Edge Computing Enabled Production Anomalies Detection and Energy-Efficient Production Decision Approach for Discrete Manufacturing Workshops

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ABSTRACT Due to the complexity and dynamics of manufacturing processes, there are various production anomalies in a discrete manufacturing workshop, which have a strong impact on manufacturing quality and productivity. Meanwhile, with the rapid development of Internet of Things technology and communication technology, data store and timely response become new challenges for production anomalies detection. Thus, an edge computing enabled production anomalies detection and energy-efficient production decision approach is proposed in this study. Firstly, an architecture of edge computing enabled production anomalies detection and energy-efficient rescheduling approach is introduced. Then, considering that the raw energy data are always large, isolated and messy, an energy consumption data preprocessing algorithm is established, and production anomaly analysis model is constructed based on long short-term memory network. When an anomaly occurs, an energy-efficient production decision making will be triggered. Finally, through a case analysis of a milling manufacturing system, the results show that the anomaly detection error of the proposed method is only 3.5%. This method realizes the combination of energy consumption data and manufacturing system anomalies detection, and can further assist production process monitoring and energy conservation.

INDEX TERMS Edge computing, production anomalies detection, energy-efficient, long short-term memory network, discrete manufacturing workshops.

I. INTRODUCTION

Due to the complexity and dynamics of manufacturing processes, various production anomalies occur frequently in a manufacturing workshop, such as spindle failure, cutting tool wear, order modification or cancellation, control system failures, timing anomaly, etc. [1]. These anomalies tend to decrease manufacturing quality and productivity, and are severe challenges for companies to maintain the best energy performance. Thus, it is significant to conduct anomaly detection to perform efficient analysis on condition data acquired from machines and processes in order to detect potential failures in early stages [2]. In order to detect abnormal conditions in the production process in time, many studies have been conducted through analyzing various manufacturing signals, such as equipment pressure [3], bearing vibration [4], energy consumption [5], multi-signal integration [6], etc. Based on these data, production anomalies can be obtained before generating a serious impact.

With the rapid development of Internet of Things technology and communication technology, the current manufacturing workshop is gradually transformed into a smart workshop, and the amount of data in the manufacturing workshop has also exponentially increased, regardless of the amount of data, the type of data, or the speed of data change. Recently, via the computing and storage capabilities of cloud centers, many cloud systems have been developed to improve accuracy and reliability in predicting resource needs and allocation, maintenance scheduling, and remaining service life of equipment [7]. Conversely,
the systems also produce the problems of big data transmission and high latency. To overcome the limitation of cloud systems, a new computing paradigm, edge computing, has been applied in many cases [8]. Edge computing has the potential to address the concerns of response time requirement, battery life constraint, bandwidth cost saving, as well as data safety and privacy [9]. Also, this method provides a new solution for production anomaly detection.

However, there are mainly two research gaps in current studies. Firstly, vibration and pressure signals are often used to predict production abnormalities, and how to combine energy consumption data with anomalies detection is still lacking. Secondly, current research on energy consumption data is often based on experimental process data. It is a challenge to mine and analyze real-time continuous energy consumption data. In order to bridge these gaps, an edge computing enabled production anomalies detection and energy-efficient control approach in discrete manufacturing workshops is proposed. The approach mainly includes two contributions: 1) Edge computing is involved in the production anomalies detection to realize the timely response, 2) Considering the continuity and dynamics of machining processes, an energy consumption data preprocessing and production anomaly detection method is established based on long short-term memory network (LSTM).

The rest of the study is organized as follows. In Section II, references on manufacturing energy data analysis and edge computing, and energy data-driven production anomaly detection are mentioned. Section III introduces an edge computing enabled production anomalies detection and energy-efficient decision architecture. Then, an energy consumption data preprocessing and production anomaly analysis approach is established based on LSTM in Section IV. Section V describes the decision making of energy-efficient rescheduling. In section VI, a case is studied to verify the feasibility of the proposed methods. The main works and future research directions are concluded in Section VII.

II. LITERATURE REVIEW

A. MANUFACTURING ENERGY DATA PROCESSING AND EDGE COMPUTING

In a discrete manufacturing process, manufacturing systems which includes a machine tool, cutting tools and fixtures are the main source of energy consumption. Thus, the study of manufacturing system energy consumption has attracted more and more researchers’ attention. In order to reduce the energy consumption of manufacturing systems, scholars have conducted research from different perspectives, e.g., optimization of processing parameters [10], the state control of machine tools [11], process planning [12], and production scheduling [13]. Due to the complexity and dynamic of manufacturing processes, the energy consumption data of manufacturing systems present the characteristics of continuity and dynamic fluctuation. The primary task of the above research is to process and analyze energy consumption data. Through establishing regression relationship models between milling parameters and energy consumption data, Zhang et al. presented a systemic optimization approach to identify the Pareto-optimal values of some key process parameters for energy-efficient milling operation [14]. Wang et al. proposed a real-time energy efficiency optimization method for energy-intensive manufacturing enterprises based on IoT technology [15].

