Blockchain and Machine Learning in the Green Economy: Pioneering Carbon Neutrality Through Innovative Trading Technologies

Fan Yang, Mohammad Zoynul Abedin, Petr Hajek, Yanan Qiao

Abstract

In response to the pressing imperative of combating climate change on a global scale, a new era of carbon neutrality is steadily emerging. Achieving carbon neutrality is critical, and in the digital economy, technology-driven business models are essential for reducing carbon emissions through effective carbon emission trading systems. However, current research on carbon emission trading suffers from inadequate privacy protection, low efficiency in data sharing and model construction, as well as insufficient capabilities in automated and autonomous model building. Therefore, this study focuses on utilizing blockchain and automated machine learning for data sharing and modeling to enhance carbon neutrality. First, we design the architecture of the system and the mechanism for storing data on the blockchain. We then devise methods for storing and trading carbon emission transactions on the blockchain and construct the process for issuing carbon credits. Additionally, our proposed method incorporates Neural Architecture Search (NAS) to develop a carbon trading price forecasting model. By leveraging data augmentation for carbon emission price time series and utilizing triplet loss for model training, we enhance the reliability and security of carbon trading investment through accurate price forecasting. The experimental results further demonstrate the robust performance and precision of our carbon emission price forecasting module. Consequently, our approach provides efficient carbon emission trading services to businesses and individuals, offering a robust solution for global carbon emission reduction and the achievement of carbon neutrality.

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Index Terms

Carbon neutrality, blockchain technology, smart contracts, automated machine learning, carbon trading price forecasting.

MANAGERIAL RELEVANCE STATEMENT

The findings of this study offer engineering managers and policymakers a clear roadmap for implementing blockchain-based carbon trading platforms, underpinned by automated machine learning (AutoML). First, our results show that organizational heads can rapidly build robust forecasting and compliance modules—even with limited in-house machine learning expertise—because AutoML reduces the need for manual feature engineering or deep data-science skill sets. Second, blockchain's transparent and tamper-evident ledger empowers regulators and trading participants to verify carbon credits and trading histories, reducing fraud and enhancing trust. This is counterintuitive to the prevalent concern that distributed ledger technology might be too slow or costly; our scalability tests indicate the system maintains efficient transaction throughput as more nodes join. Third, by coupling Neural Architecture Search (NAS) with data augmentation, policymakers gain improved accuracy in carbon price forecasting, which can inform carbon allowance policies and market interventions. Additionally, the triplet loss approach for smaller samples reveals that accurate forecasts do not necessarily require massive datasets. Engineering managers can leverage these findings by (i) adopting private or consortium blockchains to ensure data security at scale; (ii) deploying AutoML pipelines to achieve cost-effective forecasting improvements; (iii) engaging in pilot programs that combine real-time carbon monitoring and forecasting, so they can tailor incentives and compliance schemes more flexibly.

I. INTRODUCTION

THE far-reaching effects of global warming have led to numerous environmental challenges that impact both the world's ecosystems and its economy. It is, therefore, crucial to leverage technological innovation and adopt efficient, technology-driven business models to achieve carbon neutrality [1], [2]. The integration of blockchain and automated machine learning technologies offers potential for innovative, technology-enabled business models that support sustainable development within the digital economy and carbon neutrality sectors [3]–[5]. This integration allows companies to implement and optimize sustainable practices aligned with economic growth and environmental concerns by enabling transparent and secure data transactions, accurate carbon footprint calculations, and efficient resource allocation. Blockchain technology is vital in carbon emission trading, providing a transparent and tamper-proof ledger system for the secure and efficient tracking, verification, and trading of carbon credits [6]. Its capability to ensure transaction integrity builds trust among stakeholders and supports real-time monitoring of carbon emission reductions [7]. Additionally, combining blockchain with machine learning technologies can enhance the carbon trading process by digitizing carbon credits as assets and facilitating their consumption, thus ensuring a smooth flow of carbon trading.

As environmental changes intensify, so does the urgency to achieve carbon neutrality. In 2009, China committed to reducing its carbon dioxide emissions, and the carbon emissions trading market established in eight pilot provinces and cities has been expanding rapidly, showing annual increases in both volume and turnover. The scarcity of carbon emission rights gives them notable trading value, drawing significant interest due to their financial and investment potential [8]–[10]. To counteract climate change effects, a balance of carbon emissions is necessary through various strategies, including renewable energy initiatives and carbon credits. Carbon neutrality is advantageous not only for the environment but also for businesses and nations. For businesses, adopting carbon neutrality strategies can boost their sustainability profile, enhance their brand reputation, and attract environmentally conscious consumers. This adoption also drives innovation and efficiency, leading to cost reductions and sustained competitiveness. Nationally, achieving carbon neutrality underscores a commitment to environmental responsibility and can positively influence international relations, trade agreements, and regulatory compliance [11].

As a result, achieving carbon neutrality is essential to building a more resilient and sustainable future for nations and enterprises alike. Along with addressing environmental issues, this revolutionary change promotes social responsibility and economic growth. Organizations and countries may actively contribute to a cleaner, greener future for everybody by pledging to achieve carbon neutrality. A technology-driven business model is therefore essential to improving the effectiveness of carbon trading and guaranteeing the successful execution of carbon neutrality programs. Transactions can be streamlined, data security can be improved, and carbon market operations can be optimized by utilizing cutting-edge technology like blockchain, smart contracts, and artificial intelligence. To minimize greenhouse gas emissions and help slow down global warming, carbon neutrality must be reached. The security of model sharing and carbon trading data is a worry since the integrity of these systems is essential to maintaining transparency and confidence in carbon markets. Ensuring the integrity and reliability of carbon trading mechanisms and advancing sustainable environmental practices worldwide require tackling these security issues with strong cybersecurity and sophisticated data protection methods.

With the implementation of the dual carbon policy, which includes carbon peaking and carbon neutrality, the efficient reduction of carbon emissions has become a prominent topic [12]–[14]. Carbon trading prices have significant implications for governments, businesses, and long-term investors who are working to address climate change challenges. Carbon pricing is a critical component of government climate policy packages aimed at reducing emissions and can also serve as a potential revenue source. In the business sector, internal carbon pricing is used to assess the impact of mandatory carbon pricing on operations. This helps in identifying climate risks and revenue opportunities. Long-term investors also use carbon pricing to reassess their investment strategies in light of environmental concerns. Given these considerations, the development and implementation of effective carbon price forecasting and trading systems are crucial for promoting energy efficiency and addressing resource and environmental issues caused by carbon emissions.

While carbon emission trading markets already exist and are being applied and promoted to some extent, they still face challenges such as insufficient security, lack of transparency, and inadequate traceability assurance mechanisms [15], [16]. These issues have significantly hindered the development of the carbon emissions trading market and have become major obstacles to its future growth. Therefore, it is essential to establish a set of long-term mechanisms for carbon trading, with specific attention given to addressing these issues in the trading process. The mechanism should cover the entire process, from the allocation of allowances to market trading, and include daily emissions monitoring to effectively regulate the entire cycle of pollutant emissions.

Climate change, driven by carbon emissions, poses a significant global challenge today. The impacts of climate change are more intense and rapid than expected, leading to increased instability in the climate system. Extreme weather and climate events are becoming more frequent, widespread, and prolonged [17], [18]. In response, countries are moving toward carbon neutrality goals. China has pledged to achieve carbon neutrality by 2060, the U.S. aims for net zero emissions by 2050, and the European Union has enacted a European Climate Law to ensure that Europe becomes the first 'climate neutral' continent by 2050. Comprehensive studies conclude that human life may be at greater risk once the future global average temperature rise exceeds the 2°C threshold. Thus, the goal of carbon peaking and carbon neutrality, as exemplified by China, requires efforts to manage carbon emissions and resources in a more efficient manner, supporting sustainable global economic and social development.

Effective carbon trading is essential for global carbon emission policies, including Chinese strategies for carbon peaking and carbon neutrality. The socio-political challenges inherent in carbon trading—such as international cooperation, equitable carbon pricing, and the risk of greenwashing—are pivotal to its effectiveness in mitigating climate change. Achieving meaningful collaboration among nations is complicated by divergent priorities, leading to fragmented approaches that undermine collective action. Furthermore, establishing an equitable carbon pricing framework remains problematic, as wealthier nations often resist potential economic burdens while developing countries frequently lack the requisite infrastructure to fully engage in carbon markets. The specter of greenwashing further obfuscates the integrity of these systems, with entities potentially exaggerating their environmental commitments to enhance public perceptions without enacting substantive changes. In this intricate landscape, the implementation of technical solutions becomes essential not only for enhancing transparency and accountability but also for ensuring secure information exchange. Given that carbon trading data is sourced from diverse institutions, robust privacy protection mechanisms can facilitate safe sharing and mitigate data silos. This fosters a collaborative environment that promotes equitable participation and ultimately strengthens the overall efficacy of carbon trading initiatives, thereby addressing the multifaceted challenges faced in the global effort against climate change.

Currently, global carbon emissions continue to rise annually, and the challenges posed by environmental issues and climate change are becoming increasingly severe. Fig. 1 illustrates the share of carbon emissions from different sectors. From Fig. 1, it is evident that the industrial, electric power, and transportation sectors constitute a substantial share of overall carbon emissions. This data underscores the critical importance of efficient carbon monitoring, which is essential for accurately identifying and tracking emission sources within these key industries. Effective carbon monitoring not only facilitates the development of targeted policies and interventions but also incentivizes various sectors to adopt more sustainable production and transportation practices. Consequently, such measures play a pivotal role in advancing the attainment of carbon neutrality objectives.

Current research on carbon emissions trading and forecasting faces several challenges. Firstly, the carbon emission trading process generates a large volume of trading data, yet existing research often overlooks the effective storage of data related to carbon emissions, timestamps, and emission statuses involved in historical trading [7], [19]. This oversight leads to inefficient data management in carbon emission systems. Secondly, current research primarily focuses on predicting carbon emission prices and does not sufficiently consider how digital tokens and related technologies could enhance the sustainability and stability of carbon trading systems, thus impeding their broader promotion and application [20]. Thirdly, most existing methods for predicting carbon trading prices rely on time

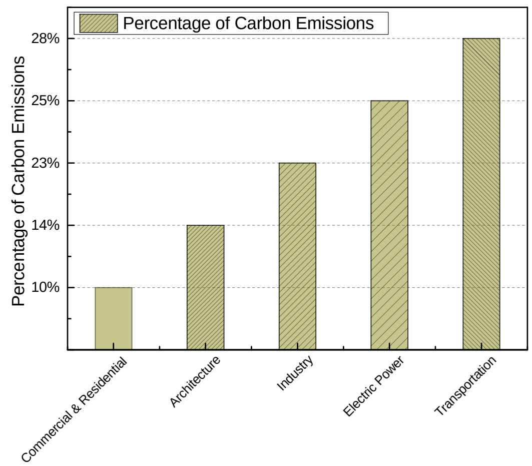


Fig. 1: Proportion of carbon emissions from different sources

series models without integrating the entire prediction process effectively [11]. In practice, machine learning requires a high level of expertise, from data preprocessing to model construction, which limits its accessibility to a broad range of users in the carbon trading system.

To overcome these limitations and complexities, we propose a novel carbon emission trading mechanism that combines automated machine learning with blockchain technology. This mechanism aims to achieve multiple objectives, including efficient on-chain storage of carbon trading data, automatic generation and trading of carbon credits, and accurate prediction of carbon trading prices. Our key contributions in this study are as follows:

- We introduce an effective method of carbon emission trading that leverages technology-driven business model innovation. This includes an on-chain carbon trading data storage system that ensures tamper-evidence and complete traceability. The trading system is fully integrated with actual requirements, and the security and stability of transactions are assured through smart contracts and privacy security mechanisms.
- To enhance the efficiency of the carbon trading system, we implement an on-chain carbon credits digital asset storage scheme. This scheme accurately represents the trading attributes of carbon credits on the blockchain, and we have designed a robust process for generating and trading carbon credits, ensuring their stability within the trading system and enhancing overall system efficiency.
- Additionally, we propose a carbon emission price prediction method using automated machine learning-based neural architecture search (NAS), combining data augmentation and triplet loss modeling methods for carbon emissions trading price time series data. This allows for efficient and automatic construction of carbon emissions price prediction models. Experimental analysis using actual EU carbon emission trading data indicates that our proposed method outperforms benchmark methods.

Therefore, this study makes significant contributions to both practice and literature in the realm of carbon emission trading systems.

- Practical contribution: This study develops a novel carbon emission trading system leveraging blockchain technology and automated machine learning, effectively addressing key challenges such as privacy protection and data sharing inefficiencies. The proposed architecture enhances transaction security and transparency, while the forecasting model—utilizing NAS and triplet loss—provides accurate price predictions, enabling informed decision-making for participants in carbon markets. This facilitates greater engagement in carbon trading, aligning with global carbon neutrality goals.

