International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8454-8471

https://doi.org/10.70517/ijhsa463723

Decentralized Energy Trading Carbon Footprint Traceability Mechanism Combining Heterogeneous Blockchain and Federated Reinforcement Learning

Guohui Lan[1] and Yashu Chen[1,*]
[1] School of Economics and Management, Anhui University of Science and Technology, Huainan, Anhui, 232001, China
Corresponding authors: (e-mail: 2003108@aust.edu.cn).

Abstract Energy, as one of the larger contributing industries to greenhouse gas emissions, has an urgent task to reduce emissions, and standardizing the carbon footprint and trading mechanism of the energy market is an important concern for the development of the current energy industry. Under the guidance of the principle of green, low-carbon and sustainable development of the energy market, this paper first uses heterogeneous blockchain and federated reinforcement learning to design a decentralized energy trading mechanism model. It is found that the model fails to realize the intelligent detection and control of carbon footprint, in this regard, on the original model, the carbon footprint origin algorithm is introduced. Combining the above models and algorithms, the current interactive energy market is explored and analyzed. Consumer user 5 has the largest net benefit, with a specific value of 15.05 million yuan, and comprehensive energy supplier 3 has the largest net benefit, with a value of 37,467,000 yuan, indicating that this paper's model implements the principle of green, low-carbon and sustainable development of energy while meeting the energy needs of consumers and suppliers, maximizing the interests of each other in the process of energy trading, which proves that this paper's research has excellent practical application value.

Index Terms heterogeneous blockchain, federated reinforcement learning, energy trading mechanism, carbon footprint traceability algorithm

I. Introduction

In the atmosphere, the increase of greenhouse gases such as carbon dioxide is one of the main causes of global warming [1]. Carbon emission is the process of releasing greenhouse gases such as carbon dioxide produced by human activities into the atmosphere, with the continuous development of global industrialization and urbanization, the issue of carbon emission is increasingly attracting people's attention, in order to mitigate the impact of climate change, decentralized energy trading and carbon footprint traceability to reduce carbon emissions is of great significance [2]-[5].

Energy trading markets control greenhouse gas emissions through market-based means, and different operational models have been formed in practice in different countries [6]. The core of the market is to convert carbon emission rights into tradable commodities, and buyers and sellers trade quotas according to their own needs, so as to minimize the cost of emission reduction [7], [8]. The trading mechanism is mainly divided into total control type and project offset type, in which the total control type sets a ceiling on the total carbon emissions of the region or industry, the government allocates or auctions emission allowances to enterprises, and enterprises whose actual emissions exceed the allowances need to purchase the difference, and the remaining allowances can be sold [9]-[11]. The EU carbon market adopts this mechanism, covering power, iron and steel and other high-energy-consuming industries, and reducing the total amount of allowances year by year according to the emission reduction target [12], [13]. Project offsetting allows enterprises to invest in emission reduction projects to obtain certified emission reductions, which are used to offset their own emissions. The Clean Development Mechanism (CDM) is a typical representative of this, in which enterprises in developed countries fund wind power and photovoltaic projects in developing countries, and obtain emission reduction credits after being certified by the United Nations [14]-[17]. And carbon footprint traceability is a method to accurately track and analyze the carbon emissions involved in products, services or behaviors [18], [19]. Specifically, carbon footprint traceability involves identifying the various stages and segments involved in the entire life cycle process of a product or service, including raw material acquisition, production, transportation, distribution, and use, and determining the carbon emissions in these segments [20]-[23]. In this way, enterprises can identify the main sources of carbon emissions, so as to take corresponding measures to reduce carbon emissions and realize sustainable development [24]-[26].

Under the dual background of interactive energy market and green low-carbon sustainable development, the energy trading mechanism model is introduced through the theoretical description of heterogeneous blockchain technology and federated reinforcement learning, and the model is constructed with the help of the above theories. Whether it is energy trading or life energy consumption, a large amount of carbon dioxide will be generated, in order to avoid the greenhouse effect and the deterioration of carbon dioxide content, through the design of the carbon footprint credible Shuoyuan algorithm to realize intelligent monitoring and control of carbon dioxide, and then provide auxiliary decision-making for the users, enterprises and the energy trading department. Finally, the models and algorithms designed in this paper are validated and analyzed with reference to relevant examples in life, aiming to promote the development of interactive energy market in the direction of green, low-carbon and sustainable development.

II. Centralized trading mechanisms for energy markets

II. A.Heterogeneous Blockchain Technology and Federated Reinforcement Learning

II. A. 1) Heterogeneous blockchain technology

Initially, the heterogeneous blockchain was developed with the intention of implementing a safe and secure distributed cash system through a digital currency called Bitcoin [27]. At this stage, the most important function of the heterogeneous blockchain is as a digital database [28]. It allows the storage and sharing of data containing digital transactions, data records, and any other form of data, such that the data is aggregated into so-called blocks, where each block is timestamped accordingly and cryptographically linked to the previous block, thus forming a chain of blocks, i.e., a heterogeneous blockchain. The infrastructure of heterogeneous blockchain is shown in Fig. 1, which is structured in five main layers, namely the data layer, the network layer, the consensus layer, the smart contract layer, and the application layer. With the advantages of decentralization, protection of personal privacy, non-tampering and traceability of data, and low cost and high speed of smart contract execution, heterogeneous blockchain technology can well solve the disadvantages of insecure transaction data, mutual distrust among users and between users and trading platforms, insufficient information openness and transparency, high transaction costs and settlement difficulties existing in centralized trading methods.

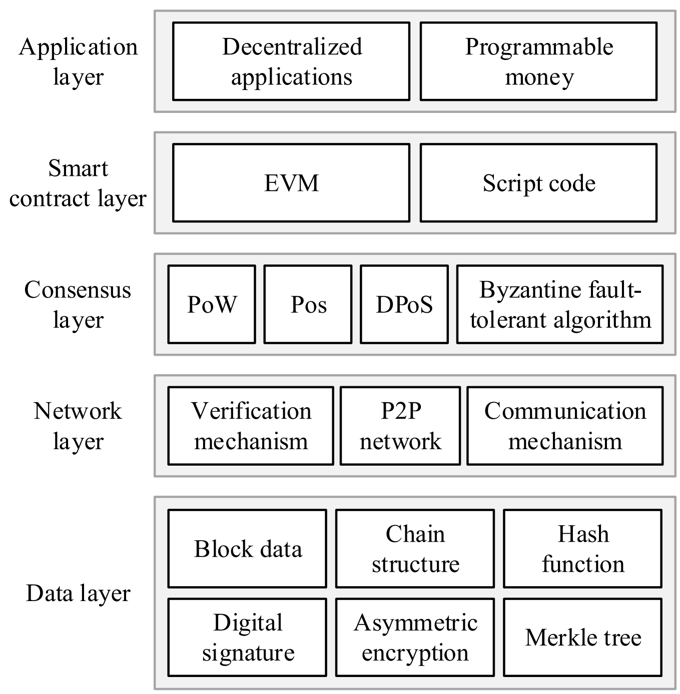

Figure 1: Heterogeneous blockchain

II. A. 2) Federal Reinforcement Learning

The combination of reinforcement learning and federated learning improves the robustness of global models to dynamic environments, which theoretically focuses only on the model architectures and does not care whether these models come from reinforcement learning or deep learning [29]. In federated learning, the global model is obtained by weighted averaging of multiple client models, which is also done in federated reinforcement learning, improves the ability to recognize attack traffic, ensures data privacy, and can be anonymous when making transactions with each other, so the privacy of each node can be protected to some extent.

II. B.Transaction Modeling Based on Heterogeneous Blockchain and Federated Reinforcement Learning

II. B. 1) Model definition

The Transaction Model for Integrated Energy Systems based on Heterogeneous Energy Blockchain and Federated Reinforcement Learning (TMIES-FRL-HEB) can be represented as a 5-tuple described in the form of an ensemble:

$$TMIES - FRL - HEB = (C_\alpha, S_\alpha, D_\alpha, ETIC, DSO) \tag{1}$$

where C_a is the energy subchain type, including C_e, C_g, C_h, C_c. denote the electric energy trading subchain, gas trading subchain, heat trading subchain, and cold energy trading subchain, respectively, and S_σ is a finite set of energy supply nodes in C_α. $S_a = \{s_i \mid i \in N^+\}$, and D_a is the finite set of energy-consuming nodes in C_a, where $ETIC$ denotes a smart contract, and DSO is the operator of the distribution system, and when a new node s_i applies for joining an energy subchain, it needs to provide node user registration information to C_α, including energy type, node location, identity information, etc., in order to obtain identity authentication. Various energy trading sub-chains are represented as a set as (electricity energy trading sub-chain for example):

$$C_e = (S_e, D_e, ECA_e) \tag{2}$$

where S_e and D_e are the power supply and power consumption node users in the electricity trading subchain, and ECA_e is the consensus algorithm in the electricity trading subchain.