With the rapid development of Internet of Things technology and communication technology, the amount of data in a manufacturing workshop has also exponentially increased, which presents the characteristics of Big Data. The technology of industrial big data also provides a new way of thinking for energy consumption analysis. In order to improve the energy efficiency of dyeing processes, Park et al. (2019) developed a cyber physical energy system through using machine learning techniques and manufacturing big data [16]. A Big Data driven analytical framework was proposed to reduce the energy consumption and carbon emission for energy-intensive manufacturing industries [17]. Considering the complexity of discrete manufacturing workshops, Zhang and Ji proposed a Big Data analysis approach for real-time carbon efficiency evaluation of discrete manufacturing workshops in an internet of things-enabled ubiquitous environment [18].

In addition, the proliferation of Internet of Things (IoT) has pushed the horizon of a new computing paradigm, edge computing, which has the potential to address the concerns of response time requirement, battery life constraint, bandwidth cost saving, as well as data safety and privacy [9]. Due to these advantages, edge computing has been used in many areas, such as mobile applications [19], video analytics, smart home and smart city [9]. Meanwhile, edge computing has been researched in smart manufacturing. Lin et al. proposed a smart manufacturing factory framework based on edge computing, and further investigated the job shop scheduling problems under such a framework [20]. In order to provide the right manufacturing resources for subsequent production steps, an IoT edge computing enabled collaborative tracking system was developed to for manufacturing resources in industrial park [21]. For the purpose of recognizing industrial equipment accurately in manufacturing systems, Lai et al. adopted the LSTM to analyze big data features and built a noninvasive load monitoring system, and edge computing was used to implement parallel computing to improve the efficiency of equipment identification [22].

From the above review, the manufacturing energy data processing have been studied in many literature, but most of them ignored the problems of data storage and latency. And these problems seriously restricts the implementation of the related methods. Edge computing brings a new solution for this problem, which store and process part of these data at the edge of the network or device terminal.
B. ENERGY DATA-DRIVEN PRODUCTION ANOMALY DETECTION

In a manufacturing workshop, production anomalies have a strong impact on manufacturing quality and productivity, and bring great challenge to production management. These anomalies include spindle failure, cutting tool wear, order modification or cancellation, control system failures, timing anomaly, etc. Thus, it is a research hotspot to detect these anomalies before a big failure. Lindemann et al. compared two data-driven self-learning approaches that are used to detect anomalies within large amounts of machine and process data, and tested the approaches on the basis of real industrial data from metal forming processes [3]. Due to the complex working conditions, bearing vibration signals always suffer from serious noise. Thus, He et al. proposed a novel method that utilizes LSTM with multi-resolution singular value decomposition to predict bearing performance degradation [4]. A data mining approach using a machine learning technique called anomaly detection was presented [23], which employed classification techniques to discriminate between defect examples of rolling-element bearing failures. Cyber-physical Systems (CPS) is a key concept for smart manufacturing, and analysis of complex machines as CPS can support anomaly detection and diagnosis by providing the required data to model different operational conditions. Thus, Saez et al. developed a hybrid model of manufacturing machines to estimate operational state based on machine functionality, dynamics, and interactions [24]. Xu et al. proposed a novel integrated model based on deep learning and multi-sensor feature fusion to realize the intelligent monitoring and diagnostics [6].

In addition, manufacturing system anomalies are also associated with energy consumption, and it has been proved that tool wear progression has a predominant influence on energy consumption at the process level [5]. Considering that Big Data driven approach has become a new trend for manufacturing optimization, Wang et al. developed an innovative Big Data enabled Intelligent Immune System to monitor, analyse and optimise machining processes over lifecycles. This method used an Artificial Neural Networks (ANNs)-based algorithm and statistical analysis tools to identify the abnormal electricity consumption patterns of manufactured components from monitored Big Data [1]. Liang et al. presented an innovative fog enabled prognosis system for machining process optimization [25]. In this system, Convolutional Neural Network (CNN) based prognosis was implemented to detect potential faults from customized machining processes.

From the above research, there are many anomaly studies on the production data, but the use of energy data is few. Although it has been proven that the production anomaly during the metal cutting processes will lead the fluctuate of energy consumption data, it is still a research difficulty that how to use energy consumption data to detect the anomalies of production systems.

