Research on the Application of Artificial Intelligence Models in Smart Energy and Carbon Emission Systems

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ABSTRACT At this critical juncture of advancing the "dual carbon" goals and transforming energy structures, the efficient coordination between smart energy systems and carbon emission monitoring systems serves as the cornerstone for implementing green development concepts and achieving sustainable growth. Artificial intelligence technologies, with their robust data processing capabilities, deep feature extraction, and intelligent decision-making prowess, offer innovative solutions to address persistent challenges in traditional energy systems — including low energy efficiency, insufficient carbon emission monitoring accuracy, and supply-demand imbalance. This study systematically examines the application status of mainstream AI models (including machine learning, deep learning, and reinforcement learning) across the entire smart energy production, transmission, and consumption chain, as well as carbon emission accounting, monitoring, and optimization processes. It thoroughly analyzes core issues such as data heterogeneity, model generalization limitations, and inadequate technological integration, while exploring practical scenarios through case studies to demonstrate the effectiveness of different AI models. Finally, the research outlines future trends in deep integration between AI and smart energy systems/carbon monitoring systems, proposing targeted optimization pathways and implementation strategies. These insights provide theoretical foundations and practical references for accelerating digital transformation in energy systems, enhancing precision carbon management, and facilitating the realization of "dual carbon" objectives

Keywords Artificial Intelligence; Smart Energy Systems; Carbon Emission Control; Energy Optimization; Machine Learning; Low-carbon Transition.

I.INTRODUCTION

1.1 Research Background

Global climate warming has emerged as a major worldwide challenge threatening human survival and development. Climate change has evolved from a singular environmental issue into a complex crisis spanning economic, social, and ecological domains. Accelerating the transition to clean and low-carbon energy structures while strictly controlling total carbon emissions has become a global consensus. As a responsible major country, China has explicitly set strategic goals: "Strive to peak carbon dioxide emissions before 2030 and achieve carbon neutrality by 2060," integrating the "dual carbon" objectives into national development frameworks. The establishment of a "1+N" policy system provides clear guidance for low-carbon energy transformation and emission control. Smart energy systems, as innovative platforms integrating energy production, transmission, storage, consumption, and dispatching through digital and intelligent technologies, enable efficient energy utilization and optimized allocation. Serving as core enablers for implementing dual carbon targets, their development level directly determines the effectiveness of low-carbon energy transition efforts.

Traditional energy systems predominantly adopt extensive management models with multiple critical shortcomings. On the production side, thermal power plants maintain persistently high coal consumption rates, while renewable energy sources like wind and solar power experience significant output fluctuations influenced by weather conditions and face challenges in grid integration. Historical wind and solar curtailment rates once exceeded 15%, hindering large-scale renewable energy adoption. In transmission networks, uneven load distribution results in sustained transmission loss rates ranging from 6% to 8%, with annual electricity losses equivalent to tens of millions of tons of standard coal equivalent – highlighting the need for improved energy transmission efficiency. At the consumption end, energy waste remains prevalent in key energy-intensive sectors including industry, construction, and transportation, with potential energy savings exceeding 20%. Meanwhile, conventional carbon emission systems struggle with low accounting efficiency, insufficient monitoring accuracy, and delayed regulatory responses, failing to meet the demands of refined and routine carbon management practices. These systemic limitations continue to impede progress toward achieving carbon peaking and carbon neutrality goals.

The rapid iteration and widespread application of artificial intelligence technology provide crucial technical support for addressing the aforementioned challenges. With its unique advantages in data-driven prediction, optimization, and management, AI enables precise scheduling of smart energy systems and dynamic carbon emission control, significantly enhancing energy utilization efficiency and carbon management effectiveness. According to calculations by the International Energy Agency (IEA), AI technology could reduce global carbon emissions from energy systems by 4 billion tons by 2030, accounting for 10% of current annual global carbon emissions, playing a pivotal role in achieving the "dual carbon" goals. Therefore, systematic research on applying AI models in smart energy and carbon emission systems, addressing implementation bottlenecks, and exploring optimization pathways holds significant theoretical value and practical implications.

1.2 Research Significance

1.2.1 Theoretical Significance

This study systematically examines the integration pathways and operational mechanisms between artificial intelligence models and smart energy systems as well as carbon emission control systems, enriching the theoretical framework for AI applications in energy and environmental fields while refining the theoretical architecture for coordinated management of smart energy and carbon emissions. Through comparative analysis of application scenarios and performance disparities among various AI models, the research provides a clear research framework and conceptual guidance for subsequent studies. It promotes in-depth interdisciplinary exploration between AI technologies and low-carbon energy transition initiatives, addressing the current gap in comprehensive scenario-based integration analysis within existing research.

1.2.2 Practical Significance

This study systematically summarizes practical experiences and application outcomes of artificial intelligence models in optimizing smart energy production, power grid dispatching, energy consumption efficiency improvement, carbon emission accounting, monitoring, and regulatory optimization through domestic and international case studies. The findings provide actionable technical solutions and implementation pathways for energy enterprises and environmental regulators. By promoting deep integration of AI technologies across relevant sectors, we can significantly enhance energy utilization efficiency, reduce carbon emission intensity, accelerate digital transformation and low-carbon transition of energy systems, and deliver robust technical support and practical safeguards for achieving the "dual carbon" goals.