II. B. 2) Configuration of transaction process subjects

(1) Node users as the main body of energy transaction: the main body of energy transaction includes a collection of distributed energy equipment supply nodes and a collection of energy consumption nodes participating in the alliance subchain. The energy supply users can broadcast their energy demand in real time at the beginning of the transaction phase according to the real-time situation of their own equipment's energy consumption, choose to purchase or sell energy, and exist as a full node in the alliance block subchain they have joined that participates in the consensus.

(2) Certification center (CA): the certification center is not a real entity, its function is similar to the centralized authority to authorize the user nodes, in the physical layer is actually based on the smart contract written and constructed by the computer executable program, in the system is responsible for obtaining the issuance of digital certificates, the user nodes need to provide the certification center with the registration information in order to obtain the authentication authorization to obtain the permission to join a certain energy sub-chain. License.

(3) Distribution System Operator (DSO): It is responsible for guaranteeing the physical security of the four types of energy distribution processes: electricity, heat, gas, and cold, as well as for the operation and maintenance tasks such as blockage checking and safety maintenance of each line.

II. C.Transaction mechanism design

II. C. 1) Smart Contracts in Energy Subchains

In the integrated energy system, there are characteristics of energy conversion, coordination and optimization, and synergy and complementarity between various energy subsystems, while in the traditional energy trading model, energy transactions between entities through "third-party" power companies are still used, which will lead to a large increase in management costs, labor and employment costs, and verification costs due to its structural inefficiency, and there are still problems such as information asymmetry, uneven sharing of main responsibilities and concentrated workload in the auction method based on "centralization". A smart contract (chaincode) is a code program that is automatically executed in a blockchain system. In the integrated energy system, the smart contract of the blockchain can act as an auction agency in the transaction process of each user, thus replacing the "third-party intermediary" of the traditional "centralized" auction, and realizing the matching auction transaction with equal status, symmetrical information, transparency and openness of users.

II. C. 2) Certification rules under price constraints

The alliance member nodes formulate the authentication rules of the authentication center after consultation and realize the authentication function through smart contracts, in order to guarantee the overall clean and environmentally friendly characteristics of the system, the alliance members within each subchain comply with the rules of clean energy priority [30]. Then the user node information is uploaded to the authentication center for authentication through public key encryption, and the uploaded information is:

$$msg_{reg} = \{Type_{node}, Type_{cquipment}, Type_{cx}, \Pr ice_{sell,\max}, \Pr ice_{buy,\max}, \inf_{per}\} \tag{3}$$

$Type_{mode}$ is the user's node type, $Type_{equipment}$ is the user's energy equipment type, $Type_{\alpha}$ is the federation block subchain that the application is made for joining, $Price_{sell.\max}, Price_{buy.\min}$ is the highest unit price of energy sold and the lowest unit price of energy purchased by the node, and $\inf_{per}$ is the actual individual or organization information of the node that applies for membership.

The authentication center obtains the alliance members' energy types and offers, and makes price interval judgments based on the types of energy equipment of registered users. For the price constraints of the electric energy trading sub-chain nodes, it is necessary to satisfy: the highest power purchase offer of the wind turbine node user < the highest power purchase offer of the storage battery node user < the highest power purchase offer of the gas turbine node user. Pure electric load node user minimum power purchase offer > electric refrigeration unit node user minimum power purchase offer > energy storage battery node user minimum household power purchase offer, i.e.:

$$P_{s,\max}^{WT} < P_{s,\max}^{STE} < P_{s,\max}^{GET} \tag{4}$$

$$P_{b,\min}^{IOAD.E} > P_{b,\min}^{EC} > P_{b,\min}^{STE} \tag{5}$$

For the gas trading sub-chain node price constraints, it needs to be satisfied that: the lowest gas purchase offer for pure gas load node users > the lowest gas purchase offer for gas turbine node users > the lowest gas purchase offer for gas boiler node users, i.e:

$$P_{b,\min}^{LOAD,G} > P_{b,\min}^{GET} > P_{b,\min}^{GHB} \tag{6}$$

For the heat trading sub-chain node price constraints, it is necessary to satisfy: gas turbine node user's highest heat selling offer < heat recovery system node user's highest heat selling offer < gas boiler node user's highest heat selling offer: pure heat load node user's lowest heat purchasing offer > absorption chiller node user's lowest heat purchasing offer > heat recovery system node user's lowest heat purchasing offer, that is:

$$P_{s,\max}^{GET} < P_{s,\max}^{HS} < P_{s,\max}^{GHB} \tag{7}$$

$$P_{b,\min}^{LOAD,H} > P_{b,\min}^{AC} > P_{b,\min}^{HS} \tag{8}$$

For the cold trading sub-chain node price constraint, it needs to be satisfied that: absorption chiller node user's highest cold selling offer < electric chiller node user's highest cold selling offer, ie:

$$P_{s,\max}^{AC} < P_{s,\max}^{EC} \tag{9}$$

After the authentication center authorizes the user node applying for registration, it uses the private key Key_{public}^{CA} to encrypt the public key Key_{pablic} of the user node to form the digital signature sign belonging to the user of the node, and the user can create a personal user energy subchain trading account according to the sign and Key_{pablic}, and the alliance members can verify the authenticity of the user $sign$ through Key_{public}^{CA}.

II. C. 3) Matching auction process

Automatically match the two sides of the transaction and execute the auction process, after the two sides of the transaction and the transaction legitimacy has been certified, the transaction will be automatically announced to all nodes in the sub-chain, for example, a user to buy energy transaction demand information for:

$$\begin{aligned} msg_b^A = \{&x^A(t), \Pr ice^A(t), sign^A, Key_{public}^A, \\ &Type_{energy}, SGS^A\left(msg_{CA}^A, msg_{DSO}^A(t)\right)\} \end{aligned} \tag{10}$$

where $x^A(t)$ is the purchased electricity demand of user A in time period t, $\mathrm{Price}^A(t)$ is the unit price of purchased energy of user A, $sign^A$ is the private key signature of user A, Key^A_{public} is the public key signature of user A, $Type_{energy}$ is the type of energy demanded, $SGS^A\left(msg^A_{CA}, msg^A_{DSO}(t)\right)$ is the double authentication information, containing the authorization information msg^A_{CA} as well as the DSO's line reliability authentication information for the user line for the time period $msg^A_{DSO}(t)$, and if it cannot be satisfied SGS^A, the user cannot be matched for the auction accordingly.

II. C. 4) Block data structure

The block structure is shown in Fig. 2, the block body adopts the Merck tree structure, which packages the transaction information two by two to take the hash and form a root hash value for storing the transaction record, which contains the name of the user of the energy purchasing node, the name of the user of the energy supplying node, the type of the energy traded, the total price of the energy traded, and the total amount of the energy traded. Block header mainly includes two parts, block header and block body, block header random number, difficulty, timestamp, including the hash value of the previous block header, the root hash value of the packaged transaction.

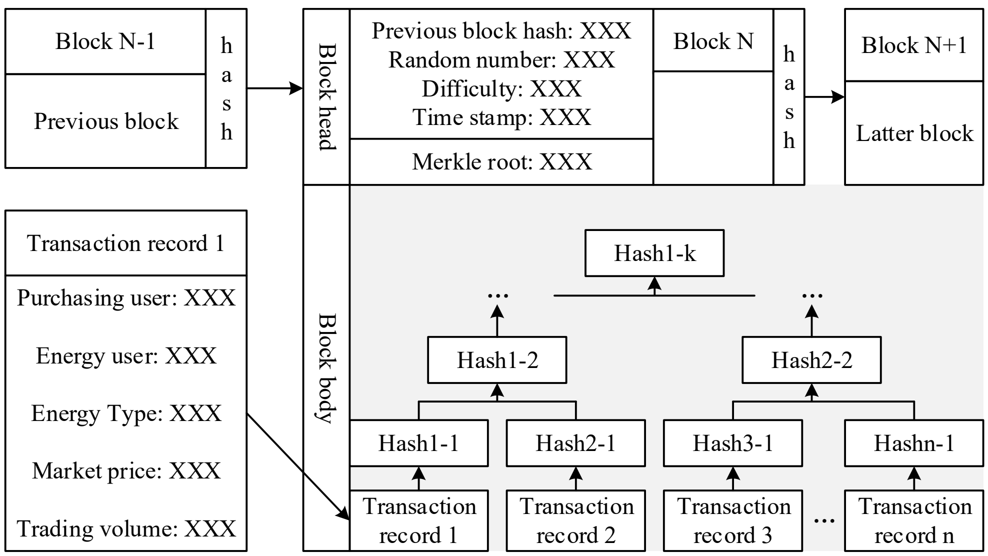

Figure 2: Block data structure

III. Carbon footprinting mechanisms for energy markets

The centralized trading mechanism for the energy market has been designed above, in order to better implement the principle of green, low-carbon and sustainable development of energy, this chapter introduces the carbon footprint algorithm on the basis of the energy trading mechanism, and the algorithm is designed from the four aspects of data modification, data addition, conflict detection and data homology detection. The design process is shown below:

III. A. Carbon footprint mechanism architecture and design

III. A. 1) Carbon Footprint Traceability Mechanism Architecture

The energy market carbon footprint traceability mechanism based on heterogeneous blockchain and federated reinforcement learning fully integrates the core features of blockchain, realizes the on-chain storage and information traceability function of the energy market, and provides a convenient and secure information storage and query for the energy market. The mechanism first collects supply chain data in the matching stage, covering identity information, equipment details and status information. Then during the energy transaction process, data such as energy consumption and order fulfillment are collected with the help of heterogeneous blockchain technology and federated reinforcement learning.

III. A. 2) Carbon footprint mechanism design

The design of the carbon footprinting mechanism is shown in Fig. 3. The network structure of the energy market carbon footprinting traceability mechanism based on heterogeneous blockchain and federated reinforcement learning is mainly composed of a data collection module, a heterogeneous blockchain and federated reinforcement learning network module, an on-chain authentication module and an application linking module. The main service object of the mechanism is the energy industry, aiming to realize the on-chain storage and traceability of the carbon footprint of the energy market.

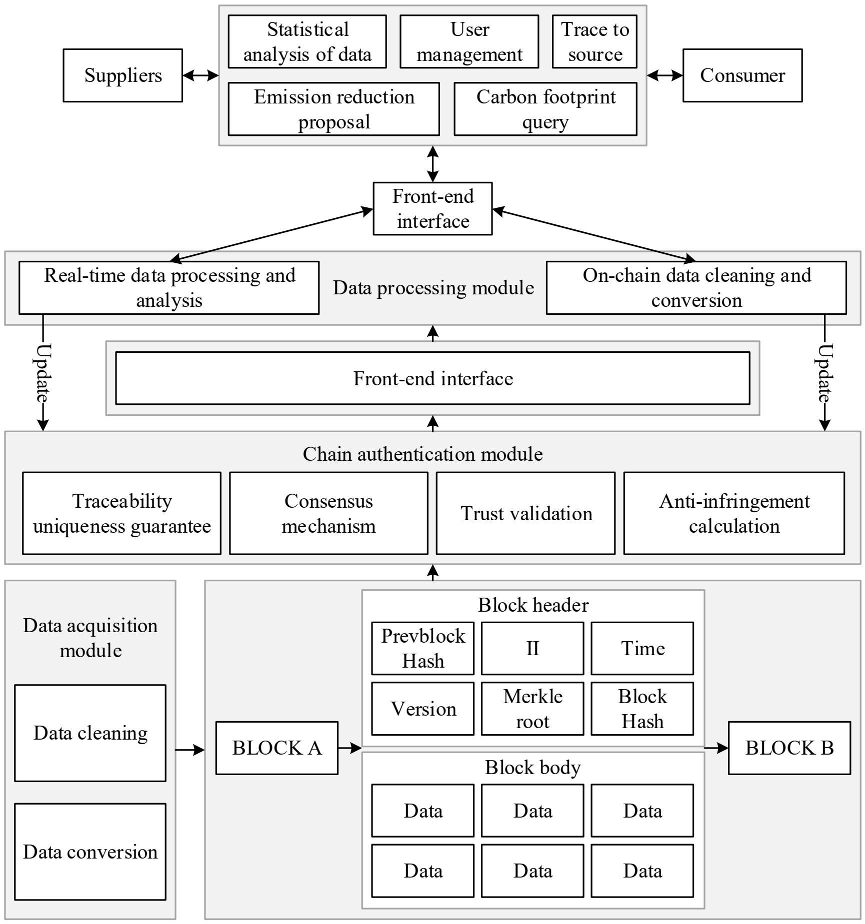

Figure 3: Carbon footprint retracing mechanism design

III. B. Carbon Footprint Trusted Traceability Algorithm Design

The core of traceability is the trustworthiness of the data, and the smart contract carries out storage control, thus determining the security of the on-chain data and user access. As the core process of traceability, it needs to complete the security verification of the on-chain data, and at the same time ensure that the data queried by the user has credibility. The carbon footprint trusted traceability algorithm is designed from the four aspects of data modification, data addition, conflict detection, and data homology verification.

III. B. 1) Data modification

For data modification, it prevents data infringement from occurring before it is uplinked. The smart contract collects the signatures of authoritative nodes selected through the consensus mechanism PoW, and after the number of signatures reaches the threshold σ through the legitimacy verification, the data is considered to have the authority to be modified on the chain. I.e.:

$$P_{\infty} = \begin{cases} 1 & L(D, S \mid s \mid s \in N_a \mid) \geq \sigma \\ 0 & \text{else} \end{cases} \tag{11}$$

The uplink modification authority P_α is confirmed by the signature authentication $L(D,S)$, where S is the set of signatures from the authoritative nodes $S=\{s \mid s \in N_a\}$, and N_a is the set of nodes constituted by the authoritative nodes. The data to be uploaded with modification authority needs to be further detected against infringement to further prevent data overlap in traceability.

III. B. 2) Increase in data

The uplinking of new data needs to be consistent with the energy trading mechanism model, which does not allow for the occurrence of the same energy industry X multiple devices consuming energy at the same moment in time T. A business review algorithm is designed for this to screen out similar conflicts.

III. B. 3) Conflict detection

The smart contract queries the driver's ID notated as id in the data D to be uploaded, and queries out all the chain historical event data to construct the chain historical work schedule $Tabel_T$. I.e:

$$Tabel_t = \{e \mid e \in H, D_{ID} = id\} \tag{12}$$

For the new data, its time period T is compared with $Tabel_T$, and the new data time period is noted as $T=[T_{start}, T_{end}]$, and retrieve whether it overlaps with any time period $[e_{start}, e_{end}]$ of e in the historical work schedule. The overlap condition is:

$$(T_{start} < e_{end}) \wedge (T_{end} > e_{start}) \tag{13}$$

If the working hours overlap then further compare the user ID information C_m and note the ID of the added data:

$$C_\alpha = \begin{cases} 1 & C_{ID} = Id \\ 0 & \text{else} \end{cases} \tag{14}$$

If matching to the chain there is a consistent user and supplier in the block, $C_{OC}=1$ indicates that the data on the outgoing chain is consistent with the data to be uploaded, and turn to data modification operation. $C_{OC}=0$ indicates that a conflict has arisen and the uplinking is stopped.

III. B. 4) Data homology validation

At the time of data input, the data is first split according to fields, splitting D into $D_1, D_2, D_3, D_4, \cdots, D_N$. According to the strong hash algorithm, including MD5, FNV and other hash functions, the local field D_1 is generated into the corresponding hash value $H_{LSH}(D_i)$. Assuming that the fingerprint length of the data x on the chain is FPL_x, and the fingerprint length of the data y to be uploaded is FPL_y, their similarity is expressed as follows:

$$\begin{cases} S(x,y) = \dfrac{d(FP_{FPL_x}(x), FP_{FPL_y}(y))}{\sum_1^k d(FP_{FPL_x}(x), FP_{FPL_y}(k))}, if\ x = y \\ S(x,y) = \dfrac{d(FP_{FPL_x}(x), FP_{FPL_x}(y))}{\sum_1^k d(FP_{FPL_x}(x), FP_{FPL_x}(k))}, if\ x < y \\ S(x,y) = \dfrac{d(FP_{FPL_y}(x), FP_{FPL_y}(y))}{\sum_1^k d(FP_{FPL_y}(x), FP_{FPL_y}(k))}, if > y \end{cases} \tag{15}$$

where k is the total number of blocks on the chain that satisfy $D_{ID} = id \wedge \neg[(T_{start} < e_{end}) \wedge (T_{end} > e_{start})]$, and $S(x,y)$ serves as the fingerprints of x versus γ similarity, and $d(FP(x), FP(y))$ as the fingerprint difference between x and y:

$$d(FP(x),FP(y))\begin{cases}\dfrac{\sum_{i=1}^{x}\{\max|count(D_i \odot D_j)|_{j=1,\dots,N}\}}{len(FP_{FPL_x}(x))}\times 100 \\ ,FPL_x < FPL_y \\ \dfrac{\sum_{j=1}^{x}\{\max|count(D_i \odot D_j)|_{j=1,\dots,N}\}}{len(FP_{FPL_y}(x))}\times 100 \\ ,FPL_x > FPL_y\end{cases} \tag{16}$$

where $count$ is the Hamming distance statistics function, $D_i \odot D_j$ denotes the same-or operation by bit for two different slice hashes in two files, and len is used to count the number of bits in a binary string.