III. EDGE COMPUTING ENABLED PRODUCTION ANOMALIES DETECTION AND ENERGY-EFFICIENT DECISION ARCHITECTURE

It has been proved that energy consumption data can indicate the working and cutting tools conditions of machine tools [25]. Meanwhile, these data are easy to be captured, therefore, these energy consumption data are collected for production anomalies detection in this study. In addition, considering the computation efficiency and latency of data transmission, edge computing paradigm is adopted to construct the system architecture. The whole architecture is illustrated in Fig. 1, and there are three layers from the bottom to the top,
i.e., data connection layer, edge layer and cloud layer. Some details will be elaborated in the Section IV and Section V.

1) DATA CONNECTION LAYER
As shown in Fig. 1, data connection layer covers the whole discrete manufacturing processes from raw materials to finished products. This layer can connect the physical machine tools and edge layer via sensor devices. Each machine tool is configured with an electric meter, and the energy consumption data of machine tools are continuously collected and transmitted to the fog layer for further processing through RS232, internet or Modbus. If an anomaly has been detected, the cloud layer will decide whether or not to make rescheduling. And the control strategies will be transmitted to the machine tools to realize the optimization of machine processes.

2) EDGE LAYER
Since the acquired original energy data are massive, isolated and littery, they cannot be used to detect the production state directly. Thus in Edge layer, a data preprocessing approach for integratedly analyzing the energy consumption data is established, which includes energy data cleansing, data partition and feature extraction. Then, abnormal situations can be detected using the trained LSTM on edge layer without relatively long transmission time of the energy consumption data to the cloud layer. The anomaly result can be fed back to the machine tool through a terminal device and it will be interrupted immediately for maintenance and adjustment process if an anomaly occurs.

3) CLOUD LAYER
After the data processing and production anomaly detection, this layer has databases to store the anomaly data for future use. Meanwhile, the LSTM model for anomaly detection will be updated periodically and redeployed on the edge layer. In addition, once a production anomaly occur, a maintenance process will be conducted. In order to reduce the influence of production anomaly on production progress, some rescheduling strategies will be adopted. And the chosen strategy will be transmitted to the data connection layer to adjust the machining processes. This layer is regarded as a resilient control system to make preventive decisions to the production system.

IV. ENERGY CONSUMPTION DATA PREPROCESSING AND PRODUCTION ANOMALIES DETECTION
A. ENERGY CONSUMPTION DATA ACQUISITION AND PREPROCESSING
The discrete manufacturing workshop covers the entire discrete manufacturing process from raw materials to semi-finished products or finished products, and a large amount of energy will be consumed during the machining processes of workpieces. For collecting energy consumption data, electric meters are deployed on each machine tool. After the real-time energy data have been captured, data transmission and integration can be achieved through Industrial Ethernet/RS232/Modbus. However, the raw energy data are always large, isolated, and messy, which cannot be directly applied to the analysis of production anomalies. Therefore, a preprocessing method for energy consumption data for production anomaly analysis has been established, including energy consumption data cleaning and data partition.

1) ENERGY CONSUMPTION DATA CLEANSING
The first step of data preprocessing is data cleansing. The purpose of this step is to detect and delete unreasonable data from energy consumption data, including noise and incomplete ones. In the actual machining process, since the machine tool, tool vibration and workpiece material will affect instantaneous power, the validity of each energy consumption data is judged mainly from the two aspects, i.e., acquisition time rationality and energy value validity. The pseudocode of data cleansing is shown in Fig. 2.

FIGURE 2. The pseudocode of energy consumption data cleansing algorithm.

2) ENERGY CONSUMPTION DATA PARTITION OF MANUFACTURING PROCESSES
For a manufacturing system, due to the continuity of machining processes, the collected energy consumption data often cover multiple machining processes. Thus the energy consumption data need to be divided and energy consumption data for different processes should be obtained. Through recording the start time and end time of a process to obtain time node information, the continuous and massive energy consumption data can be divided according to specific process. In addition, according to the energy consumption curve of a machining process in Fig. 3, it can be seen that a process mainly contains five states: downtime, standby, idle, air cutting and cutting [26]. Since the difference among energy consumption data of different states is obvious, the energy data of each state needs to be obtained for production anomalies analysis. To this end, the data clustering method is adopted to extract the energy data of different states.

