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Big Data Analysis Approach for Real-Time Carbon Efficiency Evaluation of Discrete Manufacturing Workshops

CHAOYANG ZHANG AND WEIXI JI
School of Mechanical Engineering, Jiangnan University, Wuxi 214122, China

Corresponding author: Chaoyang Zhang (cyzhang@jiangnan.edu.cn)

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ABSTRACT Due to the huge consumption of materials and energy during machining processes, reduction of manufacturing carbon emission is an essential key to decrease the environmental burden of various manufacturing systems. To achieve this target, one critical step is to calculate and evaluate the carbon emissions of machining processes. However, this step is a little difficult for discrete manufacturing processes, because they are always complex and the data sources are diverse. Considering the complexity of discrete manufacturing workshops, a Big Data analysis approach for real-time carbon efficiency evaluation of discrete manufacturing workshops is proposed in an internet of things-enabled ubiquitous environment. Firstly, the deployment of data acquisition devices is introduced to create a ubiquitous manufacturing workshop, and data modeling of production state and carbon emission is described to realize data acquisition and storage. Then, a data-driven multi-level carbon efficiency evaluation of manufacturing workshop is established based on Big Data analysis approaches. Finally, an auto parts manufacturing workshop is studied to verify the feasibility and applicability of the proposed methods. This method realizes the combination of manufacturing Big Data and low-carbon production. Meanwhile, the evaluation method can be used in other production information systems and then assist the production decision-making.

INDEX TERMS Big data analysis, data acquisition network, carbon emission, carbon efficiency evaluation, discrete manufacturing workshops.

I. INTRODUCTION

The growing energy and resource consumption has led to concerns about economic development in many countries. Manufacturing, as the backbone of industrialized society, is one of the main energy consumers and greenhouse gas contributors [1]. Statistics have shown that the greenhouse gas from manufacturing accounts for more than 37% even 50% of the world's total greenhouse gas emissions [2]. Additionally, the rising carbon emission reduction awareness of customers always drives them to choose a product with lower life-cycle carbon emission. Therefore, it is imperative for the manufacturing companies to take low carbon emission measures to achieve sustainable manufacturing.

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In academia, the study related to carbon emission reduction in the manufacturing industry has gradually been a focus. The concept of low-carbon manufacturing was proposed as well, which is referred to the manufacturing process that generates low carbon emission intensity and utilizes energy and resources efficiently and effectively. In order to reduce the energy consumption or carbon emission, carbon emission or carbon efficiency evaluation is an effective way, and many researchers have concentrated on this topic. The research mainly covers three levels, i.e., machine tool level, workpiece level and workshop level. For the machine tool level, the effects of machining parameters on the energy consumption or carbon emission are researched [3]. A multi-granularity numerical control (NC) program optimization approach for energy efficient machining has been developed [4]. For the workpiece level, Ciceri *et al.* proposed an easy-to-use methodology to estimate the materials embodied energy and manufacturing energy for a product [5]. And for the workshop level, a systematic approach is proposed to assess the carbon emissions in production systems by using a hybrid emission analysis model [6].

However, there are mainly two research gaps in the state-of-the-art studies. Firstly, the study on manufacturing carbon emission and carbon efficiency evaluation based on real-time data and Big Data analysis is not enough, especially for discrete manufacturing workshops. Secondly, since discrete manufacturing processes are always complex, their data sources are diverse and the quantity of data are huge. Thus there need special methods to process the vast data and the complex relationship between manufacturing resources. In order to bridge these gaps, a Big Data analysis approach for real-time carbon efficiency evaluation of discrete manufacturing workshops is proposed. The approach focuses on the real-time data analysis and processing of manufacturing carbon emission, and mainly contains two contributions: 1) a Big Data analysis about production states and carbon emission is proposed to filter and compress the raw data, which will provide data support for carbon emission evaluation; 2) Considering the complexity of manufacturing processes, a data-driven multi-level carbon efficiency evaluation method is proposed.

The rest of the study is organized as follows. In Section II, a literature survey on manufacturing carbon emission evaluation and manufacturing Big Data analysis is reviewed. Section III introduces the construction of data acquisition network to create a ubiquitous manufacturing environment, and a data modeling of production state and carbon emission is described. Then, the data-driven multi-level carbon efficiency evaluation of manufacturing workshop is established based on Big Data analysis for production in Section IV. Section V gives a typical case study to verify the feasibility and applicability of the proposed model. Section VI concludes with the main contributions and future research directions.

II. LITERATURE REVIEW

A. MANUFACTURING CARBON EMISSION EVALUATION

Since manufacturing processes consume a large amount of energy and raw materials, the manufacturing carbon emission evaluation has attracted much attention. Firstly, a large number of studies have been undertaken from the perspective of energy consumption analysis and optimization. Some researchers conducted machining experiments and regression analysis to minimize the power or energy consumption. For example, Campatelli *et al.* focused on the efficiency of the machining centers, and developed a quadratic regression model through an experimental approach to evaluate and optimize the process parameters in order to minimize the power consumption in a milling process [7]. Experimental investigations were conducted to establish relationships between cutting speed, feed rate, depth of cut and nose radius and power consumption and tool life in computer numerical control (CNC) turning of 7075 Al alloy 15 wt% SiC composite by using the response surface analysis [8]. Lv *et al.* aims to model the spindle acceleration energy consumption of CNC lathes, and to investigate potential approaches to reduce this part of consumption [9]. Meanwhile, Rahimifard *et al.* modeled the detailed breakdown of energy required to produce a single product to provide greater transparency on energy inefficiencies throughout a manufacturing system and find the improvements in production and product design [10]. In addition, with the development of sensor networks and information technologies, some real-time data processing methods of energy consumption are researched. He *et al.* analyzed the energy consumption characteristics driven by task flow in machining manufacturing system and proposed a modeling method of task-oriented energy consumption for machining manufacturing system [11]. A manufacturing energy consumption model for the order fulfilment is constructed according to the bill of materials, in which the computation is triggered by a radio frequency identification device (RFID) read event [12]. An internet-of-things (IoT) and cloud-based novel approach for product energy consumption and evaluation analysis is proposed in which the IoT technologies are employed for real-time and dynamic collection of energy consumption-related data, and various energy consumption evaluation and analysis functions are developed and encapsulated into services [13]. Wang *et al.* presented a real-time energy efficiency optimization method for energy-intensive manufacturing enterprises based on internet of things technology [14].

Except the above energy consumption analysis, many researchers studied the carbon emission of manufacturing processes from the viewpoint of carbon footprint and carbon efficiency. Winter *et al.* presented a generic regression model to describe and analyze the influence of grinding process parameters in conjunction with different cutting fluids on surface roughness, cost and carbon footprint, and applied the sensitivity analysis to reveal the trends of each process parameter in relation to the preference of technological, economic and environmental objectives [15]. In the aspect of carbon emission assessment of machining processes, Branker and Jeswiet proposed a new economic model for optimum machining parameter selection in a milling example [16]. Cao *et al.* presented a carbon efficiency approach to quantitatively characterize the life-cycle carbon emissions of machine tools, in which carbon efficiency is defined as the ratio of capacity or service value provided by a machine tool to the corresponding carbon emissions [17]. And Fang *et al.* established a new mathematical programming model of the flow shop scheduling problem, which considers peak power load, energy consumption, and associated carbon footprint in addition to cycle time [18]. Narita *et al.* developed an environmental burden analyzer for machine tool operations, which can evaluate an NC program from the view point of an environment burden by simulating a cutting process and using emission intensities [19]. In this study, the influence of the peripheral devices of a machine tool, the spindle and

TABLE 1. Resent research of manufacturing big data analysis.

