

## Article

# Data Acquisition Network Configuration and Real-Time Energy Consumption Characteristic Analysis in Intelligent Workshops for Social Manufacturing

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**Abstract:** To achieve energy-saving production, one critical step is to calculate and analyze the energy consumption and energy efficiency of machining processes. However, considering the complexity and uncertainty of discrete manufacturing job shops, it is a significant challenge to conduct data acquisition and energy consumption data processing of manufacturing systems. Meanwhile, under the growing trend of personalization, social manufacturing is an emerging technical practice that allows prosumers to build individualized services with their partners, which produces new requirements for energy data processing. Thus, a real-time energy consumption characteristic analysis method in intelligent workshops for social manufacturing is established to realize data processing and energy efficiency evaluation automatically. First, an energy-conservation production architecture for intelligent manufacturing processes is introduced, and the configuration of a data acquisition network is described to create a ubiquitous manufacturing environment. Then, an energy consumption characteristic analysis method is proposed based on the process time window. Finally, a case study of coupling-part manufacturing verifies the feasibility and applicability of the proposed method. This method realizes a combination of social manufacturing and real-time energy characteristic analysis. Meanwhile, the energy consumption characteristics provide a decision basis for the energy-saving control of intelligent manufacturing workshops.

**Keywords:** data acquisition network; real-time energy consumption; characteristic analysis; intelligent workshops; social manufacturing



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## 1. Introduction

Nowadays, the increasing emissions of carbon dioxide have made a crucial contribution to global warming, especially in industrial fields. With the improvements made around the awareness of saving energy and the enhancement of environmental concerns, energy-efficient and low-carbon emissions should be considered as key factors in many fields, such as transportation facilities [1], manufacturing management [2] and disassembly sequencing [3]. Owing to the explosive demand for energy worldwide, energy efficiency in manufacturing processes has become a challenging goal. In the last few years, the reduction in energy consumption has attracted many researchers. A survey on electric energy consumption showed that up to 54% of electric energy is used in production processes, or more accurately, production machines. Therefore, the energy conservation of machine tools can significantly reduce carbon emissions in manufacturing. To realize the energy conservation of machine tools and environmentally friendly production, researchers have conducted many theoretical and practical studies, which mainly include machining

parameter optimization [4], the state control of machine tools [5], process planning [6] and production scheduling [7].

Meanwhile, under the growing trend of personalization and socialization, social manufacturing (SM) is an emerging technical and business practice that allows prosumers to build personalized products and individualized services with their partners [8]. SM can realize a customer's requirements "from mind to products", and fulfill tangible and intangible needs of a prosumer, i.e., a producer and consumer at the same time [9]. By establishing a cyber-physical-social connection via decentralized social media, various communities can be formed as complex, dynamic, autonomous systems to cocreate customized and personalized products and services [10]. From the principle of SM, the consumers are acting as prosumers and participate in the energy production and consumption process over the Internet [11]. For a manufacturing workshop, its operation state will be focused on by several prosumers, such as equipment providers, manufacturers and consumers [12]. How to solve these different demands is a new problem. With the development of the Internet of Things (IoT) technology, many kinds of data are generated in a manufacturing workshop, and these data present some characteristics of big data, such as large volume, high variety and velocity. Thus, it becomes a research focus to acquire and process these data, and various data analysis methods have been proposed, including fog computing [13], deep-learning approaches [14] and big-data analytics [2]. Meanwhile, many energy-conservation models and algorithms have been proposed for single-machine tools [15] or closed-loop flow-shop plants [16]. However, there are still two research gaps in the recent research. First, many models and algorithms for data acquisition and analysis have been proposed to mine knowledge and guide the production process. Most of these studies neglect the adaptability of manufacturing data network on the shop floor. Since discrete manufacturing is a manufacturing process that does not follow sequential steps or formulas to develop products, the production process in discrete manufacturing job shops has stochasticity. The data of energy and processes that need to be acquired are dynamic and diverse, and so is the energy data acquisition network. Second, although there are many studies on energy data analysis and evaluation from different perspectives, most of them focus on the study of theoretical models. Scant sustainability research has been conducted on SM [17]. It is still an application difficulty to combine this production information with real-time energy consumption data in an intelligent workshop for SM.