Data clustering is a method to divide the data of the same category into a specific number of groups. Since the power curve of a process is dynamic and continuously changing,
some transient process data cannot be absolutely divided into a certain stage. Thus, this clustering problem is a fuzzy one. The most successful technique in fuzzy cluster analysis is Fuzzy C-means (FCM) clustering, which has been widely used in the theory and practical application, especially time series data [27]. FCM clustering is a fuzzy clustering method proposed by Bezdek [28]. In this study, the input data is the energy consumption data \( P = \{p_1, p_2, \ldots, p_i, \ldots, p_n\} \) which have been cleansed, and the aim is to cluster the above data set into \( C \) clusters and achieve the least distance of each input energy consumption data set in its cluster to its cluster center. The total distance of the data set \( P \) can be defined as:

\[
J_\beta (P, V, U) = \sum_{j=1}^{C} \sum_{i=1}^{n} u_{i,j}^\beta d^2(p_i, v_j)
\] (1)

where \( \beta \) is the weighted index of fuzzy degree (\( \beta > 1 \)), \( C \) is the number of cluster centers, \( p_i \) represents the input energy consumption data, \( u_{i,j} \) represents the membership degree of a certain data, \( v_j \) represents the \( j \)th cluster center, and \( d(p_i, v_j) \) is the distance between the energy consumption data \( p_i \) and the cluster center \( v_j \). Through analyzing the energy consumption curve, it can be seen that four states are important for energy consumption, i.e., standby, idle, air cutting, and cutting. Thus the number of cluster center \( C = 4 \). \( J_\beta \) should be minimized under the constraints below:

\[
0 \leq u_{i,j} \leq 1, \quad \forall i, j
\] (2)

\[
0 \leq \sum_{i=1}^{n} u_{i,j} \leq n, \quad \forall j
\] (3)

\[
\sum_{j=1}^{C} u_{i,j} = 1, \quad \forall i
\] (4)

The process of minimizing \( J_\beta \) is implemented through an iterative algorithm. In each iteration, the values of \( u_{i,j} \) and \( v_j \) are updated by using the following formula:

\[
v_j = \frac{\sum_{i=1}^{n} u_{i,j}^\beta p_i}{\sum_{i=1}^{n} u_{i,j}^\beta}
\] (5)

\[
u_{i,j} = \frac{1}{\sum_{k=1}^{4} \left( \frac{d(p_i, v_k)}{d(p_i, v_j)} \right)^{2/(\beta-1)}}
\] (6)

B. PRODUCTION ANOMALY ANALYSIS BASED ON LSTM

1) ENERGY DATA MODELING FOR PRODUCTION ANOMALY ANALYSIS

For a manufacturing process, its production anomalies can be divided into two categories: dominant anomalies and recessive anomalies [29]. Here, the former one refer to tool breakage, machine breakdown, rush orders, and shortage of material supply, etc., which play a decisive role in the normal manufacturing operations. The latter one refer to those anomalies that influence the manufacturing operations of a production system as the accumulation of anomalies, e.g., tool wear, machine tool degradation, etc [30] Since dominant anomalies are easy to be detected, only the recessive anomalies are analyzed in this study, i.e., tool wear and machine degradation. These two anomalies are highly related with energy consumption [1]. Thus, the pre-processed energy consumption data are used to detect the recessive anomalies in time.

Since the energy consumption data of different states fluctuates dynamically, some statistical feature parameters are extracted as the input data, including the maximum, minimum, average and standard deviation. In order to ensure the accuracy of the analysis, the analysis interval is set as 3 minutes, so that the operator can find the production anomaly in time and prepare in advance. The maximum and minimum energy consumption data for each processing state within a certain period of time are denoted as follows:

\[
Max_i^t = \max_{p_i' \in P_i^t} p_i'
\]

\[
Min_i^t = \min_{p_i' \in P_i^t} p_i'
\]

where \( Max_i^t \) and \( Min_i^t \) represent the maximum and minimum energy consumption data of the \( i \)th machining state, \( i = 1, 2, 3, 4 \) which indicate standby, idle, air cutting and cutting, \( P_i^t \) represents the energy consumption data set, and \( p_i' \) represents the \( j \)th energy consumption data for the \( i \)th machining state.

The average value and standard deviation of energy consumption data are denoted as follows:

\[
Mean_i^t = \frac{1}{N_i^t} \sum_{j=1}^{N_i^t} p_i^t
\]

\[
Var_i^t = \sqrt{\frac{1}{N_i^t-1} \sum_{j=1}^{N_i^t} (p_i^t - Mean_i^t)^2}
\]

where \( N_i^t \) represents the energy consumption data number of the \( i \)-th machining state \( P_i^t \).

Considering the continuity feature of energy consumption data, LSTM is adopted to establish a production anomaly analysis model, and its input data contain the above statistical feature parameters:

\[
x^t = [\text{Max}_1^t, \text{Min}_1^t, \text{Mean}_1^t, \text{Var}_1^t],
\]

\[
[\text{Max}_2^t, \text{Min}_2^t, \text{Mean}_2^t, \text{Var}_2^t],
\]

\[
[\text{Max}_3^t, \text{Min}_3^t, \text{Mean}_3^t, \text{Var}_3^t],
\]

\[
[\text{Max}_4^t, \text{Min}_4^t, \text{Mean}_4^t, \text{Var}_4^t]
\] (11)
In a machining process, the above energy feature parameters can be used to judge whether there is a production anomaly. As mentioned earlier, in this study, each manufacturing system mainly has three anomalies, i.e., no anomaly, machine tool degradation and tool wear.