Authors	Data inputs	Research methods	Research purpose
Lee *et al.* (2014) [25]	Industrial Big Data	Cyber Physical Systems and knowledge extraction	Machine health awareness analytics and decision support analytics
Wu *et al.* (2014) [24]	Information sources	Big Data processing model	Analyze several challenges at the data, model, and system levels
Yang *et al.* (2014) [26]	Structured data and unstructured data	Process mining	Manufacturing Process Analysis
Zhong *et al.* (2015) [23]	RFID-enabled logistics data	Map table and Big Data approach	Logistics trajectory excavation
Zhong *et al.* (2015) [27]	RFID logistics data	Data structure and Data interpretation	Logistics decision-making
Wang *et al.* (2018) [29]	Energy data	An ANNs-based algorithm and an intelligent immune mechanism	Achieve energy efficient manufacturing
Zhang *et al.* (2018) [30]	Energy Big Data	Energy Big Data acquisition and energy Big Data mining	Reduce the energy consumption and emission for energy-intensive manufacturing industries
Ji and Wang (2017) [28]	Data of machining tasks, resources, and machining processes	Data attributes, cleansing and integration	Shop floor scheduling
Park *et al.* (2019) [36]	Data of the dyeing process	Machine learning techniques and manufacturing Big Data	Saving energy of the dyeing process

the servo motors, the coolant, the lubricant oil, the cutting tool and the metal chips to global warming is introduced in detail. In the shop flow level, in order to meet the increasing requirement of practical low-carbon thinking in manufacturing, a systematic approach is proposed to assess the carbon emissions in production systems by using a hybrid emission analysis model [6]. Li *et al.* proposed an analytical method of quantifying carbon emissions of a CNC-based machining system [20]. In particular, this study discussed the breakdown of the processes that contribute to the overall carbon emissions of a CNC-based machining system, such as electricity, cutting fluid, wear and tear of cutting tools, material consumption and disposal of chips, etc. In addition, Zhou *et al.* proposed a carbon emission quantitation strategy to quantify the overall carbon emissions of a part machining process [21].

Although the energy consumption and carbon emission evaluation methods have been studied in many literatures, the study on manufacturing carbon emission and carbon efficiency analysis based on real-time data and Big Data analysis is not enough, especially for discrete manufacturing workshops. Meanwhile, the models only consider the theoretical perspective. Since discrete manufacturing processes are always complex, their data sources of carbon emission are diverse and the quantity of data are huge. Thus special methods are in demand to process the vast data and the complex relationship between manufacturing resources.

B. MANUFACTURING BIG DATA ANALYSIS AND PROCESSING

As the development of the sensing and communications technology, the manufacturing has the features as highly correlated, deep integration, dynamic integration, and huge volume of data [22]. The range of manufacturing data has been experiencing an exponential explosive growth, and presents three characteristics, i.e., volume, variety, and velocity. Since manufacturing carries huge number of data [23], many manufacturing Big Data analysis methods have been proposed, as shown in Table 1.

Big Data concern large-volume, complex, growing data sets with multiple, autonomous sources. Wu *et al.* presented a HACE theorem that characterizes the features of the Big Data revolution, and proposes a Big Data processing model, from the data mining perspective [24]. Since in an Industry 4.0 factory, machines are connected as a collaborative community, Lee *et al.* addressed the trends of manufacturing service transformation in Big Data environment, as well as the readiness of smart predictive informatics tools to manage Big Data, thereby achieving transparency and productivity [25]. Yang *et al.* suggested a manufacturing data analysis system that collects event logs from so-called Big Data and analyzes the collected logs with process mining [26]. This study considered two kinds of Big Data generated from manufacturing processes, i.e., structured data and unstructured data. Zhong *et al.* proposed a holistic Big Data approach to excavate frequent trajectory from massive RFID-enabled shopfloor logistics data with several innovations highlighted [23]. Through extending the Physical Internet concept into manufacturing shop floors by using IoT and wireless technologies, a Big Data Analytics was introduced for RFID logistics data by defining different behaviours of smart manufacturing objects [27]. Considering the current task scheduling mainly concerns the availability of machining resources, rather than the potential errors after scheduling, Ji and Wang presented a Big Data analytics based fault prediction approach for shop floor scheduling [28]. An innovative Big Data enabled Intelligent Immune System was developed to monitor, analyze and optimize machining processes over lifecycles in order to achieve energy efficient manufacturing [29]. Since energy-intensive industries account for almost 51% of energy consumption in China, a Big Data driven analytical framework is proposed to reduce the energy consumption and emission for energy-intensive manufacturing industries [30]. In this study, two key technologies of the proposed framework, namely energy Big Data acquisition and energy Big Data mining, are utilized to implement energy Big Data analytics. A deep learning methodology for energy-efficient strategies selection of CNC machine tools using deep belief networks is established to realize the real-time and accurate control of machine tools [31]. Ding *et al.* proposed a manufacturing data processing to realize real-time data-driven operations control of digital twin-based cyber-physical production system, which includes two phases, i.e., local data processing and global data processing [32]. Auto-ID computing, rule-based reasoning and big data analytics are used for real-time data processing and analysis of real-time production and transportation data to monitor task progress and states, which is helpful to manage the inter-enterprise production processes [33]. To generalize the energy-aware parametric optimization for multiple machining configurations, a two-stage knowledge-driven method was proposed by integrating data mining (DM) techniques and fuzzy logic theory [34]. In addition, Ren *et al.* conducted a comprehensive overview of Big Data in smart manufacturing, and proposed a conceptual framework from the perspective of product lifecycle [35]. This framework allows analyzing potential applications and key advantages, and the discussion of current challenges and future research directions provides valuable insights for academia and industry.

From the literature, the current Big Data analysis methods focused production data, fault data, logistics data and energy data, but the carbon emission data analysis is lacked, especially for the real time carbon emission data, which includes cutting tools and buffers, logistics, etc. Meanwhile, these analysis methods about manufacturing does not consider the data complexity of discrete manufacturing workshops.

III. DATA ACQUISITION NETWORK CONSTRUCTION OF CARBON EMISSION

A. DATA ACQUISITION NETWORK CONSTRUCTION FOR UBIQUITOUS PRODUCTION SYSTEM

This study is based on a real-time ubiquitous production system in a discrete manufacturing workshop. For a machine tool, its carbon mission mainly comes from the energy consumption, the consumption of cutting tools and cutting fluid. Carbon emission of cutting tools is estimated from the viewpoint of tool life. And some cutting tools, particularly those for a solid end mill, are recovered by regrinding after reaching their life limit. The data acquisition network construction for ubiquitous production system is shown in Fig. 1. The logical flow from Step 1 to 7 represents discrete production processes from raw materials to finished products. First, raw materials will be packaged and delivered to the in-stock of a specific machine tool via a logistics device. When the machine is

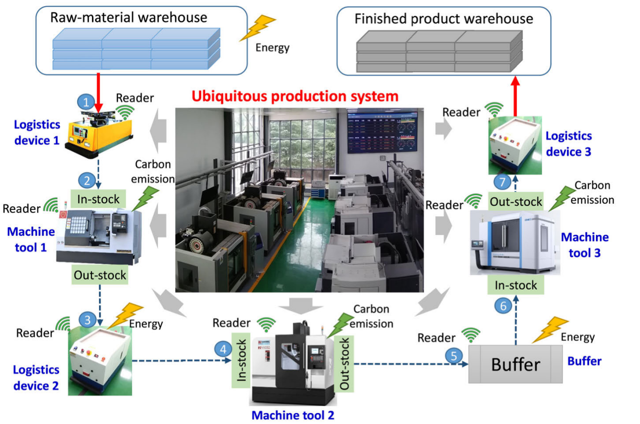

FIGURE 1. **Data acquisition network construction for ubiquitous production system.**

ready, a machining operator can clamp a workpiece and carry on the processing. Once the workpiece is finished, it will be demounted and put in the out-stock. If a logistics device is ready, the workpiece in the out-stock will be delivered to the next machine. The above steps are repeated until all the processing stages are fulfilled. The finished workpiece will be delivered to Finished Product Buffer. In this ubiquitous environment, the production state and carbon emission data can be perceived. Carbon emission of different production states needs to be obtained to evaluate carbon efficiency of machine tools and workpieces. Carbon emission data are useless if they are disconnected from the production process, thus the data of production state and carbon emission are both necessary for carbon emission evaluation. Since the manufacturing carbon emission mainly comes from the energy consumption and material consumption, the data acquisition includes four aspects, i.e., machining process, logistics process, storage process and supporting process.

