Providing a Model for Enhancing Energy Consumption Efficiency in Industrial Units Based on Artificial Intelligence

Fatemeh Kharaghani[1],Ahmadreza Kasrai[2]*,Hasan Mehrmanesh[1]
1.Department of Industrial Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran.
2. Department of Industrial Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran (Corresponding Author).

*** Corresponding author email address**: kasrai49@yahoo.com

Received: 2024-01-15 **Reviewed:** 2024-01-25 **Revised:** 2024-03-03 **Accepted:** 2024-03-19 **Published:** 2024-03-31

Abstract

Improving electricity consumption efficiency in industrial units using advanced technologies, particularly artificial intelligence, has become a crucial factor in reducing operational costs and increasing productivity. The objective of this study was to provide a model for enhancing the efficiency of electricity consumption in industrial units based on artificial intelligence. This study is applied in terms of research objective and qualitative in methodology, adopting a grounded theory approach. Methodological triangulation was observed in this research through various data collection methods, such as literature reviews, examination of specialized sources and texts, as well as semi-structured interviews. Based on purposive sampling, interviews were conducted with 14 managers and experts from companies active in the electricity industry in 2024. The conducted interviews were coded using ATLAS.TI software. To validate the results obtained, data were evaluated and analyzed for validity based on triangulation. Based on the analysis, six causal conditions (monitoring and data analysis, predictive and optimization models, intelligent automation and control, load and demand management, failure detection and prevention, and collaboration and data sharing), two contextual conditions (technological infrastructure and sociocultural factors), four intervening conditions (regulations and laws, individual and human factors, financial support, and security conditions), four strategies (technological resources, knowledge resources, use of renewable energy sources, and managerial factors), and five outcomes (improvement of production processes, enhanced learning, power grid sustainability, carbon emission reduction, and competitiveness) were identified. Improving electricity consumption efficiency in industrial units through artificial intelligence provides unique opportunities to reduce costs, increase efficiency, and protect the environment. Artificial intelligence systems help identify weaknesses and offer optimization solutions by accurately analyzing data and recognizing energy consumption patterns. These technologies can automatically apply optimal settings to prevent energy waste, directly resulting in reduced operational costs.

Keywords: *energy consumption, energy consumption efficiency, artificial intelligence, industrial electricity*.

How to cite this article:

Kharaghani F, Kasrai A, Mehrmanesh H. (2024). Providing a Model for Enhancing Energy Consumption Efficiency in Industrial Units Based on Artificial Intelligence. Management Strategies and Engineering Sciences, 6(1), 141-150.

1. Introduction

Energy consumption encompasses the use of various energy sources by living beings, machines, and systems to conduct necessary activities. These sources include electricity, gas, oil, coal, and renewables like wind and solar energy, each consumed across sectors such as industrial, residential, commercial, and transportation [1, 2]. Each sector has unique energy demands and usage patterns. In industrial settings, energy is predominantly used for production processes and various operational activities, whereas in residential sectors, energy is primarily consumed for heating, cooling, lighting, and appliances. Efficient energy management and optimization are critical due to their direct impact on costs, efficiency, and environmental sustainability. As technology advances, tools like artificial intelligence (AI) and smart energy management systems have been developed to monitor, manage, and improve energy efficiency by analyzing data and offering optimization strategies [3].

Energy consumption efficiency refers to the optimal use of energy resources to accomplish specific tasks with minimal waste and maximum effectiveness. This concept is essential in industrial, residential, commercial, and transportation sectors, as it reduces costs, enhances efficiency, and lessens environmental impacts [4]. For instance, in industry, energy efficiency can be achieved by employing advanced technology and automation systems, reducing energy use in production and improving equipment performance. In residential and commercial sectors, energy efficiency can be enhanced through high-efficiency devices, improved building insulation, and intelligent energy management systems, which collectively reduce consumption and energy costs while aiding environmental protection by lowering greenhouse gas emissions [5, 6].

Artificial intelligence, a computer science branch, enables systems and programs to perform tasks typically requiring human intelligence, such as learning, reasoning, problem-solving, and decision-making [7]. By integrating advanced algorithms and big data, AI can make intelligent decisions and optimize various processes. In energy management, AI supports supply chain optimization, production efficiency, and equipment failure prediction. For industrial power consumption, AI-driven automation and monitoring reduce operational costs, enhance productivity, and mitigate environmental impact, helping industries optimize power use for sustainability. Various studies have leveraged AI techniques like particle swarm optimization and genetic algorithms to predict and manage future energy demands across sectors, underlining AI's critical role in future energy efficiency [8].

Improving electricity consumption efficiency in industrial units using advanced technologies, particularly artificial intelligence, has become one of the key factors in reducing operational costs and increasing productivity [9]. Artificial intelligence can identify consumption patterns and offer optimization solutions by accurately analyzing energy consumption data. This technology is capable of real-time monitoring of energy consumption and can automatically make the necessary adjustments to improve efficiency. This leads to reduced energy consumption, cost savings, and enhanced overall performance of industrial equipment [10].