2) CONSTRUCTION OF LSTM MODEL

In order to analyze its anomaly, an analysis method based on LSTM is constructed. LSTM is a type of recurrent neural network (RNN). RNN is a feed-forward neural network that enhances the performance of the network by building links that span adjacent time steps. These links are connected by self-circulation in time, creating a time dimension for the RNN model, as shown in Fig. 4.

![Figure 4. Basic structure of RNN.](image)

FIGURE 4. Basic structure of RNN.

Suppose that there is a set of energy consumption characteristic data \( X = [x^1, x^2, \ldots, x^t, \ldots, x^T] \). Since these input data have different magnitudes, they need to be normalized:

\[
\begin{align*}
\text{Max}_i'' &= \frac{\text{Max}_i' - \text{Max}_i^b}{\text{Max}_i^u - \text{Max}_i^b}, \quad i = 1, 2, 3, 4 \\
\text{Min}_i'' &= \frac{\text{Min}_i' - \text{Min}_i^b}{\text{Min}_i^u - \text{Min}_i^b}, \quad i = 1, 2, 3, 4 \\
\text{Mean}_i'' &= \frac{\text{Mean}_i' - \text{Mean}_i^b}{\text{Mean}_i^u - \text{Mean}_i^b}, \quad i = 1, 2, 3, 4 \\
\text{Var}_i'' &= \frac{\text{Var}_i' - \text{Var}_i^b}{\text{Var}_i^u - \text{Var}_i^b}, \quad i = 1, 2, 3, 4
\end{align*}
\]

where \( \text{Max}_i^u, \text{Min}_i^u, \text{Mean}_i^u, \text{Var}_i^u \) represent the upper limit values of the maximum, minimum, mean value and standard variance of energy consumption data, respectively. \( \text{Max}_i^b, \text{Min}_i^b, \text{Mean}_i^b, \text{Var}_i^b \) denote the lower limit values of the maximum, mean value and standard variance of energy consumption data.

According to Fig. 4, at time \( t \), the hidden layer obtains the input data \( x^t \) from the input layer, and also obtains \( h^{t-1} \) from the previous state value. The output \( y^t \) at this time can be expressed as:

\[
\begin{align*}
h^t &= f(W_x x^t + W_h h^{t-1} + b_h) \\
y^t &= g(W_y h^t + b_y)
\end{align*}
\]

where \( f(\cdot) \) and \( g(\cdot) \) represent the activation function, \( y^t \) represents the output of the RNN at time \( t \), \( W_x \) represents the weight parameter between the input layer and the hidden layer, and \( W_h \) represents the hidden layer, \( W_y \) represents the weight parameter between the hidden layer and the output, and \( b_h \) and \( b_y \) represent the offset of the RNN.

Unlike feed-forward neural networks, RNN can use internal state parameters to record changes of input data over time. The training of RNN is similar to the ordinary neural network using back propagation. But due to the additional time dimension, the training process has the problem of gradient disappearance, which makes it impossible to capture long-term memory of time series data [31]. As an improvement of RNN, Hochreiter and Schmidhuber proposed LSTM to overcome the above problems by introducing long-term memory and short-term memory [32]. The overall structure of LSTM model is shown in Fig. 5. An LSTM cell consists of an input gate, a forget gate and an output gate. These functional gates can effectively control the data flow in the unit and the network to realize the retention and screening of the information at the previous time [6]. The input gate \( f^t \) is used to control the input information, the forget gate \( f^t \) determines the amount of information forgotten in the previous cell, and the output gate \( o^t \) is to control the output information of the hidden layer unit.

![Figure 5. LSTM model for production anomaly analysis.](image)

FIGURE 5. LSTM model for production anomaly analysis.

1) The forget gate

\[
f^t = \sigma (W_f \cdot [h^{t-1}, x^t] + b_f)
\]

where \( \sigma (\cdot) \) represent the activation function, and \( W_f \) and \( b_f \) represent the weight parameter and offset of the forget gate.

2) The input gate

\[
\hat{f} = \sigma (W_i \cdot [h^{t-1}, x^t] + b_i)
\]

where \( \sigma (\cdot) \) represent the activation function, and \( W_i \) and \( b_i \) represent the weight parameter and offset of the input gate.