- Contribution to literature: The research advances existing literature by introducing automated model development techniques in carbon trading. By applying NAS and data augmentation strategies, it contributes to a deeper theoretical understanding of carbon pricing dynamics and predictive modeling. This work serves as a foundation for future research on technological innovations in environmental economics, promoting enhanced climate change mitigation strategies.

The structure of the paper is divided into eight sections. Section II includes a literature review on current studies of blockchain technology and carbon emissions research. Section III presents the main techniques and key steps of the proposed carbon trading scheme. Section IV details the key steps of the proposed carbon trading price forecasting mechanism. Section V compares and analyzes the performance of the carbon trading scheme. Section VI presents the results of the carbon price forecasting experiments. Section VII analyzes the primary application prospects and policy implications of our proposed carbon emission trading scheme. Section VIII summarizes the contributions of this paper and presents an outlook on future research.

II. Related Work

This section introduces related research from three perspectives: 1) carbon emission trading research, 2) blockchain technology and automated machine learning, and 3) carbon emission data sharing research.

A. *Carbon emissions trading in engineering management*

In the field of engineering management, an increasing number of scholars are focusing on the research surrounding carbon neutrality and carbon trading. Current studies primarily concentrate on three key areas: 1) ensuring the effectiveness of carbon emission allowance allocation mechanisms; 2) developing comprehensive incentive structures for low-carbon technology investments; and 3) enhancing the efficiency of carbon trading price forecasting models. Within this research landscape, Chen et al. [21] contribute to the understanding of carbon emission quota allocation regulations by demonstrating that benchmarking allocation encourages higher investments in low-carbon technology compared to grandfathering allocation, despite potentially leading to greater total carbon emissions under certain conditions. Furthermore, it highlights that ensuring the effectiveness of carbon emission quota allocation mechanisms is an urgent issue that needs to be addressed in the field of engineering management. Ma et al. [22] introduce a comprehensive decision-making model for assessing mainstream carbon dioxide removal (CDR) technologies, utilizing advanced methodologies such as text mining and the extended MULTIMOORA method to produce data-driven insights. Furthermore, it reveals that establishing robust incentive mechanisms for ensuring investments in low-carbon technologies and guiding decision-making within the field of engineering management is an urgent issue that requires attention. Chen et al. [23] provide insights into the financial strategies of electricity enterprises by comparing the impacts of carbon quota sale financing and carbon quota pledge financing on renewable energy investments and carbon emissions under various constraints. It emphasizes the need for effective strategies to balance financial

TABLE I: Goals of blockchain for carbon neutrality

Goal	Carbon neutrality contribution
Transparency	All participants can share the trading information, enhancing transparency and trust.
Security	Data encryption and distributed storage provide a high level of security.
Decentralization	No need for central authorities, reducing the risk of single points of failure and increasing system stability.
Automation	Smart contracts and automatic execution simplify transaction processes, increasing efficiency.
Privacy	Protecting personal data privacy while ensuring compliance.
Scalability	Scale blockchain networks according to demand to adapt to various business scenarios.
Traceability	Track the source of each operation and data change, ensuring data provenance traceability and transparency.

constraints and renewable energy preferences in achieving carbon neutrality goals. Kou et al. [24] integrate quantum theory and picture fuzzy rough sets to create a novel decision-making model that accounts for causal relationships among indicators in evaluating carbon neutrality policies in the transportation industry. It highlights a critical gap in engineering management research, where existing models overlook these causal directions, necessitating the development of more comprehensive evaluation frameworks to support effective carbon neutrality strategies.

An analysis of research on carbon neutrality and carbon trading in engineering management identifies three critical issues: 1) Effectiveness of carbon emission allowance allocation mechanisms: There is a need to investigate the long-term impacts of various allocation methods (e.g., unregulated, grandfathering, and benchmark allocation) on low-carbon technology investment and emissions. 2) Incentive mechanisms for low-carbon technology investment: While benchmark allocation can increase low-carbon investments, it may also raise overall emissions, prompting questions about balancing technological advancement with environmental protection. 3) Efficiency of carbon trading price forecasting models: Current predictive models often lack accuracy and efficiency, necessitating the adoption of advanced techniques like machine learning to improve forecasting capabilities. This would better inform investors and enhance market stability and transparency. This study proposes integrating blockchain and automated machine learning to address these challenges effectively.

B. Blockchain technology and Automated machine learning

Blockchain technology, an important innovation introduced by Satoshi Nakamoto, plays a critical role in numerous sectors of the modern economy and society. It offers foundational technical support for reconfiguring models of art transactions, among others. Table I presents the goals of blockchain for achieving carbon neutrality. Through Table I, it is evident that blockchain is instrumental in meeting carbon neutrality goals, particularly through enhancing data transparency, traceability, and decentralization. These capabilities support the advancement of technology-driven business models towards greater data security and efficiency, thereby facilitating the carbon neutrality process.

Currently, there are several widely used AutoML systems. In AutoML systems, NAS is an automated methodology that efficiently explores various neural network architectures to identify the best configurations for specific tasks. In the context of building carbon time series forecasting models, NAS is particularly significant as it can uncover tailored architectures that optimize predictive performance, ultimately improving accuracy and robustness in forecasting future events based on historical data. Auto-sklearn [25] is a prominent AutoML system that optimizes machine learning pipelines. This system explores a search space that includes algorithms from scikit-learn [26], utilizing a Bayesian optimization approach with the general-purpose algorithm configurator SMAC [27]. The automatically constructed pipelines in auto-sklearn encompass preprocessing, feature engineering, and machine learning model components. Another notable system, Auto-Keras [28], specializes in NAS. It employs network morphisms and Bayesian optimization to efficiently search for high-performance neural network architectures.

It is evident that existing approaches for automated machine learning not only cover a comprehensive pipeline of processes but also include model building methods for NAS. However, these methods often show less satisfactory performance in time series classification, especially when dealing with inadequately labeled training sets. To address this issue, we propose a preprocessing method aimed at improving the classification performance of various time series methods, including those used in automated machine learning, particularly for datasets with small sample sizes.

C. *Carbon emission data sharing research*

Significant progress has also been made in enhancing carbon data sharing and security in carbon emissions trading systems. Pan et al. [29] developed a system dynamics model to evaluate the efficacy of carbon emission trading programs and the interrelations among internal system components. An et al. [30] used a two-phase data envelopment analysis to assess resource allocation in an actual carbon emissions trading system, including sensitivity analysis based on stringent criteria for baseline carbon emission quotas. Hu et al. [31] introduced a Blockchain-enabled Distributed ETS (BD-ETS) to increase system efficiency and security, converting centralized carbon emissions permit trading into a decentralized platform using smart contracts executed on Hyperledger Fabric. Al Sadawi et al. [32] proposed a blockchain-based method to monitor carbon emission reductions, capitalizing on blockchain's security, immutability, transparency, traceability, and trust. Chi et al. [33] created a system dynamics model to simulate and evaluate carbon emissions allocation methods under various scenarios related to electricity reform. Muzumdar et al. [34] and Shu et al. [35] explored using permissioned blockchain and smart contracts to create a reliable and motivating emission trading system, enhancing MRV (Measurement, Reporting, and Verification) and transparent carbon credit trading.

Through the aforementioned studies, it is evident that emerging research efforts have been focused on addressing key challenges within carbon trading, such as system security, data sharing effectiveness, and overall transparency. Table II presents a comparison between existing representative studies and our research in terms of key features such as data protection, data sharing, and traceability.

Incorporating insights from recent economic and policy studies on carbon markets reveals significant deficiencies that our technological innovations seek to address. Research has identified persistent challenges, such as market inefficiencies, inadequate transparency, and hurdles in monitoring and verification processes. Our proposed applications of blockchain technology enhance transparency and traceability in carbon transactions, effectively mitigating risks associated with fraud and double counting, as highlighted in the literature. Furthermore, existing studies underscore the necessity for advanced data analytics to inform policy development; our AutoML solutions are designed to fulfill this need by enabling more precise and data-driven decision-making. By situating our technical contributions within the context of these identified gaps, we aim to advance the discourse on enhancing the efficacy and resilience of carbon market mechanisms.

TABLE II: Summary of technologies used in existing carbon emission trading research

Study	Traceability of transactions	Carbon data sharing	Trading data regulatory	Data privacy protection	Collaborative model construction
[29]			✓		
[30]		✓			
[31]	✓	✓			
[32]	✓	✓			
[33]		✓			
[34]	✓	✓	✓		
[35]	✓				
This study	✓	✓	✓	✓	✓

Through the analysis of existing studies, we can therefore conclude that there is still an urgent need for a secure and reliable trading system for carbon emission trading mechanism, which provides an efficient carbon emission trading mechanism and at the same time requires a suitable incentive mechanism to promote stable trading. Therefore, in our study, we consider the introduction of blockchain and automated machine learning technologies to design a carbon emissions trading system with incentives to further improve the efficiency and scalability of carbon emissions trading. Furthermore, through the literature review, we observe that existing studies widely indicate that blockchain-based carbon trading methods offer significant advantages in terms of transparency, traceability, and efficiency. These characteristics align well with the current industrial practices and are essential for enhancing the functioning of the carbon trading market. Therefore, our proposed blockchain-based carbon trading approach not only meets the needs of the industry but also has the potential to play a positive role in existing practices.

III. Methodology

A. *Overall theoretical framework*

The primary goal of enhancing the security and effectiveness of carbon neutrality information systems is to integrate blockchain technology with automated machine learning. This integration aims to optimize carbon trading data sharing and model building. By enabling decentralized data transmission and storage, blockchain technology enhances the security of carbon neutrality information systems. It ensures the integrity and transparency of carbon trade data, effectively preventing fraud and tampering. Additionally, automated machine learning can process and analyze large volumes of data accurately and efficiently, thus improving the quality and processing efficiency of carbon trading data. This supports carbon neutrality information systems robustly. Fig. 2 illustrates the framework of the proposed sharing and modeling method for carbon neutrality.

By combining blockchain and automated machine learning, the following objectives can be achieved:

- Secure sharing of carbon trading data: Blockchain technology facilitates secure data storage and transmission channels, ensuring the security and privacy protection of carbon trading data. This enables stakeholders to share carbon trading data securely.

- Efficiency in model building: Automated machine learning is utilized to analyze and model carbon trading data, enhancing the efficiency and accuracy of model construction, and providing precise data support for carbon neutrality information systems.
- Intelligent decision-making: The integration of automated machine learning allows for real-time analysis and prediction of carbon trading data, offering intelligent support for decision-making and aiding businesses in better managing carbon emissions and trading activities.

The theoretical foundation of this study involves merging automated machine learning with blockchain technology within the context of carbon trading data modeling and sharing. As depicted in Fig. 2, the upper half of the theoretical framework addresses the secure sharing of data through blockchain, while the lower half focuses on model building via automated machine learning. The adoption of blockchain technology ensures data integrity and transparency by providing a decentralized and secure platform for carbon trading data sharing and storage. Concurrently, automated machine learning facilitates the rapid and effective modeling and analysis of vast amounts of information, thereby simplifying the development of precise prediction models for carbon trading.

B. Blockchain-based approach for carbon emissions trading

Blockchain technology, recognized as a decentralized database, stores data in blocks that are continuously linked and neatly arranged, creating a robust and tamper-evident chain [36], [37]. Each block in the chain is encrypted, making it difficult to tamper with or delete any specific credit information by attacking just one storage device. Furthermore, this data is stored on every computer within the blockchain network, and each entity that collects and processes information shares and stores it in encrypted form. This system enables real-time collection, generation, querying, and updates of data. The distributed and decentralized nature of blockchain reduces the time lag in information processing and shortens the entire credit business chain.

A non-fungible token (NFT) is a unique data unit on a digital ledger that certifies a digital asset as unique and non-interchangeable [38]. NFTs represent items like images, videos, and audio, providing the owner with exclusive access to the original file, although copies may exist elsewhere. Similarly, utilizing blockchain technology in carbon emission trading can enhance the process's efficiency and security, which is vital for carbon offsetting technology. A blockchain-based carbon emission trading system includes all transactions within a distributed database. If all participants involved in carbon transactions are integrated as nodes in this network, the system remains secure and reliable as long as the majority of nodes are uncompromised. Each transaction is packaged into a block, with subsequent transactions forming new blocks that link sequentially. All transaction blocks are interconnected and stored in a distributed database. Nodes can freely leave or join the network without affecting the integrity of the data. By ensuring the data's authenticity and adding anti-counterfeit measures, a traceable chain is established, enabling a new system of industry practices and rules for carbon emission transactions and maintaining market stability.