For the machining process, energy monitors are deployed to gather energy consumption data, whereas serial communication of machine tools and adapters are used to acquire the data about the usage data of cutting tools and cutting fluid. For the logistics process, RFID technology is adopted to monitor the states of workpieces in process. Each workpiece will be bound with an RIFD tag. Meanwhile, two types of RFID readers are used. Specifically, each machine tool contains an in-stock buffer and an out-stock buffer, which are deployed with a kind of stationary RFID reader to accurately monitor machining processes. When a machining process is finished, a batch of jobs will be transferred to the next machine tool by a logistics operator, and a handheld RFID reader is used due to his frequent movement. Through the deployment of RFID, all the data of production state and process progress are able to be acquired. Then for the storage processes, energy monitors are adopted to obtain the energy data of each buffer and warehouse. In addition, for the supporting process, gas/liquid flow sensors are deployed to monitor the usage amount of compressed air and liquids during the manufacturing processes.

TABLE 2. Deployment information of data acquisition devices.

No	Data acquisition devices	Monitoring process	Objective
1	Energy meters	Machining process and storage process	Acquire the energy data of machine tools, buffers, warehouses
2	Serial com. and adapters	Machining process	Acquire the usage data of cutting tools and cutting fluid
3	RFID readers/tags	Logistics process	Acquire the data of production state and process progress
4	Gas flow sensors	Supporting process	Acquire the consumption data of auxiliary gas
5	Liquid flow sensors	Supporting process	Acquire the consumption data of auxiliary liquid

The deployment information of data acquisition devices is listed in detail in Table 2.

Through the above deployment of RFID, energy consumption and flow monitors, a ubiquitous production environment for carbon efficiency evaluation is established. Within this manufacturing system, machining processes and logistics operations are reengineered and rationalized. The production progress and carbon emission data of workpieces can be captured, which will provide a data support for the later carbon emission and carbon efficiency evaluation.

B. DATA MODELING OF PRODUCTION STATE AND CARBON EMISSION

Since the collected original data are isolated and littery, they cannot be used to evaluate carbon emission directly. In order to easily access useful information and analyze the carbon mession, the data modeling of production state and carbon emission are conducted firstly. The obtained data are stored in database based on the following data models.

Data Model 1: The energy consumption data of machining processes are modeled as $ME = < MEID, MID, EData, T >$, where $MEID$ is the index of machining energy data, MID is the machine tool index, $EData$ and T denote the collected energy data and corresponding time, respectively. The frequency of data collection is three in one second, and the gathered data will be stored in a temporary database.

Data Model 2: The progress data of a workpiece are modeled as $WP = < WPID, WID, PID, PName, PData, T >$, where $WPID$ is the index of progress data of a workpiece, WID is the workpiece index, PID and $PName$ represent the process index and process name, respectively. $PData$ denotes the position data of a workpiece at corresponding time T. This data is collected via a handheld or stationary RFID reader. The frequency of RFID reader is ten in one second. The data of WP will be stored in database when a workpiece is monitored.

Data Model 3: The energy consumption data of a storage unit are modeled as $SE = < SEID, BID, EData, T >$, where $SEID$ is the index of energy consumption data of a storage unit, BID is the index of a buffer or a warehouse. This data are collected via energy consumption meters. The frequency of data collection is three in one second, and the gathered data will be stored in database.

Data Model 4: The usage data of a cutting tool are modeled as $CT = < CTID, MID, STime, ETime >$, where $CTID$ is the index of a cutting tool, $STime$ and $ETime$ represent the starting usage time and end usage time of a cutting tool. This data are collected through the serial communication of a machine tool and adapters.

Data Model 5: The usage data of cutting fluids are modeled as $CF = < CFID, MID, STime, ETime >$, where $CFID$ is the category index of cutting fluid, $STime$ and $ETime$ represent the starting usage time and end usage time of the cutting fluid.

Data Model 6: The consumption data of supporting materials are modeled as $SM = < SMID, WID, PID, PName, SMCategory, STime, ETime >$, where $SMCategory$ is the category index of a supporting material.

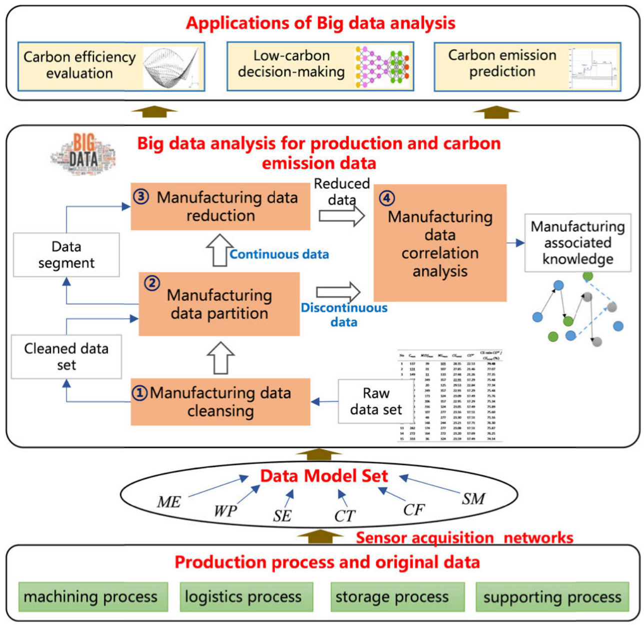

FIGURE 2. Framework of big data analysis for carbon efficiency evaluation.

IV. BIG DATA ANALYSIS APPROACH FOR CARBON EFFICIENCY EVALUATION

After obtaining the original data, the data are massive, isolated and littery, and cannot be used to evaluate carbon efficiency directly. Thus a Big Data analysis approach of production state and carbon emission is established. The overall framework of the Big Data analytics is presented in Fig. 2. Through the deployment of various data acquisition sensors, the production process and original data can be obtained. Through the data model described in Section III.B, the original data will be stored in the data warehouse. Then Big Data analysis methods can be used to acquire manufacturing associated knowledge, which includes manufacturing data cleansing, manufacturing data partition, manufacturing data reduction and manufacturing data correlation analysis. The concrete details of each data processing algorithms will be described in Section IV.A and Section IV.B. For different kinds of data, different algorithms will be adopted.

For continuous data, e.g., energy data (Data Model 1 and Data Model 3), supporting material consumption data (Data Model 6), data reduciton and feature extraction will be used to compress the amount of data. Whereas for discontinuous data, e.g., workpiece progress data (Data Model 2), cutting tool/fluid usage data (Data Model 4 and Data Model 5), these data will be taken out directly to conduct data correlation analysis. The main purpose of Big Data analysis is to excavate manufacturing associated knowledge. After the Big Data analysis for production and carbon emission data, some applications can be provided, such as carbon efficiency evaluation, low-carbon decision-making and carbon emission prediction.

A. DATA PREPRESSING OF PRODUCTION STATE AND CARBON EMISSION

Since the collected production data and energy consumption data are continuous and littery, these raw data are unusable for the carbon emission evaluation directly. Thus, several preprocessing algorithms are proposed to dispose the original manufacturing data, which includes three steps: manufacturing data cleansing, manufacturing data partition and manufacturing data reduction, as shown in Fig. 3.