1.3 Current Research Status at Home and Abroad

1.3.1 Current Status of International Research

Foreign countries have pioneered research in integrating artificial intelligence with smart energy systems and carbon emission management, establishing mature technical frameworks and application models. Developed nations such as the United States, Japan, and the European Union have incorporated AI technologies into their low-carbon energy transition strategies, focusing on applications like renewable energy output forecasting, smart grid operations, and precise carbon monitoring. For instance, Google's DeepMind developed an AI prediction model for the UK power grid that reduced wind power output prediction errors by 15%, saving approximately £40 million in annual operational costs. Through the Horizon 2020 initiative, the EU prioritized AI research for smart energy systems, enhancing distributed energy integration with grid optimization and significantly improving renewable energy absorption capacity. Additionally, international scholars have conducted extensive foundational studies on carbon accounting model optimization and full lifecycle carbon footprint tracking. By refining calculation parameters through machine learning models, they have substantially improved data accuracy and computational efficiency in carbon emission assessments.

1.3.2 Current Domestic Research Status

In recent years, China has placed great emphasis on the integrated development of artificial intelligence with smart energy and carbon emission fields, with related research and applications showing rapid growth trends, gradually forming application paths with Chinese characteristics. In the field of smart energy, Chinese scholars have conducted extensive empirical studies on research directions such as renewable energy output forecasting, smart grid dispatching, and industrial energy conservation. For example, TBEA Xinjiang New Energy Co., Ltd. established an industrial internet platform for the full lifecycle management of power stations, utilizing artificial intelligence algorithms to build models for power prediction and fault diagnosis, resulting in a 5.39% increase in power generation and a 15.26% reduction in operating costs, achieving intelligent operation and maintenance of new energy power stations. In the field of carbon emissions, research focuses on intelligent carbon emission accounting, carbon monitoring and early warning, and carbon optimization regulation. A data-driven carbon emission accounting method based on large AI models was proposed, enabling minute-level real-time carbon emission calculations and significantly improving accounting accuracy and efficiency. However, overall, China's related research still faces numerous shortcomings, such as poor model generalization, prominent data silos between different systems, and insufficient depth of technological integration, leaving a gap compared to developed countries that urgently requires further in-depth research and improvement.

1.4 Research Content and Methods

1.4.1 Research Content

This study first systematically categorizes core types and technical characteristics of artificial intelligence models, clarifying their application advantages and suitable scenarios in smart energy systems and carbon emission management systems. Secondly, it explores specific implementation pathways for AI models across the entire energy production, transmission, and consumption chain, as well as carbon emission accounting, monitoring, and optimization control processes, with case studies demonstrating their practical effectiveness. Thirdly, the research conducts a comprehensive analysis of existing challenges and bottlenecks in AI model applications, covering data integration, model development, technological implementation, talent acquisition, and policy coordination. Finally, based on the developmental requirements of smart energy and carbon emission systems, targeted optimization strategies are proposed alongside future trend projections.

1.4.2 Research Methods

This study employs a combination of multiple research methods to ensure scientific rigor, methodological soundness, and practical applicability, specifically including:

- Literature review method: Systematically analyze domestic and international research literature, policy documents, and technical reports related to artificial intelligence, smart energy, and carbon emissions to comprehensively understand the current research status and development trends in these fields, thereby establishing a theoretical foundation for the study.
- Case Study Methodology: Select representative cases of artificial intelligence applications in smart energy and carbon emission systems from domestic and international sources, conduct in-depth analysis of their implementation models, technical approaches, and outcomes to provide robust practical support for research.
- Summarization and induction method: Systematically summarize the application scenarios and existing issues of artificial intelligence models, extract core conclusions, and propose targeted optimization strategies to ensure the rationality and relevance of research findings.
- Comparative analysis method: Compare the performance differences of various artificial intelligence models in the same application scenario, as well as the development gaps in related applications domestically and internationally, to clarify research priorities and directions, thereby enhancing the relevance and innovativeness of the study.

1.5 Research Innovations and Limitations

1.5.1 Research Innovations

The innovation of this paper is primarily reflected in two aspects: First, it establishes a comprehensive application framework for artificial intelligence models in smart energy and carbon emission systems, covering all core stages including energy production, transmission, consumption, carbon emission accounting, monitoring, and optimization regulation, thereby achieving systematic coverage of application scenarios. Second, aligning with China's "dual carbon" goals and actual energy transition needs, the study proposes targeted optimization strategies that integrate theoretical research with practical applications. These solutions demonstrate strong applicability and relevance, providing direct references for relevant practical work.