In addition, the blockchain architecture's assumption of technological homogeneity among participants necessitates careful consideration in the context of carbon markets, where a diverse array of actors with varying technological capabilities exists. Acknowledging this assumption is vital, as it highlights potential disparities that could impede effective integration. To address these challenges, strategies such as providing targeted technological support for less

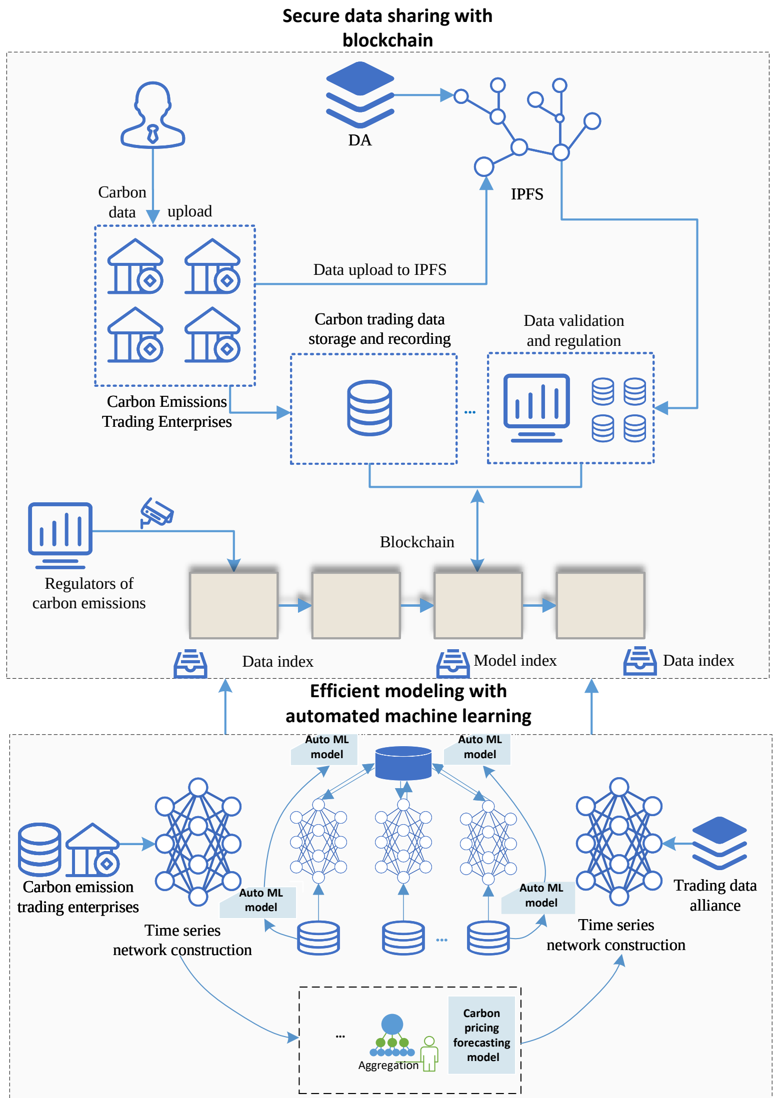


Fig. 2: Theoretical framework of data sharing and modeling for carbon neutrality

advanced participants can be implemented. Additionally, developing simplified user interfaces can facilitate access to blockchain technology, ensuring that all market actors can engage meaningfully. By adopting these approaches, the carbon market can enhance inclusivity and operational efficiency, fostering broader participation across diverse stakeholder groups.

Blockchain technology is increasingly recognized as a potent tool for addressing various contemporary challenges due to its decentralized nature and transparency. By providing an immutable record of transactions, blockchain can significantly enhance the reliability of data across multiple sectors, particularly in the context of environmental sustainability. Specifically, it has the capacity to facilitate real-time monitoring and management of carbon emissions, thus equipping businesses and governments with accurate data to support their carbon neutrality objectives. Therefore, it becomes evident that blockchain not only offers practical tools for the implementation of carbon neutrality but also provides robust data to inform policy development in this critical area.

Fig. 3 illustrates the architecture of this blockchain-based carbon emission trading system. In this system, the trading information of enterprises and individuals is interconnected and shared. Regulatory authorities manage and supervise the platform and its blockchain system, while financial institutions, such as carbon emission exchanges, can perform comprehensive assessments, diagnostics, and analyses on the information of enterprises applying for credits through the system.

The carbon emission trading system utilizes smart contracts and oracles to achieve efficient carbon management and trading. First, in the process of smart contracts, the system establishes carbon emission standards and rules, clearly defining the rights and obligations of each participant, and encodes these agreements onto the blockchain to ensure transparency and immutability. When participants engage in the buying and selling of carbon credits, the smart contract automatically verifies the transaction conditions, such as whether the carbon allowances are sufficient or if they meet compliance requirements, and updates account information after the transaction is completed. Meanwhile, the oracle acts as a bridge connecting the blockchain to the real world. It retrieves external data in real-time, such as carbon emission data collected from environmental monitoring sensors, market price fluctuations, and policy changes, and transmits this information to the smart contract, enabling it to make informed decisions based on the latest data. Through this collaborative work, the entire carbon emission trading system not only enhances the efficiency and reliability of transactions but also increases regulatory transparency, promoting the goals of sustainable development.

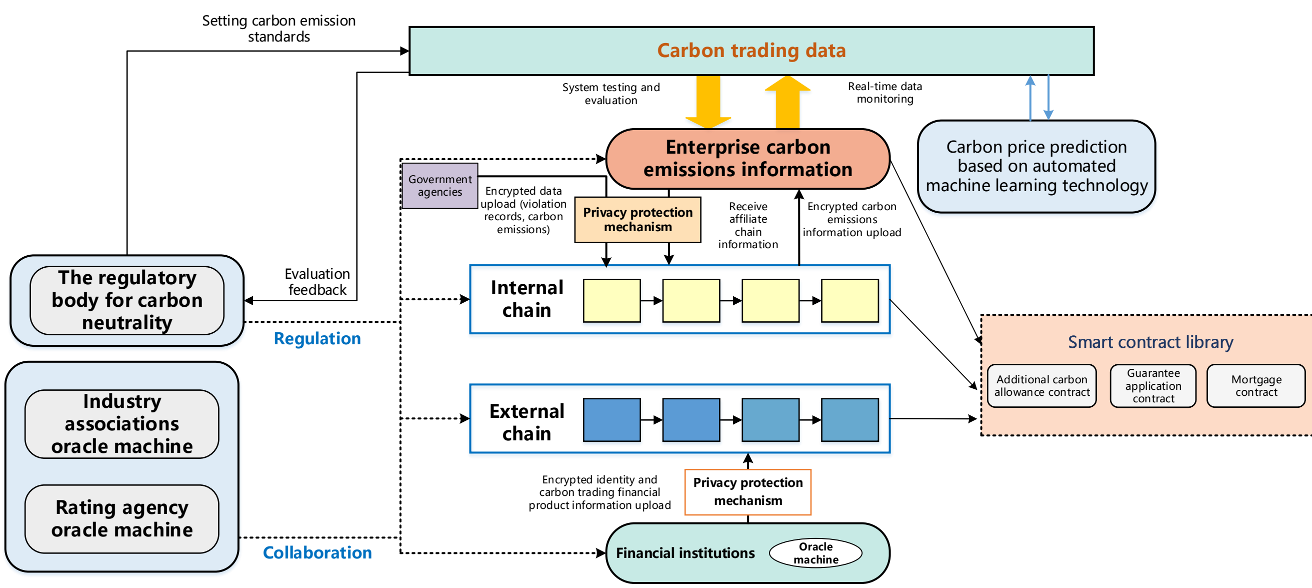


Fig. 3: Architecture of carbon emissions trading method

C. Blockchain representation of carbon trading credits

In this section, we explore the intricate nature of digital assets within the blockchain, characterized by complex states, association relationships, and ownership structures. To adequately manage these complexities, we treat subjects, assets, and contracts as distinct and identifiable objects within the blockchain architecture. This separation allows assets to have independent control over their state transitions. We establish a mechanism for expressing and executing the association relationships between objects, enabling the blockchain to recognize complex transaction semantics and relationships. Furthermore, a sophisticated state transition model is designed to ensure the linear progression of asset states and prevent issues like double-spending.

The blockchain consists of digital objects such as subjects, assets, and contracts, each with a globally unique identity. The state of the subjects and assets evolves continuously with transactions, while contracts serve solely as controllers of asset state transitions. Contracts encapsulate the transaction rules and state transition rules into code, which remains relatively constant.

In our blockchain-based carbon emissions trading scheme, carbon credit assets are no longer mere variables within a contract; instead, they possess an independent state transition control process. To ensure the uniqueness of these digital assets, hash functions are used to generate unique identifiers, enhancing asset distinctiveness through parallel verification with existing assets. This approach increases verification efficiency.

The asset uniqueness identifier is created by the asset issuer based on key attributes such as the asset's type and ID. The formula is expressed as follows:

$$C_i \cdot UIC = \mathrm{Hash}\left(C_i \cdot Attr_x, \ldots, C_i \cdot Attr_z\right) \tag{1}$$

During the consensus process, the system checks for unique identifiers of all new assets to ensure no duplicates. It also performs parallel verification of new and existing assets to prevent duplication of unique identifiers.

Fig. 4 illustrates the core functionality of our blockchain-based carbon emissions trading system, while Fig. 5 shows the data interaction and storage processes within this system. In Fig. 4 and Fig. 5, carbon emission transaction data are securely chained to prevent tampering. Once data are uniformly integrated into the blockchain, it becomes extremely difficult for any entity to alter. Blockchain bookkeeping, which replaces traditional centralized bookkeeping, involves linking multiple sub-blocks in tandem. Each sub-block not only records transactions for its specific time period but also includes the hash value of the previous period's transactions. This creates a complete and traceable chain from the first to the most recent transaction. Should any block's transaction information be compromised, the alteration of the hash values allows for timely detection and data recovery.

D. Consistency in trade execution during trading

Each carbon asset object independently maintains a sequence of transactions specific to that object. These transactions are ordered according to the timing of each transaction, allowing for the expression of state and timing biases and constructing a deterministic transaction execution sequence for the asset. The timing of the transactions for the asset object is represented as follows:

$$TM = < D, H, S > \tag{2}$$

where D denotes the unique identifier of the asset object; H ensures the validity of the asset's state, preventing the transaction from engaging with an outdated state during execution; S represents the transaction's temporal number, which is critical for sequencing and executing transactions properly.