Considering these two research gaps, a real-time energy consumption characteristic analysis method for intelligent manufacturing (IM) workshops is established, which involves the manufacturing data acquisition network configuration and energy consumption characteristic analysis of machining processes. The contributions of the paper include two aspects. First, the configuration of a data acquisition network is described to create a ubiquitous manufacturing environment, which can deal with the complexity of discrete manufacturing processes. Second, an energy consumption characteristic analysis method is proposed based on the process time window. This method realizes the combination of production information with real-time energy consumption data. The remainder of this paper is organized as follows. A literature survey on the data acquisition of IM workshops and energy consumption data evaluation is reviewed in Section 2. Section 3 introduces an energy-conservation production architecture for IM processes, and the configuration of a data acquisition network is described to create a ubiquitous manufacturing environment. Then, an energy consumption characteristic analysis method is established based on the process time window in Section 4. A case study on coupling-part manufacturing is presented to verify the feasibility and applicability of the proposed methods in Section 5. We conclude with the main contributions and future research directions in Section 6.

## 2. Literature Review

### 2.1. Data Acquisition and Analysis of IM Workshops

With the development of sensor network technology, the industry is increasingly moving towards digitally enabled "smart factories" that utilize the IoT to realize IM [18]. A

large amount of data is gathered in a manufacturing workshop, and these data, including on energy consumption, present some characteristics of big data, such as large volume, high variety and velocity [19]. Thus, the acquisition and processing of these data are research focuses. With the beginning of the era of big data, an enormous amount of real-time data was used for the risk analysis of various industrial applications, and Ding et al. proposed a real-time big-data-gathering algorithm based on an indoor wireless sensor network for the risk analysis of industrial operations [20]. In this algorithm, sensor nodes can screen the data collected from the environment and equipment according to the requirements of the risk analysis. As managing industrial big data has become a challenging task for factories, designing a generic architecture for implementing cyber-physical systems in manufacturing is necessary. Thus, Lee et al. proposed a systematic architecture for applying cyber-physical systems in manufacturing to automate and centralize data processing, health assessments and prognostics [21].

In addition to data acquisition, an increasing number of researchers have focused on data analysis and data mining in various applications. Industrial big-data integration and sharing (IBDIS) is of great significance in managing and providing data for big-data analysis in manufacturing systems; thus, Wang et al. proposed a novel fog-computing-based IBDIS approach to integrate and share industrial big data with high raw-data security and low network-traffic loads by moving the integration task from the cloud to the edge of networks [13]. A deep-learning approach for anomaly detection with industrial time-series data in a refrigerator manufacturing enterprise was proposed, and was designed to be deployed in a decision support system to assist human operators [14]. Zhong et al. extended the physical Internet concept to manufacturing shop floors where typical logistics resources were converted into smart manufacturing objects by using the IoT and wireless technologies [22]. This study introduced big-data analytics for radio frequency identification device (RFID) logistics data by defining different behaviors of smart manufacturing objects. Since current task scheduling is mainly concerned with the availability of machining resources rather than the potential errors after scheduling, Ji and Wang presented a fault prediction approach based on big-data analytics for shop-floor scheduling to minimize such errors in advance [23]. An innovative, big-data-enabled, intelligent immune system has been developed to monitor, analyze and optimize machining processes over lifecycles in order to achieve energy-efficient manufacturing [2]. The novelty of this study is that big-data analytics and intelligent immune mechanisms have been integrated systematically to achieve condition monitoring, analysis and energy-efficient optimization over manufacturing execution lifecycles. According to the literature, big-data analytics and smart manufacturing have been individually researched in academia and industry [24]. To provide theoretical foundations for the research community to further develop scientific insights into applying big-data analytics to smart manufacturing, a comprehensive overview of big data in smart manufacturing was conducted, and a conceptual framework was proposed from the perspective of the product lifecycle. A review of the literature suggests that production research enabled by data has shifted from analytical models to data-driven models [25]. Ghahramani et al. proposed a dynamic algorithm for gaining useful insights about semiconductor manufacturing processes and to address various challenges [26]. White et al. developed a fault diagnosis tool, which can robustly detect, locate and isolate occurred faults in an Industry 4.0 context [27]. Ding and Jiang provided an RFID-based production data analysis method for production control in IoT-enabled smart job shops [28]. Yuan et al. established an integrated, deep-learning, continuous time network structure that consists of a sequential encoder, a state decoder and a derivative module to learn the deterministic state-space model from thickening systems [29].