1.5.2 Research Limitations

The limitations of this study are primarily reflected in two aspects: Firstly, constrained by data availability, the data analysis for certain cases lacks depth, and the quantitative assessment of AI model application effectiveness remains incomplete, failing to fully demonstrate the quantifiable value of model implementation. Secondly, the exploration of emerging AI technologies such as generative AI, digital twins, and AI integration in smart energy and carbon emission systems remains preliminary, with further research needed to clarify their integration pathways and practical effectiveness.

2 Relevant Theoretical Foundations

2.1 Smart Energy System

Smart energy systems are innovative energy frameworks that leverage digitalization and intelligent technologies to integrate the entire energy lifecycle—from production and transmission to storage, consumption, and dispatching—achieving efficient utilization, optimized allocation, enhanced security, and low-carbon emissions. Characterized by digitalization, intelligence, collaboration, and low-carbon sustainability, these systems enable real-time supply-demand matching, continuous energy efficiency improvements, and precise carbon emission control. Spanning renewable energy generation, smart grids, energy storage, and energy conservation, smart energy systems serve as pivotal drivers for energy transition and the realization of carbon peaking and carbon neutrality goals. Within the theoretical framework of smart spatial science, energy systems have evolved from traditional "supporting elements" into intelligent metabolic systems with four core capabilities: multidimensional perception integration, intelligent decision optimization, dynamic collaborative control, and self-organizing evolution. These advancements provide theoretical foundations for advancing smart energy systems through intelligent development.

2.2 Carbon Emission System

The carbon emission system is a comprehensive framework encompassing the entire lifecycle of carbon emissions, including generation, accounting, monitoring, regulation, and reduction. Its core objectives are to achieve precise measurement, effective monitoring, and scientific regulation of carbon emissions, drive continuous reductions in emission intensity, and support the realization of the "dual carbon" goals. Key components of this system include carbon accounting, emission monitoring, and emission reduction optimization, spanning high-energy-consuming sectors such as industry, construction, transportation, and energy. With advancements in digitalization and intelligent technologies, carbon emission systems are transitioning from traditional "post-event accounting" models to "pre-event forecasting and real-time regulation" approaches. This evolution enables intelligent carbon flow management across entire life cycles, paving the way for refined emission control mechanisms.

2.3 Core Types and Technical Characteristics of Artificial Intelligence Models

The artificial intelligence models studied in this paper primarily include mainstream types such as machine learning, deep learning, and reinforcement learning. The core technical characteristics and application advantages of these models exhibit significant differences, as detailed below:

2.3.1 machine learning model

Machine learning stands as a cornerstone technology in artificial intelligence, leveraging algorithms to enable computers to autonomously identify inherent patterns within massive datasets, thereby facilitating prediction and classification of unknown data. Commonly employed models include linear regression, decision trees, random forests, and support vector machines. These techniques are characterized by relatively simple model architectures and high training efficiency, making them particularly suitable for applications with moderate data volumes and well-defined features. They find extensive applications in energy load forecasting and carbon emission accounting. For instance, random forest models enable precise electricity load predictions, providing reliable technical support for grid dispatching. Meanwhile, support vector machine models optimize carbon emission accounting parameters, significantly enhancing calculation accuracy and minimizing computational errors.

2.3.2 Deep Learning Models

Deep learning represents a crucial extension of machine learning, employing neural networks to construct multi-layer model architectures that automatically extract deep features from data. It proves particularly effective in scenarios involving massive datasets and complex feature structures. Common deep learning models include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTM), and Transformers. Their core technological strengths lie in robust feature extraction capabilities and nonlinear fitting precision, demonstrating significant advantages in applications such as renewable energy output forecasting and carbon emission monitoring through image recognition. For instance, LSTM models effectively capture long-term dependencies in time-series data, achieving over 15% higher accuracy than traditional models in wind power output prediction. Meanwhile, CNN models enhance transmission line defect detection by significantly improving monitoring efficiency and diagnostic accuracy.

2.3.3 Reinforcement Learning Model

Reinforcement learning enables agents to autonomously develop optimal decision-making strategies through continuous interaction with external environments and a trial-and-error mechanism, making it particularly suitable for dynamic and complex scenarios. Its core technological features include real-time decision-making and dynamic optimization capabilities, with extensive applications in smart grid management, energy consumption optimization, and carbon emission control. For instance, reinforcement learning models can facilitate dynamic load scheduling in power grids, enhance coordination between renewable energy sources and energy storage systems, and significantly improve energy utilization efficiency. In carbon reduction initiatives, these models dynamically adjust emission reduction strategies to achieve optimal balance between cost-effectiveness and environmental outcomes.

2.3.4 Other Artificial Intelligence Technologies

Beyond mainstream models, the integration of technologies such as digital twins, IoT, blockchain, and artificial intelligence has provided new technical foundations for smart energy systems and carbon emission management. Digital twin technology enables virtual mirroring of energy and carbon emission systems, combining AI models to facilitate simulation and optimization decisions, thereby enhancing operational scientific rigor. IoT technology facilitates real-time collection of energy and carbon emission data, offering robust data support for AI model training and application. Blockchain technology ensures tamper-proof recording and full-process traceability of carbon emissions, significantly improving the credibility and authority of emission accounting.

