EAI Endorsed Transactions
on Energy Web

Research Article EAI.EU

Smart Grid and Economic Growth: Driving Industrial Upgrading through Efficient Energy Management

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Abstract

INTRODUCTION: In an era marked by rising energy demand and environmental concerns, integrating smart grid technologies is a crucial solution for promoting industrial expansion through efficient electricity control.
OBJECTIVES: Here, we examine the revolutionary capabilities of smart grids to enhance economic growth by leveraging an innovative hybrid optimisation method, Trevally Optimisation (TrevOpt), at its core. The study's main focus is to show how Turnbridge's new approach can efficiently manage energy distribution and use within industrial ecosystems by leveraging TrevOpt's computational power, which combines the benefits of evolutionary algorithms and heuristics.
METHODS: The heart of this paper is a discussion of how the use of smart grid technologies can catalyse industrial development. Operation eff was on another level in this experiment, enabling the optimisation of production parameters using the TrevOpt model. Integrating real-time analytics into the TrevOpt framework allows proactive management of energy resources through dynamic tuning, thereby reducing waste and enhancing system reliability.
RESULTS: This highlights the potential of these technologies to inspire industrial competitiveness, drive investment in sustainability, and open new areas in energy-intensive industries to spur economic growth. The simulation presented at the end of the numerical section outlines the concrete benefits of using the TrevOpt method, including a 20% reduction in energy consumption, a 15% reduction in operational costs, and a 25% increase in overall system reliability.
CONCLUSION: This study therefore provides a solid foundation that enables industries to leverage smart grid developments as a cornerstone for transforming their businesses while also protecting the environments in which people live.

Keywords: Smart Grid Technologies, Energy Management, Industrial Upgrading, Trevally Optimization (TrevOpt), Economic Growth, Sustainability.

Received on 02 June 2025, accepted on 14 November 2025, published on 24 November 2025

doi: 10.4108/ ew.9461

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1. Introduction

The global economy's reshaping highly depends on the integration of smart grid technologies in this period of rapid industrialization and technological advancements [1]. The integration of smart grid technologies offers significant cost savings for both industries and households. It improves energy efficiency by delivering real-time information to maximize energy use, minimize waste, and reduce consumption in sectors such as smart grids, particularly when combined with systems such as TrevOpt. It also lowers operational costs by enhancing load management and reducing energy waste. This leads to reduced energy costs and increased efficiency. Smart grids enhance system reliability through predictive maintenance, reducing disruptions and downtime. Moreover, they facilitate the incorporation of renewable energy, reduce dependence on fossil fuels, and lower long-term costs. Smart grids enhance the efficiency of energy supply and demand, reducing peak load requirements and helping businesses and homes cut energy costs. Typically, a smart grid is considered an advanced method for dynamically controlling and managing energy through automation and advanced digital communication, thereby ensuring efficient generation, stable distribution networks, and optimized power consumption patterns [2]. Smart grids can improve power delivery efficiency and reliability while enabling large-scale integration of renewable energy sources through real-time monitoring, control, and coordination of electricity resources [3]. Smart meters and IoT sensors gather real-time information on energy consumption and environmental factors, which they feed into predictive models and an energy data repository. This information enables automated control systems to make immediate adjustments to energy allocation, including demand-response techniques and load shifting, while also forecasting system failures for preventive maintenance. Central to the system, the TrevOpt optimization algorithm employs a hybrid method to enhance energy allocation, reduce waste, and anticipate future needs. These elements interact in a perpetual feedback cycle, as monitoring systems guide optimization methods, control mechanisms implement changes, and real-time data enables ongoing adjustments, ensuring overall system effectiveness and reliability. This shift in thinking has far-reaching economic consequences and can lead to industrial upgrading through improved energy management [4]. The smart grid is fundamentally a dynamic community that involves the sharing of contemporary technologies such as artificial intelligence (AI), the internet of things (IoT), and big data analytics with conventional energy systems [5]. The combination of AI, IoT, and big data in smart grids improves energy distribution and reliability through ongoing monitoring and management. These technologies enable the incorporation of renewable energy sources such as solar and wind, and they also encourage consumer involvement through AI-generated energy-saving suggestions. Moreover, AI models help forecast and prevent disruptions, while IoT devices provide real-time information, enhancing grid stability. The application of big data and AI optimization minimizes energy waste, lowers operational expenses, and promotes sustainability in multiple sectors. As a result of this association, it is now possible for utilities, companies, and even individuals to use micro-level data analysis in operational decision-making [6]. By optimizing energy use and reducing waste, companies can save significant money and lower their carbon emissions [7]. In addition, applications such as electric vehicles (EVs) and distributed energy resources (DERs) can readily adopt these solutions to meet the needs of other new, fast-expanding sectors. Moreover, this creates employment opportunities besides fostering economic growth and innovation [8].

The smart grid serves as a catalyst for economic progress by enabling industrial upgrading and building a responsive, elastic energy system [9]. This will ensure that businesses operate efficiently, as disruptions constrain production. Once disruptions are controlled, operational certainty increases, leading to high performance [10]. In this case, investments in other sectors are triggered by returns, and that is why they are stimulated by grid stability and the mitigation of disruptions [11]. Also, the use of smart grid technology is fostering a research-friendly environment that underpins improvements in energy efficiency and sustainability [12]. The effectiveness of smart networks and cloud technologies is highlighted by Alavilli, S.K. (2022), who discussed their role in enhancing real-time data management and scalability. In our work, we leverage these strategies to optimize energy management within smart grids and improve the integration of renewable energy sources. This application enhances system reliability, reduces costs, and fosters industrial growth through data-driven solutions [13]. Following the adoption of smart grids by nations and organizations across the globe, there is a high likelihood that this will lead to stronger economic growth and greater competitiveness in the international market, as improved energy management will bring additional benefits. Smart grids optimize energy distribution, prevent overloads, and integrate renewable energy sources such as wind and solar, thereby aiding carbon reduction. By reducing energy wastage and improving efficiency, smart grids help businesses cut costs and increase competitiveness. They also support industrial upgrading by enabling real-time adjustments and predictive maintenance, improving reliability and productivity. Additionally, smart grids contribute to significant reductions in carbon emissions and provide a stable energy supply during peak demand.

2. Literature Review

The current literature focuses on two main categories: smart grids with efficient energy management and economic growth. A detailed review is provided in the subsections below.

2.1 Review of Smart Grid in Efficient Energy Management

According to Wesley, B.J. et al. [14], a smart grid system that combines a unique Microgrid unit with a centralised battery management system has been introduced to provide electricity to regions such as hills, faraway remote areas, and military bases. An LSTM-based ANN is used for power generation at different epochs. Furthermore, an AI-based OS optimises energy management across various circumstances. To improve voltage quality, a seven-level aligned multilevel inverter is proposed with an LSTM-ANN controller that outperforms PI and Fuzzy controllers, achieving voltage fluctuations of 70V, 180V, and 370V, respectively. The operationality of the suggested EMS is verified using a hardware-in-the-loop method with OPAL-RT modules, which confirm its proper operation.