Based on the current research, data acquisition and data analysis have become research hotspots, and many models and algorithms have been proposed to mine knowledge and guide production processes in turn. However, this research mainly focused on data processing and data analysis, especially big-data analysis, and data acquisition network configuration was rarely studied. Meanwhile, the theory research about data mining in an ideal

manufacturing environment was very deep, which neglected the complexity and dynamics of an actual production environment. Considering the complexity of manufacturing processes, it is still difficult for operators to configure the data acquisition network, especially when the production processes experience frequent adjustments. Thus, a configuration method of the sensor network is proposed for dynamic manufacturing tasks.

## 2.2. Energy consumption Data Processing and Evaluation

After the production data acquisition, energy data processing and evaluation needs to be conducted to obtain the characteristics and energy efficiency of manufacturing processes. Many manufacturing energy data processing and evaluation methods have been proposed. For example, considering that the energy consumption evaluation and analysis of a product's entire life cycle is a key issue for realizing green and sustainable manufacturing, an IoT and cloud-based novel approach for product energy consumption evaluation and analysis was proposed, in which the IoT technologies were employed for real-time and dynamic collection of energy consumption-related data [30]. For a machine process, its energy consumption can be decomposed into two parts: energy consumption of the steady state and energy consumption of the transient state. Jia et al. proposed a finite-state, machine-based energy consumption modeling method for the machining transient state [31]. Cai et al. proposed the use of energy benchmarking to strengthen the evaluation of energy demand and achieve efficiency improvements for machining systems, in which drivers for energy benchmarking and their characteristics were analyzed first [32]. Finkbeiner et al. explored the current status of a life-cycle sustainability assessment for products and processes [33]. Saxena et al. considered the sustainability metrics in tandem with other traditional manufacturing metrics such as time, flexibility and quality, and presented a novel framework that integrates information and requirements from computer-aided technology systems [34]. Swarnakar et al. identified and prioritized experts' consensus on the structured set of triple-bottom-line indicators through an open-ended questionnaire [35]. However, these evaluation methods cannot realize the real-time evaluation of manufacturing processes, and they neglect data acquisition and the processing process. Wang et al. presented a real-time energy efficiency optimization method for energy-intensive manufacturing enterprises [36]. In this study, a multilevel event model and complex event processing were used to obtain real-time, energy-related, key performance indicators that extend the production performance indicators to the energy efficiency area. Owing to the complicated energy flow and dynamic energy changes of the machining workshop, Chen et al. proposed an energy efficiency monitoring and management system with the support of the newly emerging IoT technology, in which the energy characteristics and energy efficiency indicators of the machining workshop were analyzed and defined [37]. To improve the generalization ability, Xiao et al. combined the machining parameters and configuration parameters into energy efficiency models, for which machine-learning algorithms were used to consider the lack of theoretical formulas [38]. Considering the complexity of discrete manufacturing workshops, a big-data-analysis approach for the real-time carbon efficiency evaluation of discrete manufacturing workshops was proposed in an IoT-enabled ubiquitous environment [39]. Based on advanced technologies such as cloud manufacturing, IoT, and cyber-physical systems, an energy-cyber-physical-system-enabled green manufacturing model for future smart factories was proposed, in which qualitative and quantitative synergistic models based on an energy-cyber-physical system were developed for cleaner manufacturing [40]. Along with the advent of globalization in the industrial sector, the distributed manufacturing systems became an important production process since they enable the efficient collaboration of multiple factories; thus, the stochastic, multiobjective modeling and optimization of an energy-conscious distributed-permutation flow-shop scheduling problem was proposed [41]. To ensure the fastest production and least energy consumption of steelmaking-continuous casting, a mixed-integer mathematical programming model was presented with the objectives of minimizing the maximum completion time, idle time penalties, and energy consumption penalties related to waiting time [42].

