International Journal of Energy
ISSN: 2957-9473 | Vol. 2, No. 3, 2023

Carbon Accounting Method based on Power System Energy Carbon Footprint Characteristics and Multi-Source Data Fusion

Lihong Ge, Xianyao Mo and Jiali Liu

Inner Mongolia Electric Power Economic and Technological Research Institute, Hohhot 010000, China

Abstract: This paper presents a novel approach to carbon accounting by utilizing the energy use carbon footprint characteristics and data fusion of the electric power system. The method involves analyzing the energy use carbon footprint characteristics of various electric power systems and employing big data analysis and artificial intelligence techniques to accurately evaluate carbon emission sources. The paper outlines the measurement content, model design principles, and model selection strategy, taking into account factors such as carbon data from different sources and the strengths and weaknesses of existing carbon accounting methods. By identifying the factors that influence the carbon footprint of the electric power system under dual carbon targets, a carbon accounting method based on data fusion and the energy use carbon footprint characteristics of the electric power system is proposed. The paper also develops a carbon emission warning model for the electric power system, which can assist businesses and organizations in setting targeted reduction goals.

Keywords: Carbon Accounting; Data Fusion; Model Design; Artificial Intelligence; Electric Power System; Carbon Footprint.

1. Introduction

Carbon accounting [1] has emerged as a critical tool in the measurement and management of carbon emissions, particularly in the context of addressing climate change. With the increasing severity of global climate change and energy crises, there is a growing global consensus on the need to reduce carbon emissions. The Paris Agreement, established in 2015, has set a global objective of achieving carbon neutrality by 2050[2-4]. Given this backdrop, effective management and reduction of carbon emissions have gained paramount importance. In this context, carbon accounting has become a prominent research area, given its significance in measuring and managing carbon emissions. Efficiently implementing dual carbon targets, understanding the carbon footprint characteristics and key influencing factors within the dual carbon system, and establishing dynamic carbon accounting models and global monitoring technologies suitable for the dual carbon system hold immense theoretical and practical importance.

Carbon accounting encompasses various methods, including measurement-based and calculation-based approaches [5,6]. Existing greenhouse gas emission accounting methods can be categorized into three main methods: the emission factor method, mass balance method, and actual measurement method [7-11]. A paper referenced as [12] delves into the challenges associated with carbon accounting and its implementation across different organizations. The authors highlight the complexity of carbon accounting, as it requires balancing accuracy, consistency, and certainty within diverse organizational contexts. Another paper referenced as [13] explores the role of carbon accounting in shaping organizations' strategic responses to evolving climate change policies. It emphasizes how carbon accounting influences the decision-making and actions of organizations in addressing climate change challenges. In [14], a position-practice perspective is employed to examine the role of strong structuration in shaping carbon accounting practices. The paper argues that the interplay between societal norms and values and the resources and capabilities of organizations significantly impacts the development and implementation of carbon accounting policies. In China, due to its extensive and diverse infrastructure, it is challenging to apply a single algorithm to cover all carbon accounting scenarios. Therefore, by incorporating multi-level data and integrating information from various sources, the accuracy and robustness of carbon accounting can be enhanced in different environmental contexts

Data fusion refers to the fundamental theory of integrating multiple sources of information [15]. It involves the automatic processing of information at multiple levels, coordinating and combining various sources of information for detection, correlation, estimation, and integration of multi-level, multi-faceted [16-18], and multi-layer information. The goal is to derive an estimate of the target state and characteristics, as well as situational and trend evaluations. Data fusion involves the combination of data from multiple sensors, regardless of whether they are of the same or different types or located in the same or different places. By fusing data from multiple sensors, the accuracy of the resulting information is generally better than what can be achieved by a single sensor alone

This article specifically examines the fusion methods for integrating data from multiple sources, considering different time scales and spatial scales. It leverages the advanced predictive capabilities of artificial intelligence technology to conduct carbon accounting within a multi-source data fusion scenario. The primary objective is to enhance the accuracy and robustness of the carbon accounting results.