In addition to economic benefits, optimizing electricity consumption using artificial intelligence also has positive environmental impacts. Reducing energy consumption directly contributes to lower greenhouse gas emissions and other environmental pollutants [11]. This not only aids in environmental conservation but also enables industrial units to comply with stricter environmental regulations. Furthermore, through predictive analysis, artificial intelligence can help identify weaknesses and opportunities for improvement in production processes, thereby leading to greater efficiency and long-term sustainability [12].

Ultimately, energy efficiency through artificial intelligence enhances the competitiveness of industrial units. Industrial units that reduce energy costs and increase efficiency can offer their products at more competitive prices and capture a larger market share [13, 14]. Additionally, improving energy efficiency can help build a positive image of corporate social and environmental responsibility, which in turn can attract more customers and investors [15]. Overall, energy consumption efficiency using artificial intelligence brings multiple benefits to industrial units, which are economically and environmentally valuable [16].

Electric energy plays a crucial role in shaping and sustaining the modern world, to the extent that many activities in the modern world are inevitably tied to the presence of electricity [17]. In this context, electricity distribution networks play an essential role in ensuring that everyone has access to this critical energy source and are considered the vital veins of the modern world. From this perspective, ensuring the health and efficiency of electricity distribution networks is of paramount importance. Equipping the distribution network with appropriate measurement methods is the first step towards monitoring its health [18]. Today, a new generation of measurement methods, called Advanced Metering Infrastructure (AMI) systems, enables continuous and precise monitoring of network capacity and consumption. An adequate volume of raw data provided by these systems allows distribution companies to conduct more intelligent monitoring at higher levels. One of the ongoing challenges for electricity distribution companies is enhancing the efficiency of electricity consumption in industrial units [1, 19].

Energy consumption and the efficient sourcing of capital and consumer products are becoming competitive advantages, and industrial units are increasingly interested in optimal process operations and supply chain design [5, 20]. Generally, in most countries, inefficiencies in electricity consumption in industrial units result from inherent network parameters, such as transmission line impedance, transformer core losses, physical phenomena, and other factors. Inefficient electricity consumption in industrial units imposes significant economic losses on the country [21]. These economic losses manifest in various domains, including reduced income from electricity sales, compromised reliability and network registration, excessive resource utilization for energy production, and consequent environmental pollution [22]. In less developed countries, inefficient electricity consumption in industrial units accounts for up to 40% of total generated energy. For example, this figure for India is estimated at $4.5 billion annually. For developed countries, this remains a major challenge, leading to annual economic losses between $1 and $6 billion for the economies of the United Kingdom and the United States [23]. Despite the importance of this issue and the extensive investments made by companies to address it, scientific communities' efforts to provide solutions seem insufficient, necessitating greater focus from research centers in this area [24].

From an engineering perspective, the method for identifying electricity consumption efficiency in industrial units involves calculating the balance between energy production and consumption across different network sections. This method requires adequate information about the network's topology. Although this solution initially appears appropriate, in practice, it is not very realistic due to technical limitations [25]. These limitations include the continuous growth and changes in network topology [26], the potential for structural breakdowns, and the need for simultaneous measurement at specific points within the network. Additionally, the high volume of non-technical losses in industrial units has necessitated finding more accurate yet low-cost solutions [27]. Consequently, the search for more precise and adaptable methods has led to the use of artificial methods to address this issue. Utilizing artificial intelligence enables the analysis of consumption profiles of industrial units and facilitates the understanding of their irregular behaviors, leading to the development of methods for monitoring abnormal consumption patterns of subscribers for the first time [28]. These methods have provided deeper insights for detecting fraudulent behaviors based on pattern learning [8]. By identifying inefficiencies in electricity consumption in industrial units, technicians can assess the underlying cause based on credible evidence and take action to resolve it [29].

A key research gap in developing AI-based models for enhancing industrial energy consumption efficiency lies in the limited integration of energy forecasting models with advanced optimization methods. While separate studies address energy consumption forecasting and optimization techniques, there remains a significant gap in combining these approaches. Energy forecasting models, which utilize historical data and machine learning algorithms to predict future demand, require optimization methods to translate predictions into practical, actionable strategies for energy management. More comprehensive research is needed to integrate these models effectively and improve their practical application. Another research gap pertains to the insufficient focus on human and organizational interactions in implementing AI for energy optimization. Most studies prioritize AI technologies and technical algorithms but overlook human and organizational factors. Detailed examination of how organizational culture, employee skills, and managerial processes impact the efficiency and adoption of AI in energy optimization could help identify and overcome implementation barriers, improving acceptance of these technologies. Additionally, there is a need for developing holistic models to assess environmental and economic sustainability in energy efficiency. While many models emphasize energy efficiency improvements, limited research assesses the environmental and economic impacts of these improvements. Developing models that simultaneously evaluate environmental, economic, and social effects could support more sustainable decision-making. Lastly, a significant gap exists in financing and implementing AI-based energy efficiency projects. Although many studies explore AI technologies and their benefits, deeper investigation is needed into financing models, required resources, and the economic viability of these projects. Further research should analyze financial challenges and funding models to provide practical, executable solutions for implementing energy optimization projects, assisting organizations in managing investment costs.