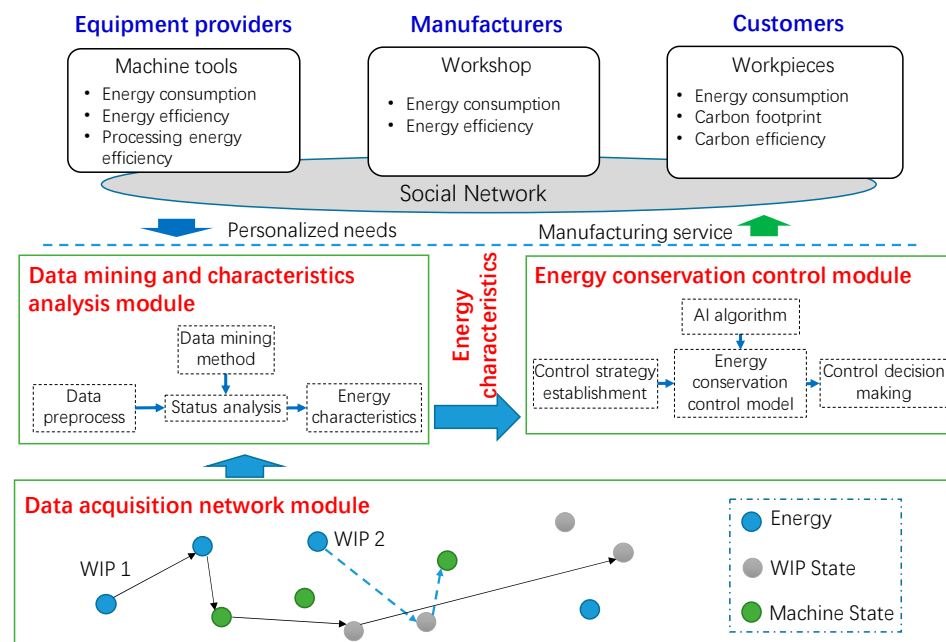
Li et al. proposed a modified dynamic programming algorithm for the optimization of total energy consumption in flexible manufacturing systems [43]. In addition, Diaz et al. outlined and discussed most of the recent research regarding the technologies and strategies to improve energy efficiency in manufacturing systems [44].

From these studies, it can be seen that there are many studies on energy data analysis and evaluation from different perspectives. However, most of them mainly focused on the study of theoretical models, and neglected the correlation between energy consumption data and manufacturing processes. Since the ultimate realization of energy savings and emission reductions is closely related to manufacturing processes, the practical application value of the current studies is limited. It is still difficult to combine production information with real-time energy consumption data in IM workshops.

### 3. Energy-Conservation Production Architecture and Data Acquisition Network Configuration

#### 3.1. Energy-Conservation Production Architecture for IM Processes

To implement energy-aware production, an energy-conservation production architecture in an intelligent workshop for SM is established, as shown in Figure 1. The architecture provides a step-by-step guide for controlling computer numerical control (CNC) machine tools and discrete manufacturing processes. The architecture is established mainly from the perspective of data processing, that is, data acquisition, data filtering, data integration, data conversion, data reduction and knowledge analysis. It consists of three modules: the data acquisition network module, energy characteristic analysis and energy-conservation control module, and energy consumption service module. Since the data of different manufacturing processes are disparate, the data acquisition network module is carried out on the basis of discrete manufacturing processes. Then, the gathered data from the data sensor network can be analyzed through the data mining and analysis module, which cannot be divorced from manufacturing processes. The energy-saving strategies generated by the energy-conservation control module must be finally implemented in discrete manufacturing processes.