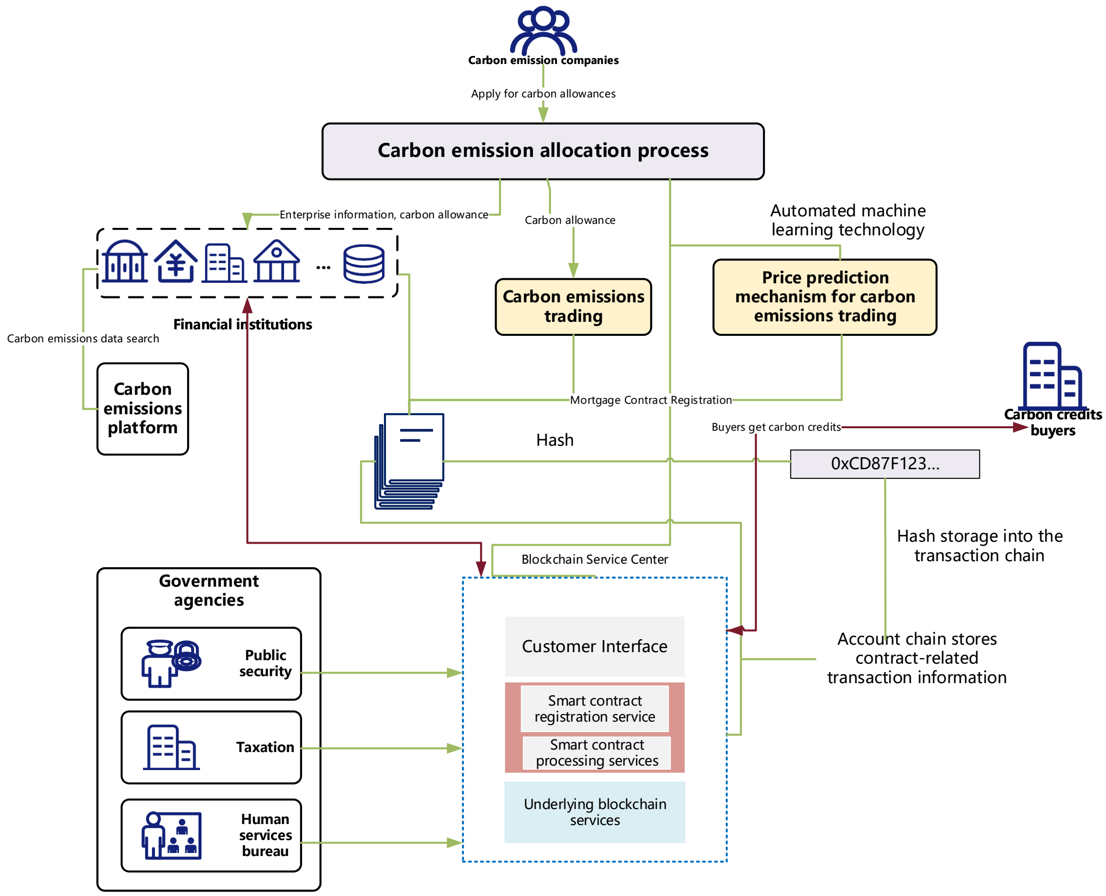


Fig. 4: Core functions of blockchain-based carbon emissions trading scheme

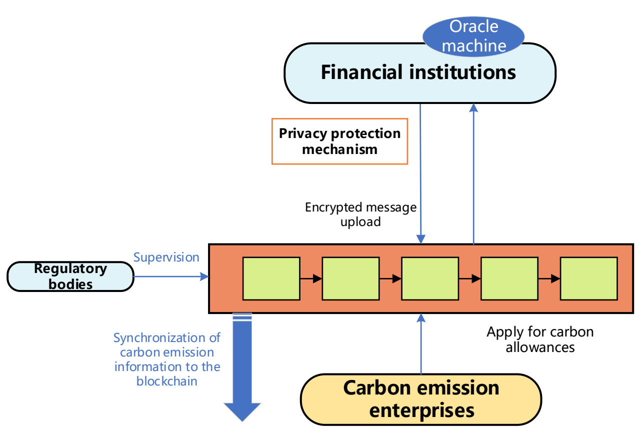
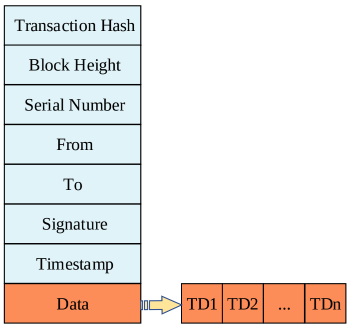
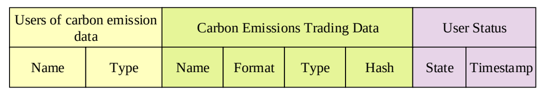


Fig. 5: Data interaction and storage in blockchain-based carbon emissions trading scheme

Fig. 6 illustrates the storage structure of carbon emission trading data within the system. This structure is designed to ensure that each transaction is accurately recorded and that the integrity and sequence of transactions are maintained, preventing any discrepancies or errors that might affect the reliability of the carbon trading data.



(a) Data structure of carbon emissions trading information



(b) Data structure for storing transaction information on the chain

Fig. 6: Structure of data storage in the carbon emissions transaction process

Fig. 6 indicates that both transactions and blocks have their own timestamps, because the time of generating credit data structure, the time of sending transactions and the time of generating blocks may not be consistent, and these time points are recorded in order to make the credit data traceability more accurate. In the data structure we designed, the storage structure of transaction and block is designed for data traceability requirements, which not only ensures the reliability of data, but also ensures that the data is not tampered with. Fig. 7 shows a demonstration of a smart contract in the carbon emissions trading process.

Fig. 6 demonstrates that both transactions and blocks within our blockchain system are timestamped. This design decision addresses the reality that the timing of credit data creation, transaction submissions, and block generation can differ. By recording these distinct timestamps, we enhance the traceability and accuracy of the credit data, crucial for verifying the integrity and authenticity of each transaction within the system. The storage structure for transactions and blocks is specifically designed to meet rigorous data traceability requirements. This structure not only ensures the reliability of the data but also safeguards against tampering, maintaining the system's integrity.

Fig. 7 provides an illustration of how a smart contract is utilized in the carbon emissions trading process. As depicted in Fig. 7, each step in the carbon emissions trading procedure is governed by predefined conditions set within the smart contract. This automation significantly enhances the efficiency of carbon emissions trading by eliminating the need for manual verification. The smart contract ensures that all transactions are executed only when these conditions are satisfactorily met, thereby streamlining operations and reducing potential errors or fraud.

E. Traceability of transactions on the blockchain

We have developed a robust data structure for traceability objects within our blockchain-based carbon emissions trading system. Although the structure can accommodate various data types within the internal network, this explanation will focus on two primary objects: ”user” and ”file”. These examples illustrate the traceability data

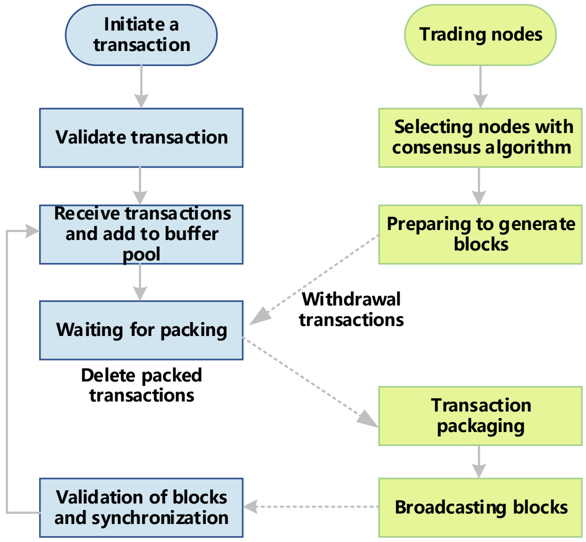


Fig. 7: The process of carbon emissions transaction

structure, which is extendable to support additional data types in practical applications. Algorithms 1, 2, and 3 in Appendix A outline the consensus mechanism for transaction traceability, the transaction data query algorithm, and the transaction data storage algorithm, respectively.

Our proposed system employs a dual-chain mechanism to separate transaction information from account information, enhancing the management of carbon emission trading. This system constructs two distinct chains: one maintains historical carbon emission trading and account credit information (the information chain), and the other processes transaction information (the transaction chain). Data generated throughout the business process is uploaded to the appropriate chain based on whether it pertains to account history or transaction behavior. This dual-chain structure improves the overall scalability of the system. Fig. 8 illustrates the system's data storage and privacy protection mechanisms.

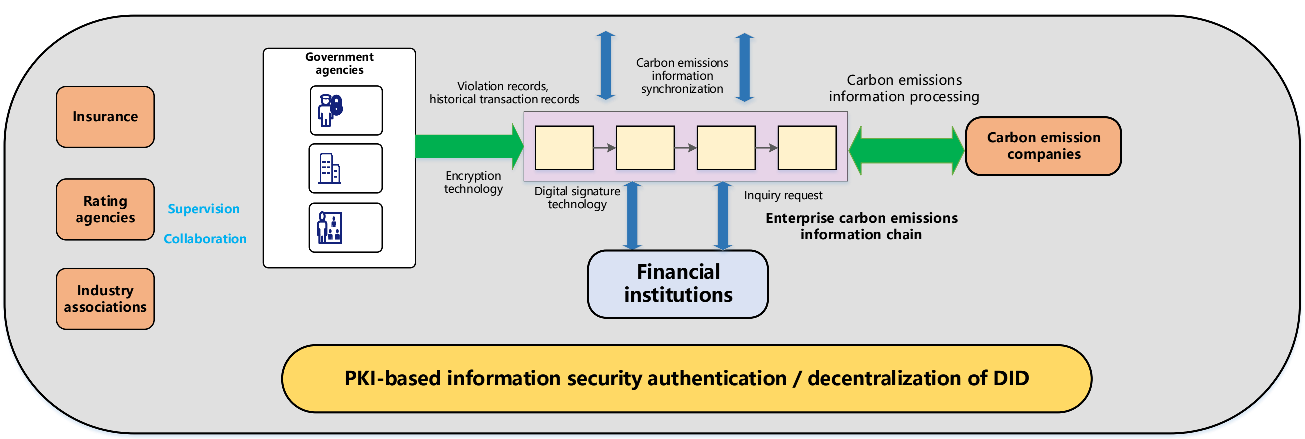


Fig. 8: Data security and privacy protection mechanisms for blockchain-based carbon emissions trading scheme

In Fig. 8, the security of carbon emissions trading communications between different computer systems is safeguarded through Public Key Infrastructure (PKI). This approach provides two core functions:

1) Authentication - Verifies that the communication is with a legitimate server or individual.
2) Encryption of carbon emissions trading information - Ensures that historical trading information remains inaccessible and unalterable by unauthorized parties.

The predominant consensus algorithms used by Bitcoin and Ethereum, known as Proof of Work (PoW) [39], [40], involve participants competing to generate blocks by solving cryptographic challenges, which can lead to excessive computational resource consumption. Given that PoW is unsuitable for internal network systems primarily serving organizational needs, it is more practical to adopt a private or federated blockchain approach in this context.

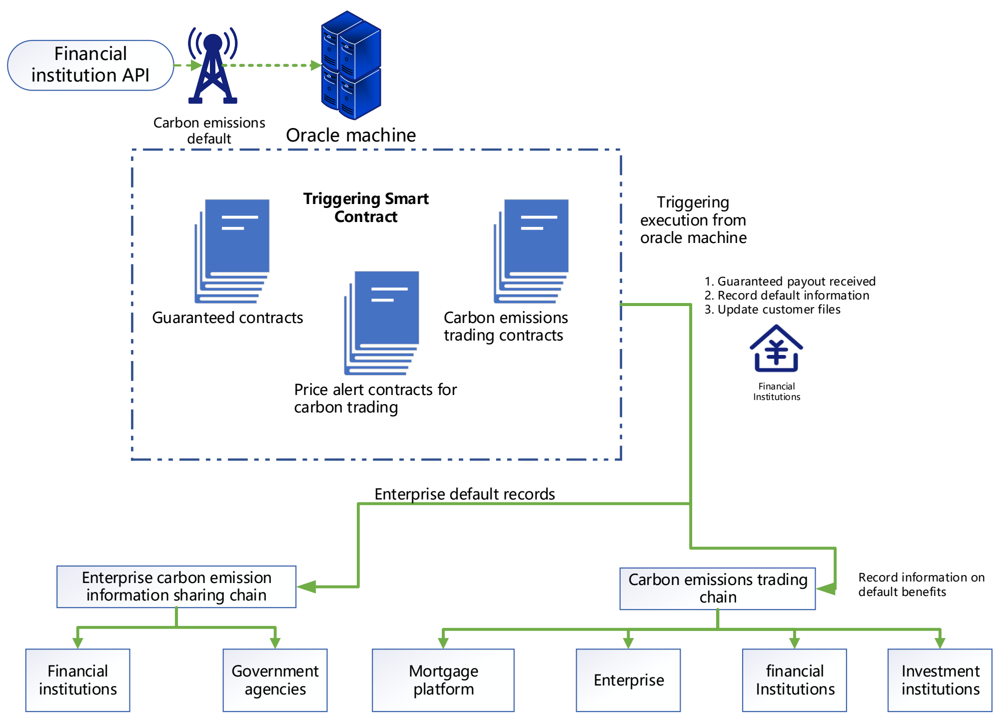


Fig. 9: Smart contracts and oracle machine for blockchain-based carbon emissions trading scheme

Fig. 9 showcases the integration of smart contracts and an oracle machine within the blockchain-based carbon emissions trading scheme. This configuration connects the data chain with smart contracts through the oracle machine, enabling data to be written into various types of smart contracts. These contracts assess the data according to the rules required by regulatory agencies, trading platforms, and other applications. This setup not only facilitates the interoperability of blockchain data with real-world data but also enhances the transparency and reliability of carbon emissions trading information.

F. On-chain carbon emissions data storage

In decentralized environments, current blockchain architectures primarily focus on achieving final ledger consistency, often overlooking the impacts of transaction execution certainty and correctness during parallel processing.

Despite the ledger's tamper-proof nature and overall consistency, it remains challenging for existing blockchain systems to maintain consistency during parallel construction of blocks, and parallel execution of blocks and transactions. This can lead to issues such as state change losses and state conflicts, where the accuracy and certainty of execution results are compromised. As illustrated in Appendix C, the blockchain-based carbon emissions trading scheme leverages smart contracts to automate the process of companies applying for additional carbon emission allowances. This automation enhances the efficiency of transactions and applications, ensuring that companies can seamlessly secure the necessary allowances without manual intervention.

Regarding data storage, the system initially stores data within its original transaction blockchain. Additionally, the Blockchain Data Ledger (BDL) system incorporates its own blockchain architecture. It first stores all data within the associated blockchain and subsequently writes the same data along with its associated hash information to the BDL blockchain. After obtaining the hash values, the data and its corresponding hash are then sent to both the original transaction chain and the BDL-associated blockchain. This method ensures that data integrity and traceability are maintained across multiple platforms, safeguarding against data manipulation and enhancing the reliability of the entire system.

G. Carbon credit trading and circulation scheme

1) Circulation between companies, government departments and individuals: Government departments are implementing various measures to encourage citizens to adopt a low-carbon lifestyle, continuously developing and enhancing the benefits of reduced carbon emissions. Actions such as green travel, using simple packaging, ordering only as needed, minimizing waste, and proper garbage separation are quantified and converted into ”carbon credits” for each individual's account. These credits are stored on the blockchain and linked to carbon trading markets, commercial consumption platforms, social organizations, and other institutions, enabling the public to reap tangible rewards.