1) MANUFACTURING DATA CLEANSING

The purpose is to detect and remove some noise data from production and energy data, which are incomplete or unreasonable. In this algorithm, each data array will be verified from the temporal rationality and data range. The data array which does not meet these conditions will be cleansed. The Input is a set of raw production and energy data $RPED = \{ME, WP, SE, CT, CF, SM\}$, and the output is a cleansed production data CD which are complete and logical.

2) MANUFACTURING PROCESS PARTITION

Since the data are always acquired continuously and automatically, the data of different processes are all mixed together. This algorithm is to divide the cleansed data to obtain production data for specific process or stage. For example, the energy data for different workpieces should be divided, because there exist unloading and loading processes between different workpieces. Similarly, the other data about cutting tool, cutting fluid and buffer defined in Section III.B also should be divided. The Input is a set of cleansed data $CD = \{ME, WP, SE, CT, CF, SM\}$, and the output is a manufacturing data segment MDS.

3) MANUFACTURING DATA REDUCTION AND FEATURE EXTRACTION

For a machining process, there are different states of a machine tool, i.e., downtime, standby, warm up, idle, air cutting, and cutting [37]. And only the energy consumption during cutting state is valuable for a machining process, whereas energy consumption of other states are auxiliary power consumption. In order to analyze carbon efficiency of a machine process, it is necessary to reduce the amount of data and extract the energy feature of different states. Its purpose is to form an advanced and succinct data structure of energy so that further query, classification, and analysis could be carried out easily. The data reduction approach thus aggregates and condenses the data record from the partition energy data of single process, then improve the data with high information density. The output is the feature data FCD. The data reduction process contains two steps: data clustering and feature extraction.

// Algorithm 1: Manufacturing data cleansing
Input: Raw production and energy data $RPED = \{ME, WP, SE, CT, CF, SM\}$, process precedence and data range condition Con
Output: Cleansed data set CD
Algorithm flow:
For each machine tool i
  For each process j
    For each data field k
      If the data array $RPED_{i,j,k}$ satisfy a condition Con_p where $Con_p \in Con$
        If $RPED_{i,j,k}$ is not vacant
          // Store this data array into CD
          $CD \leftarrow RPED_{i,j,k}$
        End if
      End if
    End for
  End for
End for
Return CD

// Algorithm 2: Manufacturing Data Partition
Input: Cleansed data set $CD = \{ME, WP, SE, CT, CF, SM\}$
Output: Manufacturing data segment MDS
Algorithm flow:
For each workpiece i
  For each process j
    When the workpiece arrives in the machine tool
      $STime \leftarrow WP.T$
    When the workpiece leaves the machine tool
      $ETime \leftarrow WP.T$
      // Obtain Manufacturing data segment of process j
      $MDS_{i,j} \leftarrow CD|_{STime}^{ETime}$
  End for
End for
Return MDS

// Algorithm 3: Manufacturing Data Reduction
Input: Manufacturing data segment MDS
Output: Feature carbon data FCD
Algorithm flow:
For each workpiece i
  For each process j
    // Obtain energy data of process j
    $x = MDS_{i,j}$
    // Obtain cluster results by using FCM clustering
    Apply FCM by using Eq.(1)-(6)
    $$v_p = \frac{\sum_{q=1}^{n} u_{pq}^{\beta} x_q}{\sum_{q=1}^{n} u_{pq}^{\beta}}, u_{pq} = \frac{1}{\sum_{k=1}^{c} (\frac{d(x_q, v_p)}{d(x_q, v_k)})^{2/(\beta-1)}}$$
    // Obtain energy consumption of different states (standby, idle, air cutting, cutting)
    $u'_{pq} = round(u_{pq})$
    $FCD_{i,j,p} = \sum_{q=1}^{n} u'_{pq} x_q / f$
    $p \in [1,2,3,4]$, f is the sampling frequency of energy consumption data
  End for
End for
Return FCD

FIGURE 3. Data preprocessing of production state and carbon emission.

The data clustering is mainly aimed to obtain the energy data of different states. Clustering is a method to divide a set of data into a specific number of groups. Since the power curves are dynamic and some data of transient processes cannot be divided into a certain stage absolutely, this clustering problem is a fuzzy one. The most successful technique in fuzzy cluster analysis is fuzzy C-means (FCM) clustering, and it is widely used in both theory and practical applications of fuzzy clustering techniques, especially time-series data [38], [39]. FCM clustering is a fuzzy clustering method and proposed by Bezdek [40].

In the FCM clustering method, the energy data are divided into fuzzy sets by minimizing sum of square error for groups. Let u_{pq}, v_p and n represent membership value, cluster center and the number of data sets, respectively. Thus, the form of the objective function tried to be minimized is shown as follows:

$$J_\beta(X, V, U) = \sum_{p=1}^{c} \sum_{q=1}^{n} u_{pq}^{\beta} d^2(x_q, v_p) \tag{1}$$

where β is weighting exponent ($\beta > 1$) of fuzzy degree, c is the number of cluster centers, and x_q represent the input energy data. Through analyzing the energy consumption data, four manufacturing states are important for energy consumption, i.e., standby, idle, air cutting, and cutting (as shown in Fig. 5). Thus $c = 4$. $d(x_q, v_p)$ is distance measure between the observation and the cluster center. J_β is tried to be minimized under the constraints given below:

$$0 \le u_{pq} \le 1, \quad \forall p, q \tag{2}$$

$$0 \le \sum_{q=1}^{n} u_{pq} \le n, \quad \forall p \tag{3}$$

$$\sum_{p=1}^{4} u_{pq} = 1, \quad \forall q \tag{4}$$

Minimization process in the FCM is performed by using an iterative algorithm. In each iteration, the values of u_{pq} and v_p are updated by using the formulas given below.

$$v_p = \frac{\sum_{q=1}^{n} u_{pq}^{\beta} x_q}{\sum_{q=1}^{n} u_{pq}^{\beta}} \tag{5}$$

$$u_{pq} = \frac{1}{\sum_{k=1}^{4} \left(\frac{d(x_q, v_p)}{d(x_q, v_k)}\right)^{2/(\beta-1)}} \tag{6}$$

After the above clustering process, the energy consumption data is divided into 4 fuzzy sets. Then energy consumption features can be obtained by multiplying energy data by sampling interval, that is, energy consumption of different stages.

The data reduction and feature extraction algorithm is shown in Algorithm 3 in Fig. 3.

B. MANUFACTURING DATA CORRELATION ANALYSIS FOR CARBON EMISSION EVALUATION

After the above data preprocessing algorithms, the feature carbon data are still disconnected with the production information, i.e., process, machine tool or workpiece. And the carbon emission of different machine tools or workpiece is also uncertain. So the data correlation analysis of the above preprocessed data is required, which is vital for carbon emission evaluation. In order to obtain the manufacturing knowledge about carbon emission, two spatio-temporal sequential patterns are defined firstly.

Definition 1 (Spatio-Temporal Sequential Pattern of Machine Tool Carbon Emission): Let $MCEP_j$ denotes a pattern of machine tool carbon emission, which involves p machining stages. Then this pattern can be described as follows:

$$\begin{aligned} MCEP_j = \{ &< WID_1, PID_1, AE_1, ME_1, CT_1, FT_1 >, \ldots \\ &< WID_k, PID_k, AE_k, ME_k, CT_k, FT_k >, \ldots \\ &< WID_p, PID_p, AE_p, ME_p, CT_p, FT_p > \} \end{aligned} \tag{7}$$

where WID_i indicates the ith workpiece, PID_{ik} is the kth process of WID_i, AE_k is the auxiliary energy consumption of PID_k during standby, idle and air-cutting stages, ME_k is the material removal energy consumption of PID_k during cutting stage, CT_k denotes the cutting tool usage time of PID_k, and FT_k represents the cutting fluid usage time of PID_k.