3 Application of Artificial Intelligence Models in Smart Energy Systems

The core objective of smart energy systems is to achieve efficient energy utilization, optimized allocation, and security assurance. Through in-depth analysis of energy data, precise forecasting, and scientific optimization, artificial intelligence models are fully integrated into the entire energy production, transmission, and consumption chain. This significantly enhances system operational efficiency and intelligence levels, providing robust support for low-carbon energy transition.

3.1 Application in Energy Production Processes

The energy production phase serves as the foundation of smart energy systems, where operational efficiency and stability directly impact the overall performance of the energy system. Artificial intelligence models are primarily applied in scenarios such as renewable energy output forecasting and optimization of fossil fuel power generation, aiming to enhance energy production efficiency, reduce energy consumption and pollutant emissions, and ensure the stability of energy production.

3.1.1 Renewable Energy Output Prediction

The output of renewable energy sources such as wind power and photovoltaics is significantly influenced by meteorological conditions like wind speed, sunlight intensity, and temperature, exhibiting pronounced volatility and uncertainty, which poses considerable challenges to grid integration and dispatching. Artificial intelligence models analyze historical meteorological data and renewable energy output data to construct precise prediction models, enabling accurate forecasting of renewable energy output and providing reliable support for grid dispatching and grid integration optimization. For example, by utilizing LSTM models combined with meteorological data (wind speed, sunlight intensity) and historical output curves, precise predictions of wind and photovoltaic power generation for the next 24 hours can be achieved, with an accuracy rate exceeding 85%. The photovoltaic power prediction model developed by TBEA Xinjiang New Energy Co., Ltd. integrates meteorological satellite data and station operation data, effectively improving the accuracy of photovoltaic output prediction and providing robust support for power station dispatching and renewable energy consumption.

3.1.2 Optimization of Fossil Fuel Power Generation

For fossil fuel power generation such as thermal power plants, artificial intelligence models can be applied to optimize power generation parameters and provide equipment fault early warnings, aiming to enhance power generation efficiency, reduce energy consumption and pollutant emissions, and extend equipment service life. For instance, by analyzing boiler combustion data (temperature, pressure, oxygen levels) and utilizing AI technology to optimize coal blending ratios and air supply parameters, coal consumption can be effectively reduced. A thermal power plant implementing this technology achieved an 8-gram reduction in coal consumption per kilowatt-hour, saving 50,000 tons of standard coal annually, significantly improving both economic efficiency and environmental performance. Additionally, deep learning models employed for real-time monitoring of critical parameters like steam turbine vibrations and bearing temperatures can detect equipment failures such as blade cracks 3-7 days in advance, minimizing downtime and enhancing power generation stability.

3.1.3 Nuclear Power Safety Monitoring

In the nuclear power sector, safe operation remains the fundamental prerequisite. Artificial intelligence models can be utilized for reactor safety monitoring by analyzing over 2,000 critical parameters in real-time, including reactor temperature, pressure, and radioactive material concentrations. These systems enable precise identification of abnormal operational patterns (such as "sudden coolant flow reduction coupled with temperature surge," which may indicate leakage risks), reducing fault response time from 30 minutes in manual monitoring to just 10 seconds. This breakthrough significantly enhances the safety and reliability of nuclear power operations.

3.2 Application in Energy Transmission Processes

The core of energy transmission lies in smart grids, where operational stability and efficiency directly impact the quality of energy transmission and utilization effectiveness. Artificial intelligence models are primarily applied in scenarios such as grid load forecasting, fault diagnosis and localization, and transmission loss optimization, aiming to enhance the stability, reliability, and efficiency of grid operations.

3.2.1 Power Grid Load Forecasting

Power grid load forecasting serves as the fundamental prerequisite for grid dispatching, with its accuracy directly impacting the scientific rigor and economic efficiency of grid operations. Artificial intelligence models analyze multi-source data including historical load records, meteorological data, and socio-economic indicators to achieve precise short-term, medium-term, and long-term load predictions. For instance, by employing models such as random forests and LSTM, accurate forecasting of residential and industrial electricity consumption can be realized (e.g., identifying 8:00 AM as the peak consumption hour during weekdays). This enables optimized generator startup/shutdown scheduling — activating peak-shaving units during high-demand periods while shutting down some units during off-peak hours — effectively reducing "idle power generation." After implementing this technology, a provincial-level power grid achieved annual electricity cost savings of 1.2 billion yuan, significantly enhancing grid operational economic performance.

3.2.2 Power Grid Fault Diagnosis and Localization

Smart grids are characterized by massive scale and complex structures, while traditional fault diagnosis and location methods remain inefficient, failing to meet the demands of rapid grid response. Artificial intelligence models can achieve rapid fault diagnosis and precise localization by analyzing operational data and fault signals, significantly improving troubleshooting efficiency. For instance, drones equipped with AI-powered image recognition systems for transmission line inspections can accurately detect defects such as insulator damage and conductor icing, achieving inspection speeds five times faster than manual methods while covering hazardous areas inaccessible to human crews like mountainous regions and valleys. When line short circuits occur, AI systems can pinpoint fault locations and isolate them within 0.1 seconds, automatically switching to backup lines to restore power supply. Traditional manual handling required over 30 minutes for such operations. After implementing this technology, a city's power grid reduced average outage durations from 4 hours to just 15 minutes, demonstrating substantial improvements in grid reliability.