In the public transportation sector, partnerships with related industries have led to the launch of a carbon emission reduction service. Carbon credits are awarded based on the carbon dioxide emissions saved during each trip, calculated by distance traveled and other factors. These credits are recorded in each traveler's account. Public transportation companies can offer coupons or discounts to frequent riders based on the carbon credits accrued. Additionally, passengers can use their carbon credits to redeem coupons or services from public transportation companies, with all redemption records being uploaded simultaneously to ensure transparency.

Environmental protection enterprises, particularly those involved in garbage recycling, encourage proper waste segregation by rewarding correct garbage classification with carbon credits and deducting credits for non-compliance. For recyclable materials like plastic bottles, cardboard boxes, and cans, the weight of the items is converted into carbon credits and added to the citizens' accounts. These enterprises also provide goods or services that can be purchased using carbon credits, further motivating public participation in carbon emission reduction activities.

2) Business-to-business transactions: Government departments enforce regulatory measures on enterprises' carbon emissions by penalizing those with excessive emissions and rewarding those that maintain low emissions. These actions are part of a broader strategy to reduce the total carbon quotas allocated to enterprises, in line with China's international commitments to carbon peaking, carbon neutrality, and climate change mitigation. This approach aims to control and reduce greenhouse gas emissions through market-driven mechanisms.

Carbon emission rights are valuable assets that can be traded like commodities in the market. Enterprises facing challenges in reducing emissions can purchase these rights from those that can more easily achieve reductions. This allows enterprises with excess emission capabilities to benefit financially by helping others meet their emission reduction targets.

The system operates on a carbon credit basis, where the government allocates specific carbon credit quotas to enterprises. Each enterprise is then accountable for emissions that do not exceed its allotted credits. Enterprises emitting less than their quota can sell their surplus credits to higher emitters, thus profiting from their efficient practices. Conversely, enterprises with higher emissions can buy additional credits to comply with their emission caps. All transactions are synchronously recorded on the blockchain, enhancing transparency and enabling better carbon asset management. Enterprises are encouraged to invest in innovative energy-saving technologies to further reduce emissions and engage in carbon trading, meeting the demands of those striving for carbon neutrality.

3) Trading between individuals and individuals and companies: Individuals can trade carbon credits with entities that demand and are willing to purchase them. Citizens can redeem their carbon credits for various benefits such as travel tickets, discounts on services, and shopping, or even use them directly to purchase household goods. To foster greater participation in the carbon credit exchange and accelerate the process toward carbon neutrality, government departments should provide policy support and economic subsidies to enterprises and organizations engaged in this market. This encouragement aims to expand the adoption of carbon trading and enhance its effectiveness as a tool for environmental sustainability.

H. Registration and issuance of carbon credits on blockchain

In our system, enterprises and individuals must first register a carbon credits account to obtain authorization for a low carbon coin wallet. Users can then accumulate carbon credits through environmentally friendly behaviors. These credits are sent to their low carbon coin wallet, akin to currency generated by the blockchain. All transaction and wallet balance information related to the issued carbon credits are synchronized with the blockchain. Before acquiring carbon credits, a user must register for a carbon credits account to open and initialize a low carbon coin wallet within the blockchain-based carbon emissions trading scheme.

Appendix E illustrates the process of applying for a carbon credit account and the allocation of carbon credits. As depicted in Appendix E, the application for a carbon credit account must be approved, ensuring the legal identity of the user. Furthermore, the system automatically allocates a specified amount of carbon credits to the user's account based on predetermined contracts triggered by the user's low-carbon behaviors.

The introduction of carbon credits not only validates the digital assets within the carbon trading system but also enhances the efficiency of the carbon emissions trading system. The process for obtaining carbon credits includes several steps:

1) Enterprises and individuals submit proof of low-carbon behaviors to an auditing platform.
2) The auditing platform reviews the authenticity of these materials.
3) Once approved, carbon credits are generated and synchronized to the personal or corporate accounts.

4) Transaction information related to these low-carbon coins is also synchronized to the blockchain.

IV. Carbon trading price forecasting mechanism

Our carbon trading price forecasting mechanism is designed using an automated machine learning (AutoML) pipeline approach, aiming to facilitate system integration and reduce the complexity of using machine learning methods. This comprehensive process automates the key workflows of data preprocessing, feature selection, model training, and model evaluation to achieve efficient and rapid forecasting of carbon emission prices.

In the forecasting module, we employ feature engineering to automatically generate and select time-series features, as emphasized in the literature [41], [42]. Utilizing TsFresh [43], [44], we compute a wide array of time-series features from carbon trading price data, which include basic statistical features such as peaks, means, maxima, and more intricate features like time-reversal symmetric statistics. TsFresh also identifies and extracts the most significant features for the regression tasks by hypothesis testing. These features are then used for building robust carbon trading price regression models.

Given a carbon price time series $\mathbf{x} = [x_1, \ldots, x_n]$ with $\mathbf{x} \in \mathbb{R}^n$ (here $\mathbb{R}^T$ is the space of possible time-series of length n), the goal is to classify $\mathbf{x}$ accurately based on historical data. Due to the frequent lack of ample time-series samples, not all data points are sufficiently informative for classifying x_i. We consider a time series dataset $D = \{(x_1, y_1), \ldots, (x_n, y_n)\}$ as a collection of pairs (x_i, y_i) where x_i is a time series with y_i its corresponding label. Our approach includes designing a classifier on D to map from the raw feature space to a probability distribution over the unique classes in D.

To overcome the challenges posed by small sample sizes, we propose data augmentation to generate an expanded dataset $\hat{\mathbf{x}}+\theta$, where the task is to classify the dataset $\hat{\mathbf{x}}+\theta$ using the model $M(f(\hat{\mathbf{x}}+\theta))$. The dataset $\mathbf{x} = [x_1, \ldots, x_n]$ is divided into training $\mathbf{x}_{\text{train}}$ and validation $\mathbf{x}_{\text{valid}}$ subsets. The embeddings generated after preprocessing are used in time series algorithms, with the classification task aimed at constructing an optimized model from $\mathbf{x}_{\text{train}}$ by minimizing the loss on $\mathbf{x}_{\text{valid}}$.

A. *Preprocessing method in automated machine learning*

The classification performance of small-sample time series data is often limited due to the scarcity of labeled instances. To address this challenge, our study introduces a new data augmentation method coupled with a novel preprocessing technique that utilizes both Timenet and triplet loss, aiming to enhance the accuracy of time series classification.

As illustrated in Fig. 10, our preprocessing approach for time series data mining builds upon the foundations of Timenet—a multilayer recurrent neural network (RNN) trained in an unsupervised manner to extract time series features [45]. We extend Timenet by integrating a triplet loss function, which is particularly effective in training models on small-sample datasets by enhancing the differentiation between classes during the training phase.

The preprocessing pipeline comprises the following steps:

1) Data augmentation for the time series dataset to address the issue of insufficient labeled samples, which is prevalent in many time series datasets.

2) Generate the necessary triplets for the triplet loss calculation, consisting of an Anchor x_{ref}, a Positive x_{pos} and a Negative x_{neg}.
3) Input x_{ref}, x_{pos}, and x_{neg} into the Timenet module. The output embeddings from Timenet are then used to enhance the feature representation of each time series instance.
4) Post-preprocessing, the enhanced embeddings can be utilized with any machine learning algorithm tailored for time series data mining, facilitating improved classification performance.

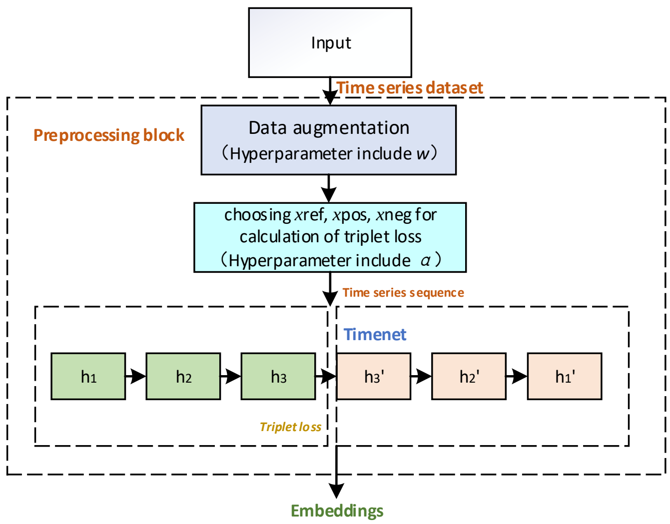


Fig. 10: Workflow of preprocessing method for time series mining. The primary process includes data augmentation, generating $\boldsymbol{x}_{ref}$,$\boldsymbol{x}_{neg}$, and $\boldsymbol{x}_{pos}$ for triplet loss, employing Timenet for training and creating embeddings for different time series data mining algorithms.

B. Carbon time series augmentation

The performance of time series classification with small samples is distinctly inferior to that with large samples [46]. Therefore, we incorporate a data augmentation method in our preprocessing to increase the training set size. Small training sets in time series samples may lead to overfitting, particularly when using the Timenet method in our preprocessing scheme. To address this, one approach is to enlarge the training sets by generating synthetic time series samples.

We propose averaging a set of time series and using the resulting averaged series as a new synthetic example. Dynamic Time Warping Barycenter Averaging (DBA) is an averaging approach tailored for time-series data. To implement this, we have developed an enhanced DBA method. The advantage of DBA [47] over linear averaging is that it preserves the inherent pattern of the time series, whereas linear averaging may obscure important features [48]. Thus, DBA does not compromise the classification results [49].

In the DBA method, for a set of carbon time series D induced by Dynamic Time Warping, the average time series is determined by minimizing $\operatorname{argmin} \sum_{i=1}^{N} DTW^2\left(\bar{D}, D_i\right)$. DBA employs an expectation-maximization strategy, refining an initial average B repeatedly by:

- Expectation: given T, select the best multiple alignment.
- Maximization: keep B constant and update T to become the best average sequence in coherence with B.

The application of the DBA algorithm facilitates the generation of new average series, thus addressing the issue of limited labeled data in small sample time series datasets. However, directly using this method does not account for the variability among different time series. If DBA is applied directly for data augmentation, the contributions of different time series to the update of T vary, especially in datasets with small samples. Therefore, we propose a method that employs a weighted averaging scheme, allowing each time series to contribute uniquely to the average. Our method enhances the alignment between the generated series and the original series.

Algorithm 4 in Appendix B outlines the procedure of our proposed method. The main idea is to calculate an average time series $\bar{D}$. In Algorithm 4, the process begins by finding suitable multiple alignment sequences using DTW. Then, weights are applied to update the sequences to achieve the best data augmentation sequences. After setting and updating the weights through subsequent steps, the augmented time series is generated.

C. Carbon price forecasting modeling method

In the design of Timenet [45], preprocessing of each time series is achieved through an encoder-decoder combination to obtain the embedding of the time series. The sequence auto-encoder (SAE) in Timenet comprises two multilayered RNNs with Gated Recurrent Units (GRUs) in the hidden layers: an encoder RNN and a decoder RNN. These RNNs are trained in tandem to minimize the reconstruction error across time series from various domains. After training, the encoder RNN of the encoder-decoder pair is used to obtain embeddings for test time series. The encoder RNN iterates over the time series data points to compute the final hidden state $\mathbf{z}t^{(i)}$. The decoder RNN, mirroring the encoder's network design, uses the hidden state $\mathbf{z}t^{(i)}$ as its initial state while reconstructing the input time series repeatedly.

To further enhance the performance of time series data mining, we introduce the triplet loss method [50] into our preprocessing strategy. Initially developed for face recognition to improve embedding quality with less variable samples [51], triplet loss calculates the distances such that the distance between the baseline (anchor) input and the positive input is minimized, while the distance between the baseline (anchor) input and the negative input is maximized. Thus, triplet loss improves our model's capability to calculate similarity across different categories of time series samples, thereby enhancing classification performance.

Fig. 11 demonstrates the implementation of triplet loss in Timenet, where the objective is to bring $\boldsymbol{x}_{pos}$ closer to $\boldsymbol{x}_{ref}$ and push $\boldsymbol{x}_{neg}$ further from $\boldsymbol{x}_{ref}$. This requirement facilitates the construction of triplets, which are trained to reduce the distance between the positive and anchor samples and increase the distance between the negative and anchor samples, thus improving the time series model's classification performance.