IV. Exploration of Energy Trading Mechanisms and Carbon Footprinting Algorithms

IV. A. Exploratory Analysis of Energy Trading Mechanisms

IV. A. 1) Exploratory Analysis Description

In order to verify the accuracy of the aforementioned theory and model, it is explored and analyzed, noting that the simulation environment in this section is on a Matlab2018a + Intel Core i7 9700k + 16GB computer, and the associated computational problems are solved using Yalmip+Cplex.

IV. A. 2) Description of relevant parameters

This section of the inquiry analysis considers a case with three integrated energy suppliers and five consumptive users, all the integrated energy suppliers can supply integrated energy of electricity, heat and gas to the large users, the values of the parameters related to the utility of the consumptive users are shown in Table 1, and the parameters of the equipment related to the integrated energy suppliers are shown in Table 2, where β^{P}, β^{HP}, β^{GP} are the parameters of electricity, heat, and gas consumption, $\alpha_1^P \sim \alpha_5^P$ are the parameters of electricity determined by the user's own will from 1 to 5, and $\alpha_1^{HP} \sim \alpha_5^{HP}$ are thermal energy parameters determined by user 1~5 own will, $\alpha_1^{GP} \sim \alpha_5^{GP}$ are gas energy parameters determined by user 1~5 own will, $\eta_1^{MT} \sim \eta_3^{MT}$ are micro gas turbine 1~3 efficiency, $\delta_1^{MT} \sim \delta_3^{MT}$ is the micro gas turbine 1~3 thermoelectric ratio, $k_1^a \sim k_3^a$ is the coefficient of the quadratic term of the operation and maintenance cost function of micro gas turbine 1~3, and $k_1^b \sim k_3^b$ primary term coefficient of O&M cost function for micro gas turbine 1~3, $\eta_1^{GB} \sim \eta_3^{GB}$ for efficiency of gas boiler 1~3, $k_1^c \sim k_3^c$ secondary term coefficient of O&M cost function for gas boiler 1~3, $k_1^d \sim k_3^d$ are the primary term coefficients of the operation and maintenance cost function for gas boilers 1~3, $k_1^e \sim k_3^e$ are the quadratic term coefficients of the carbon allowance consumption function for micro-gas turbines 1~3, $k_1^f \sim k_3^f$ are the carbon allowances consumption function for micro-gas turbines 1~3, and k_1^f are the carbon allowances consumption function for micro-gas turbines 1~3. The primary term coefficients of the consumption function, $k_1^g \sim k_3^g$ are the carbon emission coefficients of the gas boiler 1~3. In addition, the carbon price $q^c = 0.01\text{Ten thousand yuan/t}$ and $\gamma = 0.639t/MWh$ in this section of the inquiry analysis.

Table 1: Consumer utility parameters

Parameter symbol	Parameter value	Parameter symbol	Parameter value
β^{P}	0.008Ten thousand yuan/MWh^2	α_2^{HP}	0.111Ten thousand yuan/MWh
β^{HP}	0.002Ten thousand yuan/MWh^2	α_3^{HP}	0.106Ten thousand yuan/MWh
β^{GP}	0.009Ten thousand yuan/MWh^2	α_4^{HP}	0.121Ten thousand yuan/MWh
α_1^{P}	0.2Ten thousand yuan/MWh^2	α_5^{HP}	0.123 Ten thousand yuan/MWh
α_2^{P}	0.22Ten thousand yuan/MWh^2	α_1^{GP}	0.116Ten thousand yuan/MWh
α_3^{P}	0.24Ten thousand yuan/MWh^2	α_2^{GP}	0.120Ten thousand yuan/MWh
α_4^{P}	0.26Ten thousand yuan/MWh^2	α_3^{GP}	0.072Ten thousand yuan/MWh
α_5^{P}	0.28Ten thousand yuan/MWh^2	α_4^{GP}	0.086Ten thousand yuan/MWh
α_1^{HP}	0.2Ten thousand yuan/MWh^2	α_5^{GP}	0.088Ten thousand yuan/MWh

Table 2: Integrated energy supplier related equipment parameters

Parameter symbol	Parameter value	Parameter symbol	Parameter value
η_1^{MT}	0.6	k_1^{c}	0.016Ten thousand yuan/MWh^2
η_2^{MT}	0.6	k_2^{c}	0.016Ten thousand yuan/MWh^2
η_3^{MT}	0.6	k_3^{c}	0.016Ten thousand yuan/MWh^2
δ_1^{MT}	4	k_1^{d}	0.006Ten thousand yuan/MWh^2
δ_2^{MT}	4	k_2^{d}	0.004Ten thousand yuan/MWh^2
δ_3^{MT}	4	k_3^{d}	0.002Ten thousand yuan/MWh^2
k_1^{a}	0.006Ten thousand yuan/MWh^2	k_1^{e}	0.1t/MWh^2
k_2^{a}	0.004Ten thousand yuan/MWh^2	k_2^{e}	0.1t/MWh^2
k_3^{a}	0.002Ten thousand yuan/MWh^2	k_3^{e}	0.1t/MWh^2
k_1^{b}	0.004Ten thousand yuan/MWh^2	k_1^{f}	0.3t/MWh
k_2^{b}	0.002Ten thousand yuan/MWh^2	k_2^{f}	0.3t/MWh
k_3^{b}	0.002Ten thousand yuan/MWh^2	k_3^{f}	0.3t/MWh
η_1^{GB}	1.8	k_1^{g}	0.4t/MWh
η_2^{GB}	1.4	k_2^{g}	0.4t/MWh
η_3^{GB}	1.6	k_3^{g}	0.4t/MWh

IV. A. 3) Data analysis

On the basis of the above basic data, the energy trading mechanism model proposed in this chapter is utilized to explore and analyze the current energy trading market, with a view to proving the effectiveness of the energy trading mechanism model in this paper.

(1) Analysis of energy production programs of integrated energy suppliers

The integrated energy supplier determines its energy provision program through the above model, and Figure 4 shows the electric power sold by the integrated energy supplier, Figure 5 shows the thermal power sold by the integrated energy supplier, and Figure 6 shows the gas power sold by the integrated energy supplier. From Figures 4 and 5, it can be seen that integrated energy supplier 3 sells the largest amount of electric and thermal power, 19.19 MW and 49.16 MW, respectively, and integrated energy supplier 1 sells the smallest amount of electric and thermal power, 15.30 MW and 42.54 MW, respectively.This is due to the fact that by producing an equal amount of integrated energy, the operation and maintenance cost of the energy production equipment of integrated energy supplier 3 is the lowest, while the operation and maintenance cost of the energy production equipment of integrated energy supplier 1 has the highest O&M cost of energy production equipment. For natural gas, it can be seen from

Figure 6 that integrated energy suppliers 1, 2, and 3 have the same gas sales power of 10.96 MW, which means that under the role of this paper's model, the three reach a consensus on the energy trading price to maximize the benefits of the three integrated energy suppliers. The model in this paper accurately reflects the current transaction costs and market share of integrated energy suppliers, and coincides with the actual situation, and maximizes the maintenance of the benefits of suppliers.