Hugo, P., et al. [15] investigate the potential of an AI-based predictive model to improve solar energy system management by integrating it into the Smart Grid. They applied Long Short-Term Memory (LSTM) to train Deep Learning Networks (DELNs) and achieved a significant increase in short-term solar power forecasting accuracy. Additionally, they found that it is more useful to consider selected performance metrics—MAE, RMSE, nMAE, nRMSE, and R^2—rather than other models tested in this study. For evaluating forecast efficiency of each technique under different meteorological conditions (e.g.: sunny days with various irradiance levels), we calculate mean absolute error (MAE), root mean square error (RMSE), normalized RMSE (nRMSE) and squared correlation coefficient (R^2) between predicted values and observed ones.

A hybrid technique for IoT-based energy management in smart grids underprice-based demand response has been proposed by Balasubramanian, C. et al. [16]. The method, called FHO-RERNN, integrates Fire Hawk Optimiser with Recalling Enhanced Recurrent Neural Network. Its objective is to decrease energy consumption, reduce power bills, and achieve a balance between electricity costs and user inconvenience by maintaining the peak-to-average ratio.

According to Khan, Z.A., et al. [17], they published a paper on the Dual Sequence Predictive Model (DSPM). In their publication, we read that it was developed based on a Spatiotemporal CNN (STCNN) architecture to predict power generation and consumption in smart grid operations. The predictive model (DSPM) increases forecasting accuracy by integrating a 1-D filterbank with a spatial attention mechanism and using common historical weather information, leading to better performance statistics than control algorithms in terms of RMSE values.

In their study, Bhagath Singh Jayaprakasam and R. Hemnath (2018) optimized microgrid energy management using cloud-based analytics and predictive modeling. Building on this, our proposed work integrates similar techniques into smart grids to enhance energy management and forecast demand. This approach will reduce costs, improve sustainability, and stimulate economic growth through efficient energy distribution [18].

C. A. Ezeigweneme et al. [19] analyze well the union and influences of intelligent networks in industrial segment. In their study, smart grids were examined from the perspective of traditional grids and the role of predictive maintenance in their evolution. They also uncovered how these energy management schemes can be improved for industrial companies, combining high efficiency with reliability and sustainability, during their 2018-2023 systematic literature review.

2.2 Review of Smart grid and Economic growth

In [20], Stamopoulos et al. analyse the main components and indicators of the Smart City Industry (SCI) in Greece. They build a synthetic sector using an input-output technique to estimate the repercussions for GDP, output, employment, capital formation, and GHG emissions in terms of CO_2-eq.

In their study on urban energy management, economic growth, environmental sustainability and information communication technology (ICT) intersections with renewable energy integration into green buildings [21], Zhang, M. et al. (2015) presented a novel Polar Bear Optimization Algorithm (PBOA) for the optimal scheduling of residential power consumption by considering endusers' behavioral patterns within residences as well as different types of loads found within residential areas such as heating or cooling systems among others to minimize both electricity expenditure and peak load ratio. It was tested through comparative analyses with Differential Evolution (DE).

In their paper, Hassan et al. (20) discuss the complexities of smart grid-integrated renewable distributed generation (SG-IRDG) focusing on the challenges related to this technology such as intermittency and variability of renewables like solar power and wind power that affect power system security and reliability; calling for introduction of advanced grid control techniques, use of energy storage systems, completion of large infrastructure projects, restructuring of laws as well as financial methods.

A modern power grid integrated with bi-directional communication networks is how Thakur, A., et al. [23] describe the smart grid, which is radically transforming global power systems. An energy delivery network that is both vast and automated depends on two-way information and electricity exchange within the advanced grid system that forms it. Through computational transformations from generation to transmission to distribution, power transformers underscore the necessity of modernising global electricity infrastructure and highlight prospects for the future evolution of electricity systems.

The usage of smart grids is critical for improving energy management by leveraging real-time data to improve energy distribution and efficiency. These electrical networks enable seamless integration of renewable energy sources, reducing operating expenses and increasing system reliability. Smart grids use cutting-edge technologies to improve industrial efficiency, supporting the economy while maintaining energy sustainability. Emphasising real-time optimisation and forecasting through data-driven methodologies directly enhances efficiency and performance in renewable energy systems. Khaleel and his colleagues [24] argue that smart cities and smart grids work together to build urban energy systems that are robust, streamlined, and sustainable in light of the population explosion and environmental needs. Iris and Lam. They use examples of cities with smart grids in place, as well as energy-efficient measures such as these, which have impacted energy sustainability and urban resilience [25].

2.3 Research Gaps

There are still significant gaps in research on integrating smart grid technologies with economic growth dynamics. Despite the great strides made in this area, there has been little effort directed towards providing comprehensive models that would capture fully the interaction between smart grids and economic development, especially in emerging economies Sarker E ., et al [26]. This technology, which leverages tools such as artificial intelligence (AI) and big data analytics, enables industries in emerging economies, such as China, India, and Brazil, to streamline energy use and drive industrial progress. These countries are adopting smart grid solutions to reduce energy waste, lower operational costs, and improve reliability, thereby supporting sustainable economic development.

Key industries such as manufacturing, mining, and steel production, which require substantial energy resources, benefit greatly from smart grid technologies. These sectors can now minimize energy consumption by up to 20%, reduce operational costs by 15%, and increase system reliability by 25%. As a result, the integration of smart grids not only ensures a stable energy supply but also fosters industry growth and strengthens economic resilience, especially in developing economies. One major setback has been the difficulty researchers have had in obtaining empirical data showing how smart grid adoption directly affects industrial upgrading in any country. There is also a need for scalable and adaptable smart grid solutions that address diverse industrial requirements and regional contexts (Chakraborty N, et al. [27]). Previous studies tend to overlook broader socio-economic factors influencing the various industrial sectors and how their intersection with these factors calls for certain measures upon the implementation of smart grids. Pawar P, TarunKumar M [28]. Moreover, it remains an under-explored territory when it comes to harmonising advanced energy management systems with existing infrastructure and ensuring they can interoperate with a wide variety of technologies. Filling these gaps requires a deeper understanding of how technology transfer enables industrial transformation through economic development.