3.2.3 Transmission Loss Optimization

Transmission loss remains a critical challenge in energy transmission systems, directly impacting energy utilization efficiency. Artificial intelligence models analyze grid transmission parameters and load distribution data to optimize transmission line operations and reduce energy losses. For instance, applying reinforcement learning models to optimize grid load allocation and adjust transmission line parameters can decrease transmission losses by 10%-15%, significantly enhancing energy transmission efficiency and minimizing resource waste.

3.3 Application in Energy Consumption Processes

The energy consumption stage serves as the terminal point of energy utilization, where energy-saving efficiency directly impacts the overall energy efficiency and total carbon emissions of the energy system. Artificial intelligence models are primarily applied to optimize energy conservation in key sectors such as industry, construction, and transportation, aiming to achieve efficient energy utilization and reduce energy consumption and carbon emissions.

3.3.1 Industrial Energy Conservation Optimization

The industrial sector stands as the primary energy consumer, accounting for a significant proportion of total societal energy consumption and holding immense potential for energy conservation. Artificial intelligence models analyze energy consumption data and production parameters during manufacturing processes to optimize workflows and equipment operations, thereby achieving energy savings. For instance, AI-powered systems monitor energy usage patterns of critical machinery such as factory motors, boilers, and air compressors, precisely identifying inefficient operations like equipment running at suboptimal loads (e.g., under 30% utilization rate). By adjusting operational parameters (e.g., reducing motor speeds from 3,000 RPM to 2,000 RPM), a car manufacturing plant implemented this technology saw a 16% reduction in overall energy consumption, significantly enhancing industrial energy efficiency. Leveraging data-driven frameworks powered by large-scale AI models enables precise energy consumption forecasting and optimization, providing scientific support for energy conservation initiatives across industrial enterprises.

3.3.2 Building Energy Efficiency Optimization

The construction sector accounts for a significant proportion of total societal energy consumption, making it a critical area for energy conservation. Artificial intelligence models can be utilized to enable intelligent regulation of building HVAC and lighting systems, thereby achieving energy efficiency. For instance, AI technology controls building air conditioning and lighting systems to automatically adjust operational parameters based on indoor occupancy and light intensity (e.g., turning off equipment when meeting rooms are empty or automatically activating lights during overcast weather). Large shopping malls implementing this technology have achieved 25% energy savings. The Shanghai Tower optimized its energy systems through AI, reducing daily carbon emissions equivalent to the annual carbon sequestration capacity of 1,500 mature trees. A global financial center enhanced its chiller unit's annual coefficient of performance (COP) from 5.2 to 6.1 via digital twin integration with AI, resulting in 2.8 million kWh of annual electricity savings and demonstrating efficient energy utilization in buildings.

3.3.3 Transportation Energy Optimization

The transportation sector stands as one of the primary sources of carbon emissions, where energy consumption and carbon emission control are critical components in achieving the "dual carbon" goals. Artificial intelligence models can be applied to optimize electric vehicle charging schedules and traffic flow management, effectively reducing energy consumption and carbon emissions in this field. For instance, AI-powered scheduling of electric bus charging times (such as during off-peak hours) significantly lowers charging costs. By recommending optimal charging solutions like "the nearest charging station with the lowest current electricity rates" to EV users, a city's public transit corporation achieved a 22% reduction in charging expenses after implementing this technology. Furthermore, AI-driven traffic flow optimization reduces vehicle congestion, decreases fuel consumption and carbon emissions, thereby promoting green and low-carbon development in the transportation sector.

4 Application of Artificial Intelligence Models in Carbon Emission Systems

The core objective of the carbon emission system is to achieve precise accounting, effective monitoring, and scientific regulation of carbon emissions. Through in-depth analysis of carbon emission data, accurate prediction, and optimized regulation, artificial intelligence models significantly enhance the intelligence level and management efficiency of the carbon emission system, providing robust support for achieving carbon reduction targets.

4.1 Application in Carbon Emission Accounting Phase

Carbon emission accounting serves as the foundation for carbon management, with its accuracy directly impacting the scientific rigor and effectiveness of emission reduction decisions. Traditional accounting methods face challenges such as low efficiency, insufficient precision, and data lag, making them inadequate for refined carbon control requirements. Artificial intelligence models address these limitations by integrating multi-source data and optimizing accounting frameworks, enabling precise and real-time emission tracking that effectively compensates for the shortcomings of conventional approaches.

