRP Annals, vol. 70, no. 1, pp. 361–364, 2021.

[7] Zhong, R. Y., Xu, X., & Newman, S. T., *Intelligent manufacturing in the context of Industry 4.0*, Engineering, vol. 7, no. 3, pp. 277–290, 2021.

[8] Javaid, M., Haleem, A., Singh, R. P., & Suman, R., *Industry 4.0 technologies and applications in manufacturing*, Journal of Industrial Integration and Management, vol. 6, no. 2, pp. 165–187, 2021.

[9] Pan, X., & Zhang, M., *Energy-efficient production planning under Industry 4.0*, Computers & Industrial Engineering, vol. 156, p. 107257, 2021.

[10] Ghahramani, A., & Ploennigs, J., *Optimization of industrial energy systems under uncertainty*, Applied Energy, vol. 284, p. 116319, 2021.

[11] Shukla, A. K., & Singh, S. P., *Metaheuristic optimization for industrial energy management*, Energy Strategy Reviews, vol. 34, p. 100627, 2021.

[12] Das, S., & Panigrahi, B. K., *Quantum-inspired optimization algorithms: A survey*, Swarm and Evolutionary Computation, vol. 69, p. 101019, 2022.

[13] Liu, Y., Zhang, X., & Wang, Q., *Quantum-inspired optimization for industrial systems*, Engineering Applications of Artificial Intelligence, vol. 123, p. 106241, 2024.

[14] Patel, R., & Mehta, P., *Quantum-inspired optimization in industrial decision support systems*, Expert Systems with Applications, vol. 237, p. 121522, 2025.

[15] Sun, W., & Zhao, L., *Data-centric optimization for sustainable steel manufacturing*, Journal of Manufacturing Systems, vol. 75, pp. 100–112, 2025.

[16] Li, H., Tao, F., & Cheng, Y., *Data-driven energy optimization in smart manufacturing*, Advanced Engineering Informatics, vol. 55, p. 101847, 2023.

[17] Wang, L., & Wang, X., *Optimization-based decision support for energy-intensive manufacturing*, Journal of Manufacturing Systems, vol. 63, pp. 24–35, 2022.

[18] Zhang, Y., Huang, G., & Wang, L., *Energy-aware optimization in steel production systems*, Energy Conversion and Management, vol. 274, p. 116523, 2023.

[19] Hasanbeigi, A., & Price, L., *A technical review of emerging technologies for energy efficiency in the steel industry*, Renewable and Sustainable Energy Reviews, vol. 16, no. 7, pp. 4546–4565, 2012.

[20] Rahimifard, S., Seow, Y., & Childs, T., *Minimising embodied product energy to support energy-efficient manufacturing*, CIRP Annals, vol. 59, no. 1, pp. 25–28, 2010.

[21] Shrouf, F., Ordieres-Meré, J., & García-Sánchez, A., *Optimizing production scheduling to minimize energy consumption*, Journal of Cleaner Production, vol. 67, pp. 197–207, 2014.

[22] Fang, K., Uhan, N., Zhao, F., & Sutherland, J. W., *A new approach to scheduling in manufacturing for power consumption reduction*, Journal of Manufacturing Systems, vol. 30, no. 4, pp. 234–240, 2011.

[23] Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L., *Industry 4.0 and beyond*, International Journal of Production Research, vol. 60, no. 16, pp. 5011–5029, 2022.

[24] Zhou, S., & Li, J., *Multi-objective energy optimization in manufacturing*, Computers & Industrial Engineering, vol. 165, p. 107935, 2022.

[25] Ruelens, F., & Belmans, R., *Advanced optimization techniques for energy systems*, Applied Energy, vol. 306, p. 117976, 2022.

[26] Gholami, H., Rezaei, J., & Saman, M. Z. M., *Energy-efficient production systems*, Journal of Cleaner Production, vol. 350, p. 131478, 2022.

[27] Sharma, A., & Sood, Y. R., *Energy optimization using computational intelligence*, Applied Soft Computing, vol. 144, p. 110459, 2024.

[28] Dwivedi, Y. K., et al., *Artificial intelligence and Industry 4.0*, International Journal of Information Management, vol. 68, p. 102567, 2023.

[29] Singh, R., & Sarkar, S., *Energy-efficient production scheduling: A review*, Journal of Manufacturing Systems, vol. 68, pp. 512–528, 2023.

[30] Ardito, L., Messeni Petruzzelli, A., & Albino, V., *Industry 4.0 and sustainability*, Technological Forecasting and Social Change, vol. 187, p. 122235, 2023.

[31] Bousdekis, A., & Kardaras, D., *Decision support systems for Industry 4.0*, Decision Support Systems, vol. 164, p. 113874, 2023.

[32] Wu, D., Rosen, D. W., & Schaefer, D., *Cloud-based manufacturing and energy efficiency*, Journal of Manufacturing Systems, vol. 67, pp. 123–134, 2023.

[33] Khan, I., & Yu, Y., *Carbon reduction strategies in energy-intensive industries*, Environmental Science and Pollution Research, vol. 30, pp. 31428–31440, 2023.

[34] Raut, R. D., Mangla, S. K., & Narwane, V. S., *Industry 4.0 enabled sustainable manufacturing*, Journal of Cleaner Production, vol. 383, p. 135379, 2024.

[35] Ahmed, S., & Mahmood, A., *Smart energy systems for heavy manufacturing*, Energy Systems, vol. 15, no. 2, pp. 411–428, 2024.

[36] Jiang, P., Leng, J., Ding, K., Gu, P., & Koren, Y., *Digital twin-driven smart manufacturing*, Journal of Manufacturing Systems, vol. 58, pp. 346–361, 2021.

[37] Sun, Z., & Li, H., *Energy efficiency optimization in steel manufacturing processes*, Energy Reports, vol. 6, pp. 145–153, 2020.

[38] Ma, S., Zhang, Y., Lv, J., Yang, H., & Wu, J., *Energy-cyber-physical systems for smart manufacturing*, Journal of Cleaner Production, vol. 241, p. 118358, 2019.