In Algorithm 5 in Appendix D, we consider a random subseries $\boldsymbol{x}_{ref}$ of a given time series $\boldsymbol{y}_i$ to apply this principle. The representation of $\boldsymbol{x}_{ref}$ should be similar to any of its subseries $\boldsymbol{x}_{pos}$ (a positive example). Conversely, the representation of another randomly chosen subseries $\boldsymbol{x}_{neg}$ (a negative example) should be distant from that of $\boldsymbol{x}_{ref}$. This approach dictates that the computed representations distinguish between $\boldsymbol{x}_{ref}$ and $\boldsymbol{x}_{neg}$, as well as assimilate $\boldsymbol{x}_{ref}$ and $\boldsymbol{x}_{pos}$. Consequently, the selection and training of triplet sets ($\boldsymbol{x}_{ref}$, $\boldsymbol{x}pos$, $\boldsymbol{x}_{neg}$) are crucial,

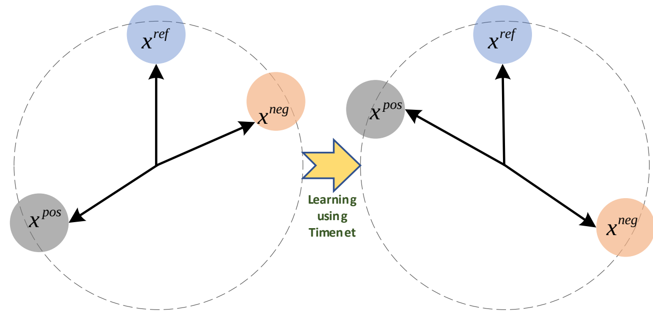


Fig. 11: Diagram of triplet loss among $\boldsymbol{x}_{ref}$,$\boldsymbol{x}_{neg}$, and $\boldsymbol{x}_{pos}$. After learning by Timenet, the objective from the left diagram to the right diagram is to achieve $\boldsymbol{x}_{pos}$ closer to $\boldsymbol{x}_{ref}$ and $\boldsymbol{x}_{neg}$ further from $\boldsymbol{x}_{ref}$.

alongside a minimization step on the corresponding loss for each pair, until training concludes. Therefore, our objective can be expressed as follows:

$$\sum_{i=1}^{N}\sum_{l=1}^{L^{(i)}}[s\left(z_{ref-l}^{(i)}-z_{ref-l}^{\prime(i)}\right)^2+\left(z_{pos-l}^{(i)}-z_{pos-l}^{\prime(i)}\right)^2 - \left(z_{ref-l}^{(i)}-z_{neg-l}^{\prime(i)}\right)^2] \tag{3}$$

where s represents the sigmoid function, $z^{\prime(i)}$ and $z^{(i)}$ denote the output and input through the Timenet network, respectively. This loss function forces is designed to ensure that the embeddings for $\boldsymbol{x}_{ref}$ and $\boldsymbol{x}_{pos}$ are similar (minimizing their squared difference), while the embeddings for $\boldsymbol{x}_{ref}$ and $\boldsymbol{x}_{neg}$ are dissimilar (maximizing their squared difference). This approach effectively distinguishes between the reference time series $\boldsymbol{x}_{ref}$ and the negative example $\boldsymbol{x}_{neg}$, as well as assimilates the reference time series with the positive example $\boldsymbol{x}_{pos}$.

For hyperparameter optimization in our preprocessing method, we use the Sequential Model-Based Optimization for General Algorithm Configuration (SMAC) method [52]. SMAC employs a model-based sequential optimization strategy using a random forest model to build a proxy model, which calculates the mean and variance as the output of each subtree. We chose SMAC because of its excellent convergence properties, achieving rapid convergence early in the iterations and continuing to explore globally as iterations progress.

Table III lists the hyperparameters of the Timenet model, including the number of hidden units N, embedding dimension C, and the number of encoder and decoder layers L. It also includes hyperparameters for triplet loss α and data augmentation $\boldsymbol{w}$, indicating the search spaces for each parameter. The dropout rate r and the learning rate g are hyperparameters for the training of the Timenet model.

TABLE III: Hyperparameters search space

Hyperparameter	α	w	N	c	L	r	g
Search space	$[0.2, 0.5]$	$[0, 0.5]$	$[20, 100]$	$[100, 200]$	$[2, 10]$	$[0, 0.5]$	$[1e-3, 1e-2]$

D. Pipeline

In the context of predicting carbon emissions trading prices, an effective machine learning pipeline necessitates rigorous feature selection to bolster model performance and interpretability. In this study, we employed the Boruta algorithm as a robust tool for feature selection. The primary objective of Boruta is to ascertain the relevance of input features by comparing their importance to that of randomly permuted copies of those features. This feature selection framework not only identifies significant predictors but also eliminates redundant and irrelevant attributes, which is critical for enhancing the predictive accuracy of the model while also mitigating the risk of overfitting.

The Boruta algorithm operates fundamentally by utilizing a random forest classifier to evaluate feature importance. The detailed parameters employed in our implementation include setting the number of trees in the random forest to 100, which provides a sufficient ensemble to ensure stable and consistent importance estimates. Additionally, we configured the ‘maxCandidate‘ parameter, which allows up to twice the number of original features to be considered for evaluation, thus ensuring a comprehensive assessment of feature significance. This algorithm utilizes a shuffled version of each feature, referred to as a ”shadow” feature, to establish a benchmark for comparison. Only those features that demonstrate greater significance than their respective shadow counterparts are deemed noteworthy.

The application of the Boruta algorithm significantly enhanced the feature selection process within our machine learning pipeline, effectively retaining only those features that exhibited a statistically significant relationship with the target variable—carbon emissions trading prices. This rigorous selection process ultimately culminated in a refined feature set that drives the subsequent predictive modeling efforts, thereby ensuring that the resultant machine learning model not only possesses higher accuracy but also enhances interpretability, thus facilitating informed decision-making in carbon trading dynamics.

V. EXPERIMENT RESULTS

A. Introduction of datasets, sampling mechanism and controls

1) Carbon trading price data: In 2004, the European Climate Exchange (ECX) was founded as a completely owned subsidiary of the Chicago Climate Exchange (CCX). It has collaborated with the London International Crude Oil Exchange (IPE) to create the first European market for trading greenhouse gas emissions by launching carbon dioxide futures contracts on the IPE’s electronic trading platform. The world’s first major carbon emissions trading system (ETS) became operational in 2005 - the European Union Emissions Trading System (EU ETS). In the short span of ten years to 2015, 17 carbon trading systems have emerged across four continents, covering an area The total GDP of the regions covered already represents 40% of the global GDP. Today, as more and more governments consider adopting carbon markets as a way to carbon markets as a policy tool for energy conservation and emission reduction, carbon trading has gradually become a key tool in the global fight against climate change.

2) Sampling mechanism: In this study, we employed a robust sampling strategy utilizing a publicly available carbon trading dataset. The dataset was randomly partitioned into two subsets: 70% was designated as the training set and 30% as the testing set. This division aims to ensure that the training and evaluation processes are statistically valid and representative of the underlying data distribution. To enhance the stability and reliability of our model, we implemented a 10-fold cross-validation technique. Specifically, the dataset was systematically divided into 10 subsets, whereby 9 subsets were utilized for training, and the remaining subset served as the validation set. This procedure was iteratively repeated for each of the 10 subsets, resulting in a comprehensive evaluation metric that reflects the model's performance across various data segments. This methodological framework not only mitigates the randomness inherent in a single data split but also fosters improved generalization capabilities of the model when applied to unseen data.

3) Control strategy: During the data preprocessing phase, we employed meticulous procedures to enhance data quality and integrity. Initially, we addressed missing values through imputation techniques to ensure that the dataset remained comprehensive and conducive to analysis. Following this, we conducted outlier detection procedures to identify and eliminate extreme data points that could potentially skew model training and adversely affect predictive accuracy. These preprocessing steps were critical in maintaining the consistency and reliability of the features utilized in the model. Furthermore, for feature selection, we adopted the Boruta feature selection method, an advanced technique rooted in random forest algorithms, which is designed to identify the most relevant features contributing to the predictive outcomes. Through the implementation of these meticulous controls, we strive to augment the accuracy and robustness of our predictive model, thereby facilitating a more nuanced understanding of the dynamics within carbon trading markets.

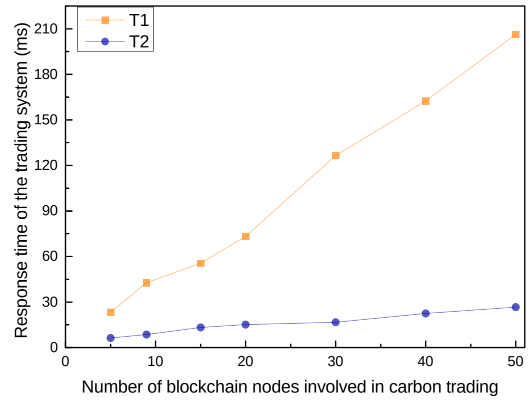
B. Analysis of results

To evaluate the reliability of the carbon trading price module in our blockchain-based carbon emissions trading scheme, we test the carbon emission price forecasting performance of our system by training the model on the EUA (European Union Allowance) price dataset from 2008-2015. We adopt mean squared error (MSE) as the evaluation indicator for different methods:

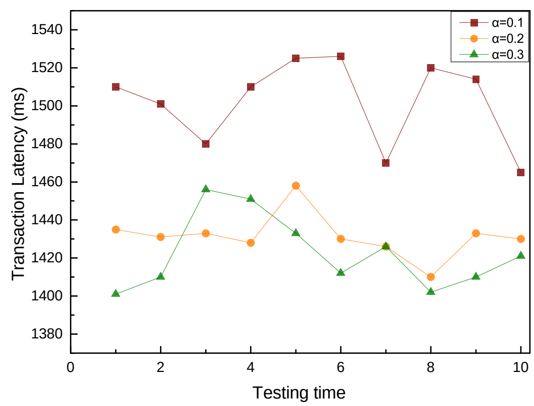
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i')^2 \tag{4}$$

where Y_i and Y_i' denote the actual and predicted carbon emission prices, respectively, for the time series trained over i time periods. In addition, RMSE (root mean squared error), MAE (mean absolute error), and MAPE (mean absolute percentage error) are considered for evaluating the accuracy of carbon emission price prediction.

We experimentally tested the performance of the blockchain-based carbon trading method. Fig. 12(a) shows that T_1 and T_2 denote the time for carbon emissions trading data traceability and the time for blockchain synchronization, respectively. The results indicate that the number of nodes significantly influences the time required for the system to reach consensus. As the number of nodes increases, the time consumption also grows. However, the time required for system consensus, credit information traceability, and overall synchronization remains within a reasonable range. Latency, the time delay in receiving information between clients, effectively evaluates the performance of different nodes in reaching consensus in a blockchain network. During the experiments, the values of the scaling factor and the number of nodes can be controlled. With a scaling factor (α) set between 0.1 and 0.5, it is observed that as the number of nodes increases, the latency corresponding to the data traceability method also increases. When the scaling factor is 0.3, the corresponding latency is minimal. These results underscore the superior performance and sustainability of our blockchain method, ensuring secure and efficient carbon trading.



(a) Impact of the number of nodes on system performance



(b) Latency of data traceability for different values of α

Fig. 12: Performance testing of a blockchain-based carbon emissions trading methodology

We compare the performance of the proposed blockchain-based carbon emissions trading scheme with automated machine learning pipelines and several commonly used time series methods, including:

- SVR (Support Vector Regression) [53], [54] is commonly used for regression analysis, focusing on finding a plane that minimizes the distances from all data points in a set.
- LSTM (Long Short-term Memory) [55], [56] is a specialized form of RNN designed to address the vanishing and exploding gradient issues in long sequence training.
- ARIMA (Auto Regressive Integrated Moving Average) [57], [58] is widely used in time series forecasting, treating the data series as a random series and predicting future values based on past and present data.
- EMD-LZ-GARCH-LSSVM [59] utilizes multi-resolution singular value decomposition and extreme learning machine optimized by an adaptive whale optimization algorithm for carbon price prediction.
- MRSVD-AWOA-ELM [60] employs a multiscale nonlinear ensemble learning paradigm for time series modeling.
- Dynamic self-learning integrating forecasting method [61] employs a noise-assisted multivariate empirical mode decomposition method to decompose multi-dimensional time series into several intrinsic mode functions concurrently.

