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Study on real-time estimation of carbon emissions based on the non-intrusive power load monitoring

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Abstract. Monitoring carbon emissions, as well as evaluating and controlling the level of carbon emissions, are important prerequisites for combating climate change and promoting sustainable development. In this paper, real-time estimation of carbon emissions based on non-intrusive electricity load monitoring is investigated, existing machine learning approaches and related issues of load identification and marginal carbon emission factors are elucidated, and existing carbon emission monitoring approaches are analyzed and summarized. The methods of real-time carbon emission measurement are summarized, and their development is anticipated. Most of the existing methods for measuring and analyzing carbon emissions in power systems are unable to meet the development needs of real-time carbon emission calculation and have the disadvantages of higher installation and maintenance costs and poorer economy of monitoring equipment. Therefore, in this paper, a real-time carbon emission monitoring scheme based on deep learning is used to estimate carbon emissions by dividing them into direct carbon emissions and indirect carbon emissions.

Keywords: Real-Time Monitoring, Carbon Emissions, Load Recognition, Long Short-Term Memory, Neural Networks.

1. Introduction

According to the International Energy Agency report, global energy-related carbon dioxide emissions increased by 0.9% in 2022, and the sector with the largest increase in carbon emissions came from electricity and heating, which increased by 1.8% [1]. Therefore, controlling greenhouse gas emissions has become an urgent issue that all of mankind must face.COP21 adopted the Paris Agreement with the goal of controlling the rise of global temperatures and combating climate change by reducing greenhouse gas emissions [2]. Since electricity is the industry with the most carbon emissions, monitoring and controlling its carbon emissions is an important part of achieving carbon neutrality, and its monitoring can be divided into direct carbon emissions and indirect carbon emissions. Most of the current monitoring focuses more on direct carbon emissions, and although researchers gradually recognize the importance of monitoring indirect carbon emissions, there are fewer results. In addition, current studies cannot achieve real-time monitoring, and the time granularity is too coarse. And most of the estimates cannot be generalized and are only applicable to a certain industry [3]. Aiming at these problems, Liu proposed a CNN-BLSTM model, which can be used to monitor carbon emissions in real time, and Liu proposed an identification method based on the multi-head self-attention mechanism and GRU, which can realize high-precision estimation [3-4]. However, this still has shortcomings. Based on this, this

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paper summarizes the existing real-time carbon emission approaches, argues that non-intrusive load identification can obtain more accurate and convenient real-time carbon emission monitoring results, and finally puts forward an outlook on it. The results of the study are conducive to a real-time understanding of the carbon emissions of the power system and promote the emission reduction actions of energy consumers and enterprises.

2. Introduction to related knowledge

2.1. Introduction to machine learning

Applying machine learning to non-intrusive load monitoring (NILM) can help identify the energy consumption of various devices in terms of electricity consumption. By processing the overall power consumption data and decomposing it into the loads of different devices, monitoring the energy consumption of each device is realized. Applying the detection results to direct carbon emission estimation allows estimation of the energy consumption of specific equipment. Obtaining real-time information on the energy consumption of equipment and calculating real-time direct carbon emissions based on the energy consumption data and the corresponding carbon emission factors can help in real-time carbon emission monitoring and control. Nowadays, there are more studies on NILM using machine learning, as shown in Table 1.

Table 1. Analysis of the current state of machine learning applications.

Name	Advantages	Disadvantages
SVM [5]	1. Intuitive and easy to explain; 2. For large-scale data sets and high-dimensional feature space, it has good scalability and generalization ability; 3. Strong resistance to noise; 4. Low memory consumption;	1. Sensitive to parameter adjustment; 2. Not applicable to large-scale data sets;
CNN [6]	1. Feature extraction is highly efficient 2. High image processing advantages 3. Having strong generalization ability	1. Relatively high quality requirements for the input image 2. The structure is more complex, and its internal mechanism is difficult to explain
MFC-ML-LSTM [7]	1. Reasonable combination of a variety of features, a comprehensive description of equipment state characteristics; 2. For the recognition task of equipment state change over time, it can better capture and understand;	1. High data quality and labeling requirements; 2. Model design and parameter tuning need to consider the data volume, data features, and task complexity and require a lot of experiments;
CNN-BLSTM [3]	1. Multi-level feature extraction to improve the accuracy of load recognition; 2. BLSTM has a bidirectional loop structure, capturing a more comprehensive context-awareness capability; 3. It can adaptively learn load features from data without manual operation;	1. The model has more parameters and the training process is relatively complex; 2. The model is poorly interpretable, and its results are relatively difficult to interpret and analyze [a];
HT-LSTM [8]	1. It can capture the characteristics and patterns of different time scales, from the whole to the local gradual classification of the state of the device, with high accuracy; 2. Able to deal with long-term dependency relationships and memorize past information to improve recognition performance;	1. High data requirements; 2. The model is relatively complex, involving multiple layers of LSTM units and parameters;

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Table 1. (Continued)