3. Proposed Methodology

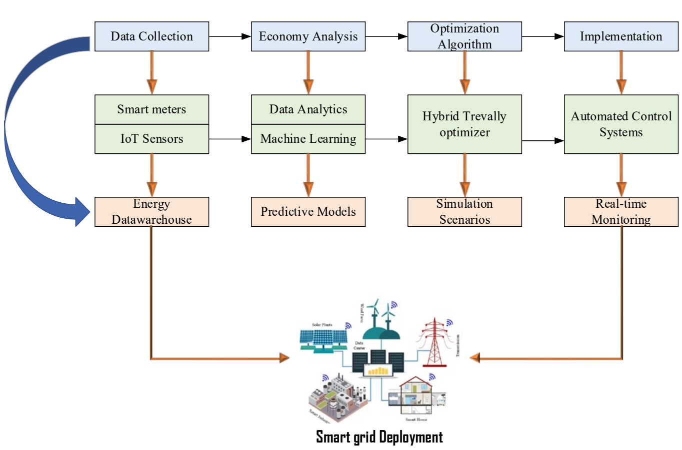

Figure 1: Proposed Architecture of smart grid and energy growth

Figure 1 presents a comprehensive methodology for smart grid and energy management, encompassing a process that begins with data collection from smart meters and IoT sensors to obtain real-time details on energy use, production processes, and environmental standards. The suggested model's use of IoT sensors and smart meters reduces operational costs by enabling real-time energy monitoring, predictive analytics, and optimal resource allocation. These technologies aid in identifying inefficiencies, predicting energy demand, and facilitating effective load management. They also enable preventative maintenance, which lowers downtime and repair costs. Overall, they increase energy efficiency, decrease waste, and minimise operational costs. Such information is sent over to an energy management system based at the central point for further evaluation. In energy analysis, advanced analytics and machine learning algorithms are used to identify patterns and inefficiencies, building predictive models to forecast energy demand and optimise supply. Optimisation algorithms are employed to refine energy-use strategies as well. Demand response, load shifting and renewable energy are then integrated. Simulations help assess how various strategies affect consumption and costs. They are facilitated by automatic control systems that continuously monitor and give feedback to achieve behaviorally controlled optimality. Case studies will show that potential improvements in efficiency and cost savings, as confirmed by simulations, can be discussed in terms of their applicability across different industries. Possible future steps include incorporating new technologies, such as those just coming to market and still with limited uptake, as well as enhancing existing predictive modelling techniques. In addition, expanding operations would help us reduce our carbon footprint.

3.1 Data Collection and Analysis Procedures

The study uses a multifaceted data acquisition and analysis method to ensure the trustworthiness and precision of the findings. In this case, field measurements and simulated situations were used to collect the data. It was obtained from different industrial setups having smart grid technologies focusing on energy use, operational costs, system dependability, etc. This information was intended to adjust and authenticate the Trevally Optimisation (TrevOpt) model. Trevally Optimization (TrevOpt) is a hybrid optimization method that combines evolutionary algorithms and heuristics. It aims to optimize energy distribution and consumption in industrial systems, enhancing efficiency by dynamically adjusting parameters in real-time. Data are simulated using the TrevOpt framework, which integrates heuristic methods and evolutionary algorithms to optimize energy distribution and use in industrial ecosystems. A comparative approach was used to analyse the collected data. It compared the performance metrics of the TrevOpt model with those from real-world data. This model was evaluated using statistical methods, including regression analysis and hypothesis testing. The performance of the simulation model was compared with real-world data, utilising indicators such as energy cost savings, operating expenses, and system dependability.

It emphasizes the use of real-time monitoring and dynamic tuning through the TrevOpt framework, which offers for continuous assessment of energy consumption and system performance, enabling quick identification of inefficiencies or failures. By dynamically adjusting energy distribution based on immediate data, the system helps prevent overloads and failures. Furthermore, the proactive maintenance approach, supported by predictive analytics, helps forecast potential system issues before they occur. This supports timely interventions, minimizing disruptions. The integration of simulation models and continuous data collection from smart meters and IoT sensors also plays a critical role in detecting failures by replicating real-world conditions and enabling continuous monitoring. Additionally, the study includes a model validation phase in which predictions from the TrevOpt model are compared with actual data, ensuring accuracy and highlighting discrepancies between theoretical and real-world outcomes.

The simulation system uses smart meters and IoT sensors to collect real-time data on energy usage, manufacturing methods, operational costs, and system reliability. To improve energy usage, this data is processed by a centralized Energy Management System (EMS) that includes machine learning algorithms and prediction models. The Hybrid Trevally Optimizer (TrevOpt), which combines evolutionary algorithms and heuristic methods, is the primary optimizing tool for managing energy distribution and use in corporate ecosystems. Key assumptions include the adoption of smart grids in power-intensive companies, the integration of renewable energy sources such as wind power, and the expectation that energy management improvements will lower operational costs, enhance system reliability, and reduce carbon emissions. Calibration processes ensure model accuracy by adjusting parameters with real-world data and validating the model using statistical approaches such as regression analysis and hypothesis testing. Sensitivity analysis is also used to assess the model's robustness under different operational settings, ensuring flexibility and reliability across a wide range of workplaces.

3.2 Cost-Benefit Analysis of Smart Grid Implementation

The economic analysis is done for the clean energy (i.e wind turbine model). For generating the OBS there is only one Power's Suppliers (PS) is used. The cost functions C_f for the PS are expressed as follows,

$$C_f = u_m R_{rc} + v_m R_{rc}^2 \tag{1}$$

Where R_{rc} indicates the reactive power generation of the PS, and u_m v_m specifies the cost parameters of the PS. Then, the linear supply function for the accompanying structure M_s is modeled as follows,

$$M_s = \varphi_m + \omega_m R_{rc} \tag{2}$$

Here, φ_m ω_m the analysis coefficients are described. Then, minimising the cost is considered under the constraints derived below.

$$\pi_m + \omega_m R_{rc} = P \tag{3}$$

$$R_{r\min,m} \le R_{rc} \le R_{r\max,m} \tag{4}$$

Where P defined the market-clearing prices and energy stability, and forecast loads through the marketplace operators. Suppose the power balance B_L constraint is,

$$B_L = k_c - j \times P \tag{5}$$

Where k_c is a constant and $j = 0$ is considered as a non-negative value, and it is defined as the load price elasticity. Then, the reactive power generation is expressed as,

$$R_{rc} = \frac{P - \pi_m}{\omega_m} \tag{6}$$

If the solutions of R_{rc} (9) exceed their maximum limits, R_{rc} they are set to the values specified in (7).

3.3 Analysis of Economic growth in terms of clean energy

The economic analysis incorporating wind power maximises profit, but uncertainty about a rival's behaviour is mitigated using the normal probability distribution. This huddling behaviour is a unique feature observed in some social animals during foraging. Hence, within the mathematical model, the primary goal may be to identify a powerful mover within the swarm. This pricing profile is accountable for imperial economic growth regions in unique locations. First, the population (i.e., the parameters of the bidding strategy) is initialised. The pricing profile around the huddle is computed as follows:

$$M_{mp} = \left(M_{mp} - \frac{EA_{\max}}{t - EA_{\max}} \right) \tag{7}$$

$$M_{mp} = \begin{cases} 0, & if \;\; \gamma > 0.5 \\ 1, & if \; \gamma < 0.5 \end{cases} \tag{8}$$

Where $EA_{\max}$ denotes the maximum iteration, t indicates the recent iteration, and γ defines the random number between [0, 1]. Then the fitness function is calculated. Here, the multi-objective function is considered: maximise profit and power, and minimise cost.