2. Analysis of Energy Characteristics

This paper focuses on analyzing the energy characteristics of a specific park. Understanding energy consumption patterns is essential for efficient resource management and allocation. To gain a deeper understanding of these patterns, the paper will conduct a detailed analysis of the park's energy

characteristics. The analysis will involve examining the load power timeline, which provides information on the park's power consumption over time. Additionally, the photovoltaic output timeline will be studied to understand the park's solar energy generation patterns. By analyzing these timelines and considering seasonal variables, the paper aims to identify representative energy data and establish typical energy use scenarios. Through this comprehensive analysis, the paper aims to provide valuable insights into the energy consumption patterns of the park, facilitating informed decision-making and efficient energy management.

2.1. Analysis of Target Selection

The energy characteristics are analyzed from four key aspects: load characteristics, distributed photovoltaic characteristics, typical scene characteristics, and other energy sources. Load Characteristics: Load characteristics refer to the patterns of energy consumption in an electric power system. This includes analyzing peak demand, daily fluctuations, and seasonal variations in energy usage. Understanding these patterns is essential for developing an accurate carbon footprint assessment, as different energy generation sources have varying carbon emissions. Moreover, comprehending load characteristics enables optimization of energy generation and distribution within the electric power system, minimizing waste and emissions. Distributed Photovoltaic Characteristics: This aspect focuses on the characteristics of distributed photovoltaic systems. Analyzing the performance, output, and utilization of solar energy generated from distributed photovoltaic sources provides insights into the contribution of renewable energy to the overall energy mix. Understanding these characteristics helps assess the environmental benefits and carbon reduction potential associated with solar energy generation. Typical Scene Characteristics: Typical scene characteristics involve studying specific scenarios or settings within the energy system. This analysis provides an understanding of the energy consumption patterns, energy demands, and related factors in different typical scenes. By examining the energy requirements and usage in these scenarios, it becomes possible to identify opportunities for energy efficiency improvements and carbon emissions reduction. Other Energy Sources: In addition to load characteristics, distributed photovoltaic systems, and typical scene characteristics, this analysis also considers other energy sources within the system. This may include fossil fuel-based energy sources, such as coal, oil, and natural gas, as well as other renewable energy sources like wind, hydro, and biomass. Analyzing the characteristics of these energy sources contributes to a comprehensive understanding of the energy mix and its implications for carbon accounting. By examining these four aspects of energy characteristics, a holistic understanding of the energy system can be obtained, facilitating accurate carbon footprint assessment, optimization of energy generation and distribution, and identification of opportunities for carbon emissions reduction.

Distributed photovoltaic (PV) systems are small-scale, decentralized solar energy generation systems typically installed on individual homes or buildings. Analyzing the energy generation characteristics of these systems is crucial in carbon accounting, as it allows for the assessment of emissions reduction potential by transitioning to renewable energy sources. The performance of distributed PV systems can vary due to factors such as weather conditions, shading, and other variables. Therefore, it is important to consider these factors when conducting a comprehensive carbon footprint analysis. By examining both load characteristics and distributed PV characteristics, a more comprehensive understanding of energy usage and emissions within an electric power system can be obtained. This analysis enables the identification of opportunities for reducing emissions through the adoption of more efficient and sustainable energy generation and consumption practices.

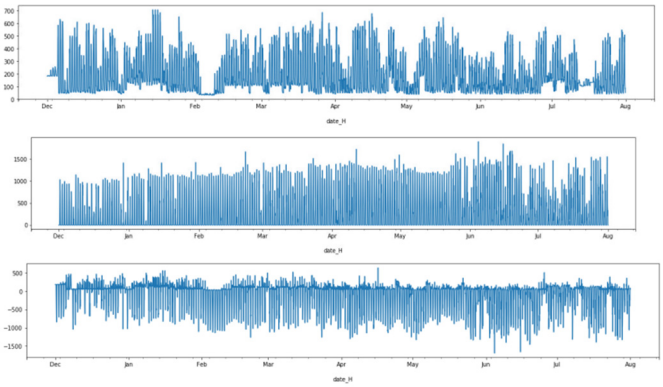


Fig 1. Temporal characteristics

In Figure 1, the load power timeline and photovoltaic output timeline of a specific park are presented. It is evident from the data that there is a notable variation in the load power across different seasons, indicating significant seasonal differences in energy consumption. When analyzing the energy use characteristics of the park, it is crucial to account for these seasonal variables. By considering the seasonal variations and incorporating typical energy use scenarios, it becomes possible to obtain representative energy data. These scenarios help capture the energy consumption patterns and provide a comprehensive understanding of the park's energy use characteristics throughout the year. Taking into account the seasonal variables and utilizing typical energy use scenarios enhance the accuracy and reliability of the analysis, enabling a more comprehensive assessment of the park's energy consumption patterns.