Methods proposed in research for detecting electricity consumption efficiency in industrial units fall into two major categories: expert systems and machine learning-based methods. Expert systems use a pre-established rule base for decision-making and perform inference accordingly. However, in machine learning-based methods, effective patterns and rules for decision-making are learned by the computer without human intervention. Previously, expert systems were more common, but today, research communities focus more on machine learning methods. In this study, by leveraging the capabilities of artificial intelligence, methods for identifying electricity consumption efficiency in industrial units will be reviewed to provide a clearer outlook for future research.

2. Methodology

This research is applied in terms of objective and qualitative in nature, adopting a grounded theory approach based on the Strauss and Corbin (1998) framework. Methodological triangulation was observed through various data collection methods, including library research, examination of specialized resources and texts, and semi-structured interviews. Data triangulation, involving the consistency check of multiple data sources within the same methodology, was also prioritized, using more than one data source. Potential participants included experts, elites, and managers of companies active in the electricity industry in 2024. The purposive sampling method was used, selecting individuals to participate in the qualitative component of the study. The primary source of data was interviews, where initial interviews were exploratory and descriptive. After each interview, the data was coded iteratively using constant comparative methods to derive theoretical codes through open coding. This process continued across 14 interviews, from which main and subcategories emerged. Notably, theoretical sampling guided the saturation of core categories, ensuring comprehensive and rich concepts in each category. For instance, the “type of change” category reached saturation after eight interviews, whereas others, like “outcomes and impacts,” required further interviews until saturation was achieved. Theoretical sampling was not based on the number of interviews but on each participant's role in enriching the categories. By the 14th interview, theoretical saturation was reached. Each interview lasted between 30 to 50 minutes. Data analysis was conducted using grounded theory in ATLAS.TI software, following three coding stages: open coding, axial coding, and selective coding.

The following questions were posed to selected participants in the qualitative sample:

- Please introduce yourself and describe your experience with energy consumption optimization and artificial intelligence (AI) applications.
- How have you contributed to improving energy efficiency in the industry using AI?
- What challenges have you observed in optimizing electricity consumption in industrial units?
- What are the primary barriers to adopting and implementing AI technologies in this field?
- Which AI technologies have had the greatest impact on energy efficiency improvements?
- Can you provide examples of successful projects using AI to reduce energy consumption?
- What types of data are needed for energy consumption analysis and optimization?
- How can AI help identify energy consumption patterns and optimal points?
- What economic and environmental benefits have resulted from AI-driven energy consumption optimization?
- What outcomes have you observed from AI-based energy optimization projects?
- What are the main steps for implementing an AI system to optimize energy consumption in industrial units?
- What advice would you give companies aiming to use AI for energy optimization?
- How do you foresee AI technologies transforming electricity consumption efficiency in the future?
- What new AI innovations could help optimize energy consumption in industries?
- How can AI use in energy optimization contribute to corporate sustainability and social responsibility?
- What roles do you see for AI in addressing climate change and reducing greenhouse gas emissions?

3. Findings

The demographic profile consists of a sample with 43% women (n=6) and 57% men (n=8). In terms of education, the majority of participants hold a master’s degree (71%, n=10), while 29% (n=4) have a doctorate or higher. Regarding work experience, 36% (n=5) have 15–20 years, 50% (n=7) have 20–25 years, and 14% (n=2) have 25 years or more. Age distribution shows that 43% (n=6) of participants are aged 30–40, another 43% are aged 40–50, and 14% (n=2) are over 50.

For open coding, all interviews were imported into ATLAS.ti, where essential reviews were conducted, and relevant codes were extracted. Codes were labeled based on interview content, and the researcher aimed to closely adhere to participants' insights to avoid potential biases. Throughout the coding process, the researcher maintained theoretical sensitivity, a core principle in grounded theory research, to enrich the study further. Table 1 displays examples of coded interviews.