3) Update of the memory unit

\[
\begin{align*}
\hat{C}^t &= \tanh (W_C \cdot [h^{t-1}, x^t] + b_C) \\
C^t &= f^t \otimes C^{t-1} + \hat{f} \otimes \hat{C}^t
\end{align*}
\]

where \( W_C \) and \( b_C \) represent the weight parameter and offset of the memory unit, \( C^t \) represents the unit state at time \( t \), and \( \otimes \) denotes array elements multiplication in turn.
(4) The output gate

\[ o' = \sigma(W_o \cdot [h^{t-1}, x^t] + b_o) \]  

\[ h^t = o' \otimes \tanh(C^t) \]  

where \( W_o \) and \( b_o \) represent the weight parameter and offset of the forget gate.

In addition, considering that a manufacturing system is usually maintained after an anomaly occurs, it is important to analyze the data after the last maintenance. In order to highlight the importance of this part of data, an attention strategy is introduced to the output. The strategy can increase the weight of the output information of this period, so as to realize the indirect correlation between the final output and the most relevant input. The attention strategy is shown as follows:

\[ a' = \tanh(W_a \cdot h^t + b_a) \]  

\[ \alpha' = \frac{\exp(u' \cdot a_u)}{\sum_{t=1}^{T} \exp(u' \cdot a_u)} \]  

\[ y' = \sum_{t} \alpha'^t h^t \]  

where \( W_a \) and \( u_a \) represent the weight parameters of the attention strategy, \( b_a \) represents the offset, and \( \alpha' \) denotes the weight parameter of the final output \( y' \).

3) TRAINING ALGORITHM OF THE LSTM MODEL

After the model construction of the LSTM, it is necessary to use the labeled energy consumption data set to train the model parameters. The training process actually means the optimization of the following loss functions:

\[ y = \frac{\sum_{t=1}^{T} (y' - y'')^2}{T} \]  

where \( T \) is the sample size, and \( y' \) and \( y'' \) denote the actual production anomaly and prediction one.

In this study, the adaptive moment estimation (Adam) [33] is chosen as the training algorithm to obtain the matrix weights and deviations of the proposed LSTM. The Adam method can adaptively adjust the learning rate and have a high training speed. And the learning rate is set to 0.001.

V. ENERGY-EFFICIENT PRODUCTION DECISION MAKING

When an anomaly occurs, the machine tool or cutting tool needs to be maintained. Then the process progress will be interfered. In order to reduce the influence of the anomaly, some rescheduling strategies need to be adopted, such as right shift rescheduling (RSR) and total rescheduling methods (TR) [34]. Different rescheduling methods have different advantages and disadvantages. The former one can quickly respond to various anomalies, and tend to maintain original schedule stability with little change. But they are usually not the best solution. Although the total rescheduling method can get a better solution, it is rarely achievable in practice because of its long response time and too many adjustment work.

Thus, different rescheduling methods need to be adopted in different scenes.

Since the rescheduling methods mainly are related with maintenance time, two critical time point are defined, i.e., \( t_{rsr}^\ast \) and \( t_{tr}^\ast \). The former one decides whether RSR method needs to be adopted, while the latter judges whether TR method needs to be adopted. For different manufacturing processes, \( t_{rsr}^\ast \) and \( t_{tr}^\ast \) will be different, which may be related with order completion date, degree of process importance, etc. these critical time point can be obtained according to production managers’ long-term experience. Then the final rescheduling method (FRM) can be obtained as follows:

\[ \text{FRM} = \begin{cases} \text{NR}, & \text{if } t_{main}^\ast < t_{rsr}^\ast \\ \text{RSR}, & \text{if } t_{rsr}^\ast < t_{main}^\ast < t_{tr}^\ast \\ \text{TR}, & \text{if } t_{tr}^\ast > t_{tr}^\ast \end{cases} \]  

where NR means no rescheduling, \( t_{main}^\ast \) denotes the maintenance time for an anomaly, which can be estimated via maintenance plan.

For the TR, it’s an optimized problem, which has been researched many times. A multi-objective optimization model is established in our previous research [13]. In this model, three objectives are considered, i.e., the makespan of all the jobs, the total energy consumption and maximal workload of machines, which can be formulated as follows:

\[ C_{\text{makespan}} = \max_{1 \leq i \leq N} C_{i,n_i} \]  

\[ \text{EC}_{\text{total}} = \sum_{i=1}^{N} (\text{EC}_{i}^{\text{standby}} + \text{EC}_{i}^{\text{idle}} + \text{EC}_{i}^{\text{aircutting}} + \text{EC}_{i}^{\text{cutting}}) \]  

where \( C_{\text{makespan}}, \text{EC}_{\text{total}} \) and \( ML_{\text{max}} \) mean the makespan of all the jobs, the total energy consumption and maximal workload of machines, \( C_{i,n_i} \) denotes the completion time of the \( i \)th workpiece, \( N \) and \( M \) represent the number of workpieces and machine tools, \( \text{EC}_{i}^{\text{standby}}, \text{EC}_{i}^{\text{idle}}, \text{EC}_{i}^{\text{aircutting}}, \text{EC}_{i}^{\text{cutting}} \) denote the energy computation during different states of the \( i \)th workpiece.