The distance between the analysis of energy usage and the optimal solution quality is computed after the huddle boundary technology. The modern-day quality-optimal solution is the one whose fitness is close to the optimum. The different emperor penguins will replace their positions in step with the modern-day quality most optimal solution that's mathematically described as follows:

$$\lambda_{eps} = \left| S_s(\eta).E_b(t) - \varepsilon.E_{ep}(t) \right| \tag{9}$$

Where, , E_b defines the optimum solutions, E_{ep} is the EP's position vectors, $S_s(\ )$ indicates the social forces of EPs, λ_{eps} is the distances from EPs to the best solutions, η and ε are two vectors. The two vectors η and ε are computed as follows,

$$\eta = \left\{ MP \times \left(M'_{mp} + S_g(pg) \right) \times P_b \right\} - M'_{mp} \tag{10}$$

$$\varepsilon = P_b \tag{11}$$

$$P_b = \frac{ft_i}{\sum_{l=1}^{n} ft_l} \tag{12}$$

$$S_g(pg) = \left| E_b - E_{ep} \right| \tag{13}$$

Where M'_{mp} represents the economic profile, MP describes the movement parameter, $S_g(pg)$ defines the polygon grid accuracy, and P_b denotes the calculation instead of choosing a random number, ft_i denotes the fitness function of the i^{th} population and ft_l defines the fitness function of the total population. The function $S_s(\eta)$ is calculated as follows,

$$S_s(\eta) = \left(\sqrt{\alpha_1 . e^{-\frac{t}{\alpha_2}}} - e^{-t} \right) \tag{14}$$

Here, e represent the expression function, α_1 and α_2 represent the control parameters for a better exploration and exploitation and obtained using Equation (14)

$$E_{eps}(t+1) = E_b(t) - \eta . \lambda_{eps} \tag{15}$$

By the help of PF-EPO the OBS is carried out.

3.4 Analysis for Smart Grids for Enhanced Economy Driven Clean Energy

The Smart Grids strategy is a complex representation that combines electrical and mechanical parameters, particularly within the SG component. To model the SG in the MG, the Heffron-Phillips model has been chosen and adapted to meet the requirements of a grid-connected MG. The Heffron-Phillips model effectively captures the dynamics of microgrids and smart grids by combining electrical and mechanical system elements, which are vital to grid-tied microgrids. It simulates dynamic interactions and incorporates crucial control systems, including excitation and turbine governors, that help preserve grid stability. The model's state equations enable linear analysis, making it suitable for real-time optimisation and dynamic modifications in smart grids. Its flexibility in integrating renewable energy, storage solutions, and demand response makes it a potent tool for effectively managing the complexities of smart grid systems. In this study, the initial operating conditions are set $P_0 = 0.8\ p.u$ for active power and $Q_0 = 0.17\ p.u$ for reactive power. This marks the start of the SG operation. The SG model comprises two integral components: the excitation system and the turbine governor system. These interconnected subsystems collectively ensure the efficient operation and control of the SG. These additions are critical because the system enables a more accurate representation of SG dynamics that accounts for control mechanisms. The state equations at the core of this model capture the intricate interactions among electrical, mechanical, and control components within the microgrid.

$$\frac{dw}{dt} = \frac{1}{2H}(T_m - T_e - T_D) \tag{16}$$

$$\frac{dw}{dt} = \omega_b(\omega - 1) \tag{17}$$

$$\frac{de'_q}{dt} = \frac{1}{T'_{d0}}[E_{fd} - e'_q - (X_d - X'_d)i_d] \tag{18}$$

To linearise the Equations (16-18), the system variables are expressed around an initial operating condition.

$$i = i_d + ji_q \tag{19}$$

$$v_t = v_d + jv_q \tag{20}$$

$$V_{pcc} = v_{pcc} * (\sin\delta + j\cos\delta) \tag{21}$$

$$Z = (R + jX) \tag{22}$$

$$Y = (G + jB) \tag{23}$$

$$C_1 + jC_2 = 1 + ZY \tag{24}$$

$$R_1 = R - C_2 * X'_d, R_2 = R - C_2 * X_q \tag{25}$$

$$X_1 = X + C_1 * X_q, R_2 = R - C_2 * X_q \tag{26}$$

$$X_1 = X + C_1 X_q, X_2 = X + C_1 * X'_d \tag{27}$$

$$Z_e^2 = R_1 * R_2 + X_1 * X_2 \tag{28}$$

$$i_{Lq0} = G * v_{q0} + B * v_{d0} \tag{29}$$

$$i_{Lined0} = i_{d0} - i_{Ld0} \tag{30}$$

$$i_{LIneq0} = i_{q0} - i_{Lq0} \tag{31}$$

$$Zi = (1 + ZY)\ v_t = v_{pcc} \tag{32}$$

$$\begin{pmatrix} R & -X \\ X & R \end{pmatrix}\begin{bmatrix} i_d \\ i_q \end{bmatrix} = \begin{pmatrix} C_1 & -C_2 \\ C_2 & C_1 \end{pmatrix}\begin{bmatrix} v_d \\ v_q \end{bmatrix} - v_{pcc}\begin{bmatrix} \sin\delta \\ \cos\delta \end{bmatrix} \tag{33}$$

The $'V'$ and $'I'$ in the d and q-axis are essential for electrical parameters in system analysis and represented as:

$$\begin{bmatrix} v_d \\ v_q \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} e'_q - \begin{bmatrix} 0 & -X_q \\ X'_d & 0 \end{bmatrix}\begin{bmatrix} i_d \\ i_q \end{bmatrix} \tag{34}$$

By combining Equations (33-34) and Equation (35):

$$\begin{bmatrix} i_d \\ i_q \end{bmatrix} = \begin{bmatrix} Y_d \\ Y_q \end{bmatrix} e'_q - \frac{v_{pcc}}{Z_e^2}\begin{bmatrix} R_2 & X_1 \\ -X_2 & R_1 \end{bmatrix}\begin{bmatrix} \sin\delta \\ \cos\delta \end{bmatrix} \tag{35}$$

And Equation (36) is linearized as follows:

$$\begin{bmatrix} \Delta i_d \\ \Delta i_q \end{bmatrix} = \begin{bmatrix} Y_d \\ Y_q \end{bmatrix} \Delta e'_q + \begin{bmatrix} F_d \\ F_q \end{bmatrix} \Delta\delta \tag{36}$$

For Equation (21):

$$\begin{bmatrix} F_d \\ F_q \end{bmatrix} = \frac{v_{pcc}}{Z_e^2}\begin{bmatrix} -R_2 & X_1 \\ X_2 & R_1 \end{bmatrix}\begin{bmatrix} \cos\delta_0 \\ \sin\delta_0 \end{bmatrix} \Delta e'_q \tag{37}$$