Understanding the energy consumption patterns of a specific area is crucial for effective resource management and allocation. Figure 1, depicting the load power timeline and photovoltaic output timeline, provides valuable insights into the energy consumption characteristics of the park being studied. One notable observation from the load power timeline is the significant variations in load power between different seasons, indicating a substantial variance in energy consumption. This highlights the importance of considering seasonal variables when analyzing energy use characteristics, as they can have a significant impact on energy consumption patterns. To conduct a comprehensive analysis of energy use characteristics, it is essential to obtain representative energy data. This can be achieved by studying typical energy use scenarios that reflect the park's energy consumption patterns. By analyzing these scenarios, a deeper understanding of the energy consumption patterns within the park can be gained, enabling informed decision-making regarding energy management and resource allocation. Taking into account the seasonal variables and utilizing representative energy data obtained through the study of typical energy use scenarios allows for a thorough analysis of energy consumption patterns. This knowledge facilitates effective energy management

practices and optimizes resource allocation based on the specific characteristics of the park.

2.2. LMDI Analysis Method Principle

The Logarithmic Mean Divisia Index (LMDI) Analysis Method is widely utilized for energy analysis and policy evaluation. It is a decomposition analysis technique employed to quantify the contributions of various factors to changes in energy consumption over time. The LMDI method provides a detailed understanding of the drivers behind energy consumption and how these drivers are influenced by factors such as economic growth, technological advancements, energy and climate policies. The LMDI method involves calculating the Logarithmic Mean Divisia Index by examining the ratio of energy consumption to a set of drivers. These drivers can include variables like GDP, population, energy prices, or any other factors that influence energy consumption. The LMDI value offers a quantitative measure of the contribution of each driver to the overall change in energy consumption over a specific time period. One of the notable strengths of the LMDI method is its capability to account for structural changes within the energy system, such as the transition from conventional energy sources to renewable energy sources. This feature makes the LMDI method a valuable tool for policy makers as they strive to reduce carbon emissions and address the challenges of climate change. By employing the LMDI analysis, policy makers can gain insights into the key drivers of energy consumption and evaluate the effectiveness of different policy measures in achieving energy efficiency and carbon reduction goals. This method aids in identifying opportunities for improving energy efficiency, optimizing resource allocation, and guiding the development of sustainable energy policies.

The LMDI decomposition method is a technique based on the extended Kaya identity. It aims to analyze the factors that influence changes in energy consumption or carbon emissions over a specific period. This method breaks down the carbon emissions scale and identifies the impact factors in a temporal dimension. It also assesses the contribution rates of energy efficiency and changes in the energy structure to carbon emissions. The analysis helps to understand the drivers behind carbon emissions changes and provides insights for policymakers in designing effective strategies to reduce emissions and promote sustainable energy practices.

The LMDI method is a simplified version of the Divisia decomposition method, utilizing exponential analysis. It involves treating the decomposition formula as a continuous and differentiable function of time (t). By differentiating and integrating over time, the exponential form of decomposition is derived:

$$V = x_1 x_2 \cdots x_n = \prod_k x_k \tag{1}$$

Where V is the target variable; x_k is the factor variable. Differentiate both sides of the equation with respect to time t:

$$\begin{aligned} \frac{dV}{dt} &= \frac{d(x_1 x_2 \cdots x_n)}{dt} \\ &= \sum_k x_1 x_2 \cdots x_{k-1} x_k x_{k+1} \cdots x_n \frac{dx_k}{dt} \\ &= \sum_k V \frac{d(\ln x_k)}{dt} \end{aligned} \tag{2}$$

By integrating both sides of the above equation over the length of a time interval, we obtain the additive form of exponential decomposition.

$$\int_0^T \frac{dV}{dt} = \int_0^T \sum_k V \frac{d(\ln x_k)}{dt} = \sum_k \int_0^T V \frac{d(\ln x_k)}{dt} \tag{3}$$

It is evident that the exponential decomposition method, in its additive form, does not include a residual term, making it particularly suitable for decomposition analyses in the energy sector. Consequently, this method is employed in the study to effectively break down and analyze the factors influencing carbon emissions.