Definition 2(Spatio-Temporal Sequential Pattern of Workpiece Carbon Emission): Let WCE_i denotes a pattern of workpiece carbon emission, which involves n machining processes. Then this pattern can be described as follows:

$$\begin{aligned} WCEP_i = \{ &< WID_i, PID_{i1}, AE_{i1}, ME_{i1}, CT_{i1}, FT_{i1}, BUF_{i1}, \\ &LOG_{i1} >, \ldots < WID_i, PID_{ik}, AE_{ik}, ME_{ik}, CT_{ik}, \\ &FT_{ik}, BUF_{ik}, LOG_{ik} >, \ldots < WID_i, PID_{in}, AE_{in}, \\ &ME_{in}, CT_{in}, FT_{in} > \} \end{aligned} \tag{8}$$

where AE_{ik} and ME_{ik} denote the auxiliary energy consumption and material removal energy consumption of the kth process of the ith workpiece,CT_{ik} and FT_{ik} represent the cutting tool usage time and the cutting fluid usage time of the kth process, BUF_{ik} is buffer usage time between PID_{ik} and PID_{ik+1}, and LOG_{ik} is logistics distance between PID_{ik} and PID_{ik+1}. Since there are not buffer and logistics after PID_{in}, BUF_{in} and LOG_{in} are removed.

In order to mine the above production patterns, a data correlation analysis method is proposed, as shown in Fig. 4. Here, the RFID data are used to determine the start time and end time of each process or machining stage, and then bind the production data and carbon emission data according to time nodes. The energy consumption data AE_k and ME_k can be obtained through the above manufacturing data reduction algorithm. The cutting tool usage time CT_k and the cutting fluid usage timeFT_k can be gathered through serial com. and adapters of a machine tool. The buffer usage time BUF_{ik} and logistics distance LOG_{ik} can be gathered via the configured RFID readers in Table 2. Finally, the spatio-temporal sequential patterns of machine tool carbon emission and workpiece carbon emission can be obtained through the iterative process.

Through the above definitions and the data correlation analysis method, some invaluable knowledge about carbon emission can be deduced. The carbon emission evaluation can be used to analyze its utilization efficiency and impact on the environment. For example, through comparing the carbon emission at different periods, the changing situations

// **Algorithm 4: Data correlation analysis method**
Input: Manufacturing data segment MDS, Feature carbon data FCD
Output: Spatio-temporal sequential patterns $MCEP_j$ and $WCEP_i$
Algorithm flow:
For each machining stage j
  When the workpiece arrives in the machine tool
    $STime_j \leftarrow WP.T$
  When the workpiece leaves the machine tool
    $ETime_j \leftarrow WP.T$
  // *Spatio-temporal sequential pattern of machining stage j*
  $MCEP_j \leftarrow < AE, ME, CT, FT > |_{STime_j}^{ETime_j}$
End For

For each workpiece i
  For each process k
    When the workpiece arrives in the machine tool
      $STime_{i,k} \leftarrow WP.T$
    When the workpiece leaves the machine tool
      $ETime_{i,k} \leftarrow WP.T$
    // *Obtain spatio-temporal sequential pattern of process j*
    $WCEP_i \leftarrow < AE, ME, CT, FT > |_{STime_{i,k}}^{ETime_{i,k}} + < BUF, LOG > |_{ETime_{i,k}}^{STime_{i,k+1}}$
  End for
End for
Return $MCEP_j$ and $WCEP_i$

FIGURE 4. Data correlation analysis method of carbon emission pattern.

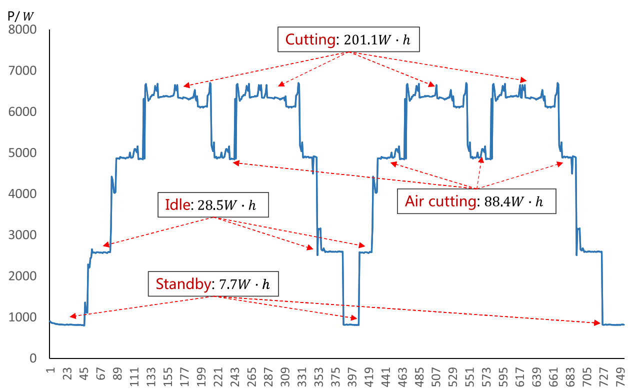

FIGURE 5. Raw energy consumption data and reduction results of test data with 750.

of machine tools can be obtained. And through comparing carbon emission of different objects, the inefficient machine tools or products can be found out.

1) CARBON EMISSION OF A MACHINE TOOL

For a machine tool, its carbon mission mainly comes from the energy consumption, the consumption of cutting tools and cutting fluid. Since raw material is not related to machine tools, it is not counted in carbon emission of machine tools. Fixture are usually recycled, so its carbon emission is neglected. Carbon emission of cutting tools is estimated from the viewpoint of tool life. And some cutting tools, particularly those for a solid end mill, are recovered by regrinding after reaching their life limit [41]. Based on the **Definition 1**, the carbon emission of a machine tool can be obtained as follows:

$$MCE_j = \sum_{k=1}^{p} ((AE_k + ME_k) \cdot emf^{el} + CT_k \cdot \omega^{tool} + FT_k \cdot \omega^{au}) \quad (9)$$

where emf^{el} is the emission factor of electric energy, ω^{tool} and ω^{au}denote carbon emission coefficient of cutting tools and cutting fluid.

2) CARBON EMISSION OF A WORKPIECE

The carbon emission of a workpiece contains the carbon emission during machining processes, logistics processes and the buffer. The energy consumption due to transportation processes in a workshop is related to the mode and the distance of transportation. Furthermore, there is a buffer to place workpieces temporarily for each machine tool, and a process will go through a number of buffers which also consume energy. Based on the **Definition 2**, the carbon emission of a wrokpiece can be obtained as follows:

$$WCE_i = \sum_{k=1}^{n} \left((AE_{ik} + ME_{ik}) \cdot emf^{el} + CT_{ik} \cdot \omega^{tool} + FT_{ik} \cdot \omega^{au}\right) + \sum_{k=1}^{n-1} ((BUF_{ik} * PBUF_{ik} + LOG_{ik} * PLOG_{ik}) \cdot emf^{el}) \quad (10)$$

where $PBUF_{ik}$ and $PLOG_{ik}$ denote the power of buffer and energy consumption per unit distance.

3) CARBON EMISSION OF THE WHOLE WORKSHOP

Except the carbon emission of workpiece, carbon emission of the whole workshop is also related with the warehouse energy consumption and some energy dissipating materials, which is expressed in (11). For a warehouse, its energy consumption is similar to the buffer. Apart from the energy consumption, many resources are consumed in a workshop, such as water, oxygen etc.

$$WSCE = \sum WCE_i + \sum SM_l \cdot T_l \cdot emf_l^{sm} \quad (11)$$

where emf_l^{sm} denotes the emission factor of an energy dissipating material.

C. DATA-DRIVEN MULTI-LEVEL CARBON EFFICIENCY EVALUATION

For a manufacturing workshop, there are many kinds of workpieces which have different production lot sizes, and their production quantity may change with the market demand. Considering these situations, it is not objective enough to only use carbon emission to evaluate the environmental burden of a workpiece or a manufacturing workshop. Here, the carbon emission only reflects the environmental influence of a workpiece or a machine tool. But their carbon efficiency can consider energy utilization ratio, production quantity or creative values per carbon emission. Therefore, based on the concept of eco-efficiency, some carbon efficiency indicators which consider production lot sizes and economic return are proposed, e.g., carbon emission efficiency, processing carbon efficiency, production carbon efficiency and economic carbon efficiency, etc. The definitions of these carbon efficiencies are show as flowers.