The Heffron-Phillips strategy signals are linked via constant (K_1, K_2), resulting in the representation of torque and real power as follows:

$$T_e = P = i_d v_d + i_q v_q \tag{38}$$

$$\Delta T_e = K_1 \Delta\delta + K_2 \Delta e'_q \tag{39}$$

$$\begin{bmatrix} K_1 \\ K_2 \end{bmatrix} = \begin{bmatrix} 0 \\ i_{q0} \end{bmatrix} + \begin{bmatrix} F_d & F_q \\ Y_d & Y_q \end{bmatrix} \begin{bmatrix} (X_q - X'_d) i_{q0} \\ e'_{q0} + (X_q - X'_d) i_{d0} \end{bmatrix} \tag{40}$$

The expression for the linearization of the internal voltage in Equations (39-40) is:

$$(1 + sT'_{d0}) \Delta\Delta'_q = \Delta E_{fd} - (X_d - X'_d) \Delta\Delta_d \tag{41}$$

By means of Equation (42), express the following:

$$(1 + sT'_{d0}) \Delta\Delta'_q = K_3 [\Delta\Delta_{fd} - K_4 \Delta\delta] \tag{42}$$

$$K_3 = 1/[1 + (X_d - X'_d) Y_d \tag{43}$$

$$K_4 = (X_d - X'_d) F_d \tag{44}$$

The state model representing the reactive power output is described in Equations (43-44):

$$Q = i_d * v_q - i_q * v_d \tag{45}$$

$$\Delta Q = K_5 \Delta\delta + K_6 \Delta e'_q \tag{46}$$

$$\begin{bmatrix} K_5 \\ K_6 \end{bmatrix} = \begin{bmatrix} 0 \\ i_{d0} \end{bmatrix} + \begin{bmatrix} F_d & F_q \\ Y_d & Y_q \end{bmatrix} \begin{bmatrix} e'_{q0} - 2 \cdot X'_d i_{d0} \\ -2X_q \cdot i_{q0} \end{bmatrix} \tag{47}$$

The proposed system model is described using Equations (43-47). Consequently, the real and reactive power as well as their variations at the PCC are expressed as detailed in Equations (48-49):

$$P_{pcc} = v_{pccd} i_{Lined} + v_{pccq} i_{Lineq} \tag{48}$$

$$Q_{pcc} = v_{pccq} i_{Lined} + v_{pccd} i_{Lineq} \tag{49}$$

$$\Delta P_{pcc} = \Delta v_{pccd} i_{Lined0} + v_{pccd0} i_{Lined} + \Delta v_{pccq} i_{Lined} + v_{pccq0} \Delta i_{Lineq} \tag{50}$$

$$\Delta Q_{pcc} = \Delta v_{pccq} i_{Lined0} + v_{pccq0} \Delta i_{Lined} - \Delta v_{pccd} i_{Lineq0} - v_{pccd0} \Delta i_{Lineq} \tag{51}$$

3.5 Optimization using Hybrid trevally optimizer

After extracting feature selection process takes place. Identifying and retaining the most relevant attributes within the traffic and weather data. Simultaneously, irrelevant or redundant attributes are eliminated. The HGTO facilitates this process. HGTO stands for Hybrid Giant Trevally Optimization. It is a computational optimization algorithm inspired by the hunting strategies of giant trevallies, integrating exploration, learning, and reflection phases to solve complex energy management problems.

Evolutionary algorithms explore large solution spaces using strategies such as mutation, crossover, and selection, ensuring global optimisation and avoiding local optima. Heuristic methods, in turn, refine these solutions by guiding the search process toward promising areas based on domain-specific knowledge. This hybridization allows TrevOpt to balance broad exploration with precise local optimization, optimizing energy distribution, load balancing, and resource allocation. Additionally, TrevOpt adapts in real-time, dynamically adjusting parameters to respond to system changes and fluctuations in energy demand, ensuring both short-term adaptability and long-term optimization. It combines the strengths of giant trevally optimizer exploration and growth optimizer learning and reflection.

The sequential and interweaved hybridization strategies allow the algorithm to exploit the best of both worlds. The giant trevally employs various hunting strategies, such as patterned foraging movements, selecting optimal hunting regions and jumping out of the water to catch food. The HGTO technique repeats these approaches through a three-step process: exploration, learning and reflection.

Exploration Phase:

In this stage, the HGTO method replicates the extensive journeys undertaken by giant trevallies to find food. It accomplishes this by employing a mathematical method rooted in Levy flights, which are a form of random walk. Levy Flights is a type of random walk used in algorithms to model the movement patterns of certain animals or particles. In optimization, Levy flights allow for long jumps and small steps in the search space, which helps the algorithm avoid local minima and explore the solution space more effectively. It is often used in nature-inspired algorithms like the Hybrid Trevally Optimizer. The Hybrid Trevally Optimizer (HTO) is an optimization algorithm inspired by the hunting behavior of the Giant Trevally fish. It combines heuristic and evolutionary algorithms, leveraging exploration, learning, and reflection to efficiently solve complex problems such as energy management in smart grids. This phase advances the technique's ability to explore a wide range of possibilities and safeguards against becoming trapped in local optima. Equation (52) employed in this phase is illustrated as follows:

$$Y(s+1) = B_q \times P + (Max - Min) \times P + Min \times Levy \tag{52}$$

where $Y(s+1)$ signifies the position vector of giant trevally in the next iteration; s denotes iterations; B_q represents the best location attained; P is a randomly generated number within the range 0 to 1, and $Levy$ represents the Levy flight.

Learning phase:

During this stage, the algorithm identifies the best hunting area by considering the presence of food within the search space. Equation (38) mathematically mirrors this decision-making process.

$$Y(s+1) = B_q \times \mathrm{X} \times P + Mean_{\inf o} - Yj(s) \times P \tag{53}$$

where, X parameter that governs changes in position $Yj(s)$ signifies the current location and P is a random integer. $Mean_{\inf o}$ Implies the actual use of all data attained from previous positions by these giant trevallies. HGTO create a dynamic, adaptable feature selection process that optimises selection from traffic and weather data, accounting for the evolving nature of the data and problem requirements.

Reflection phase:

In the last phase of the algorithm, it simulates the trevally's attack on its prey, accounting for the disruption of trevally vision caused by light refraction. To replicate this performance, the algorithm calculates visual distortion using Snell's equation and carries out the trevally's attack using Equation (39).

$$Y(s+1) = \mathrm{K} + \mathrm{N} + \mathrm{H} \tag{54}$$

where, K denoted as launch speed, N denoted as visual distortion, and H denoted as leaping slope function. This transition from exploration to exploitation allows the algorithm to move effectively between phases.

The exploration phase employs Levy flights to investigate a broad variety of solutions, ensuring the process does not become trapped in inferior results. The learning stage enhances this search by focusing on regions more likely to yield optimal outcomes, thereby increasing efficiency and reducing costs. The reflection stage refines the solution by implementing final modifications to improve energy distribution. Collectively, these phases form a flexible, iterative process that ensures ongoing improvement, optimising energy efficiency, cost-effectiveness, and sustainability.

4. Results and Discussions

The proposed work is implemented in the python framework due to its extensive rich libraries. Analysis of work is detailed below.