Traditional carbon emission accounting primarily employs emission factor-based methodologies that rely on manual statistical data collection, resulting in lengthy calculation cycles and significant errors, making them inadequate for routine carbon management needs. Artificial intelligence models utilize real-time data from industrial production, energy consumption, and transportation sectors (including energy consumption metrics, production process parameters, and meteorological data) to develop carbon emission accounting frameworks through machine learning and deep learning algorithms, enabling real-time emission tracking and dynamic updates. For instance, AI-powered enterprise carbon emission models leverage large-scale AI models' deep semantic representation capabilities to establish multi-source heterogeneous data integration frameworks. By incorporating dynamic electricity-carbon emission factors and green power trading certificate adjustments, these models achieve minute-level real-time emission calculations with minimal annual accounting discrepancies. In the construction sector, AI models combined with building energy consumption data and carbon emission factors enable precise emission accounting and dynamic monitoring, providing data-driven support for carbon reduction initiatives.

4.2 Application in Carbon Emission Monitoring

Carbon emission monitoring is a critical component for tracking carbon emission dynamics, identifying abnormal carbon emissions, and implementing carbon reduction responsibilities. Artificial intelligence models integrate technologies such as the Internet of Things (IoT), satellite remote sensing, and image recognition to achieve comprehensive and high-precision monitoring of carbon emissions, thereby enhancing the efficiency and accuracy of carbon monitoring.

In regional carbon emission monitoring, integrating satellite remote sensing data with deep learning models enables precise tracking of total carbon emissions and their spatial distribution, accurately identifying carbon hotspots to provide data-driven support for regional emission reduction strategies. For corporate carbon monitoring, IoT devices collect real-time emission data during production processes, while AI models conduct in-depth analysis to deliver instant alerts for abnormal emissions and promptly detect compliance violations. For instance, Convolutional Neural Network (CNN) models can analyze industrial flue gas images to rapidly assess pollutant concentrations and carbon emission levels, facilitating real-time monitoring and anomaly detection. In power grid applications, AI systems continuously monitor carbon emissions during operational processes, offering precise data support for carbon management initiatives.

4.3 Application in Carbon Emission Optimization Regulation

Optimal carbon emission regulation serves as the cornerstone for achieving carbon reduction targets. Its essence lies in implementing scientific strategic adjustments to achieve synergistic optimization between carbon emissions and energy utilization, thereby reducing carbon footprint while ensuring sustainable socio-economic development. Artificial intelligence models analyze multi-source data including carbon emission records and energy consumption metrics to develop carbon reduction optimization frameworks. These models propose evidence-based strategies that enhance the scientific rigor and practical effectiveness of emission reduction efforts.

At the regional level, enhanced learning and deep learning models are utilized in conjunction with data on energy structures, industrial layouts, and current carbon emission levels to optimize regional energy frameworks, adjust industrial distribution patterns, and develop differentiated carbon reduction targets and strategies. This approach achieves coordinated progress between regional carbon mitigation efforts and economic development. At the enterprise level, artificial intelligence models are employed to streamline production processes and optimize energy consumption structures, establishing an optimal balance between carbon reduction costs and effectiveness while boosting corporate commitment to emission reduction initiatives. For instance, a major automotive parts manufacturer implemented an AI-powered carbon emission control model to refine production processes and energy consumption patterns, significantly reducing carbon intensity and realizing sustainable green development. In carbon trading markets, AI models facilitate carbon price forecasting and quota allocation optimization, enhancing market efficiency, encouraging proactive corporate participation in emission reduction, and improving resource allocation efficiency within carbon trading systems.

5 Issues and Bottlenecks in the Application Process of Artificial Intelligence Models

Although artificial intelligence models have been widely applied in smart energy and carbon emission systems with remarkable achievements, numerous challenges and bottlenecks persist in practical implementation due to constraints from multiple factors including data availability, model limitations, technological constraints, talent shortages, and policy barriers. These issues hinder the full realization of their application potential and urgently require further resolution.

5.1 Data Level: Data heterogeneity, low data quality, and data silos

The training and application of artificial intelligence models heavily rely on large-scale, high-quality multidimensional data. However, current smart energy and carbon emission systems face significant data challenges that severely limit AI model performance: Firstly, data heterogeneity persists. Energy data (e.g., generation, transmission, consumption metrics) and carbon emission data (e.g., accounting and monitoring records) originate from disparate systems and domains with inconsistent formats and standards, hindering effective multi-source integration and sharing. Secondly, data quality remains suboptimal, with issues like missing values, errors, and delays compromising model training outcomes and affecting predictive accuracy and optimization efficiency. Thirdly, data silos remain prevalent due to inadequate cross-enterprise and cross-departmental data sharing mechanisms, preventing efficient data circulation and utilization. This results in AI models lacking comprehensive data support and failing to fully leverage their data-driven core advantages. For instance, some photovoltaic power stations exhibit low digital transformation levels and insufficient data aggregation, which impairs AI model performance in operational maintenance and power forecasting applications.