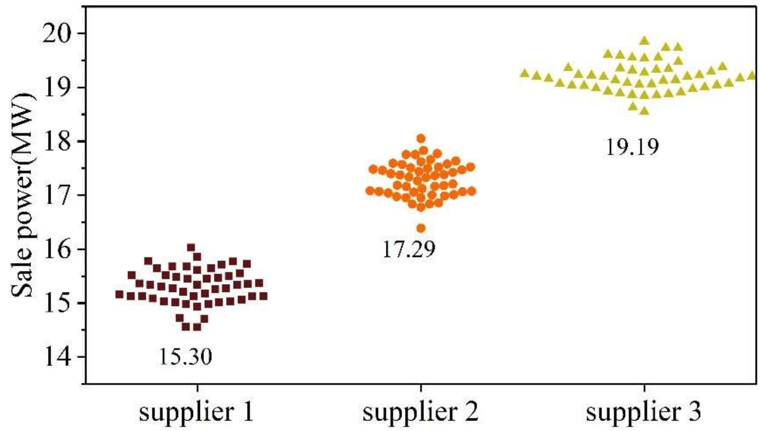

Figure 4: Integrated energy providers sell electric power

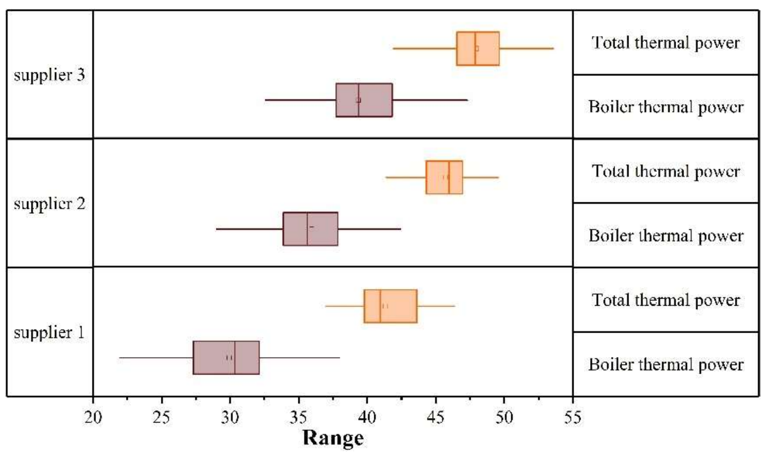

Figure 5: Integrated energy providers sell thermal power

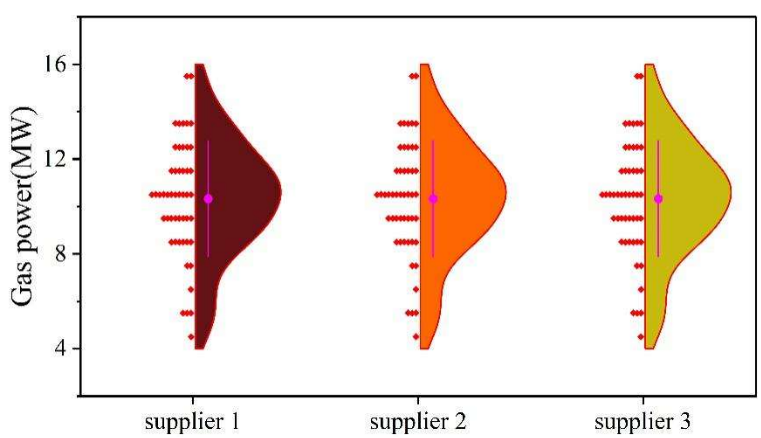

Figure 6: Integrated energy providers sell gas power

(2) Analysis of energy consumption programs for consumer-type users

Consumption-oriented users can reasonably choose energy demand through the energy trading mechanism model, and Figures 7, 8 and 9 show the power of electricity, heat and gas consumed by consumption-oriented users, respectively. Consumer 5 consumes the largest amount of combined electricity, heat and gas energy, which is 15.87 MW, 36.37 MW and 8.42 MW, respectively, while Consumer 1 consumes the smallest amount of combined electricity, heat and gas energy, which is 5.26 MW, 18.29 MW and 4.09 MW, respectively, The reason for this result is that Consumer 5 has the largest coefficient of positive primary term in the utility function of energy consumption, while Consumer 1 has the largest coefficient of positive primary term in the utility function of energy consumption, and Consumer 1 has the largest coefficient of positive primary term in the utility function of energy consumption. The positive primary coefficient of the energy use utility function of user 1 is the smallest, and this positive primary coefficient can reflect the amount of utility brought about by the consumption of an equal amount of integrated energy by large users of integrated energy, i.e., the utility brought about by the consumption of an equal amount of integrated energy by consumer user 5 is the largest, while the utility brought about by the consumption of an equal amount of integrated energy by consumer user 1 is the smallest. Through the energy trading mechanism model calculates the final electricity price, heat price, gas price of 0.0767 million yuan / MWh, 0.0788 million yuan / MWh and 0.0376 million yuan / MWh, respectively, indicating that the model of this paper according to the user's actual energy demand, to give the most reasonable energy trading program.

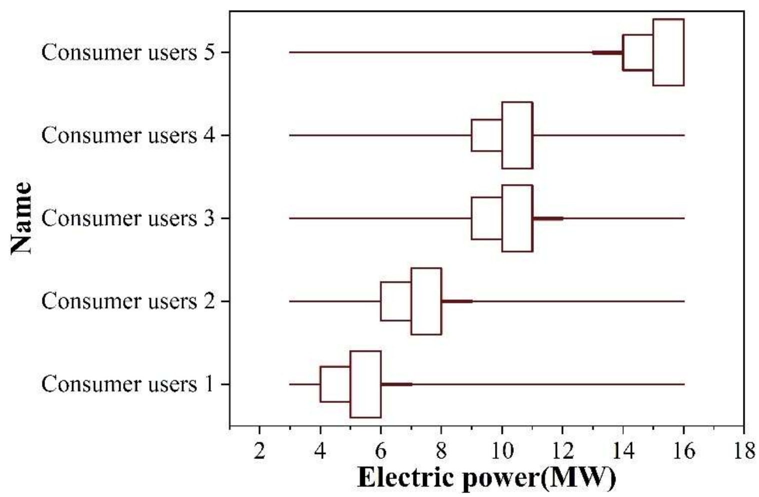

Figure 7: Consumer users consume electrical power

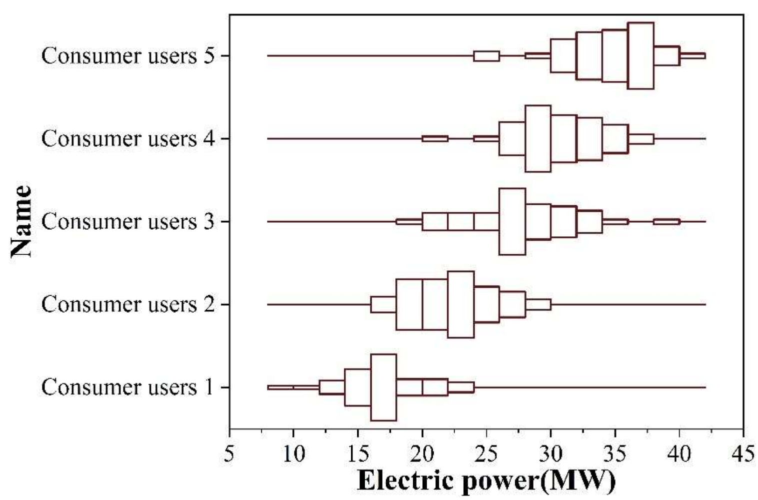

Figure 8: Consumer users consume thermal power

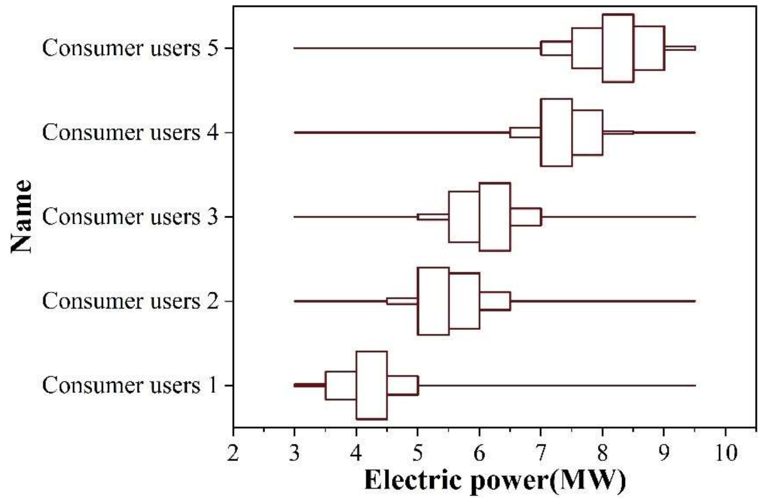

Figure 9: Consumer users consume gas power

On this basis, the net benefits for integrated energy suppliers and consumer users are analyzed. Fig. 10 as well as Fig. 11 show the net benefits of integrated energy suppliers and consumer-type users through the integrated energy distributed exchange, respectively. As can be seen from Figure 10, integrated energy supplier 3 has the largest net gain of $374.67 million. Integrated Energy Supplier 1 has the smallest net gain of $30.05 million. This result is due to the fact that Integrated Energy Suppliers 3 and 1 have the lowest versus the highest operating and maintenance costs for energy production equipment, respectively. As can be seen in Figure 11, Consumptive User 5 has the largest net benefit of $15.05 million. Consumption-based user 1 has the smallest net benefit of $0.402 million. This result is due to the fact that the positive primary term coefficients of the utility functions of consumer users 5 and 1 are the largest and the smallest, respectively. In addition, all integrated energy suppliers and consumer users have positive net returns, which satisfies the individual rationality required by the market mechanism, and to a certain extent verifies that the energy trading mechanism model in this paper can well satisfy the needs of consumers and suppliers, thus maximizing the interests of consumers and suppliers.