Table 1. Examples of Coded Interviews

Interview Content	Identified Codes
By implementing AI, we established advanced systems for monitoring and managing energy consumption in our industrial unit. These systems can analyze energy consumption patterns and identify weaknesses. For example, using machine learning algorithms, we optimized energy use in production processes and prevented energy waste through automatic equipment adjustments.	Improved energy efficiency with AI, use of machine learning algorithms, analysis of energy consumption patterns
One main challenge in optimizing electricity consumption in industrial units is the diversity and complexity of production processes, each requiring specific adjustments and optimizations. Additionally, access to accurate and comprehensive data remains a major obstacle, and changing staff and managerial attitudes toward adopting and implementing new technologies is also challenging.	Staff attitudes, managerial attitudes, acceptance and implementation of new technologies, diversity and complexity of production processes
The primary barriers to adopting and implementing AI technologies include high initial costs, the need for technical expertise, and resistance to change. Many managers and employees still lack full confidence in AI capabilities and benefits, slowing implementation.	High initial costs, need for technical expertise, resistance to change, slow implementation
Several AI technologies have significantly impacted energy efficiency improvement, including machine learning, deep neural networks, and big data analytics. These technologies assist in identifying consumption patterns, predicting energy needs, and optimizing production processes.	Machine learning, deep neural networks, big data analytics, energy needs prediction, production process optimization
In one of our successful projects, we implemented a smart energy management system in the production line. By using machine learning algorithms, we reduced energy consumption by 20%. This system automatically applies optimal settings, identifying and correcting weaknesses in real time.	Energy consumption reduction
Comprehensive and accurate data on energy consumption in each section, equipment performance, and environmental data are essential for analyzing and optimizing energy use. These data can be collected from sensors, monitoring systems, and network-connected devices.	Comprehensive and accurate energy consumption data, equipment and environmental data, monitoring systems and network-connected devices
AI can analyze collected data to identify energy consumption patterns and determine optimal points. For example, it can detect peak consumption times and suggest adjustments to reduce this consumption.	Detection of energy consumption patterns
Using AI in energy consumption optimization can yield significant economic benefits, including reduced energy costs and increased efficiency. Additionally, reducing energy consumption helps lower greenhouse gas emissions and supports environmental conservation.	Reduced energy costs and increased efficiency, reduced energy consumption, reduced greenhouse gas emissions, environmental conservation
For companies aiming to use AI for energy optimization, I recommend starting with a comprehensive needs and potential analysis. Engaging experts and specialists in this area can also enhance successful implementation. Furthermore, creating an organizational culture that embraces change and new technologies is crucial.	Engaging experts and specialists, creating an organizational culture receptive to change and new technologies
AI technologies are expected to play a greater role in improving energy consumption efficiency in the future. As algorithms and processing capabilities advance, AI can enable more precise analysis, better predictions, and further optimization.	Algorithms and processing capabilities, AI
New AI innovations include using deep neural networks to analyze more complex data, developing self-learning systems, and employing the Internet of Things (IoT) to gather more comprehensive data. These innovations can improve energy consumption efficiency and reduce waste.	Innovations, complex data analysis, development of self-learning systems, use of IoT
Using AI in energy consumption optimization can contribute to corporate sustainability and social responsibility. Reducing energy use and greenhouse gas emissions aids environmental conservation and reflects a company's commitment to environmental and social responsibilities.	Corporate commitment to environmental and social responsibilities, reducing energy use and greenhouse gas emissions
AI can play an essential role in addressing climate change and reducing greenhouse gas emissions. Through energy optimization and waste reduction, AI can help mitigate climate change impacts and conserve natural resources. Additionally, AI can support innovative solutions for efficiently using renewable energy resources.	Energy optimization and waste reduction, mitigating climate change impacts, conserving natural resources

Table 2 categorize identified codes according to Strauss and Corbin's (1998) grounded theory model dimensions.

Table 2. Selective Codes with Categories and Initial Codes

Selective Code	Core Category	Initial Code
Causal Conditions	Monitoring and Data Analysis	Continuous data collection and analysis - Identifying high-consumption points - Use of sensors and smart tools

	Prediction and Optimization Models	Machine learning - Neural network algorithms - Energy consumption prediction algorithms - Process optimization algorithms
	Smart Automation and Control	Equipping industrial units - Automatic and data-driven smart control systems - Automatic settings for temperature, lighting, etc.
	Load and Demand Management	Load and demand management systems - Smart peak time systems - Low-consumption time management
	Fault Detection and Prevention	Fault detection algorithms - Device lifecycle management - Maintenance cost management
	Collaboration and Data Sharing	Collaboration between industrial units - Data-sharing agreements - Creating a common data language
Strategic Conditions	Technological Resources	Blockchain and decentralized governance - Energy substitution technologies - Reactive demand management - Energy storage
	Knowledge Resources	Expertise in energy management, AI, ICT, sustainable development, renewable energy, IoT, and maintenance
	Use of Renewable Energy Resources	Solar panels - Wind turbines - Reducing reliance on fossil fuels - Energy Internet
	Managerial Factors	Commitment to large-scale electricity use - Flat organizational structure - Managing uncertainty - Strategic project planning
Outcomes	Improvement of Production Processes	Reducing energy waste - Early fault detection - Increased efficiency - Extending equipment lifespan - AI-driven improvements
	Learning Improvement	Learning by Doing - Learning by Interacting - Learning by Using - Organizational Science and Technology System
	Power Grid Sustainability	Reducing grid load - Smart management - Predicting energy needs - Environmental compliance - Reduced emissions
	Carbon Emission Reduction	
	Competitiveness	Quality improvement - Cost reduction - Profit increase - Efficient market positioning
Contextual Conditions	Technological Infrastructure	Advanced processors, sensors, ICT infrastructure - Open internet access - Real-time monitoring - System integration
	Cultural and Social Factors	Promoting energy culture - Trust-building - Information exchange - Sustainable development commitment
Intervening Conditions	Laws and Regulations	Energy standards - Emission reduction requirements - Legal compliance - IP protection
	Individual and Human Factors	Acceptance of change - Technological skills - Public awareness - Specialist training
	Financial Resources	Funding for transformative energy technologies - Network economics
	Security Conditions	Data protection - Cybersecurity - Continuous auditing - Preventing unauthorized access

Following data analysis and evaluation, the final research model was presented.