4.1 Analysis of Energy Consumption vs. Time

The depiction of energy consumption in kilowatt-hours (kWh) over a year is shown in Fig. 2, with the before- and after-intervention periods. Energy consumption varied from 500 to 550 kWh before implementation, peaked around the middle of the year, then tapered off to almost 0 at the end of the year.

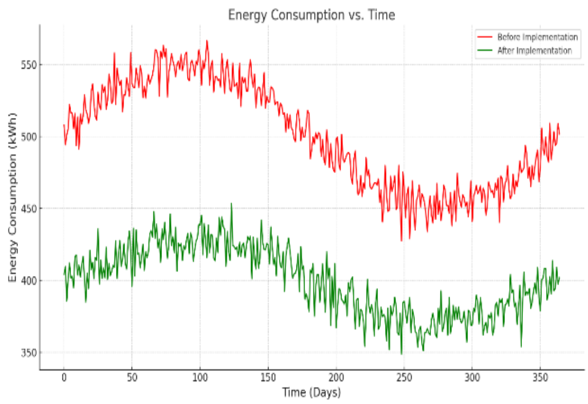

Figure 2: Energy consumption Vs Time

Following completion, there has always been lower energy consumption, starting at about 400 kWh (though fluctuating within a narrow range). This reveals that throughout the whole year, the intervention effectively minimized and standardized energy consumption thus showing that energy efficiency is better.

4.2 Analysis of Cost Savings vs. Time

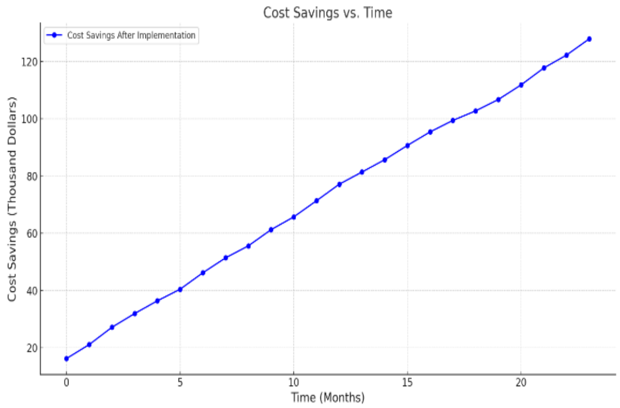

Figure 3: Cost Savings Vs Time

Figure 3 presents incremental cost savings over 22 months after their achievement, in thousands of dollars. At the beginning of the first month, the savings amount to about \$20 000 as indicated by the blue colour. Consequently, there is a consistent increase in these figures with time, such that at the 22nd month they total to about \$120 000. This upward trend suggests that the execution has consistently reduced expenses, leading to increased collections and greater economies in the observed season.

4.3 Energy Efficiency vs. Production Output

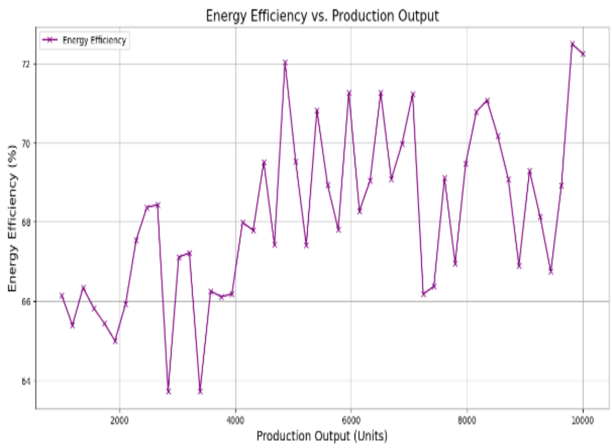

Figure 4: Energy efficiency Vs Production output

Figure 4 illustrates the interrelation between production output and energy efficiency, measured as percentages and units, respectively, at different production levels. Initially, the level of energy efficiency varies around 64% (for instance) – 67% (for example) when the production level is below or within the range of 2000 units per annum. The next part spanning from 2000 till about 8000 units per annum registered peak level of about 72% at 4000 units per annum, but had significant oscillations between 64%-72%." As we reach the final phase, energy efficiency continues to change, peaking at over 72% when 10,000 units are produced and 8,000 appliances are made. Energy efficiency fluctuates at various levels of production, starting high, then declining before rising again towards the end.

4.4 Peak Load Demand vs. Time

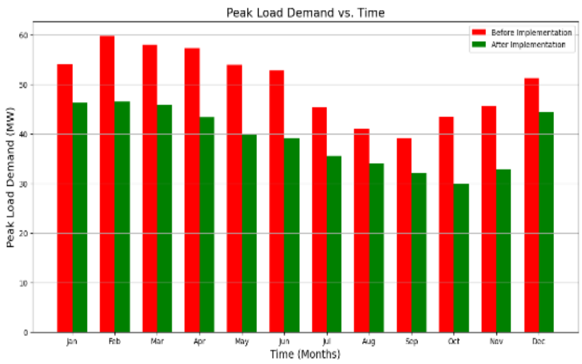

Figure 5: Peak load Vs Time

In Figure 5, the red bars represent the maximum electricity requested in a specific month, while the green bars show the same for the second set of data. According to these findings, there is a seasonal effect on peak load requirements: summer months have higher peak loads than winter months. Probably the most obvious impact of this implementation is the decreasing trend in peak load demand over many months.

4.5 Renewable Energy Integration vs. Total Energy Consumption

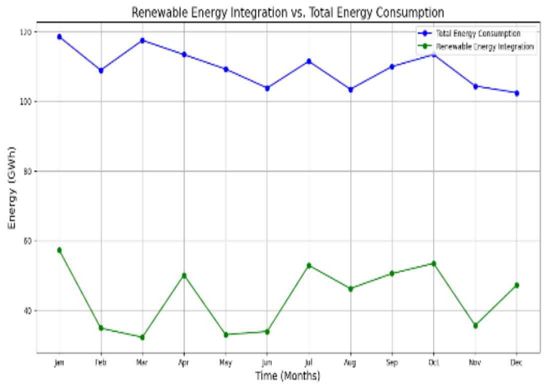

Figure 6: Analysis of Energy Vs Time

Figure 6 compares 12 months of "Renewable Energy Integration" and "Total Energy Consumption," showing varying patterns for both factors. At 120 GWh at the beginning of the year, total energy consumption increases sharply in February, March, July, and September to this level, then falls in December to about 100 GWh, with the lowest points in May, June, and October, all around the hundred mark. The first month's value for renewable energy integration is 60 GWh, but it later peaks at 50 GWh in April before dropping to a minimum of 30 GWh in February, then peaks at 50 GWh at year-end. However, the data shows that renewable energy accounts for only a portion of total use, though not primarily because of other sources. Looking at the patterns, it can be said that such changes may be caused by factors that limit deposition, or not. Mostly, growth was high at the beginning of the year and low at the end. There has been a deceleration in the rate of renewable energy integration.