Name	Advantages	Disadvantages
LSTM-PNN [9]	1. It can capture the pattern and law of equipment state evolution over time; 2. With parallel computing capability, high accuracy and robustness, reducing the computational burden; 3. With rich feature representation capability;	1. Requiring a large number of training samples and computational resources; 2. Requiring careful model design and parameter adjustment; 3. High requirements on data samples and carbon emission labels;
TSCNN [10]	1. Effectively capture time series features and patterns with high accuracy; 2. No need to manually design features, reducing the complexity of feature engineering;	1. Lack of sufficient data may lead to model performance degradation; 2. Requiring larger computational resources and training time, while poor interpretability [b];
TCN-CRF [11]	1. It can capture the long-term dependence in time series data, with translation invariance, better modeling of patterns in time series; 2. It can label and classify the state sequence of the equipment to improve the accuracy;	1. High data quality requirements; 2. Multiple hyperparameters exist in the method, and experimental verification is required for their adjustment;
Multiple Self-Attention Mechanisms and GRUs [4]	1. allowing parallel processing of different feature subspaces to improve computational efficiency; 2. Able to better understand the prediction results of the mode;	1. Difficult to deal with long sequences; 2. High requirements on data quality;
[a] The model has a high complexity and is prone to overfitting when the training data is insufficient or the tuning parameter is inappropriate. [b] The layers and parameters in the model need to be adjusted and optimized, and multiple training sessions are required to find the best model configuration, which increases the requirement for computational resources and training time.		

It can be seen that equipment load recognition can be solved using machine learning methods. All the above methods have their own advantages in equipment load recognition. For example, SVM is a traditional machine learning method with better performance for simple device classification. The use of CNN, on the other hand, captures the visual features of the equipment and has better generalization ability. Moreover, they can all be used in industrial equipment monitoring, building energy efficiency management, equipment intelligence, and IoT applications for equipment monitoring and optimal energy management through real-time monitoring.

2.2. Load identification based on NILM

This paper carries out direct carbon emission monitoring based on load identification of NILM, which is a monitoring method that analyzes the energy consumption data of the whole grid and identifies the working status of the equipment with the help of intelligent algorithms by installing a monitoring device at the entrance of the user bus. Because of its high economic efficiency and the fact that it can be monitored in real time, it is more suitable for carbon emission monitoring than ILM.

2.2.1. Real-time monitoring. Since NILM analyzes the energy consumption of the entire grid and carries out load identification based on machine learning, it can effectively achieve the purpose of real-time monitoring of carbon emissions. Specifically:

In terms of data acquisition, NILM can utilize global energy consumption data to estimate and monitor carbon emissions. In contrast, ILM installs meters on each device to obtain data, which is costly and cumbersome, and cannot directly obtain the energy consumption information of the whole grid, so it is not suitable for real-time monitoring.

In terms of algorithm processing, the NILM system is based on deep learning to identify the contribution of energy consumption of equipment, and then combined with the carbon emission factor to estimate energy consumption, so as to realize the purpose of calculating carbon emissions in a short period of time. The ILM system, on the other hand, takes a long time and cannot monitor in real time due to the fact that the meter receives the energy consumption of each electrical appliance and then collects and integrates the data.

2.2.2. High economic efficiency. Compared with ILM, NILM has higher economic benefits; specifically, it has a low cost, high user acceptance, high practicality, is easy to popularize, and has wide application value. First, NILM does not require the installation of sensors on each device, so it has lower installation and maintenance costs. Second, NILM does not need to change the user's equipment use habits or affect the normal operation of the equipment, so it is less disruptive to the user and easy to be widely accepted. In addition, the NILM system is highly practical and can accurately identify the energy contribution of equipment and obtain valuable information from it. It is also characterized by easy popularization, relying mainly on software algorithms for energy consumption analysis, which reduces the need for hardware equipment and is therefore more likely to be popularized.

2.3. Marginal Carbon Emission Factor (MCEF)

MCEF is a factor used to estimate the carbon emissions generated by a specific activity or equipment, which refers to the additional carbon emissions caused by a unit of energy consumption or economic activity that increases one unit of energy consumption or output. Existing studies have adopted different marginal carbon emission factor accounting methods to measure the marginal carbon emission factor based on different application scenarios and natural endowments. The current status of specific applications is shown in Tables 2:

Table 2. Analysis of Current Status of Marginal Carbon Emission Factors.

Name	Definition	Advantages	Disadvantages
Location Marginal Price (LMP) [12]	Marginal carbon emissions corresponding to the generation of a unit of electricity at a given location or node;	Providing a more accurate picture of carbon emission changes based on actual electricity market clearing mechanisms;	Lacks of regional specificity regarding pollutant emission factors to account for more than one marginal unit and has not yet been validated;
Emission factor (EF) for large pollutants [13]	Emissions of a specific air pollutant per unit of energy generated or consumed;	Calculations can also be performed in intermittent combustion installations;	Calculation of emissions based on average or predicted values, high uncertainty;

Table 2. (Continued)