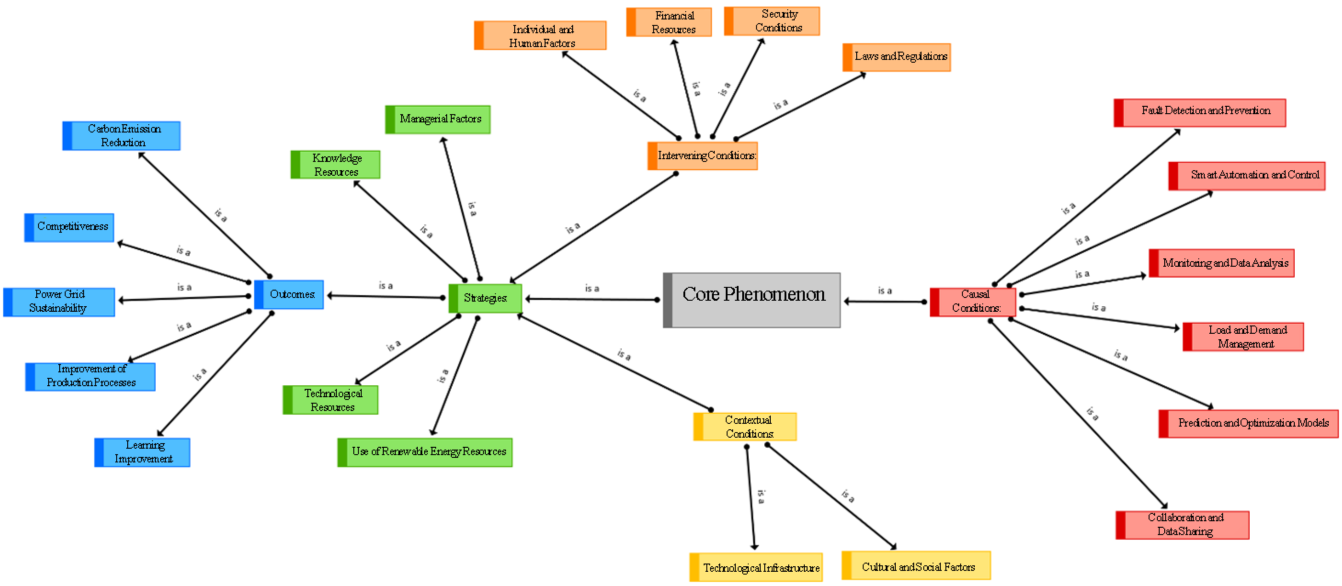

Figure 1. Final Model of The Study

4. Discussion and Conclusion

The study aimed to enhance the efficiency of electricity consumption in industrial units through artificial intelligence

(AI) based on grounded theory techniques. The analysis identified six causal conditions (monitoring and data analysis, predictive and optimization models, smart automation and control, load and demand management, fault detection and prevention, and collaboration and data sharing), two contextual conditions (technological infrastructure and cultural and social factors), four intervening conditions (laws and regulations, individual and human factors, financing, and security conditions), four strategies (technological resources, knowledge resources, renewable energy resources, and management factors), and five outcomes (improvement of production processes, enhanced learning, grid sustainability, reduced carbon emissions, and competitiveness). Within the AI-based model for enhancing electricity consumption efficiency, monitoring and data analysis criteria play a critical role, involving real-time data collection, use of advanced sensors, and smart monitoring systems to provide precise information on industrial equipment performance. Predictive and optimization models, based on collected data, analyze consumption patterns and offer energy optimization predictions. Using machine learning algorithms, these models help identify optimal energy consumption points and reduce energy usage by adjusting various parameters.

Smart automation and control serve as another key component in this model, with smart automation systems utilizing AI algorithms and predictive data to control and adjust industrial processes automatically, optimizing energy use. Load and demand management helps reduce grid load by analyzing consumption patterns and identifying peak times, preventing excessive consumption through optimal energy distribution. Fault detection and prevention, using predictive algorithms and data analysis, aid in early problem identification, preventing sudden breakdowns. Lastly, collaboration and data sharing among industrial units and systems improve energy consumption coordination and optimization through a shared information network, allowing for experience and best practice exchange, leading to increased efficiency and productivity on a broader scale.

Technological infrastructure criteria are fundamental to the AI-based model for enhancing electricity consumption efficiency in industrial units, requiring investment in advanced technologies like sensors, data-mining systems, and smart communication networks for data collection and analysis. Effective implementation of these technologies requires suitable hardware and software infrastructure capable of supporting big data processing and complex analyses while consistently updating technology. Integrating various industrial systems with AI requires a unified, secure communication infrastructure for data exchange and system coordination. Cultural and social factors also significantly impact the adoption and success of the model, as organizational culture and the perspectives of managers and employees on new technologies influence AI system implementation and usage. Success depends on shifting perspectives and appropriately training staff on new technologies and energy efficiency importance. Support from senior managers and employee incentives can facilitate quicker, more effective technology adoption, and a positive organizational culture toward AI use for energy optimization can foster sustainable development and corporate social responsibility.