3. Multivariate Data Fusion

Artificial intelligence technologies have undergone notable progress in recent years, and these advancements have had significant implications for carbon accounting. The field has benefited from the emergence of Convolutional Neural Networks (CNNs), a type of deep learning algorithm extensively utilized in diverse domains like image classification, speech recognition, and natural language processing. CNNs excel at handling vast quantities of data and identifying patterns within that data. In the realm of carbon accounting and the examination of power system energy carbon footprints, CNNs hold immense potential for enhancing the accuracy and efficiency of the carbon accounting process.

CNNs possess a key strength in their capability to autonomously acquire features and representations from raw data. This attribute proves especially advantageous when analyzing intricate datasets, including those generated by power systems. By learning pertinent features and representations, such as temporal energy usage patterns, CNNs can effectively forecast future energy consumption and carbon emissions.

Another benefit of CNNs lies in their capacity to be trained on large-scale datasets, enabling them to handle highly variable and non-linear data patterns. This attribute renders them well-suited for carbon accounting in power systems, where energy usage and carbon emissions are influenced by a wide array of factors, including weather conditions, economic circumstances, and energy policies.

By integrating CNNs with other machine learning algorithms like decision trees, random forests, and support vector machines, it is possible to achieve enhanced accuracy and robustness in carbon accounting. The outputs obtained from a CNN can be utilized as inputs for decision trees or random forests, enabling these algorithms to make more informed decisions based on the features learned by the CNN.

Artificial intelligence technology, with its capability to analyze big data and train complex models, offers a new avenue for improving the accuracy and reliability of carbon accounting results. The diagram provided illustrates a typical neural network structure.

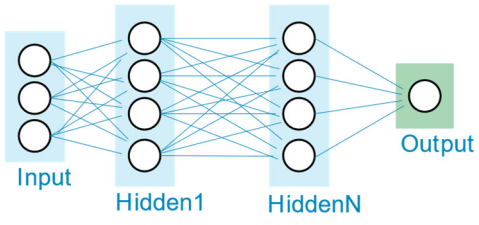


Fig 2. Architecture of CNN

Each feature matrix in a network layer undergoes a linear

transformation using the weights learned from previous feature layers. This linear transformation is followed by a non-linear activation function, as represented by the provided formula.

$$y = \text{Activation}(x \cdot W + B) \quad (4)$$

Where: $x \cdot W + B$ represents the linear transformation used to fit any region, and Activation represents the activation function used to transform from linear to nonlinear. Artificial neural networks repeatedly train and learn from a limited number of samples, continuously correcting and improving during the learning and training process in order to grasp the inherent laws hidden within the limited samples.

The integration of multiple data involves combining data from different sources into a unified dataset. This integration process enhances the accuracy and reliability of carbon accounting by leveraging the complementary nature of various data sources. It can be categorized into pre-feature integration and post-feature integration, as depicted in the diagram provided.

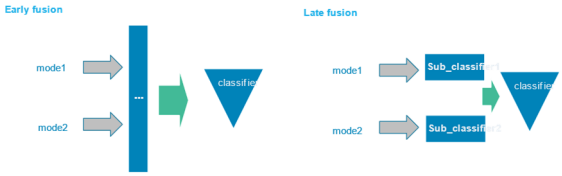


Fig 3. Fusion stage

In this study, the late-stage fusion approach is utilized to accurately calculate carbon emissions data by leveraging the distinct characteristics of data from various sources. The fusion of multi-modal data elements involves six components, namely: 1. Branch flow distribution, 2. Unit injection distribution, 3. Load distribution, 4. Node active power, 5. Branch carbon flow rate distribution, and 6. Load carbon flow rate. The overall structure of the fusion process is depicted as shown.