5.2 Model Level: Insufficient generalizability, poor adaptability, and lack of unified standards

Current applications of artificial intelligence models in smart energy and carbon emission systems face challenges such as insufficient model generalization and poor adaptability. These issues manifest in three key aspects: First, most models are trained for specific scenarios and datasets, lacking universal applicability. When application contexts or data characteristics change, model prediction accuracy and optimization performance significantly decline, making it difficult to meet diverse operational requirements. Second, while different AI models demonstrate distinct advantages in specific application scenarios, practical implementations often lack scientific selection criteria and optimization mechanisms, resulting in underutilized model capabilities. Third, the absence of unified technical standards and guidelines for AI model deployment in smart energy and carbon emission systems creates challenges in comparing and evaluating model performance across different implementations. For instance, significant variations in carbon emission accounting models adopted by enterprises lead to non-comparable calculation results, hindering the systematic advancement of carbon management initiatives.

5.3 Technical aspects: Insufficient technological integration and inadequate hardware support

The depth of technological integration and hardware support capabilities are critical factors influencing the application efficiency of artificial intelligence models. Current challenges in this field remain significant: Firstly, the integration between AI technologies and smart energy systems, as well as carbon emission management systems, lacks depth. Most applications remain superficial, failing to achieve deep integration with core processes such as energy production, transmission, consumption, carbon emission accounting, monitoring, and regulation. This prevents the full utilization of AI's core advantages. Secondly, insufficient hardware support is evident. Intelligent hardware devices for smart energy and carbon emission systems (e.g., IoT sensors and smart monitoring equipment) have low coverage rates, with some devices lacking precision and stability to enable real-time, accurate data collection. This results in inadequate data support for AI models. Thirdly, the integration of technologies like digital twins and IoT with AI remains immature, failing to leverage synergistic effects from multi-technology convergence. This hinders comprehensive, intelligent system management. For instance, insufficient smart transformation efforts in some energy enterprises and outdated hardware equipment prevent adequate real-time data supply for AI models, thereby limiting their application effectiveness.

5.4 Talent and Policy Level: Shortage of Professional Talent and Incomplete Policy Support

Talent and policy frameworks serve as critical enablers for advancing the deep integration of AI models in smart energy and carbon emission systems. However, three key challenges persist in these fields: First, there is a shortage of interdisciplinary professionals skilled in both AI technology and energy/carbon management. The scarcity of experts proficient in both domains significantly hinders AI model development, implementation, and optimization. Second, inadequate policy support remains evident. Current incentive mechanisms for AI applications in smart energy and carbon systems are underdeveloped, while high implementation costs deter corporate adoption. Third, legal regulations lack clarity regarding carbon data privacy protection and sharing protocols, creating barriers to effective data utilization and posing challenges for AI model deployment.

6 Optimization Strategies for Artificial Intelligence Model Applications

To address the aforementioned challenges and bottlenecks while aligning with the development needs of smart energy and carbon emission systems, this paper proposes targeted optimization strategies across five dimensions—data, models, technology, talent, and policy—to facilitate the deep application of artificial intelligence models, enhance system operational efficiency, and contribute to achieving the "dual carbon" goals.

6.1 Improve the data system and break down data silos

First, establish unified data standards and specifications by clarifying formats, collection criteria, and storage protocols for energy data and carbon emission data to achieve standardization and normalization, thereby laying the foundation for multi-source data integration and sharing. Second, strengthen data quality control through mechanisms for data cleansing, validation, and supplementation, promptly addressing missing, erroneous, or delayed data to enhance quality and provide reliable support for AI model training and applications. Third, develop robust data sharing frameworks to break down data silos between enterprises and departments, facilitating efficient circulation and sharing of energy and carbon emission data. Establish a unified data platform to enable centralized management and optimal utilization of multi-source data. For instance, integrate meteorological and grid data with operational data from substations and contract transaction records to support intelligent transformation of energy facilities like photovoltaic power plants, thereby maximizing data value.

6.2 Optimizing Model Design to Enhance Model Adaptability and Generalization

First, enhance model versatility development by integrating common requirements of smart energy systems and carbon emission management systems to construct universal artificial intelligence models. This improves model generalization capabilities, enabling adaptation to diverse scenarios and data application needs. Second, establish model selection and optimization mechanisms. Scientifically choose appropriate AI models based on application-specific characteristics and requirements, while optimizing model parameters for targeted scenarios to enhance compatibility and operational efficiency. Third, develop unified technical standards and specifications that clarify requirements for model training, validation, and deployment processes. This standardization facilitates model comparison and evaluation, promoting standardized application practices. For instance, optimizing parameter settings for LSTM and ARDL models can improve accuracy in renewable energy output forecasting and carbon emission calculations, thereby enhancing practical value.

6.3 Deepening technological integration and strengthening hardware support

First, we will promote deep integration of artificial intelligence technologies with smart energy systems and carbon emission management systems. By embedding AI models into core processes including energy production, transmission, consumption, carbon emission accounting, monitoring, and regulation, we can fully leverage AI's predictive capabilities, optimization functions, and control mechanisms to achieve comprehensive intelligent management. Second, hardware infrastructure development should be prioritized to expand coverage of smart devices (e.g., IoT sensors and intelligent monitoring equipment), enhance device precision and stability, and enable real-time, accurate data collection that provides robust support for AI models. Third, we will advance the convergence of digital twin technology, IoT, blockchain, and AI to establish integrated smart energy and carbon emission control systems. This multi-technology synergy will maximize operational efficiency and scientific rigor. For instance, constructing digital twins of energy systems combined with AI models enables simulation and optimization decision-making. Strengthening secondary power security measures ensures secure data transmission and storage, providing robust safeguards for model applications.