In the AI-based model for enhancing industrial energy efficiency, laws and regulations play an essential role in shaping and implementing energy optimization strategies. These may include national and international energy consumption standards, carbon emission reduction requirements, and environmental protection regulations. Compliance with these regulations ensures legal alignment, improves organizational reputation, and reduces legal risks. Constant regulatory updates and adaptation to technological changes enable organizations to leverage the latest scientific advancements and benefit from their financial and environmental advantages. Individual and human factors are also significant in this model's success, with staff acceptance and proficiency in new technologies, such as AI, relying on individual skills and education. Training programs should be continuously updated to equip employees with the ability to manage and analyze energy data effectively. Financing is another crucial element, as implementing AI and the necessary infrastructure requires substantial funding. Security conditions also need careful consideration and assurance, as protecting sensitive data and preventing cyber-attacks are critical for maintaining the integrity and functionality of AI systems, ensuring an effective and uninterrupted energy optimization process.

Technological resources are considered the foundation of successful AI-based energy efficiency initiatives, encompassing advanced equipment, data analysis software, and communication infrastructure for data collection, processing, and analysis. Technologies such as sensors, high-speed communication networks, and smart energy management systems are essential technological resources for implementing AI algorithms effectively and optimizing energy use. Optimal use of these technologies can assist in energy consumption simulation and forecasting, reducing costs, and increasing efficiency. Knowledge resources also play a vital role, as technical and specialized knowledge in data analysis, AI, and energy management is essential for designing and executing optimization strategies. Investing in workforce education and development to increase knowledge and expertise in related fields improves the systems' accuracy and efficiency. Utilizing renewable energy sources is also a significant aspect of enhancing energy efficiency, as it reduces dependence on non-renewable energy sources and mitigates environmental impact. Finally, management factors, including effective strategy development, team coordination, implementation oversight, and continuous performance evaluation, enhance AI-based systems' functionality and help achieve energy efficiency goals.

In the AI-based model for enhancing industrial electricity consumption efficiency, improving production processes directly impacts increased efficiency and reduced energy consumption. AI can aid in simulating and accurately analyzing production processes, identifying weaknesses and inefficiencies, and improving them. AI algorithms analyze real and historical data to predict energy needs and optimize machinery and production line settings. These improvements in production processes can reduce energy consumption, lower costs, and enhance product quality. Enhanced learning and power grid sustainability are also key criteria in this model. AI algorithms can identify consumption patterns and predict grid load changes, leading to optimized consumption management and preventing overload. Grid stability, supported by accurate data and advanced analytics, facilitates reduced fluctuations and improved energy supply quality. Additionally, carbon emission reduction is effectively achieved through renewable energy use and energy consumption optimization, which helps reduce the environmental impact of energy use. Finally, increased industrial competitiveness is achieved by lowering costs, improving product quality, and enhancing energy efficiency, enabling organizations to compete more effectively in global markets and achieve sustainable growth and development.

Using AI to optimize electricity consumption in industrial units offers unique opportunities to reduce costs, increase efficiency, and protect the environment. AI systems provide detailed data analysis and energy consumption pattern identification, assisting in identifying weaknesses and providing optimization solutions. These technologies can automatically apply optimal settings to prevent energy waste, directly reducing operational costs. AI plays a critical role in reducing the environmental impact of industrial units by optimizing energy consumption, decreasing greenhouse gas emissions and pollutants, which helps preserve the environment and combat climate change. Smart energy management systems not only improve efficiency but also allow companies to comply with stricter environmental regulations and demonstrate social responsibility. Finally, using AI for industrial electricity consumption optimization brings economic and environmental benefits, creating a competitive advantage for companies. Those utilizing this technology can offer their products at more competitive prices by lowering energy costs and improving efficiency, capturing a larger market share. Given AI technology's continuous advancements and increasing processing capabilities, the future of electricity consumption optimization in industries appears promising and bright.

To further enhance industrial electricity consumption efficiency with AI, several practical recommendations can be offered:

- Smart energy management systems should continuously collect and analyze energy consumption data, identifying usage patterns and automatically applying optimal settings.
- Machine learning algorithms can be employed to predict energy needs and optimize production processes, improving consumption patterns based on historical data and current conditions, and preventing energy waste.
- Installing advanced sensors and connecting equipment to the Internet of Things (IoT) can provide precise, real-time data on energy consumption, aiding AI systems in achieving greater accuracy and efficiency.
- AI can optimize the scheduling of high-consumption activities to occur during lower-demand times, reducing peak loads and energy costs.
- AI systems can predict equipment failures and facilitate preventive maintenance, increasing equipment lifespan and reducing energy consumption due to inefficient operations.
- Training employees and creating an organizational culture focused on energy efficiency is also essential. Staff should be familiarized with new technologies and their optimal use to actively contribute to improving energy efficiency.
- Detailed data analysis and AI models can identify and optimize optimal energy consumption points

within production processes, including more precise machinery settings, production process adjustments, and sustainable production techniques.
- Special energy optimization software using AI algorithms can assist in detailed analysis and provide optimization solutions, helping managers and engineers make better and faster decisions.