For the above multi-objective optimization problem, a modified non-dominated sorting genetic algorithm II is used to solve it, and the details for the optimization algorithm can be found out in our previous research [13].

VI. CASE STUDY

A. CASE DESCRIPTION

In order to verify the validity of the above production anomaly detection model, an example of a manufacturing system in an elevator component manufacturing workshop is studied. The manufacturing workshop mainly has four kinds of machine tools, i.e., CNC lathe (M1), milling machine (M2), worm grinding machine (M3), and machining center (M4). Worm and box parts of traction machines are processed in this workshop.
For the manufacturing workshop, the energy consumption data collection network was first established through the Janitza UMG 604E, and a real-time production anomaly analysis platform on a terminal device was developed accordingly, as shown in Fig. 6. The system uses a browser/server (B/S) architecture, uses the Spring-Struts2-Hibernate framework under the Java Web environment on the server side and HTML5/CSS/JavaScript development on the browser side. Through this system, energy consumption data collection, preprocessing and anomaly analysis are realized.

Due to the large difference in energy consumption data of different machine tools, there are also differences in the production anomalies of different machine tools. Since the milling machine (M2) has a high occurrence frequency of production anomalies, M2 is analyzed as an example to verify the proposed method. Through the above energy consumption analysis platform, 1000 data on milling machine energy consumption and abnormal production results were obtained as sample data, some of which are listed in Table 1. In fact, a manufacturing system degenerates very slowly under the reasonable production conditions (e.g., skilled operator, appropriate cutting parameters, timely tool replacement and regular machine maintenance), and seldom production anomalies can be detected. Thus, some human-intervened methods are taken during the data collection to accelerate the emergence of production anomalies, such as making use of old cutting tools or reducing maintenance frequency of machine tools. The first 800 data from the energy consumption data are selected as training samples, while the last 200 data are set as test samples. The LSTM model is tested on a computer equipped with a 3.2 GHz Intel Core i7 processor and 8GB RAM.

| $t$ | Standby | Idle | Air cutting | Cutting | Anomaly |
|-----|---------|------|-------------|---------|---------|
| 1   | [394,4, 340.9, 486.8, 30.2] | [1525.0, 741.3, 832.0, 61.1] | [3264.1, 2385.4, 2753.9, 78.4] | [4862.1, 3442.0, 4071.4, 68.3] | 1       |
| 2   | [647.8, 339.3, 483.0, 27.5] | [1593.8, 724.9, 916.8, 62.0] | [2871.9, 2593.7, 2949.4, 76.6] | [4769.2, 3826.2, 4270.5, 63.0] | 1       |
| 3   | [629.3, 263.8, 435.9, 28.1] | [1582.6, 744.2, 938.4, 59.3] | [3027.1, 2480.0, 2743.6, 75.8] | [5011.9, 3840.4, 4322.9, 61.2] | 1       |
| 4   | [686.2, 342.6, 498.6, 28.8] | [1472.3, 735.5, 965.8, 62.7] | [3361.1, 3245.9, 2897.7, 75.1] | [5028.9, 3686.2, 4340.9, 60.4] | 2       |
| 5   | [659.4, 355.3, 499.0, 27.9] | [1477.1, 746.5, 863.5, 63.5] | [3092.4, 2699.0, 2847.0, 80.2] | [4644.1, 3087.6, 3282.5, 61.6] | 1       |
| 6   | [574.9, 307.5, 428.3, 30.3] | [1429.1, 726.3, 831.1, 63.5] | [2862.9, 3056.2, 2831.8, 79.6] | [4765.7, 3971.3, 4063.5, 61.9] | 1       |
| 7   | [568.8, 310.9, 509.2, 27.3] | [1412.9, 721.7, 834.2, 58.6] | [2962.5, 2825.9, 2920.1, 76.7] | [4828.3, 3380.0, 4029.5, 64.8] | 1       |
| 8   | [668.3, 215.3, 436.0, 27.9] | [1415.7, 734.9, 964.2, 56.3] | [3289.1, 2129.1, 2683.3, 75.6] | [4270.7, 4609.4, 4353.5, 66.8] | 1       |
| 9   | [647.8, 307.5, 440.5, 27.7] | [1429.4, 742.6, 882.2, 56.6] | [3068.0, 2252.2, 2650.1, 78.7] | [5023.9, 4287.1, 4485.1, 67.7] | 3       |
| 10  | [642.7, 305.3, 467.4, 30.5] | [1539.8, 726.5, 892.1, 61.9] | [2873.9, 2345.2, 2543.3, 78.6] | [4246.3, 3850.1, 3948.6, 65.0] | 1       |

Note: the numbers (i.e., 1,2,3) in the column of “Anomaly” represents no anomaly, machine degradiation, and tool wear.