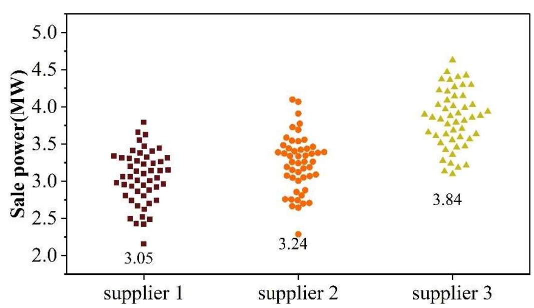

Figure 10: Consolidated energy supplier net income

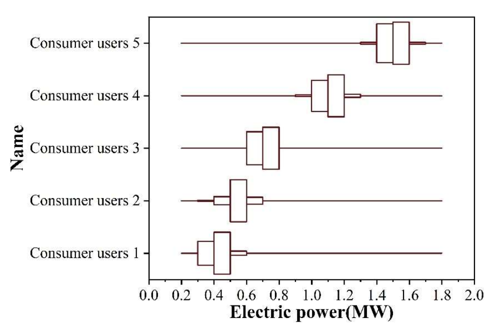

Figure 11: Net revenue from consumer users

(3) Multi-time period analysis of integrated energy distributed trading

In order to further verify the validity of the energy trading mechanism model proposed in this chapter, this section carries out a study of integrated energy trading for multiple time periods of 24 hours, which is represented in Fig. 12, Fig. 13, and Fig. 14, respectively, where the parameters of the utility function of electricity, heat, and gas of a 24-hour consumer $\left(\alpha_i^P, \alpha_i^{HP}, \alpha_i^{GP}\right)$ take values. Note that for the coefficients of the quadratic term constants of the consumer user utility function, the values in Table 1 are still used in this section, and for the parameters related to the integrated energy supplier, the values in Table 2 are still used in this section. Figure 15 shows the electricity, heat and gas prices obtained from the energy trading mechanism based on the energy trading mechanism proposed in this chapter for multiple time periods. Using the energy trading mechanism model in this paper, the maximum electricity, heat and gas consumption power of large integrated energy users can be calculated. For the whole consisting of consumer users 1 to 5, their maximum electricity, heat and gas power consumption is increasing from 1:00 to 11:00 and decreasing from 11:00 to 24:00. The composite energy trading price increases from 1 to 11 o'clock. Specifically, the price of electricity increases from 0.0768 million Yuan/MWh to 0.1735 million Yuan/MWh, the price of heat increases from 0.0788 million Yuan/MWh to 0.2039 million Yuan/MWh, and the price of gas increases from 0.0376 million Yuan/MWh to 0.1088 million Yuan/MWh. In addition, the composite energy trading price decreases from 11:00 to 24:00 hours. Specifically, the price of electricity decreased from 0.2035 million Yuan/MWh to 0.0798 million Yuan/MWh. the price of heat decreased from 0.1981 million Yuan/MWh to 0.0860 million Yuan/MWh. the price of gas decreased from 0.2223 million Yuan/MWh to 0.0532 million Yuan/MWh. the above trend of changes in the comprehensive energy trading price is consistent with the trend of changes in demand, i.e., in the case of a constant supply The larger the comprehensive energy demand, the higher the trading price, which is in line with the basic laws of economics and also verifies the validity of the proposed energy trading mechanism model from the side, while the supply side remains unchanged.

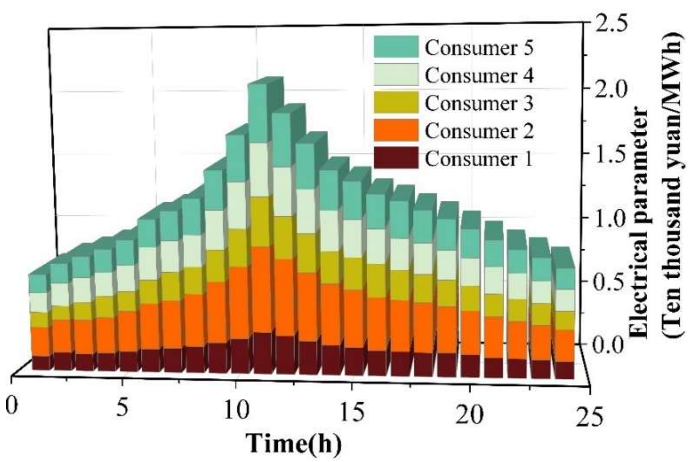

Figure 12: Electric energy utility parameters of α_i^P consumer type users

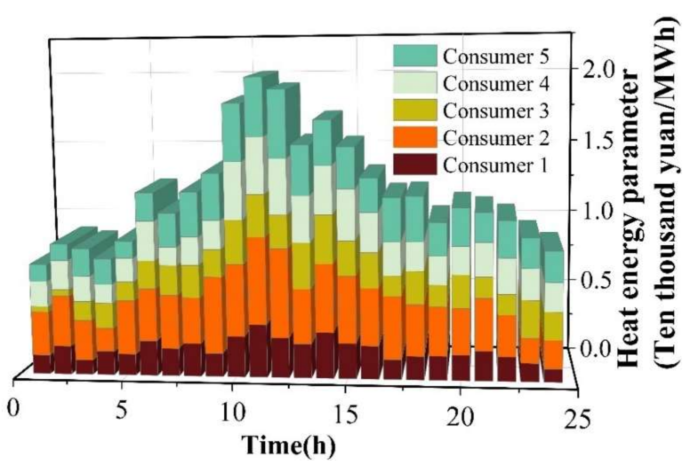

Figure 13: Thermal energy utility parameters of α_i^{HP} consumptive users

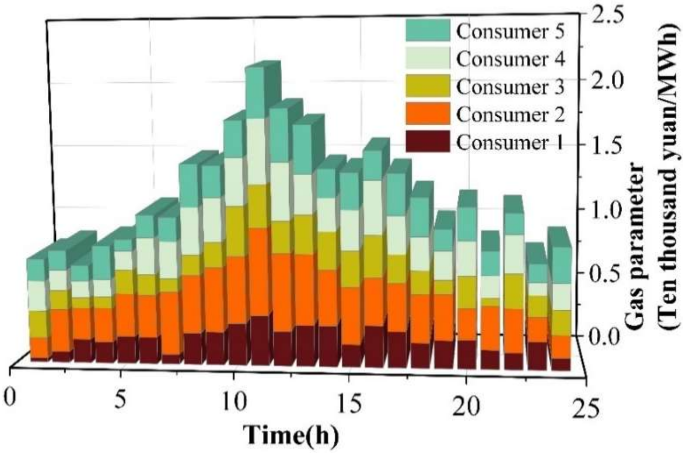

Figure 14: Thermal energy utility parameters of α_i^{GP} consumptive users

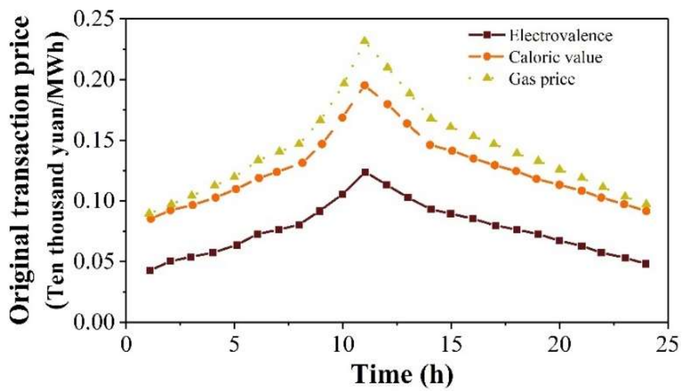

Figure 15: Multi-time integrated energy trading prices

IV. B. Carbon Footprinting Algorithm Analysis

In this paper, we establish a carbon footprint source algorithm, which is suitable for all kinds of energy trading. This chapter intends to take actual data as an example to demonstrate two main processes of carbon footprint source algorithm based on heterogeneous blockchain and federated reinforcement learning: (1) the traceability query and control access implementation of "energy trading-market-method-source data" based on blockchain and federated reinforcement learning, and (2) the carbon footprint accounting method, data source and data source traceability based on heterogeneous blockchain and federated reinforcement learning, so as to improve the transparency and comparability of the energy market and reduce the carbon dioxide content in the energy market transaction process.