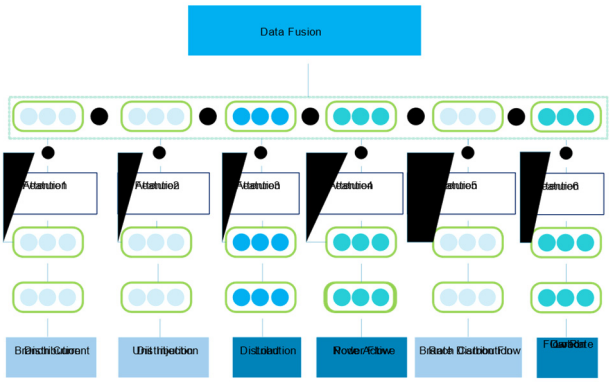


Fig 4. Overall illustration of data fusion

The cross-modal adversarial methods are employed to seek the optimal solution for effective universal sub-modules. These methods operate based on the maximum-minimum principle, aiming to achieve the best possible outcome for the integration of different modalities.

$$\min_{\bar{I}}\max_{\bar{D}} L_D = E_{x-px^1}\left[\log\left(D(I(x))\right)\right] + E_{x-px^2}\left[\log\left(1 - D(I(x))\right)\right] \quad (5)$$

Where px^1 and px^2 are the distributions of two different modes. With I fixed, the optimal discriminator D is.

$$D_I^*(x) = \frac{px^1(x)}{px^1(x)+px^2(x)} \quad (6)$$

With this optimal solution, then solving the preceding max-min equation is

$$L_D = -\log(4) + 2 \cdot JSD(px^1 \| px^2) \quad (7)$$

Since the JSD divergence between two distributions is always greater than or equal to zero, the equation obtains the global minimum value only when. This is exactly the goal of cross-modal adversarial learning. By utilizing the backpropagation optimization of the model parameters, the final output is a carbon emission accounting model under multiple scenarios.

4. Based on Flow Tracking, Carbon Flow Calculation

This study focuses on the analysis of the IEEE 33 node standard distribution system. The system consists of 32 branches and 5 disconnected tie switch branches, forming a radial distribution network. The network structure is illustrated in the accompanying figure, providing a visual representation of the distribution system configuration.

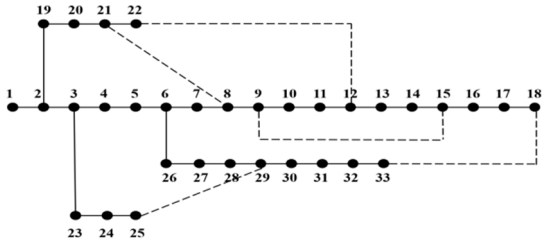


Fig 5. Carbon flow calculation

The carbon potential data at each node is show in following table.

Table 1. Carbon Potential Data

Node	Carbon potential/$gCO_2 \cdot (kW \cdot h)^{-1}$	Node	Carbon potential/$gCO_2 \cdot (kW \cdot h)^{-1}$
1	850	18	431
2	850	19	850
3	850	20	662
4	850	21	0
5	850	22	0
6	850	23	850
7	850	24	850
8	850	25	256
9	681	26	850
10	681	27	850
11	681	28	850
12	681	29	850
13	681	30	850
14	681	31	850
15	430	32	850
16	430	33	850
17	430		

Based on the analysis, it is determined that Node 21 and Node 22 receive their output from distributed photovoltaics, resulting in a carbon potential of 0 for these nodes. Node 25 has a relatively low carbon potential of 256, mainly due to a significant portion of its output being sourced from

distributed photovoltaics. On the other hand, Nodes 1-8 and Nodes 26-33 receive their output from the public grid, originating from Node 1. Consequently, these nodes have the highest carbon potential at 850. The carbon potential of the other nodes decreases accordingly, as some of their output comes from gas turbines or distributed photovoltaics. By considering the energy characteristics analysis and the LMDI analysis, the carbon flow calculation incorporates seasonal variations in energy consumption and the distribution of carbon emissions across the system. This approach provides a more accurate assessment of the system's carbon footprint, enabling informed decision-making to effectively reduce carbon emissions.

5. Summary

In this study, a carbon accounting method is proposed that utilizes the characteristics of energy carbon footprint in the power system and incorporates multi-dimensional data fusion. By analyzing different types of energy carbon footprint characteristics in the power system and leveraging big data analysis and artificial intelligence technology, this method aims to achieve a more detailed and accurate evaluation of carbon emission sources. The experimental results demonstrate the effectiveness and feasibility of the proposed method.