Implementing these practical recommendations can help industrial units optimize energy consumption, reduce costs, and contribute to environmental sustainability.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] H. Alizadeh, B. Kheiri, and A. Heiydari, "An Investigation of the Brand-Consumer Relationship Model Based On Digital Marketing in the Hotel Industry," *International Journal of Management,* vol. 11, no. 8, pp. 1075-1093, 2020, doi: 10.34218/IJM.11.8.2020.097.

[2] P. Kofinas, A. I. Dounis, and G. A. Vouros, "Fuzzy q-learning for multi-agent decentralized energy management in microgrids," *Applied Energy,* vol. 219, pp. 53-67, 2018, doi: 10.1016/j.apenergy.2018.03.017.

[3] K. Yan, C. Zhong, and J. Huang, "Semi-supervised learning for early detection and diagnosis of various air handling unit faults," *Energy and Buildings,* 2018, doi: 10.1016/j.enbuild.2018.10.016.

[4] Y. Zhou and S. Zheng, "Machine-learning based hybrid demand-side controller for high-rise office buildings with high energy flexibilities," *Applied Energy,* vol. 262, p. 114416, 2020, doi: 10.1016/j.apenergy.2019.114416.

[5] H. Alizadeh and M. Ghasemi, "The effect of tourists' preferences on the competitiveness of the hotel industry," *Quarterly Journal of Tourism Research and Sustainable Development,* vol. 5, no. 3, pp. 25-40, 2023, doi: 10.34218/IJM.11.8.2020.097.

[6] M. Babar, M. U. Tariq, and M. A. Jan, "Secure and resilient demand side management engine using machine learning for IoT-enabled smart grid," *Sustainable Cities and Society,* vol. 62, p. 102370, 2020, doi: 10.1016/j.scs.2020.102370.

[7] Y. Wu, J. M. Guerrero, and J. C. Vasquez, "Decentralized transactive energy community in edge grid with positive buildings and interactive electric vehicles," *International Journal of Electrical Power & Energy Systems,* vol. 135, p. 107510, 2022, doi: 10.1016/j.ijepes.2021.107510.

[8] X. Wang, H. Wang, and S. H. Ahn, "Demand-side management for off-grid solar-powered microgrids: A case study of rural electrification in Tanzania," *Energy,* vol. 224, p. 120229, 2021, doi: 10.1016/j.energy.2021.120229.

[9] X. Wang, H. Wang, and B. Bhandari, "AI-Empowered Methods for Smart Energy Consumption: A Review of Load Forecasting, Anomaly Detection and Demand Response," *International Journal of Precision Engineering and Manufacturing - Green Technology,* vol. 11, pp. 963-993, 2024, doi: 10.1007/s40684-023-00537-0.

[10] R. Lu and S. H. Hong, "Incentive-based demand response for smart grid with reinforcement learning and deep neural network," *Applied Energy,* vol. 236, pp. 937-949, 2019, doi: 10.1016/j.apenergy.2018.12.061.

[11] H. Shakouri and A. Kazemi, "Multi-objective cost-load optimization for demand side management of a residential area in smart grids," *Sustainable Cities and Society,* vol. 32, pp. 171-180, 2017, doi: 10.1016/j.scs.2017.03.018.

[12] D. Zhao, H. Wang, J. Huang, and X. Lin, "Time-of-use pricing for energy storage investment," *IEEE Transactions on Smart Grid*, 2021, doi: 10.1109/TSG.2021.3136650.

[13] B. Alhammadi, K. Khalid, S. Z. Ahmad, and R. Davidson, "Examining the interplay between managerial ties, dynamic capabilities and innovation climate in driving balanced and combined ambidextrous innovation," *Journal of Asia Business Studies,* 2024, doi: 10.1108/JABS-10-2023-0407.

[14] S. Zhou, Z. Hu, W. Gu, M. Jiang, and X. P. Zhang, "Artificial intelligence based smart energy community management: A reinforcement learning approach," *CSEE Journal of Power and Energy Systems*, vol. 5, no. 1, pp. 1-10, 2019, doi: 10.17775/CSEEJPES.2018.00840.

[15] H. Alizadeh and M. Jalali filshour, " Proposing a Mixed Model of a Digital Marketing in the Financial Services Sector with an Emphasis on Artificial Intelligence Tools," in 30th National and 11th International Conference on Insurance and Development, 2023. [Online]. Available: https://civilica.com/doc/1578810/..

[16] L. Tronchin, M. Manfren, and B. Nastasi, "Energy efficiency, demand side management and energy storage technologies - a critical analysis of possible paths of integration in the built environment," *Renewable and Sustainable Energy Reviews,* vol. 95, pp. 341-353, 2018, doi: 10.1016/j.rser.2018.06.060.

[17] P. Li, H. Wang, and B. Zhang, "A distributed online pricing strategy for demand response programs," *IEEE Transactions on Smart Grid,* vol. 10, no. 1, pp. 350-360, 2019, doi: 10.1109/TSG.2017.2739021.

[18] J. Campillo, E. Dahlquist, F. Wallin, and I. Vassileva, "Is real-time electricity pricing suitable for residential users without demand-side management?," *Energy,* vol. 109, pp. 310-325, 2016, doi: 10.1016/j.energy.2016.04.105.