IV. B. 1) Data acquisition

Through the above processes of enterprise information collection and inventory data determination, the carbon footprint of energy market trading is obtained. Using the algorithm of this paper, the carbon footprint within the energy trading boundary is obtained as 135.16 kg CO_2eq. The contribution of carbon footprint of emission sources in different time periods is analyzed as shown in Figure 16. Users have the largest proportion of carbon footprint at 23:00 and 20:00, accounting for 24.09% and 19.12%, respectively, followed by 24:00, 22:00 and 21:00, accounting for 16.14%, 14.29% and 13.87%, respectively, and lastly 18:00 and 19:00, accounting for 8.44% and 4.05%, respectively.

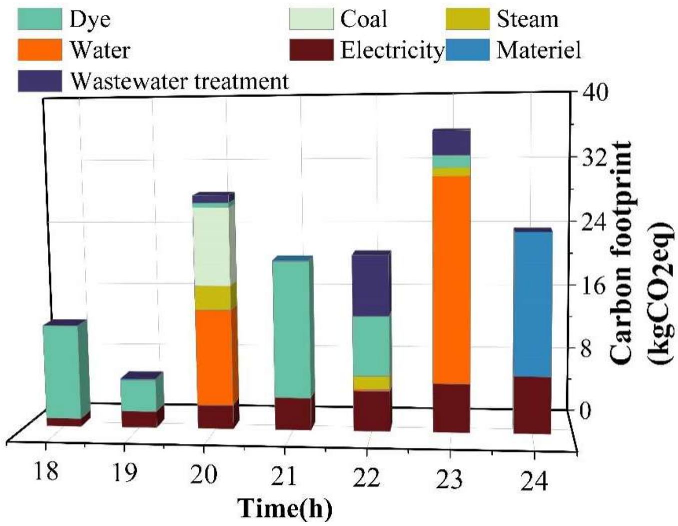

Figure 16: Carbon footprint contribution analysis of emission sources

The correspondence between the final score and the data quality level is shown in Table 3, and the results of the quantitative analysis of carbon footprint uncertainty in energy market trading are shown in Table 4. The quantitative analysis of carbon footprint uncertainty is to comprehensively assess the quality of the inventory data (classified into five levels, namely 1, 3, 5, 7, and 9) through the indexes of statistical representativeness, temporal representativeness, data source, geographic representativeness and technological representativeness. The data quality score of an emission item in a certain process is obtained by weighting the indicators (1/3 for each of the three indicators of statistical representativeness, temporal representativeness, data source, 1/2 for each of the two indicators of geographic representativeness and technological representativeness), and the data score of an emission item is then obtained by weighting the percentage of the carbon footprint of each process. Similarly, the final data quality score of the inventory is weighted according to the proportion of each item in the total carbon footprint of the product. A high final score is associated with good data quality and low uncertainty. Conversely, a low score is associated with poor data quality and high uncertainty. The carbon footprint data quality rating of energy market trading is 7.943, the inventory data quality is high and the uncertainty is low, so the quality of the energy carbon footprint value calculated based on these inventory data is also high, which confirms the practical application value of the carbon footprint solving algorithm in this paper.

Table 3: The relationship between the final score and the data quality level

Points	Data Quality	Uncertainty size
8≤Uncertainty≤9	The highest	Minimum
7≤Uncertainty≤8	Higher	Lesser
6≤Uncertainty ≤7	Range	Larger
Uncertainty≤6	Bad	Very large

Table 4: Quantitative analysis of carbon footprint uncertainty

Name	Electricity	Water	Steam	Coal	Natural gas	Dyes and auxiliaries	Materiel	Wastewater treatment
18	7.659					7.633		
19	7.316	7.659				7.633		
20	8.316	8.316	8.316	8.316		8.316	8.316	8.316
21	7.659	8.316				8.316		
22	8.316		8.316		8.316	8.005	8.659	7.633
23	8.005	8.005	8.005					7.633
24	8.005	8.005						
Energy carbon Total footprint index	7.816	8.008	8.116	8.316	8.316	7.836	8.005	7.711
Uncertainty	Smaller	Min	Min	Min	Min	Smaller	Min	Smaller
Total (less)	7.934							

Table 5: Carbon Footprint accounting method traced to module 1

Account entry	Activity data source	Basis of allocation.	Emission factor(kgCO_2eq/kg or m^3 or kW·h)
Ink	Process single ratio conversion	Distribution according to quality	8.512
Baking soda	Process single ratio conversion	Distribution according to quality	2.031
Urea	Process single ratio conversion	Distribution according to quality	1.515
Sizing material	Process single ratio conversion	Distribution according to quality	1.827
Soap agent	Process single ratio conversion	Distribution according to quality	1.827
Softener	Process single ratio conversion	Distribution according to quality	1.827
Color fixing agent	Process single ratio conversion	Distribution according to quality	1.827
Water	Monthly statistics	Distribution according to quality	0.0915
Electricity	Monthly statistics	Distribution according to quality	0.786
Steam	Monthly statistics	Distribution according to quality	0.047
Soda ash	Monthly statistics	Distribution according to quality	1.866
PAM (Polyacrylamide)	Monthly statistics	Distribution according to quality	0.846
PAC (Poly aluminum chloride)	Monthly statistics	Distribution according to quality	0.846
Decolorizing agent	Monthly statistics	Distribution according to quality	0.927
Water consumption for wastewater treatment	Monthly statistics	Distribution according to quality	0.087
Waste water treatment consumes electricity	Monthly statistics	Distribution according to quality	0.786
Sludge	Monthly statistics	Distribution according to quality	1.88
COD treatment of wastewater	Monthly statistics	Distribution according to quality	5.321

IV. B. 2) Algorithmic Traceability and Hierarchical Control of Access Processes

(1) Brands, suppliers and consumers

Brands, suppliers and consumers trace the carbon footprint of products with the same traceability path and different permissions. Connect to the web front-end of the blockchain browser by parsing the safety traceability logo, register the node and send an access request, get the product carbon footprint evaluation result through the number and batch number, access the node query and get the page returned by the system after the Key1, the content includes energy information, energy carbon footprint accounting results and analysis, and quantitative analysis results of the uncertainty of the carbon footprint of the product, and get the corresponding key through the verification. The corresponding key can be verified to obtain the carbon footprint of the corresponding module.

(2) Accounting Party, Audit and Supervision Organization

The accountant and the audit and supervision agency use the same traceability path and different permissions to trace the carbon footprint of the module access node by retrieving the carbon footprint module attribute code to query the carbon footprint of the module, and obtain the page returned by the system after Key2, including the final accounting energy carbon footprint value of the module, the main energy carbon footprint value of the module, the amount of raw materials consumed in this stage of energy, the raw materials consumed at this stage and the module attribute code.

IV. B. 3) Carbon footprint traceability and multidimensional comparison

Through the traceability process example in the previous section, it can be seen that the traceability algorithm based on heterogeneous blockchain and Federated Reinforcement Learning (FRL) for carbon footprint of energy trading can realize “energy-module-method-source-data” and achieve layer-by-layer traceability query and control access. Such a traceability brings information transparency, traceability and multi-dimensional comparability of the carbon footprint of energy transactions. Assuming that the permissions of this accounting party can be traced back to the module carbon footprint accounting method as shown in Tables 5 and 6 by accessing the corresponding Key3 of the supplier through the access control policy respectively. The authority of the accounting party can obtain the Key4 corresponding to the two modules through the access control policy, respectively, which can be traced back to the original data list, the processing enterprise information and the detailed energy trading process to assist in the decision-making of the invocation. To assist the call decision.