TABLE 3. Data-driven carbon efficiency evaluation indicators.

Evaluation levels	Evaluation indicators	Description	Computing methods
Single machine tool	Energy efficiency	Machine tool energy efficiency	$CEF_1^{mach} = \frac{\sum_{k=1}^{p} ME_k}{\sum_{k=1}^{p}(ME_k + AE_k)}$
	Carbon emission efficiency	Machine tool carbon efficiency	$CEF_2^{mach} = \frac{\sum_{k=1}^{p} ME_k \cdot emf^{el}}{MCE_j}$
	Processing carbon efficiency	Specific carbon emission of a machine tool	$CEF_3^{mach} = \frac{V}{MCE_j}$
Single workpiece	Carbon emission efficiency	Carbon efficiency of a workpiece	$CEF_1^{part} = \frac{\sum_{k=1}^{n} ME_{ik} \cdot emf^{el}}{WCE_i}$
	Production carbon efficiency	Specific carbon efficiency of a kind of workpiece	$CEF_2^{part} = \frac{Q_i}{WCE_i}$
	Economic carbon efficiency	Economic benefit of specific carbon emission of a workpiece	$CEF_3^{part} = \frac{Q_i \cdot P_i}{WCE_i}$
The whole workshop	Carbon emission efficiency	Carbon efficiency of workshop	$CEF_1^{shop} = \frac{\sum_{k=1}^{n} ME_{ik} \cdot emf^{el}}{WSCE}$
	Economic carbon efficiency	Economic benefit of specific carbon emission of a workshop	$CEF_2^{shop} = \frac{\sum Q_i \cdot P_i}{WSCE}$

Note: V represents the cutting volume of a machine tool, Q_i and P_i denote the quantity and unit price of a workpiece, respectively.

Definition 3: Energy efficiency is defined as the ratio of material removal energy consumption to the total energy consumption of a machine tool.

Definition: Carbon emission efficiency is defined as the ratio of carbon emission caused by material removal energy consumption to the total carbon emissions of a machine tool or a workpiece.

Definition 5: Processing carbon efficiency is defined as the ratio of material removal volumes to the total carbon emissions of a machine tool or a workpiece.

Definition 6: Production carbon efficiency is defined as the ratio of production rate of a product to the total carbon emissions of a workpiece or the whole manufacturing shop. This efficiency combines the production rate and carbon emission.

Definition 7: Economic carbon efficiency is defined as the ratio of economic return of a workpiece or a workshop to their total carbon emissions. Economic return can be understood as the economic benefits created by all the products during a certain time, which may vary with the change of the market demand.

The detailed indicators in different levels are listed in Table 3. Through the indicators, the carbon efficiency of different products in different periods can be estimated, which can be used to adjust the productive process of a workshop, such as batch configuration, production scheduling, process planning and so on.

V. CASE STUDY

A. CASE DESCRIPTION

In this paper, an auto parts manufacturing workshop which mainly conducts the rough machining of gears is researched to demonstrating the feasibility of the proposed carbon emission evaluation approach. The manufacturing shop contains three machine tools, i.e., a CNC lathe (M1), a drilling machine (M2), a gear-hobbing machine (M3).

To evaluate the carbon emission of this workshop, the following parameters are set:

1) Since the AE of a machine tool have little effect on the total carbon emission of the machine tool, it's assumed that they are constant when processing different kinds of workpieces. The main parameters of the machine tools are listed in Table 4. In addition, the water consumption is considered, which is also listed in Table 4.

TABLE 4. The main parameters of the workshop.

Machine Parameters	$AE(kJ)$	$\omega^{au}(kg\ CO_2-e/h)$
M1	15	0.16
M2	20	0.076
M3	31	0.188
$Q^{water}(L/h)$	35	

TABLE 5. The main parameters of three types of gears.

Parameters	Gear 1	Gear 2	Gear 3
Modulus(mm)	2.5	3	2.5
No. of teeth	30	40	25
Tooth width(mm)	30	30	30
Diameter of bore(mm)	22	25	13
Gear material	HT200	45#steel	HT200
Earning (Yuan)	7.4	6.5	3.5
Production rate(set/h)	16	22	18

2) In this case study, three typical types of gears are selected to evaluate the carbon emission and carbon efficiency of the workshop. The main parameters of these gears are listed in Table 5. In order to analyze the carbon emission, three different periods are chosen, and the production quantities of the gears in different periods are listed in Table 6.
3) Since the machining processes are complex, three key processes are chosen to make analysis, i.e. turning, drilling and gear-hobbing, and each process could be

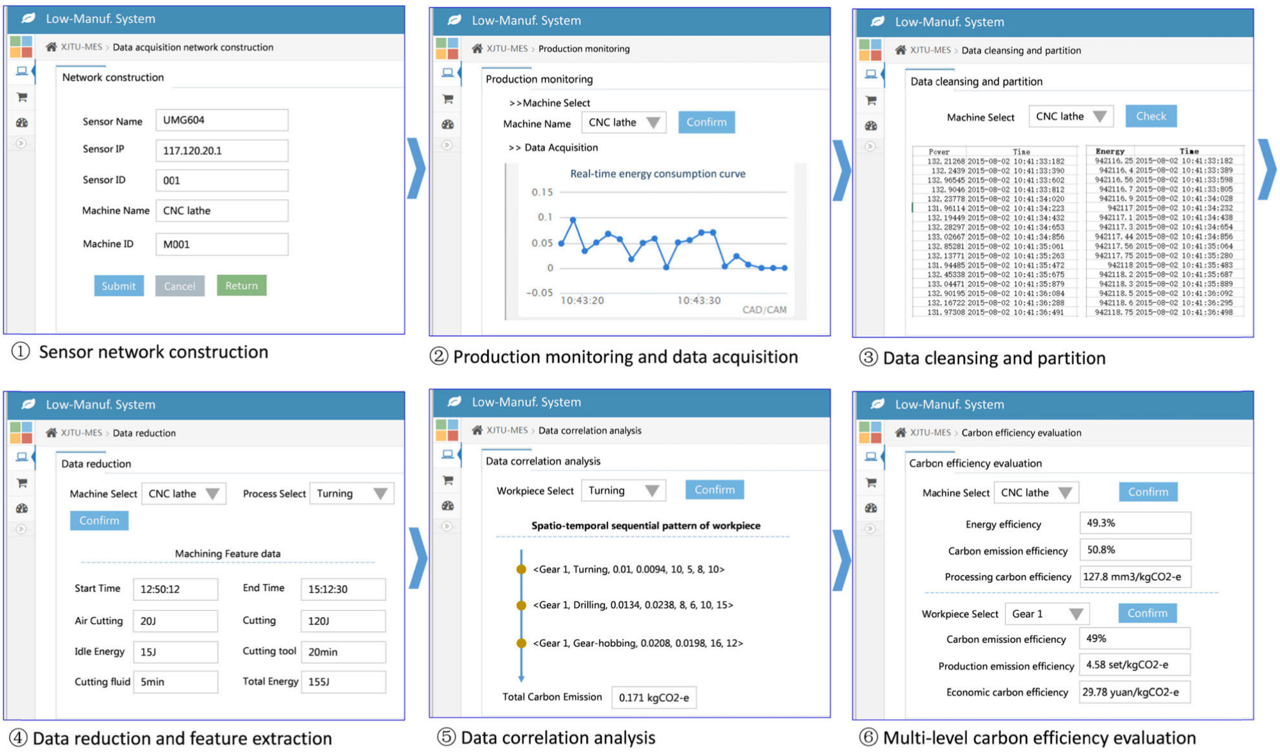

FIGURE 6. Prototype system of big data analysis and carbon efficiency evaluation.

TABLE 6. The production quantities of the gears in different periods.