The application of this method can benefit enterprises, organizations, government departments, and research institutions. It enables accurate assessment of carbon emission levels and trends, facilitating the formulation of targeted emission reduction targets. Additionally, it provides detailed and accurate carbon emission evaluation results, helping to address the challenges posed by climate change.

However, there are still areas for improvement in this method. These include enhancing the acquisition and calibration of carbon emission data and improving the accuracy of the models used. In future work, the researchers intend to explore more efficient and accurate carbon accounting methods. They also plan to validate and refine these methods through real-world applications.

Acknowledgments

This research is supported by Science and Technology Projects of Inner Mongolia Electric Power Economic and Technological Research Institute, Inner Mongolia Electric Power (Group) Co., Ltd. (LX34219124).

References

[1] Stechemesser, K., & Guenther, E. Carbon accounting: A systematic literature review[J]. Journal of Cleaner Production, 2012, 36 , 17-38.

[2] Cai N Z, Dong B H, Cheng Y J, Bo X, Qun Z, Song Q P, Connotation and pathway of world energy transition and its significance for carbon neutral. Acta Petrolei Sin, 2021 42(2):233.

[3] Zhao C Y. Carbon Neutrality: aiming for a net-zero carbon future[J]. Carbon Neutrality, 2022, 1:2.

[4] Lau HC, Ramakrishna S, Zhang K, Radhamani AV. The Role of Carbon Capture and Storage in the Energy Transition[J]. Energy Fuels, 2012 35(9):7364–7386.

[5] Black, C. M. Accounting for carbon emission allowances in the European Union: In search of consistency[J]. Accounting in Europe, 2013, 10, 223-239.

[6] Bebbington J., Larrinaga-González C. Carbon trading: Accounting and reporting issues[J]. European Accounting Review, 2008, 17: 697-717.

[7] Tang, Q. Towards a framework of carbon accounting and its role in corporate carbon management systems: A holistic approach. In W. S. University (Ed.), Working paper. SSRN, 2017.

[8] Tauringana, V., Chithambo, L. The effect of DEFRA guidance on greenhouse gas disclosure[J]. The British Accounting Review, 2015, 47, 425-444.

[9] Warwick, P., Ng, C. The 'cost' of climate change: How carbon emissions allowances are accounted for amongst European union companies[J]. Australian Accounting Review, 2012, 22, 54-67.

[10] Young, A. Greenhouse gas accounting: Global problem, national policy, local fugitives[J]. Sustainability Accounting, Management and Policy Journal, 2010, 1, 89-95.

[11] Hartmann, F., Perego, P., & Young A. Carbon accounting: Challenges for research in management control and performance measurement[J]. Abacus, 2013, 49, 539-563.

[12] Bowen, F., Wittneben B. Carbon accounting: Negotiating accuracy, consistency and certainty across organisational fields. Accounting[J], Auditing & Accountability Journal, 2011, 24, 1022-1036.

[13] Bui B., Fowler. Strategic responses to changing climate change policies: The role played by carbon accounting[J]. Australian Accounting Review, 2019, 29, 360-375.

[14] Moore, D. R. J., McPhail. Strong structuration and carbon accounting: A position-practice perspective of policy development at the macro, industry and organizational levels[J]. Accounting, Auditing & Accountability Journal, 2016, 29, 1204-1233.

[15] Alofi A, Alghamdi A, Alahmadi R. A Review of Data Fusion Techniques[J]. International Journal of Computer Applications, 2017, 167(7):37-41.

[16] Abdulhafiz, Waleed A., and Alaa Khamis. Handling Data Uncertainty and Inconsistency Using Multisensor Data Fusion [J]. Advances in Artificial Intelligence 2013: 1-11.

[17] Azimirad, Ehsan, And, Javad Haddadnia. A Comprehensive Review of The Multi-Sensor Data Fusion Architectures[J]. Journal of Theoretical and Applied Information Technology, 2015, 71.1992-8645.

[18] Castanedo, Federico. A Review of Data Fusion Techniques[J]. The Scientific World Journal, 2013 (2013):1-19.