**B. PRODUCTION ANOMALY ANALYSIS AND DISCUSSION**

As described above, the cleansed energy data will be divided through the data partition method based on FCM cluster. In order to verify the effectiveness of this method, three energy consumption data sets with different data sizes were used in the milling process, i.e., 1240, 2730 and 4920. The weighted index of fuzzy degree $\beta$ is set to 2, the number of cluster centers $C$ is 4, and the minimum improvement of FCM is $10^{-6}$. The test results are shown in Table 2. It can be found that the average computation time is 0.18s when the sample size is 1240. For other test samples, the average calculation time does not exceed 0.7s, which means that the
TABLE 2. Results of the energy data partition algorithm.

| No. | Sample size | Average computation time (s) | Average accuracy (%) |
|-----|-------------|------------------------------|----------------------|
| 1   | 1240        | 0.18                         | 99.4                 |
| 2   | 2730        | 0.39                         | 99.1                 |
| 3   | 4920        | 0.63                         | 98.5                 |

Algorithm is effective for energy consumption data partition problem. In addition, all the average accuracies of the three tests exceed 98%, especially for sample size of 1240, whose average accuracy reaches 99.4%. This result proves that the energy data partition algorithm based on FCM clustering has high accuracy.

In order to verify the effectiveness of the above anomaly analysis method, the proposed LSTM method is compared with other four commonly used classification methods, including back propagation neutral network (BPNN), support vector machine (SVM), random forests (RF) and stacked auto-encoder (SAE). Two performance indicators are used, i.e., analysis error rate (%) and computation time (min). The results are shown in Fig. 7 and Fig. 8.

It can be seen from Fig. 7 that the analysis error of LSTM method is the lowest, which can reach 3.5%, and the analysis result of SAE ranks second. The prediction errors of other three methods are much higher, which means that the LSTM method has obvious advantages in processing continuous energy consumption data for production anomaly analysis. In terms of computation time, SVM owns the fastest calculation speed, but its analysis error is also high, which indicates that it is easy to obtain a local optimal solution. The computation times of other four methods range from 1.24 to 2.67.

Considering that an anomaly analysis error will affect the normal production progress, the analysis accuracy is regarded as the prime factor. In addition, in Fig. 8, it can be seen that the anomaly state of analysis error is mainly concentrated in “no anomaly”, while that of the other four methods are “machine degradation” and “tool wear”, which means that production anomalies are not fully detected. In a word, the LSTM method can obtain a better analysis result for the production anomaly of manufacturing systems in this study.

For the manufacturing shopfloor, the production system usually experience breakdown because of various anomaly, including the issues of machines tools and cutting tools. Through the above production control methods, the rescheduling strategies will be adopted when an anomaly occurs. Then the efficiency of energy consumption and production are both improved 21.3% and 13.7% after the rescheduling decision making, as shown in Fig. 9.

VII. CONCLUSION

The production anomalies of manufacturing systems seriously affect product quality and production schedule. In order to reduce this impact, an edge computing enabled production anomalies detection and energy-efficient decision approach is proposed in this study. Firstly, an architecture of edge computing enabled production anomalies detection and energy-efficient decision is introduced. Then, an energy consumption data preprocessing and production anomaly detection is established based on LSTM. When an anomaly occurs, a decision making of energy-efficient rescheduling decision will be triggered. Finally, through a case analysis of a milling manufacturing system in an elevator manufacturing
workshop, the results show that the anomaly detection error of the proposed method is only 3.5%. This method realizes the combination of energy consumption data and anomaly analysis of the manufacturing system, and can further assist the production process monitoring and production decision-making, so as to reduce the production failure rate and achieve the quality and efficiency of the production process.

In addition, there are also some limitations in this study which will be researched in the future work. 1) The actual manufacturing processes are more complex, and only considering energy consumption data may not be comprehensive for production anomalies detection. Thus a multi-data fusion model should be established for production monitoring based on edge computing. 2) The proposed methods mainly detect known production anomalies, but for a new anomaly, these methods will not work. It needs to be considered in the future work to improve the robustness of the model. 3) Although the anomaly detection error of the proposed method based on LSTM is only 3.5%, an erroneous detection result may influence the normal process progress. Thus a more efficient algorithm is still needed.

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