Gear/set	Period 1	Period 2	Period 3
Gear 1	150	220	250
Gear 2	200	370	200
Gear 3	150	50	100

TABLE 7. The processing parameters of each process.

Machines	M1			M2			M3		
Parameters	t	V	ω^{tool}	t	V	ω^{tool}	t	V	ω^{tool}
Gear 1	21	6.62	0.162	16	11.4	0.058	42	9.5	0.250
Gear 2	13	7.54	0.144	20	14.73	0.062	35	8.8	0.194
Gear 3	11	4.18	0.122	13	3.98	0.068	26	7.9	0.228

executed on the corresponding machines. The processing parameters of each process are listed in Table 7, which include the processing time $t(s)$, the removal volume $V(cm^3)$ and $\omega^{tool}(kgCO_2 - e/h)$ of cutting tools.

B. PROTOTYPE SYSTEM FOR THE REAL-TIME CARBON EFFICIENCY EVALUATION

For the manufacturing workshop, data acquisition networks are established firstly through monitoring devices in Table 2. The energy consumption data of machine tools and buffers are monitored by Janitza UMG 604E, whereas Gears are located through Alien ALR-F800 RFIDs. Meanwhile, some flowmeters are deployed to record the quantity of flow. Based on the data acquisition networks, a prototype system is developed to realize the carbon efficiency evaluation, as show in Fig. 6. This prototype system is a browser/server (B/S) architecture, which is developed by using Spring–Struts2–Hibernate (SSH2) framework under Java Web environment on the server side, and HTML5/ CSS/JavaScript on the browser side. It is recommended to use Google browser for browsing. There are mainly six function blocks, i.e., sensor network construction, production monitoring and data acquisition, data cleansing and partition, data reduction and feature extraction, data correlation analysis and multi-level carbon efficiency evaluation.

The operation procedures of the prototype system are described as follows:

1) SENSOR NETWORK CONSTRUCTION

Several sensors are deployed on machine tools, buffers and transportation facilities, and the connection between equipment and sensors is built.

2) PRODUCTION MONITORING AND DATA ACQUISITION

After the sensor configuration, the production state data can be acquired through the stationary RFID readers and handheld RFID readers. Meanwhile, the data of energy consumption, cutting tool and cutting fluid about a machine tool can be gathered. And then the real-time energy curve will be plotted and the frequency of data collection is three in one second. The workshop has been monitored and analyzed for two weeks continuously to achieve carbon efficiency evaluation. Measured data is transmitted through the Internet-router embedded in monitoring devices, and then stored in Hadoop for Big Data processing and analysis.

3) DATA CLEANSING AND PARTITION

The rural data are detected and remove some noise data for production and energy data, which are incomplete or unreasonable.

4) DATA REDUCTION AND FEATURE EXTRACTION

For the cleansed data, the data reduction algorithm based on FCM clustering is used to divide the continuous energy consumption data according to machining process and machining stage of a machine tool.

TABLE 8. Validity test of the data reduction algorithm.

Test No.	Sample size	Average time (s)	Average iterations (times)	Average accuracy (%)
1	750	0.12	16	99.5
2	4685	0.47	18	99.2
3	8325	0.85	28	98.9

In order to verify the efficiency of the proposed algorithm, three test data with different sizes during turning process are used, i.e, 750, 4685 and 8325. The weighting exponent of fuzzy degree β is set as 2, the number of cluster centers$c$ is 4, and the minimum amount of improvement for FCM is 10^{-7}. The test results are listed in Table 8. From the results, it can be seen that the average time is 0.12s for sample data with 750, which means the algorithm is efficient for the energy consumption data clustering. Meanwhile, for these three tests, all the average accuracies are above 98%, and for sample data with 750, the average accuracy reaches 99.5.

And then the energy consumption of each process and each machining stage can be deduces. For sample data with 750, the raw energy consumption data and reduction results are shown in Fig. 5. The energy consumption of standy, idle, air cutting and cutting states are 7.7W·h, 28.5W·h, 88.4W·h and 201.1W·h, respectively. Meanwhile, it can be clearly seen that there is much energy consumption which is not used to cutting workpiece, which will be analyzed in detail in Section V.C. This algorithm can aggregate and condense the data record, then improve the data with high information density.

5) DATA CORRELATION ANALYSIS FOR CARBON EMISSION PATTERN

Based on the feature data, the data correlation analysis is conducted to mine the spatio-temporal sequential patterns of carbon emission. Also, carbon emission of different levels can be obtained.

6) MULTI-LEVEL CARBON EFFICIENCY EVALUATION

Based on the proposed evaluation method in Section IV.C, the carbon efficiency evaluation can be conducted to calculate the carbon efficiency of each machine tool, a workpiece or the whole workshop. The evaluation results will be used to support production control decision.

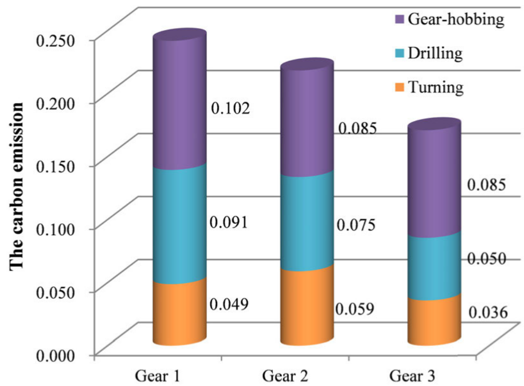

FIGURE 7. Carbon emission of the three gears and their processes.

C. CARBON EFFICIENCY EVALUATION AND DISCUSSIONS

Based on the proposed Big Data analysis and carbon efficiency evaluation methods, the carbon emission and carbon efficiency are analyzed from three aspects, i.e., machine tool, processes, workpiece and workshop. Firstly, the carbon emission of the gears and their processes are obtained as illustrated in Fig. 7. It can be clearly seen that the carbon emission of Gear 1 is more than that of other gears, and Gear 3 generates the least carbon emission, which is about 0.171 $kgCO_2 - e$. In terms of processes, the gear-hobbing process is the most carbon-intensive in the machining processes of a gear, which is responsible for about 40%-50% of carbon emission of each gear. And the second is drilling process. Therefore, the machining parameter adjustment and optimization of the gear-hobbing and drilling process are more effective to reduce the carbon emissions of gears, especially for Gear 3.

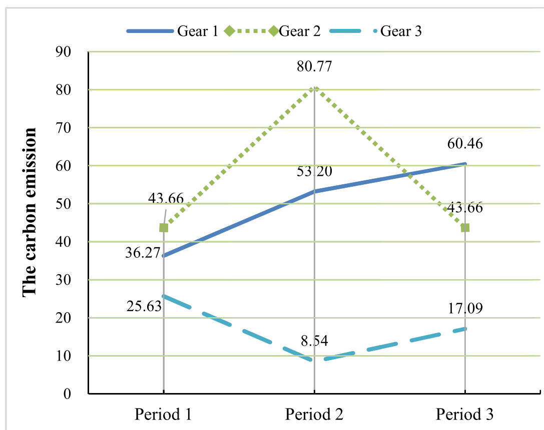

FIGURE 8. Carbon emission of the three gears in different periods.

Then, the carbon emission of the gears in different periods are analyzed, as shown in Fig. 8. The carbon emission in

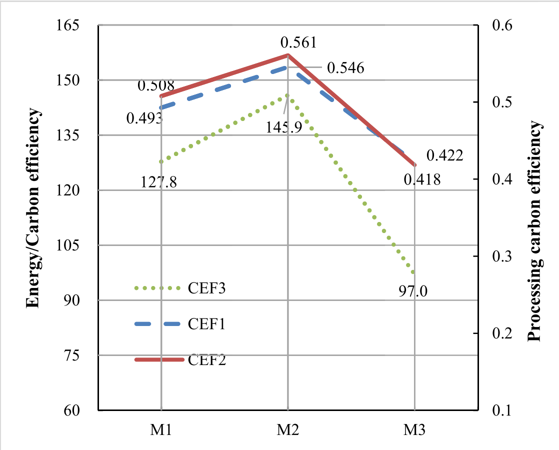

FIGURE 9. Carbon efficiency of machine tools in Period 1.