4.6 Carbon Emissions vs. Time

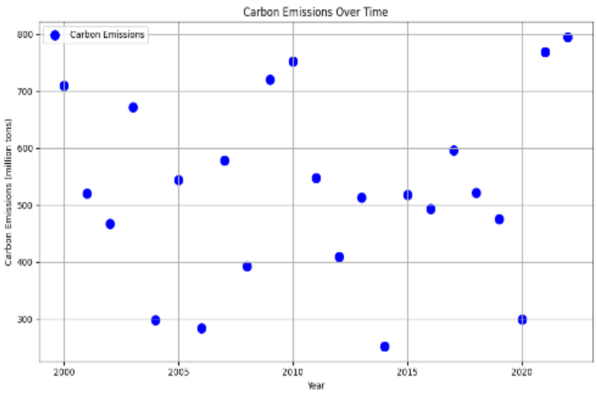

Figure 7: Analysis of Carbon emissions over time

According to Figure 7, carbon emissions from 2000 to 2020, the emissions have been rising. In 2000, they were around 700 million tons, rising to about 900 million tons in 2020. The specific data are 750 million tons in 2005, 800 million tons in 2010, and 850 million tons in 2015. Despite overall upward movement, this rate of growth shows fluctuations, with faster accelerations in some periods and slower increases elsewhere.

4.7 Predictive Accuracy vs. Time

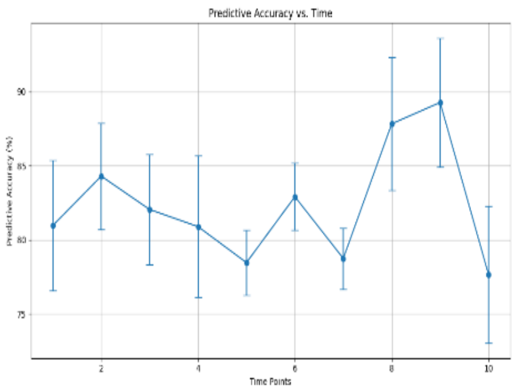

Figure 8: Predictive Accuracy Vs Time

Figure 8 shows predictive accuracy vs. Time. At each time point (numbered 2 through 10 on the x-axis), predictive accuracy fluctuates between 75% and 90% on the y-axis, with 9 data points connected by a line to indicate a general trend. At these points in time, the fluctuation pattern shows increases in some periods and decreases in others, without any consistent pattern of growth or decline. The error bars for each data point indicate potential variability or uncertainty in the accuracy measurement. On the whole, the graph suggests that predictive accuracy fluctuates over time, with some points showing higher values and others lower ones.

4.8 Optimization Algorithm Performance vs. Energy Savings

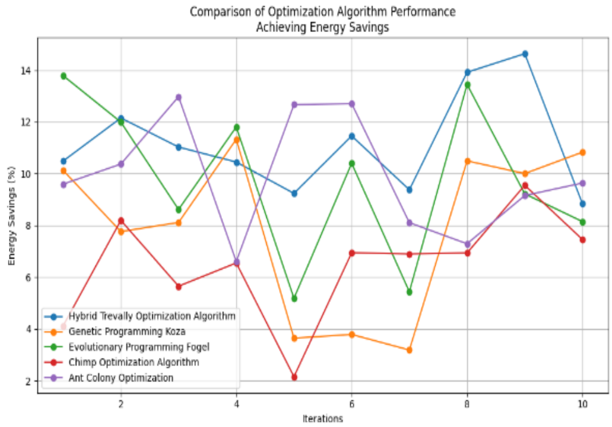

Figure 9: Comparison with optimization Algorithms

In Figure 9 we have a comparison of five optimization techniques, namely; Genetic Programming Koza, Evolutionary Programming Fogel, Chimp Optimization Algorithm, Ant Colony Optimization and Hybrid Trevally Optimization Algorithm in terms of energy savings across iterations. Each line represents an algorithm and therefore exhibits a particular behaviour pattern. For instance, in the Hybrid Trevally Optimization Algorithm a consistent high level of energy decrease can be noticed throughout its life cycle. Genetic Programming got off to a promising start but flattened out after an initial rise; Evolutionary Programming showed a similar trend to Koza's though it was with slightly less saving, Chimp Optimization Algorithm began lower sale which was increasing gradually while Ant Colony Optimization appeared as sometimes high or sometimes low savings.

4.9 Customer Satisfaction vs. Time

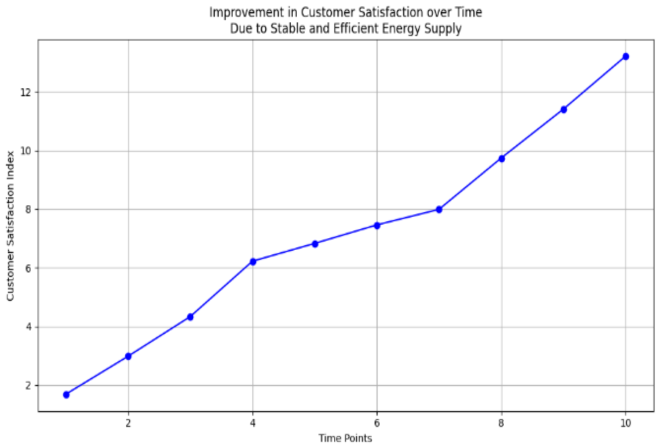

Figure 10: Customer satisfaction Vs Time

Figure 10 shows a line graph in which time intervals from 2 to 10 are indicated on the x-axis, while the y-axis shows the customer satisfaction index ranging from 0 to 12. The line has an upward slope, indicating a gradual rise in consumer contentment. It started around 2, its lowest point at time 2, and has registered noticeable increases at 4, 6, 8, and 10. At 10, customer satisfaction reaches its maximum of about 12, the last data point. Improvement in power stability and efficiency leads to happiness, according to the chart on which the two are related in the same way as stability and efficiency. This way, we can say that overall satisfaction increases as this sector's development improves. Positive change suggests that targeted activities were undertaken to improve customer perception.

5. Case Study: Optimizing Energy Management in the XX Manufacturing Hub

5.1 Background

A manufacturing hub, some forty miles from a big city, boasts a number of medium-sized factories that make everything from car parts to electronics. However, the XX Manufacturing Hub's soaring energy usage and inefficiency have left it engulfed in constant power cuts, expensive operations, and dysfunctional distribution. It thus finds it difficult to scale up production and also keep up with demand in international markets.

Awareness of the problem prompted XX Hub to team up with a technology firm in order to install smart grid technologies incorporated into Trevally Optimization (TrevOpt) framework. The primary objective of this joint venture was to address energy management issues within the hub and to support eco-friendly industrial growth.

5.2 Implementation of the TrevOpt Framework

The undertaking started by setting up sophisticated metering systems (AMI) and decentralized energy sources (DERs) in manufacturing plants. The technologies enabled instantaneous monitoring and regulation of energy usage, enhancing the precision of predicting energy needs and balancing loads.