[19] N. Javaid, G. Hafeez, S. Iqbal, N. Alrajeh, M. S. Alabed, and M. Guizani, "Energy efficient integration of renewable energy sources in the smart grid for demand side management," *IEEE Access,* vol. 6, pp. 77077-77096, 2018, doi: 10.1109/ACCESS.2018.2866461.

[20] M. Patel, D. Dabhi, R. Patel, and J. Patel, "Long term electrical load forecasting considering temperature effect using multi-layer perceptron neural network and k-nearest neighbor algorithms," *International Journal of Research in Electronics and Computer Engineering*, 2019, doi: 10.13140/RG.2.2.29592.65288.

[21] A. Rezaei and B. Moradi, "Optimization of electric energy consumption based on residents' behavioral patterns in smart homes using a data mining algorithm, employing smart grid systems and renewable energy sources," *Computational Intelligence in Electrical Engineering*, vol. 12, no. 2, pp. 1-14, 2021. [Online]. Available: https://isee.ui.ac.ir/article_25639.html.

[22] Y. Himeur, K. Ghanem, A. Alsalemi, F. Bensaali, and A. Amira, "Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives," *Applied Energy*, vol. 287, p. 116601, 2021, doi: 10.1016/j.apenergy.2021.116601.

[23] S. Mischos, E. Dalagdi, and D. Vrakas, "Intelligent energy management systems: a review," *Artificial Intelligence Review*, vol. 56, pp. 11635-11674, 2023, doi: 10.1007/s10462-023-10441-3.

[24] Y. Ming and J. Cao, "Electrical load prediction in energy internet via linear correlation coefficient approach," 2018, pp. 157-162, doi: 10.1109/ICEI.2018.00036.

[25] G. R. Babu, P. V. Chintalapati, P. K. Sree, G. R. L. M. Tayaru, P. Raju, and K. S. Kumar, "An Advanced Artificial Intelligence-Driven Smart Home Towards Ontology-Based Energy Efficiency Management System," 2024, vol. 972: Springer, Singapore, doi: 10.1007/978-981-97-3466-5_24.

[26] A. Rafiei, "Investigating the application of artificial intelligence to detect non-technical losses and energy theft in power distribution networks," Hamedan, 2018. [Online]. Available: https://elmnet.ir/article/20915596-12214/%D8%A8%D8%B1%D8%B1%D8%B3%DB%8C-%DA%A9%D8%A7%D8%B1%D8%A8%D8%B1%D8%AF-%D9%87%D9%88%D8%B4-%D9%85%D8%B5%D9%86%D9%88%D8%B9%DB%8C-%D8%A8%D8%B1%D8%A7%DB%8C-%D8%AA%D8%B4%D8%AE%DB%8C%D8%B5-%D8%AA%D9%84%D9%81%D8%A7%D8%AA-%D8%BA%DB%8C%D8%B1%D9%81%D9%86%DB%8C-%D9%88-%D8%B3%D8%B1%D9%82%D8%AA-%D8%A7%D9%86%D8%B1%DA%98%DB%8C-%D8%AF%D8%B1-%D8%B4%D8%A8%DA%A9%D9%87-%D9%87%D8%A7%DB%8C-%D8%AA%D9%88%D8%B2%DB%8C%D8%B9-%D8%A8%D8%B1%D9%82. [Online]. Available: https://elmnet.ir/article/20915596-12214/%D8%A8%D8%B1%D8%B1%D8%B3%DB%8C-%DA%A9%D8%A7%D8%B1%D8%A8%D8%B1%D8%AF-%D9%87%D9%88%D8%B4-%D9%85%D8%B5%D9%86%D9%88%D8%B9%DB%8C-%D8%A8%D8%B1%D8%A7%DB%8C-%D8%AA%D8%B4%D8%AE%DB%8C%D8%B5-%D8%AA%D9%84%D9%81%D8%A7%D8%AA-%D8%BA%DB%8C%D8%B1%D9%81%D9%86%DB%8C-%D9%88-%D8%B3%D8%B1%D9%82%D8%AA-%D8%A7%D9%86%D8%B1%DA%98%DB%8C-%D8%AF%D8%B1-%D8%B4%D8%A8%DA%A9%D9%87-%D9%87%D8%A7%DB%8C-%D8%AA%D9%88%D8%B2%DB%8C%D8%B9-%D8%A8%D8%B1%D9%82

[27] B. Yildiz, J. I. Bilbao, and A. B. Sproul, "A review and analysis of regression and machine learning models on commercial building electricity load forecasting," *Renewable and Sustainable Energy Reviews*, vol. 73, pp. 1104-1122, 2017, doi: 10.1016/j.rser.2017.02.023.

[28] L. Chen, Z. Chen, and Y. Zhang, "Artificial intelligence-based solutions for climate change: a review," *Environmental Chemistry Letters*, vol. 21, pp. 2525-2557, 2023, doi: 10.1007/s10311-023-01617-y.

[29] X. Wang, Z. Yao, and M. Papaefthymiou, "A real-time electrical load forecasting and unsupervised anomaly detection framework," *Applied Energy*, vol. 330, p. 120279, 2023, doi: 10.1016/j.apenergy.2022.120279.