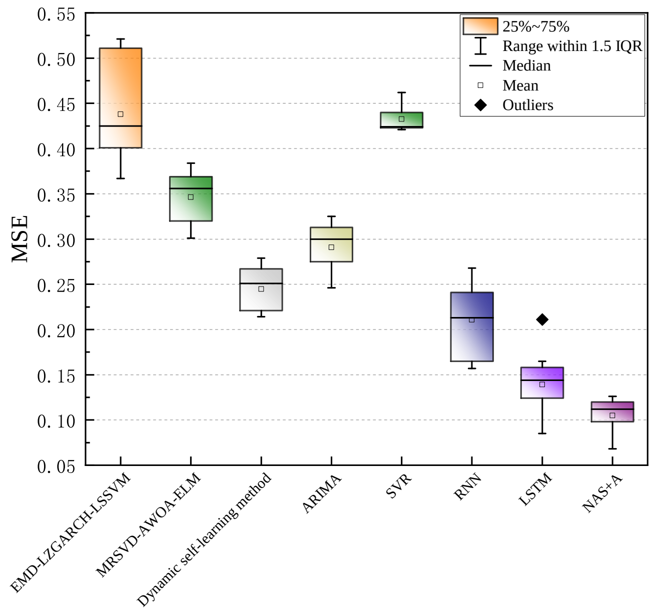


Fig. 13: Comparison results of the MSE distribution under the carbon price dataset

The MSE distribution illustrated in Fig. 13 clearly demonstrates that our NAS+A method achieves a lower MSE on the carbon emission dataset. This superior performance is primarily due to the NAS method, which offers enhanced regression capabilities over methods that rely on manual tuning. Notably, the LSTM method ranks second in performance in both phase two datasets, primarily because of its robust capability to mine time series features and its superior long-term forecasting performance compared to traditional RNNs.

Fig. 13 further shows that, compared to other benchmark methods, our NAS-A method—constructed using automatic machine learning models—exhibits better performance in terms of MSE metrics. This improvement is largely attributed to the complexities of carbon emissions trading data, where the size of the dataset and the intricacies of model construction significantly influence the accuracy of the predictions. Our proposed method enhances performance from two angles: firstly, through data augmentation, which expands the dataset, and secondly, via an efficient NAS process that ensures the discovery of the optimal model within the given search scope.

Additionally, the experimental results highlight the strong performance of the dynamic self-learning integrating forecasting method in terms of model effectiveness. This method excels by capturing more nuanced time series features, which is essential for constructing robust time series models. However, its lack of a data augmentation component means that it may underperform compared to our NAS method, particularly with shorter time series lengths.

VI. Results of the Carbon Price Forecasting Experiments

For our experiments, we selected a mix of traditional time series data mining algorithms and three advanced deep learning methods for comparative analysis. The experiments were conducted on an Intel Xeon 8269CY CPU with 8 cores and 2.50 GHz clock speed, supplemented by 16 GB of RAM. Hyperparameters were optimized based on the latest advancements in time series classification models documented in the literature.

We utilized the Time Series Archive from the University of California, Riverside (UCR), last updated in 2018. The creators of the UCR archive recommend evaluating models across all 128 datasets and require explicit justification for any dataset exclusions. For the scope of our study, we selected 24 datasets, each with a training sample size of fewer than 2000 observations. This selection was aimed at evaluating the performance of our models on time series data with smaller training sets.

In addition to contrasting traditional time series data mining methods with deep learning approaches, our study also incorporates an analysis using automated machine learning techniques. We employed Auto-Keras [28], an open-source library that facilitates the offline construction of neural network structures. Auto-Keras leverages the Efficient NAS (ENAS), making the model search process notably efficient.

To establish the optimal time budget for our experiments, we analyzed the effect of varying time budgets on classification accuracy. Fig. 14 illustrates the classification accuracy's change curve and error across different time budgets, based on ten repetitions of each experiment. Consequently, we set the time budget at 150 minutes for each Auto-Keras run, and each experiment was repeated 25 times. The key experimental settings are summarized in Table IV.

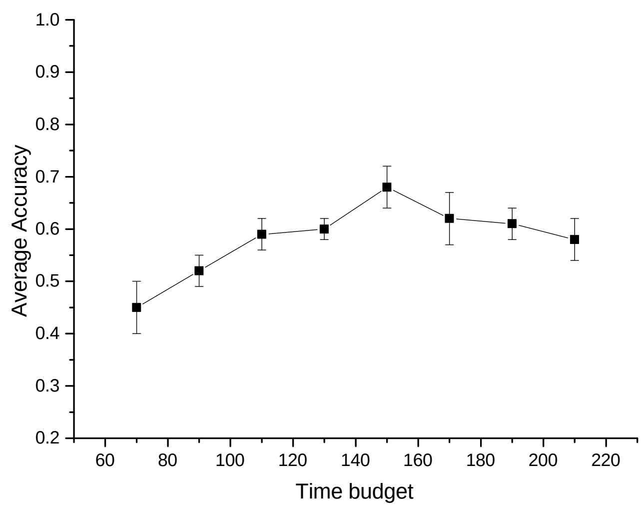


Fig. 14: Curve of average accuracy with time budget

TABLE IV: Evaluation settings

Time budget	150 min
Validation time limit	5 min
Test time limit	15 min
Number of repetitions	25 times

Our comparative experiments included a review of results with and without a preprocessing method for NAS. As indicated in Tables V and VI, the NAS method demonstrated an improvement in accuracy compared to traditional time series methods. These experiments were conducted using carbon emissions trading price data from February

TABLE V: Comparison of our proposed method on time series data mining performance for NAS method. The NAS method used here is Auto-Keras, NAS-A refers to the addition of the preprocessing method.

Method	Dataset size	MAE	MSE	MAPE	RMSE	Cohen's κ
NAS	500-1000	0.3047	0.1289	0.06284	0.3590	0.1256
NAS-A	500-1000	**0.1557**	**0.0519**	**0.0389**	0.2278	0.1785
NAS	0-500	0.3856	0.2218	0.0894	0.4709	0.1456
NAS-A	0-500	**0.1429**	**0.0616**	**0.0348**	0.2481	0.1652

2014. We conducted the Wilcoxon test on the three NAS combination methods, confirming that all results are statistically significant with $p < 0.05$.

Tables V and VI reveal significant performance enhancements due to the inclusion of triplet loss and Timenet in our preprocessing method, especially in datasets with smaller sample sizes. This suggests that our preprocessing approach effectively extracts more comprehensive time series features by generating embeddings. The data also confirm that our method, when combined with Auto-Keras and our preprocessing scheme, shows a notable improvement in performance for time series training datasets of two sizes: under 500 and between 500-1000 samples.

Our innovative approach, which leverages automated machine learning models, offers a more efficient means of developing predictive models for carbon trading prices. This efficiency is largely due to the substantial impacts of time series data volume and the detailed, comprehensive nature of model construction on predictive accuracy.

By strategically combining the precise search capabilities of NAS with data augmentation techniques, our methodology ensures optimal model selection within the search space and significantly enhances the performance of the final carbon trading prediction model.

Furthermore, the application of advanced automated machine learning techniques for carbon offsetting improves accuracy and efficiency in modeling carbon trading prices. This approach not only sharpens decision-making through precise insights but also enables organizations to adapt swiftly to changing market conditions and regulatory requirements. Leveraging real-time data analysis capabilities allows businesses to adjust their trading strategies proactively, maintaining a competitive edge in the market. This agile and responsive approach not only streamlines decision-making processes but also supports advancing environmental sustainability initiatives. Through the utilization of automated machine learning, companies can navigate the complexities of carbon trading with enhanced precision, contributing to progress towards a more sustainable future.

A. Extend

1) Cross-Validation: In the context of carbon trading price prediction, where market volatility and complexity are prominent, the importance of model generalization becomes particularly critical. In k-fold cross-validation, the dataset is divided into k equally sized subsets, with each subset serving as a validation set in turn, while the remaining k-1 subsets are used for model training. This cyclical training and validation process allows for obtaining performance metrics for the model across various subsets. Cross-validation effectively reduces the risk of model overfitting and provides more reliable and robust evaluation results, thereby enhancing the credibility of the research and offering valuable decision support to participants in the carbon trading market.

TABLE VI: Testing results of carbon price forecasting performance

Dataset	training set size	testing set size	time series length	NAS	NAS+ Timenet	NAS+ +DBA	NAS+ Timenet +DBA
1	230	230	470	0.6524	0.6014	0.5324	**0.3254**
2	330	900	128	0.6845	0.6052	0.5344	**0.3658**
3	328	328	286	0.6568	0.6457	0.5584	**0.3168**
4	316	306	345	0.6785	0.6014	0.5324	**0.3254**
5	323	861	136	0.6524	0.6145	0.5587	**0.3254**
3	100	100	96	0.6521	0.6245	0.5257	**0.3257**
7	324	388	350	0.6854	0.6075	0.5254	**0.3124**
8	350	150	150	0.6854	0.6125	0.5254	**0.3857**
9	155	308	1092	0.6528	0.6145	0.5287	**0.3287**
10	100	550	1882	0.6254	0.6011	0.5254	**0.3124**
11	467	1029	524	0.6857	0.6025	0.5254	**0.3254**
12	260	361	637	0.6587	0.6024	0.5254	**0.3352**
13	370	373	319	0.6527	0.6078	0.5311	**0.3257**
14	381	760	499	0.6685	0.6145	0.5257	**0.3254**
15	420	1252	484	0.6874	0.6014	0.5254	**0.3125**
16	430	430	570	0.6547	0.6025	0.5154	**0.3354**
17	360	601	370	0.6685	0.6154	0.5457	**0.3365**
18	427	953	465	0.6985	0.6024	0.5254	**0.3145**
19	325	995	398	0.6587	0.6014	0.5254	**0.3145**
20	300	300	360	0.6257	0.6077	0.5254	**0.3124**
21	100	100	275	0.6524	0.6014	0.5324	**0.3257**
22	423	1139	482	0.6851	0.6258	0.5257	**0.3147**

2) External Data Validation: External data validation is an important approach for assessing the generalization ability of machine learning models, particularly in rapidly changing market environments such as carbon trading price prediction. By applying the trained model to novel and previously unseen datasets, researchers can examine the model's applicability and predictive accuracy in real-world contexts. External data in the carbon market may come from different market environments, time periods, or regions, which helps capture the impacts of market changes on carbon prices. When a model maintains a high level of predictive accuracy on external datasets, it indicates strong stability and universality, thus enhancing the credibility and external validity of the research conclusions. Moreover, by contrasting the model's performance on training data and external validation data, researchers can identify potential limitations and areas for improvement, providing a theoretical basis for subsequent algorithm optimization and contributing to the sustainable development and effective operation of the carbon trading market.

To further validate the performance of our carbon trading model and ensure its suitability for different carbon trading markets, we conducted additional experimental analyses using data from various carbon trading markets. The carbon trading market data we utilized includes the California Cap-and-Trade Program, the China Carbon Exchange (including data from Beijing and Shanghai), and the Swiss ETS.

Table VII and Table VIII respectively present the results of the statistical analysis of machine learning models on

TABLE VII: Results of statistical analysis of machine learning models on different datasets

Dataset	Coefficient β	Standard error (SE)	P-value	95% confidence interval	Effect size (Cohen's d)
California	0.08	0.02	0.005	[0.04, 0.12]	0.45
China Beijing	1.5	0.5	0.010	[0.5,2.5]	0.60
Swiss	-0.5	0.3	0.100	[-1.1, 0.1]	0.50
China Shanghai	2.0	1.0	0.050	[0.02, 3.83]	0.35

TABLE VIII: Testing results of carbon price forecasting performance

Model	MSE	RMSE	MAE	MAPE	R^2
LSTM	0.151	0.389	0.172	8.36%	0.812
ARIMA	0.298	0.546	0.162	6.72%	0.854
EMD-LZ-GARCH-LSSVM	0.443	0.666	0.237	10.83%	0.807
MRSVD-AWOA-ELM	0.346	0.588	0.197	8.77%	0.805
Our proposed method	0.113	0.336	0.132	4.76%	0.783

different datasets and the testing results of carbon price forecasting performance. As shown in Table VII, during the comparative analysis of model performance across various datasets, the statistical metrics indicate that the model's performance remains within a relatively stable range. Table VIII illustrates that, compared to baseline methods, our proposed approach demonstrates superior overall performance after averaging the results across 50 experimental trials, as reflected in various model evaluation metrics. This enhancement can primarily be attributed to our method's capability to effectively capture the characteristics of carbon trading time series data. By employing NAS method in the proposed forecasting model, we were able to extract time series features comprehensively, thereby improving the predictive performance of the model.

VII. Policy Application of Carbon Emissions Trading Scheme

The integration of blockchain technology and automated machine learning with other emerging technologies holds considerable potential for accelerating technology-enabled business model innovation in both the digital economy and carbon neutrality sectors. Blockchain technology plays a pivotal role by ensuring transparency, security, and integrity of data transactions, which is essential for building trust and accountability in carbon emissions trading and related activities. Moreover, automated machine learning facilitates efficient data analysis and decision-making, enabling precise calculations of carbon footprints, effective emissions reduction strategies, and optimal resource allocation. This integration empowers businesses to implement sustainable practices, striking a balance between economic prosperity and environmental stewardship.

However, the carbon trading model faces several critical challenges, including privacy concerns, vulnerabilities, and the need for improved accuracy of prediction models. Privacy issues can arise from the potential exposure of user data, while system vulnerabilities may lead to inappropriate trading activities and market manipulation. Additionally, existing prediction models might not sufficiently reflect market dynamics, impacting their reliability. To address these challenges, future research should focus on implementing advanced privacy protection techniques, such as zero-knowledge proofs, to safeguard user information. Enhancing system security measures will be essential to mitigate vulnerabilities. Furthermore, exploring parallel execution processes can improve computational efficiency, while leveraging advanced machine learning techniques, such as ensemble learning and deep learning, can significantly boost the accuracy of prediction models. This multifaceted approach will contribute to creating a more secure, reliable, and efficient carbon trading environment.