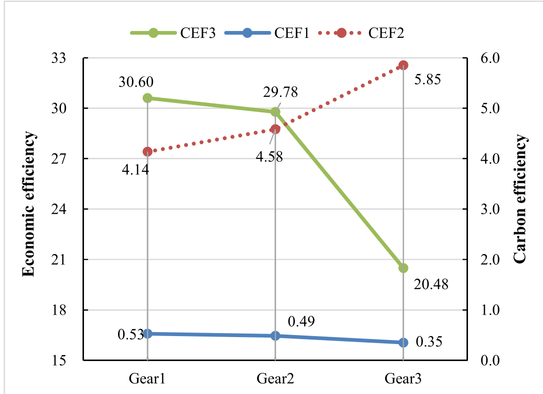

FIGURE 10. Carbon efficiency of the three gears in Period 1.

different periods are various, and that of Period 2 are the most, which reaches $142.51 kgCO_2 - e$. Whereas that of Period 1 is the least. In terms of workpieces, Gear 3 is always the least in the three periods. Gear 2 takes the highest proportion in Period 1 and Period 2. Whereas Gear 1 takes the highest proportion in Period 3, which reaches $60.46 kgCO_2 - e$. Although the total carbon emission is related to the quantity of each gear, the carbon emission of each gear has a bigger influence. For example, in Period 1, the quantity of Gear 1 and Gear 3 is the same, but the carbon emission of them is different. Meanwhile, from the total carbon emission, it can be also seen that Gear 2 takes a larger carbon proportion, and some methods should be taken to improve its carbon efficiency to reduce the total carbon emission.

The carbon efficiency of machine tools in Period 1 is analyzed in Fig. 9. From the results, it can be seen that the energy efficiency of M2 are the best, which reaches 0.546, and that of the other two machine tools cannot surpass 50%. Similar to the energy efficiency, the carbon efficiency of M2 are the highest, which is 0.561. The results show that the efficiency of M2, that is, the drilling machine, is the best in the workshop. Most of the energy consumption or carbon emission of M2 are used in machining processes. For the processing carbon efficiency, M2 is also the best, which reaches $145.9 cm^3/kgCO_2 - e$. In above, M2 is the most efficient in this workshop. M3 is the least and should be improved.

In Period 1, the carbon efficiency and economic efficiency of gears are calculated, which is shown in Fig. 10. It's obvious that the carbon efficiency of Gear 1 is the highest, which reaches 0.53. That of Gear 3 is the least, which means Gear 3 wasted lots of carbon emissions. For production carbon efficiency, Gear 3 is the best, which is 5.85 $set/kgCO_2 - e$. By comparing the production carbon efficiency with the carbon emission of a gear, they have an inverse proportion relationship. For the workshop, its production carbon efficiency has a linear combination relationship with the production quantities of the gears, and varies with time because the production carbon efficiency of each gear is different. Moreover, the economic carbon efficiency of Gear 1 is the best, which is 30.60 $yuan/kgCO_2 - e$. That means Gear 1 will create the most economic value by generating the same carbon emission.

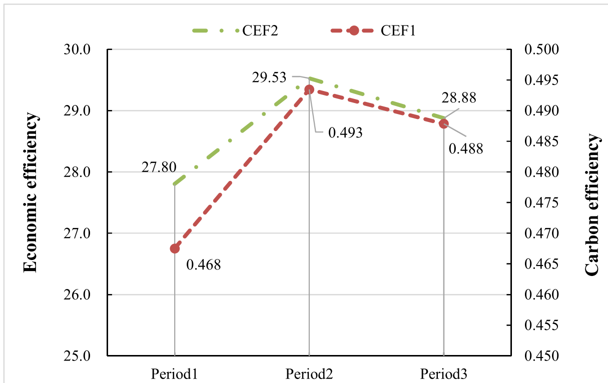

FIGURE 11. Carbon efficiency of the workshop in different periods.

In addition, the carbon efficiency of workshop in different periods is analyzed in Figure 11. The workshop in Period 2 realizes the most carbon efficiency, which is 0.493. But the carbon efficiency of the workshop in different periods change little, which is 46.8%, 49.3% and 48.8% successively. Moreover, it's found that the economic efficiency of the workshop increases from 27.8 $Yuan/kgCO_2 - e$ to 29.53 $Yuan/kgCO_2 - e$ from Period 1 to Period 2. Since only Gear 1 and Gear 2 increase from Period 1 to Period 2, these two gears have a positive influence on the whole economic efficiency. Therefore, it is an efficient method to increase the production quantity of Gear 1 and Gear 2 to improve the economic carbon efficiency of the whole workshop.

From the above comparison and analysis, the proposed Big Data analysis and carbon efficiency evaluation approach is an efficient one for solving the carbon emission evaluation problem. In the real implementation process, some observations and insights can be drawn as follows:

1) The proposed method integrates IoT, Big Data analysis, and low-carbon manufacturing, which is an important

content of intelligent manufacturing. This method will have a wide application prospect under the background of industrial Internet and low-carbon manufacturing.

2) The method can be used to evaluate the carbon emission of mechanical product, which can also be integrated into low-carbon design of products. Meanwhile, the carbon efficiency evaluation can be used as a performance evaluation index of a machine tool or a workshop to realize the improvement of a production system.
3) In addition, there are also some drawbacks in the proposed method which will be researched in the future work. For example, even though the proposed method can apply to discrete manufacturing shops, some complicated situations have been neglected, such as machine tool fault, production halts, or process adjustment, etc.

VI. CONCLUSION

In order to reduce the carbon emission of a discrete manufacturing workshop, a Big Data analysis approach for real-time carbon efficiency evaluation of discrete manufacturing workshops is proposed. Firstly, the deployment of data acquisition devices is introduced to create a ubiquitous manufacturing workshop, and a data modeling of production state and carbon emission is described. Then, a real-time multi-level carbon efficiency evaluation method of manufacturing workshops is established based on Big Data analysis approach. This method involves manufacturing data cleansing, data partition, data reduction and data correlation analysis. The proposed method in this paper realizes the combination of manufacturing Big Data and low-carbon production. Meanwhile, the evaluation method can be used in other production information systems and then assist the production decision-making, e.g., product design, process planning and production scheduling.

Future research in this area will include the establishment of association relationship between carbon efficiency and critical production parameter to find the carbon-intensive factors at the bottom of a workshop. Although the proposed method can apply to discrete manufacturing shops, some complicated situations have been neglected, such as machine tool fault, production halts, or process adjustment, etc. So more pragmatic approaches need to be established. Furthermore, based on the proposed carbon efficiency method, some optimization methods can be adopted to optimize the production lot size or the scheduling plan to reduce the carbon emission.

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CHAOYANG ZHANG received the B.S. degree from the China University of Mining and Technology, Xuzhou, China, in 2011, and the Ph.D. degree from Xi'an Jiaotong University, Xi'an, China, in 2016, both in mechanical engineering.

He is currently a Lecturer with the Department of Mechanical Engineering, Jiangnan University, Wuxi, China. His current research interests include low-carbon manufacturing, cleaner production, and manufacturing execution systems.

WEIXI JI received the Ph.D. degree in mechanical engineering from the Nanjing University of Aeronautics and Astronautics. He is currently a Professor with the School of Mechanical Engineering, Jiangnan University, Wuxi, China. His research interests include product digital design, intelligent manufacturing, and advanced manufacturing technology.