Table 6: Carbon footprint accounting method traced to module 2

Account entry	Activity data source	Basis of allocation.	Emission factor(kgCO_2eq/kg or m^3 or kW·h)
Acid blue	Process single ratio conversion	/	8.512
Acid red	Process single ratio conversion	/	8.512
Acid ash	Process single ratio conversion	/	8.512
Levelling agent	Process single ratio conversion	/	8.512
Additive: Soft oil	Process single ratio conversion	/	8.512
Water	Process single ratio conversion	/	0.087
.Electricity	Process single ratio conversion	/	0.786
Steam	Process single ratio conversion	/	0.217
Soda ash	Process single ratio conversion	/	2.155
Waste water treatment consumes electricity	Monthly statistics	/	0.786
Water consumption for wastewater treatment	Monthly statistics	/	0.087
PAM (Polyacrylamide)	Monthly statistics	/	0.846
PAC (Poly aluminum chloride)	Monthly statistics	/	0.927
Decolorizing agent	Monthly statistics	/	1.244
Sludge	Monthly statistics	/	0.927
COD treatment of wastewater	Monthly statistics	/	1.325

V. Conclusion

In this paper, in order to better practice the principle of green, low-carbon and sustainable development of energy in the context of interactive energy market, a decentralized energy trading mechanism model and a carbon footprint traceability algorithm are constructed by using heterogeneous blockchain and federated reinforcement learning, respectively, and the above models and algorithms are explored and analyzed in the context of the actual situation of the energy market. The energy transaction prices of users are derived, in which the electricity price, heat price, and gas price are 0.0767 million yuan/MWh, 0.0788 million yuan/MWh, and 0.0376 million yuan/MWh, respectively, which maximize the benefits of integrated energy suppliers and consumer users, indicating that the economic benefits of the energy market are well maintained under the role of this paper's model, and thus verifying the actual efficacy of the model. In addition, the algorithm in this paper accurately captures the carbon footprint in the process of energy trading, provides intelligent control for relevant users, enterprises and management, and promotes the green, low-carbon and sustainable development of the energy market.

Funding

This work was supported by Anhui Provincial Social Science Innovation and Development Research Project: “Reshaping the Competitiveness of Resource-Based Cities in Anhui Province from the Perspective of Innovation Drive” (2024CX069).

References

[1] Tran, N., Ta, Q. T. H., & Nguyen, P. K. T. (2022). Transformation of carbon dioxide, a greenhouse gas, into useful components and reducing global warming: A comprehensive review. International Journal of Energy Research, 46(13), 17926-17951.

[2] Huang, L., Krigsvoll, G., Johansen, F., Liu, Y., & Zhang, X. (2018). Carbon emission of global construction sector. Renewable and sustainable energy reviews, 81, 1906-1916.

[3] Liu, Z., Deng, Z., Davis, S. J., Giron, C., & Ciais, P. (2022). Monitoring global carbon emissions in 2021. Nature Reviews Earth & Environment, 3(4), 217-219.

[4] Waheed, R., Sarwar, S., & Wei, C. (2019). The survey of economic growth, energy consumption and carbon emission. Energy Reports, 5, 1103-1115.

[5] Xu, J., Guan, Y., Oldfield, J., Guan, D., & Shan, Y. (2024). China carbon emission accounts 2020-2021. Applied Energy, 360, 122837.

[6] Khorasany, M., Mishra, Y., & Ledwich, G. (2018). Market framework for local energy trading: A review of potential designs and market clearing approaches. IET Generation, Transmission & Distribution, 12(22), 5899-5908.

[7] Soto, E. A., Bosman, L. B., Wollega, E., & Leon-Salas, W. D. (2021). Peer-to-peer energy trading: A review of the literature. Applied energy, 283, 116268.

[8] Chen, Y., Wei, W., Liu, F., Sauma, E. E., & Mei, S. (2018). Energy trading and market equilibrium in integrated heat-power distribution systems. IEEE Transactions on Smart Grid, 10(4), 4080-4094.

[9] Wang, S., Wan, L., Li, T., Luo, B., & Wang, C. (2018). Exploring the effect of cap-and-trade mechanism on firm's production planning and emission reduction strategy. Journal of cleaner production, 172, 591-601.

[10] Chai, Q., Xiao, Z., Lai, K. H., & Zhou, G. (2018). Can carbon cap and trade mechanism be beneficial for remanufacturing?. International Journal of Production Economics, 203, 311-321.

[11] Zhang, Y., Chen, W., & Chun, W. (2025). Research status and trend prospects of the carbon cap-and-trade mechanism. Environment, Development and Sustainability, 27(2), 5097-5130.

[12] Wei, C., Li-Feng, Z., & Hong-Yan, D. (2021). Impact of cap-and-trade mechanisms on investments in renewable energy and marketing effort. Sustainable Production and Consumption, 28, 1333-1342.

[13] Li, G., Zheng, H., Ji, X., & Li, H. (2018). Game theoretical analysis of firms' operational low-carbon strategy under various cap-and-trade mechanisms. Journal of cleaner production, 197, 124-133.

[14] Ba, F., Thiers, P. R., & Liu, Y. (2018). The evolution of China's emission trading mechanisms: From international offset market to domestic Emission Trading Scheme. Environment and Planning C: Politics and Space, 36(7), 1214-1233.

[15] Kim, W., Son, Y., Lee, W. K., & Cho, Y. (2018). Analyzing the potential of offset credits in the Korean emission trading scheme focusing on clean development mechanism projects. Journal of Climate Change Research, 9(4), 453-460.

[16] Woo, H., Acuna, M., Choi, B., & Kim, J. (2021). Net Revenue of Forest Carbon Offset Projects: Application of the Korean Emission Trading System in the Forestry Sector. Forests, 12(6), 742.

[17] Rawhouser, H., Cummings, M. E., & Hiatt, S. R. (2019). Does a common mechanism engender common results? Sustainable development trade-offs in the global carbon offset market. Academy of Management Discoveries, 5(4), 514-529.

[18] Ju, C., Shen, Z., Bao, F., Weng, P., Xu, Y., & Xu, C. (2022). A novel credible carbon footprint traceability system for low carbon economy using blockchain technology. International journal of environmental research and public health, 19(16), 10316.

[19] da Cruz, A. M. R., Santos, F., Mendes, P., & Cruz, E. F. (2020, May). Blockchain-based Traceability of Carbon Footprint: A Solidity Smart Contract for Ethereum. In ICEIS (2) (pp. 258-268).

[20] Bausch, P., Weyand, A., Weigold, M., & Metternich, J. (2023). Design Model For Traceability-Supported Assessment Of Product Carbon Footprint. ESSN: 2701-6277, 107-117.

[21] Zhang, C., Xu, Y., & Zheng, Y. (2024). Blockchain Traceability Adoption in Low-Carbon Supply Chains: An Evolutionary Game Analysis. Sustainability, 16(5), 1817.

[22] Camel, A., Belhadi, A., Kamble, S., Tiwari, S., & Touriki, F. E. (2024). Integrating smart Green Product Platforming for carbon footprint reduction: The role of blockchain technology and stakeholders influence within the agri-food supply chain. International journal of production economics, 272, 109251.

[23] Agbelusi, J., Arowosegbe, O. B., Alomaja, O. A., Odunfa, O. A., & Ballali, C. (2024). Strategies for minimizing carbon footprint in the agricultural supply chain: leveraging sustainable practices and emerging technologies. World Journal of Advanced Research and Reviews, 23(3), 2625-2646.

[24] Mofatteh, M. Y., Davallou, R., Ishimwe, C. N., Divekar, S. S., & Valilai, O. F. (2024). Developing a Blockchain Based Supply Chain CO 2 Footprint Tracking Framework Enabled by IoT. International Journal of Advanced Computer Science & Applications, 15(10).

[25] Peng, J., Kimmig, A., Wang, D., Niu, Z., Liu, X., Tao, X., & Ovtcharova, J. (2024). Carbon footprint tracing and pattern recognition framework based on visual analytics. Sustainable Production and Consumption, 50, 327-346.

[26] Huang, R., & Mao, S. (2024). Carbon footprint management in global supply chains: A data-driven approach utilizing artificial intelligence algorithms. IEEE Access.

[27] Ahmed Elkhalil,Jiashu Zhang & Rashad Elhabob. (2021). An efficient heterogeneous blockchain-based online/offline signcryption systems for internet of vehicles. Cluster Computing,24(3),1-18.

[28] Nkurunziza Egide,Lawrence Tandoh,Issameldeen Elfadul & Mwitende Gervais. (2023). AP-HBSG: Authentication protocol for heterogeneous blockchain-based smart grid environment. Computer Communications,212,212-226.

[29] Rafael Teixeira,Leonardo Almeida,Mário Antunes,Diogo Gomes & Rui L. Aguiar. (2025). Efficient training: Federated learning cost analysis. Big Data Research,40,100510-100510.

[30] Mohammad Yaser Mofatteh,Ujjwal Khadka & Omid Fatahi Valilai. (2025). EnerChain: A decentralized knowledge management framework for smart energy systems with smart manufacturing agents via blockchain technology. Journal of Open Innovation: Technology, Market, and Complexity,11(1), 100499-100499.