A. Policy analysis

The application of automated machine learning and blockchain technology in carbon emissions trading mechanisms offers substantial benefits for carbon neutrality policies, emphasizing sustainable development in both the digital economy and carbon neutrality. Key advantages include:

- Enhanced accuracy and efficiency: Automated machine learning algorithms effectively analyze and predict carbon emissions data, facilitating the timely identification of emission sources and delivering accurate pricing signals. This accuracy enhances carbon management and reduction strategies, supporting the shift towards a carbon-neutral future.
- Transparency and trust: Blockchain technology enhances the transparency and security of carbon emissions trading. Its decentralized nature ensures the immutability and public accessibility of transaction records, reducing informational asymmetries and fostering trust among market participants. This level of transparency promotes fair and reliable trading and instills confidence in the carbon market.
- Incentivizing participation: The synergy of automated machine learning and blockchain technology creates an appealing environment for companies and institutions to engage in carbon markets actively. This setup encourages broader participation, helping businesses manage and reduce their emissions effectively and fostering the development of innovative sustainability technologies.
- Data-driven policy-making and sustainable digital economy: The deployment of these technologies provides crucial data support and regulatory tools for carbon neutrality policies. Accurate and reliable data aid policymakers in informed decision-making and effective regulation crafting to meet carbon neutrality objectives. Furthermore, the fusion of digital technologies propels the growth of a sustainable digital economy, where digital innovations drive decarbonization efforts alongside economic expansion.

B. Implications for the application of carbon neutrality

Blockchain and artificial intelligence (AI) are instrumental in achieving carbon neutrality. Blockchain's value lies in its ability to securely track and verify carbon offset transactions throughout their lifecycle, ensuring transparency and accountability. This capability allows for efficient and trustworthy verification of carbon offsets, enhancing the effectiveness of carbon offsetting efforts. Moreover, automated machine learning expedites the development of carbon trading price prediction models, increasing the accuracy and efficiency of carbon trading.

The global governance of carbon emissions is a critical issue in the 21st century, and the carbon emissions trading market provides innovative solutions through its creative design. Our proposed blockchain-based carbon emissions trading system offers significant application value in reducing carbon emissions, including:

- By storing carbon emissions data tamper-evidently using blockchain technology, our system enables enterprises to enhance energy use efficiency and reduce emissions from a profit and loss perspective. This encourages businesses to transition towards green and low-carbon operations, contributing positively to the global development of a low-carbon society.
- Individuals can earn carbon credits through effective emission reduction measures, and by integrating NFT technology, we facilitate the tradeability of carbon credits. This integration not only motivates individuals to reduce emissions but also enhances the efficiency of carbon-neutral solutions by assigning value to carbon credits.
- Our system includes a machine learning-based carbon trading price forecasting mechanism, allowing companies and individuals to make informed carbon asset purchase decisions based on trends in carbon emission prices. Effective price forecasting aids investors in carbon financial instruments to manage risks wisely and helps businesses reduce operating costs through efficient and stable carbon trading.

C. Potential Limitations and Suggested Measures

The proposed carbon emission trading system that integrates blockchain technology and AutoML methods presents promising opportunities for enhancing transparency, efficiency, and automation in carbon trading. However, there are several potential risks and limitations associated with these technologies within the context of carbon neutrality policy that need to be addressed.

1) Potential risks and limitations:

- While blockchain provides a secure and immutable ledger, the reliability of the data entered into the system is critical. If inaccurate or manipulated data is fed into the blockchain, it can lead to erroneous conclusions about carbon credits, undermining the system's integrity.
- The integration of AutoML and blockchain technology might create a steep learning curve for stakeholders, especially smaller entities or those in developing regions. This may lead to unequal access and participation in the carbon trading marketplace.
- The rapidly evolving nature of blockchain technology and AI-driven analytics may outpace existing regulatory frameworks. There is a risk that the system could fall into legal gray areas, leading to challenges in compliance with national and international carbon neutrality policies.
- The reliance on historical data in forecasting models for carbon markets entails limitations, particularly due to the inherent volatility and influence of external factors such as policy changes and economic shocks. These models may struggle to capture the complex dynamics and uncertainties present in the market, potentially leading to inaccuracies in price predictions.

2) Suggested measures to mitigate risks:

- Implement multi-layered verification processes for data entering the blockchain, including third-party audits and the use of trusted sensors for real-time carbon monitoring to ensure data integrity and accuracy.
- Develop user-friendly platforms and provide training programs for stakeholders on how to utilize blockchain and AutoML effectively. This will ensure broader participation and equitable access to the trading system.

- Promote the development and adoption of energy-efficient blockchain technologies, such as proof-of-stake mechanisms, to minimize the carbon footprint of the system. Additionally, consider utilizing carbon offsets to compensate for any emissions resulting from blockchain operations.
- Incorporate real-time data and external variables into automated machine learning frameworks. For instance, integrating sentiment analysis from news sources or social media, alongside macroeconomic indicators, could provide richer context for model predictions. Additionally, employing adaptive algorithms that continuously learn from new data can help models better adjust to sudden changes in market conditions.

By addressing these risks through proactive measures, the integration of blockchain and AutoML in carbon emission trading systems can foster a more equitable and sustainable approach to achieving carbon neutrality.

D. Real-world applications and case studies

Currently, several real-world applications of blockchain and AutoML technologies in carbon emissions trading systems illustrate their potential to enhance transparency and efficiency within carbon markets.

One prominent case study involves the collaboration between Power Ledger and various renewable energy companies, which utilizes blockchain to facilitate peer-to-peer trading of renewable energy credits. This innovative system enables individuals and businesses to trade surplus renewable energy along with associated carbon credits directly, thereby fostering a more decentralized and transparent marketplace. The immutable nature of blockchain technology ensures that all transactions are securely recorded, enhancing trust among participants and stimulating the adoption of renewable energy sources while contributing to effective carbon offsetting.

Another example can be observed in the Climate Trade platform, which leverages blockchain to streamline carbon credit transactions by connecting companies seeking to offset their emissions with projects that generate carbon credits. This platform offers a transparent ledger of credits and associated projects, allowing users to verify the legitimacy of their carbon offsets. Furthermore, the integration of AutoML facilitates the analysis of user data and emission trends, optimizing recommendations for companies in pursuit of purchasing tailored carbon credits. This enhancement not only encourages participation in the carbon market but also bolsters sustainability efforts on a broader scale.

E. The managerial implications of this study

This study provides significant managerial implications regarding blockchain-based carbon trading systems. Firstly, engineering managers can leverage the findings of this research to optimize carbon credit trading mechanisms by harnessing the advantages of blockchain technology. The immutable nature of blockchain and its decentralized ledger characteristic enable real-time recording and traceability of each transaction, thereby enhancing trust among market participants. This transparency not only mitigates the risk of fraud in market transactions but also effectively curbs malpractices, which in turn enhances the overall efficiency and liquidity of the carbon market. Secondly, policymakers can utilize the insights from this study to formulate more precise and adaptive policy frameworks that support and regulate blockchain-based carbon trading systems. The research highlights innovative mechanisms for the generation, allocation, and trading of carbon credits, allowing policymakers to assess and adjust existing regulations aimed at creating a more incentivizing environment for the adoption and development of emerging technologies.

Furthermore, by integrating the research findings, policymakers can design more forward-looking carbon market policies that promote the achievement of sustainable development goals.

In terms of additional benefits, the implementation of this research is anticipated to reduce transaction costs for organizations while enhancing resource allocation efficiency. The introduction of blockchain technology in carbon trading systems can create higher economic value for organizations by lowering intermediary costs and accelerating transaction speeds, ultimately achieving superior environmental outcomes. This not only enhances an organization's sense of social responsibility but also increases its competitiveness in achieving carbon neutrality goals. Specific action plans include: first, fostering deeper collaboration with technology developers and relevant stakeholders to jointly design a blockchain carbon trading platform that aligns with regional needs; second, implementing educational and training programs for stakeholders to enhance their understanding and acceptance of blockchain technology and its application in carbon trading; and finally, regularly assessing and iterating existing policy frameworks to ensure that they can promptly respond to technological advancements and further optimize carbon trading mechanisms to achieve environmental protection objectives. It is also necessary to assess the practical impact of the carbon trading model on market outcomes in future research. Such research is vital for elucidating how the model's predictions may translate into actual trading behaviors and influence overall market dynamics.

VIII. CONCLUSION AND FUTURE WORK

Climate change poses a significant global threat to ecosystems, driven by the continual rise in greenhouse gas emissions, including carbon dioxide, from countries worldwide. To combat this pressing issue, controlling carbon emissions becomes crucial, with achieving carbon peak and subsequent carbon neutrality as pivotal steps. This study introduces an innovative carbon emission trading mechanism that leverages blockchain and automated machine learning technologies. By digitizing carbon credits, our approach promotes efficient and streamlined carbon trading. Furthermore, employing automated machine learning for accurate carbon trading price predictions provides an effective solution for both enterprises and individuals to participate in carbon emission trading. This initiative plays a vital role in fostering a collaborative effort towards establishing a low-carbon and environmentally sustainable society.

Thorough baseline comparisons, multiple metrics, real data with cross-validation, careful data augmentation, and robust blockchain scalability testing constitute important components of the paper's research rigor. Comparisons against state-of-the-art prediction methods show that the model is not just marginally better than a naive baseline but outperforms a diverse set of recognized techniques. External validity is increased by training and testing on real market data over many folds, mitigating the randomness that can occur in a single train–test split. In addition, the proposed data augmentation and triplet loss strengthens the reliability of the results, especially when historical data may be limited, by ensuring the model learns more robust features. Finally, the operational stress test of blockchain performance confirms that as the number of nodes and transactions grows, the framework remains performant and stable.

Our research reveals several important—and sometimes unexpected—findings. First, while many well-established time-series forecasting methods such as LSTM remain popular and are considered close to optimal for such tasks, our results show that the combined use of NAS and data augmentation can outperform these approaches by a wide margin.

Second, one of the more unexpected results is how effectively the integration of triplet loss with Timenet improves embedding quality—even with limited historical carbon price data. Third, contrary to the common belief that carbon price modeling demands extensive manual feature engineering, our automated pipeline (including data augmentation and AutoML) finds high-quality configurations without domain-specific "handcrafting." Fourth, despite skepticism about blockchain's overheads, experiments with varying numbers of network nodes show that consensus latency and transaction throughput remain within practical bounds. A common criticism of blockchain-based solutions is that they can be slowed down by encryption, consensus protocols, and transaction verification. However, our measurements confirm that real-time traceability and robust privacy guarantees can be achieved with only modest overhead.

Our proposed methodology enhances transparency, security, and traceability in carbon offsetting processes, thereby facilitating more efficient and trustworthy practices towards achieving carbon neutrality. The integration of blockchain and machine learning technologies not only enables precise data analysis and modeling but also improves the effectiveness and impact assessment of carbon offset projects. Successful implementation of this framework has the potential to advance the carbon trading industry by standardizing secure data sharing and developing predictive models. This progress fosters trust among stakeholders, streamlines decision-making processes, and encourages the adoption of sustainable practices aimed at achieving carbon neutrality goals. The findings and methodologies of this research could serve as a blueprint for other industries aiming to enhance data security, efficiency, and accuracy through the integration of blockchain and automated machine learning technologies.

Despite the promising features of our proposed blockchain-based carbon trading mechanism, several critical challenges warrant further investigation in future research. Firstly, the generation and distribution of carbon credits raises significant concerns regarding user privacy, necessitating the exploration of high-privacy carbon credit trading mechanisms. A pertinent research question in this domain is: How can we architect a system that safeguards user data while maintaining the necessary transparency of transactions? Secondly, ensuring consistency and security during the concurrent execution of processes across multiple nodes within a consortium poses substantial challenges that require rigorous examination. Future inquiries might address the question: What methodologies can be devised to ensure synchronized and secure operations amongst multiple nodes operated by different consortium members? Furthermore, the accuracy of our carbon trading price prediction model demands enhancement. This involves refining the feature selection process and advancing time series regression algorithms. A relevant research question in this context is: How can we integrate state-of-the-art forecasting techniques to improve the predictive accuracy of carbon trading prices? Additionally, there is potential for incorporating key technologies derived from the metaverse to create immersive and engaging environments for carbon trading participants. Exploring this intersection gives rise to the question: What innovative applications of metaverse technologies can enhance user experience and participation in carbon trading platforms? By addressing these pressing research gaps, we aim to establish a robust foundation for the evolution of blockchain-based carbon trading solutions, contributing to both theoretical advancements and practical applications in the field.

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