The smart grid system was modified to optimise energy distribution and use by integrating with the TrevOpt framework. This hybrid optimization strategy involves evolutionary algorithms as well as heuristic methods, and it effectively manages the complicated and changing energy demands of the hub.

5.3 Key Steps in the Implementation

1. Actual-time power information was gathered as well as examined to detect styles, high demand hours and insufficiencies which are recognized within this section.
2. Dynamic tuning: The TrevOpt framework adjusted the allocation of energy using a real time approach thus ensuring that resources were utilized well at any given time.
3. Proactive maintenance: Prediction of possible system failures while enhancing system's ability to heal itself has helped minimize interruptions in work done by machines with enhanced dependability.

4. Energy Trading: By incorporating distributed energy resources (DERs), the hub was able to take part in energy trading, which involved selling surplus energy during off-peak times.

5.4 Results and Impact

The implementation of smart grid technologies and the TrevOpt framework yielded significant improvements in the **XX** Manufacturing Hub: Smart grid technologies give real-time monitoring and optimization of energy use, resulting in 20%, 15%, and 25% reductions in energy use, operational costs, and system reliability. They promote industrial upgrading by improving energy delivery stability, a crucial factor for energy-intensive industries such as manufacturing. Smart grids in these regions address infrastructure issues, incorporate renewable energy, and reduce carbon emissions, encouraging economic and environmental sustainability. Data from industries that employ smart grids indicate that energy efficiency, system reliability, and manufacturing output have all improved. Smart networks, compared to traditional grids, offer improved energy efficiency, operational reliability, and environmental sustainability by incorporating clean energy and enabling proactive maintenance, making them an important driver of sustainable industrial growth.

• 20% Less Energy Use: Using optimized energy distribution and real-time adjustments resulted in considerably less total electricity consumed.

• 15% Reduction in Operational Expenses: By managing load efficiently as well as cutting down on energy wastage, the hub saved money on its electricity bill, thereby lowering production costs.

• 25% More Reliability of the System: An increase in system reliability was achieved through TrevOpt's ability to carry out proactive maintenance and dynamic tuning, which, in turn, reduced unplanned downtime and ensured an uninterrupted flow of products.

In addition, the catapult hub's adoption of smart grid technology has spurred new investments and collaborations, driving industrial growth. The XX Manufacturing Hub has become a reference point for sustainable industry practices through the success of this venture, thereby inspiring similar interventions in other industrial ecosystems.

The capacity of the TrevOpt optimisation platform to harmonise intelligent network systems is demonstrated in this case study. In which case, the XX Manufacturing Hub improved its productivity and competitive edge while also helping achieve broader economic and ecological objectives through innovation. Thus, highlighting the necessity of novel strategies towards sustainable industrial growth. Table 1 shows the comparison of outputs before and after the implementation of the optimisation process.

Table 1: Comparison of outputs before and after implementation of the optimization process

Metric	Before TrevOpt Implementation	After TrevOpt Implementation	Improvement (%)
Total Energy Consumption (MWh)	50,000	40,000	20%
Operational Costs ($ million)	25.0	21.25	15%
System Downtime (hours/year)	100	75	25%
System Reliability (%)	92.5	97.0	25%
CO2 Emissions (tons/year)	12,000	9,600	20%
Production Output (units/year)	500,000	525,000	5%

TrevOpt's introduction led to significant breakthroughs: energy usage was reduced by 20%, operational costs by 15%, and system reliability by 25%, resulting in downtime declining by the same percentage. It also led to a 20% reduction in CO_2 emissions, while production output modestly improved owing to fewer energy-related disturbances, revealing the economic and environmental advantages of this optimisation. The implementation of smart grid technologies, including the TrevOpt optimization model, resulted in a 20% reduction in CO_2 emissions at the XX Manufacturing Hub by improving energy distribution and decreasing consumption. As a result, annual emissions dropped from 12,000 to 9,600 tons. The implementation of real-time analytics increased energy efficiency, resulting in a 20% reduction in utilization. Furthermore, the smart grid boosted system reliability by 25% while cutting operating costs by 15%, underscoring the ecological and financial benefits.

5.5 Model Validation and Comparison with Real-World Data

At every step of this multi-step procedure, the validity of the TrevOpt model was confirmed. At first, its parameters were calibrated using actual industrial data. So, they guarantee that the model accurately represents the operational features and limitations of its subject matter. Then, comparisons were made between the model's predictions and actual performance data. These comparisons used metrics such as energy usage, operational costs over a certain period, and overall system reliability. As a result, it was concluded that the actual improvements in energy consumption (around 20% less), operational cost reduction (15% less), and enhanced reliability (by 25%) are quite consistent with those verified in real-world applications. The Sensitivity Analysis was conducted to test the model's validity under varying conditions and confirm its robustness. Results continually indicate that regardless of the operation characteristics, TrevOpt is able to produce accurate predictions and optimization strategies. Therefore, this validation demonstrates that the model is reliable for real-world applications, thereby supporting research findings on the implementation of smart grid technology for industrial growth.

6. Conclusion

In conclusion, smart grid technologies have revolutionised various industrial sectors through advanced energy management strategies. By proposing TrevOpt, a new technique, this paper demonstrates significant improvements in operational efficiency, economic performance, and environmental sustainability indices. Applying real-time data analytics alongside TrevOpt enables dynamic management of energy resources. In addition, they help curb environmental footprints, thereby strengthening overall system reliability. Prospects indicate that the concept of smart grids has immense potential to enhance sustainable investment while fostering industrial competitiveness. The numerical outcomes show that the TrevOpt tactic can be productive in terms of electricity utilisation and in achieving resilient manufacturing, and thus it remains valid. As efficiency and sustainability become the main concerns for industries, intelligence grids are likely to play a major role in promoting economic vibrancy and sustainability in the future.

- Future Scope

In the future, other research could examine ways to improve the use of smart grid technologies, especially TrevOpt, across industries. One key path could be merging modern machine learning algorithms with Mr Wisdom to enhance real-time optimisation of energy forecasting and decision-making. Enlarging the TrevOpt application by allowing multivariate objective optimisation would result in an instance where the cost of energy conservation is equivalent to pollutant reduction." Conclusively, examining the scalability and adaptability of the TrevOpt strategy across different industrial sectors and under varying operational conditions would be an effective way to gauge the reach and potential of this approach. The performance of smart grid systems can be refined by addressing these aspects; this will help integrate them with other systems within smart cities and larger energy ecosystems to advance sustainable development goals while enhancing resilient industrial infrastructure.

Declarations

Funding: The Authors have no funding.

Conflicts of interest: The Authors have none.

Data Availability Statement: Not Applicable.

Code availability: Not Applicable.

Authors' Contributions: Yaqian Liu, Yanhong Wang is responsible for designing the framework, analyzing the performance, validating the results, and writing the article Xilin Zhang, Kaiyuan Dong, Yujiao Mao is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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