6.4 Cultivating Professional Talent and Enhancing Policy Support

First, strengthen talent cultivation by fostering in-depth collaboration between universities, research institutions, and enterprises. Establish interdisciplinary programs in artificial intelligence and smart energy systems, as well as carbon emission-related fields, to nurture professionals proficient in both AI technologies and energy/carbon emission knowledge. Enhance training for existing practitioners to improve their technical skills and comprehensive competencies, addressing the demand for talent in model development, application, and optimization. Second, improve policy support through targeted incentive measures. Increase financial subsidies and tax incentives for AI applications in smart energy systems and carbon emission management, reducing implementation costs and boosting corporate adoption of AI technologies. Third, refine relevant laws and regulations to clarify privacy protections and data sharing requirements for carbon emission data. Standardize effective data utilization and sharing practices, providing legal safeguards for AI model applications to ensure orderly implementation of related initiatives.

7 Future Development Outlook

With the continuous iteration and upgrading of artificial intelligence technologies, coupled with the deepening implementation of the "dual carbon" goals, the application of AI models in smart energy and carbon emission systems will demonstrate broader development prospects. In the future, these systems will steadily evolve toward intelligentization, collaboration, greening, and integration, providing stronger support for low-carbon energy transition and carbon management.

Firstly, the intelligence level of models continues to advance. With the ongoing development of technologies such as deep learning and reinforcement learning, AI models will gain enhanced autonomous learning and decision-making capabilities, enabling dynamic optimization and precise control of smart energy systems and carbon emission systems. The application of generative AI will further improve model R&D efficiency and practical effectiveness, facilitating rapid iteration and optimization of models, thereby driving their application to higher levels of sophistication.

Secondly, multi-technology integration is advancing at an accelerated pace. Artificial intelligence will deeply integrate with emerging technologies such as digital twins, the Internet of Things (IoT), blockchain, and 5G to establish smarter and more efficient smart energy systems and carbon emission control frameworks, enabling comprehensive management across the entire energy lifecycle and emission pathways. The synergy between digital twins and AI will facilitate virtual simulation and real-time optimization of energy and carbon emission systems, significantly enhancing operational safety, reliability, and efficiency.

Thirdly, application scenarios are continuously expanding. Artificial intelligence models will gradually extend beyond current applications such as energy production, transmission, consumption, carbon emission accounting, and monitoring to broader domains including carbon trading, carbon finance, and energy internet, achieving synergistic development between smart energy systems and carbon emission management systems. In the construction sector, this evolution will transition from individual building optimization to coordinated urban-scale building management, establishing intelligent nodes for regional energy internet networks to drive green and low-carbon development in the construction industry.

Fourth, regional coordination and international cooperation are continuously strengthening. Artificial intelligence models will facilitate energy coordination and carbon emission reduction collaboration among regions, achieving optimal resource allocation and promoting green and low-carbon coordinated development. Meanwhile, international technological exchanges and cooperation will deepen, jointly advancing the application of AI technologies in global low-carbon energy transition and contributing China's wisdom and solutions to global climate governance.

8.Conclusion

This study systematically investigates the application of artificial intelligence models in smart energy and carbon emission systems. By reviewing relevant theoretical foundations, it analyzes specific implementation scenarios and performance metrics of AI models across the entire energy value chain — including production, transmission, and consumption—as well as carbon emission accounting, monitoring, and optimization control. The research identifies existing challenges and bottlenecks in current applications at data, modeling, technological, talent, and policy levels, proposes targeted optimization strategies, and ultimately outlines future development trends.

Research indicates that artificial intelligence models, with their robust capabilities in data processing, feature extraction, and intelligent decision-making, hold significant potential for application in smart energy systems and carbon emission management. These models can effectively enhance energy utilization efficiency, reduce carbon emission intensity, and provide crucial support for achieving the "dual carbon" goals. Core methodologies such as machine learning, deep learning, and reinforcement learning play pivotal roles across various application scenarios. When integrated with technologies like digital twins and the Internet of Things, they further elevate system intelligence levels and operational efficiency, driving digital transformation and low-carbon transition in energy systems. However, current AI model implementations still face challenges including data silos, limited model generalization capacity, insufficient technological integration, and talent shortages. To fully leverage their core advantages, it is essential to adopt measures such as optimizing data frameworks, refining model designs, deepening technological convergence, cultivating specialized talent pools, and strengthening policy support to facilitate deeper AI model adoption.

In the future, with the continuous development and innovation of artificial intelligence technology and the deepening of the "dual carbon" goals, AI models will achieve deeper integration with smart energy and carbon emission systems. Application scenarios will continue to expand, and application efficiency will keep improving, providing stronger support for the digital and low-carbon transformation of energy systems, and contributing China's wisdom and solutions to global climate governance.

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