Name	Definition	Advantages	Disadvantages
Marginal emissions based on real-time market (PJM) [5]	Calculating and measuring the indirect carbon emissions of the power system in a specific time period through the real-time market mechanism;	It can accurately reflect the carbon emissions at different nodes or time periods in the power system;	It mainly focuses on the impact of electricity price and power generation type on carbon emissions, without comprehensively considering the impact of other factors;
Location Marginal Emissions (LME) [14]	It refers to the additional carbon emissions triggered by a unit of energy consumption in a specific geographic location and time period;	It accurately assesses the impact of energy choices on carbon emissions by considering the carbon emission characteristics of different power generation methods in the power system;	It needs to consider complex system interactions and data uncertainty;
Marginal carbon emission factor (MCEF) [4]	Measurement of additional carbon emissions per unit of electricity energy consumed;	It can be specific in spatial and temporal dimensions to achieve accurate measurement;	Requiring high power energy data and high computational complexity: the calculation may involve consideration of multiple factors and variables in the power system;

In summary, load characteristics can be identified from the monitoring data of the power system using machine learning, which in turn predicts direct carbon emissions. Marginal carbon emission factors are then used for the calculation and assessment of indirect carbon emissions to realize carbon emission monitoring. The advantage of machine learning is that it improves accuracy through model training, but it still has some challenges in terms of interpretability and data requirements. In contrast, the marginal carbon emission factor to measure indirect carbon emissions is more mature but not accurate or new enough.

3. Framework for estimating carbon emissions in power systems

Real-time monitoring of carbon emissions can be obtained by adding up the direct and indirect carbon emissions after monitoring them separately, and this section will introduce the calculation of the two parts separately.

3.1. Research on direct carbon emissions based on grid average emission factors

Direct carbon emissions are the carbon emissions directly generated by a specific activity or equipment Real-time monitoring of direct carbon emissions based on machine learning involves the use of historical and real-time data to infer and estimate the level of direct carbon emissions from a specific activity or equipment by training and optimizing a machine learning model.

The resulting calculation of direct carbon emissions requires the use of load identification, which consists of five main parts: data measurement, data processing, event detection, feature extraction, and load identification. The last three parts are the core of the process, which require the use of suitable machine learning models to classify and identify loads, multiply the identified appliances by their carbon intensity at this point in time, and then add up the direct carbon emissions of all the appliances to obtain the total direct carbon emissions of all the appliances in the range.

$$\alpha_x = \sum_{i=1}^{d} DEI_i \times x \tag{1}$$

Where α is the total direct carbon emissions, d is the number of devices, x is the measured length of time (h), and DEI is the carbon intensity of the device, which indicates how many kilograms of carbon dioxide will be emitted per kilowatt-hour of electricity consumed by the device in this state [3].

3.2. Research on indirect carbon emissions based on marginal emission factors

Indirect carbon emission is the carbon emission caused by the production and consumption of electricity on the user side. This is usually associated with the processes of energy production, supply, and use. This paper focuses on the method of calculating indirect carbon emissions through marginal emission factors, which is based on the principle of selecting appropriate marginal emission factors to estimate the indirect carbon emissions caused by different segments in the life cycle of industrial activities or products according to their impact on carbon emissions. The marginal emission factor refers to the carbon emissions generated by a unit of activity or a unit of product. Depending on the factors taken into account, their calculation may vary to some extent, and they are mainly affected by regional differences, improvements in energy technology, and seasonal and weather variations.

4. Discussion

Through the introduction above, it can be found that the real-time carbon emission estimation based on load recognition can be divided into direct and indirect carbon emissions for calculation, respectively. In the calculation of direct carbon emissions, through the load recognition of machine learning, the real-time analysis of the power equipment at this time is combined with the intensity of the emission state. In terms of indirect carbon emissions, it is necessary to select a suitable carbon emission factor and multiply it with the indirect power consumption at this time. On this basis, this paper argues that non-intrusive load identification can obtain more accurate and convenient real-time carbon emission monitoring results. Although this paper summarizes the development process of real-time monitoring of carbon emissions, it only focuses on the research of monitoring methods and does not consider the design and use of monitoring instruments.

Finally, the paper gives an outlook on the data and modeling requirements of the monitoring method: Firstly, the current real-time monitoring of carbon emissions has high data requirements, requiring high-frequency power data at the second level, which is difficult to realize and therefore still remains in the testing stage. Further research is needed for wide-scale implementation. Secondly, although today's machine learning models can make predictions, they have poor interpretations of the internal workings and processes, making it difficult to validate the results, which can be explored more subsequently. Finally, most of the existing methods for measuring carbon emissions from power systems are unable to meet real-time calculations and have the disadvantage of poor economy, which can be improved by both algorithms and hardware equipment.

5. Conclusion

Real-time monitoring of carbon emissions is of vital importance in the process of achieving carbon neutrality, which provides us with an accurate data base and effectively promotes emission reduction and sustainable development. This paper summarizes the existing ways to monitor real-time carbon emissions by measuring direct and indirect carbon emissions, and finds that non-intrusive load identification can solve the problem of not being able to monitor carbon emissions in real-time, thus perfecting the research on the theory of real-time monitoring of carbon emissions, and finally gives an outlook on the results of the present study.

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