**Figure 1.** Energy-conservation production architecture in intelligent workshops for SM.

##### 3.1.1. Data Acquisition Network Module

As the basic layer of the architecture, discrete manufacturing processes reflect the physical resource configuration of a workshop, including facility layout, selection of ma-

chine and tools, setting of processing parameters and process planning. In the process flow, there are three types of flows: energy flow, raw material flow and operation flow. The inputs of the process flow are raw materials, energy and supporting materials. The outputs are semifinished or end products, and waste materials or effluent. In each step of the process flow, the emissions from the energy and supporting materials occur at all times. Based on manufacturing processes, an energy-acquisition sensor network is established to gather the relative data for realizing energy-saving production, for example, on the energy consumption of machine tools, the state of the work-in-process (WIP) and machine tools. Initially, each machine may be configured with different sensors that contain energy sensors, position sensors and testing sensors. However, for different production tasks, disparate sensors are integrated into a sensor network involved in real production. Therefore, the data acquisition network varies constantly from time to time, as discussed in Section 3.2.

### 3.1.2. Energy Characteristic Analysis and Energy-Conservation Control Module

For the gathered data from the data sensor network, data processing needs to be implemented first, which includes data filtering, data integration, data conversion and data interaction [45]. As the first step, the data filter needs to be adopted to remove useless data because many data are continuous and abundant. Then, data integration needs to be used to deal with each single data point for comparison and analysis. Data conversion and interaction must be adopted for the entire manufacturing system. Then, the data need to be converted into information on the state of machine tools and WIPs. Using the above information, the energy characteristics can be analyzed, which will be used to support the energy-conservation control of CNC machine tools.

To realize energy-aware production, the energy-conservation control model is based on an artificial intelligence algorithm. The input of this model is the above energy characteristic values (that can reflect the machining state and energy efficiency), and the output is the selection of energy-conservation strategies.

### 3.1.3. Energy Consumption Service Module

Through the above energy consumption analysis, energy characteristics of different layers in a workshop can be obtained, which include the machine tool layer, workshop layer and workpiece layer. Different SM participants can put forward the personalized manufacturing and service needs through the social network. Meanwhile, different data and services will be provided to them.

## 3.2. Configuration of Manufacturing Data Acquisition Network

Here, the manufacturing data acquisition network is aimed at energy-conservation manufacturing, and the acquired data include energy consumption, state of the machine tools, and WIPs. Considering the real production processes, the configuration of the sensor network contains two parts: the static and the dynamic network constructions. The static network configuration is realized after the design of a manufacturing system, which is a part of the physical configuration process of the manufacturing system. On the other hand, the dynamic sensor network is mainly applied to one or several certain production tasks after production planning and scheduling. After the dynamic network construction, the required data can be acquired and the usage effectiveness of the sensors will be improved.

### 3.2.1. The Static Sensor Network Configuration

This configuration process uses a rule-based inference engine to realize the intelligent configuration of the data acquisition network of machine tools, as shown in Figure 2. The configuration process consists of three parts: establishment of a configuration knowledge base, construction of rules and the case base, and realization of the reasoning engine.

The configuration knowledge base is the extraction and description of the related knowledge based on ontology, including feature description information, precision information, key parameters, etc. The rule and instance base is a configuration case that

contains expert experience and the actual case, and the ontology rule base is generated based on this case. The reasoning engine is a combination of case-based reasoning and ontology-based reasoning approaches. First, case-based reasoning is performed based on similarity matching. If the configuration does not meet the requirements, ontology rules are used to determine a new configuration scheme. The process of ontology rule matching is an iterative process that may not meet the requirements one time. The new data acquisition network configuration plan will be stored in the instance library for later use. The input of the configuration process includes the demand information of the machining features, and the output is a viable data acquisition network for the machine tool.

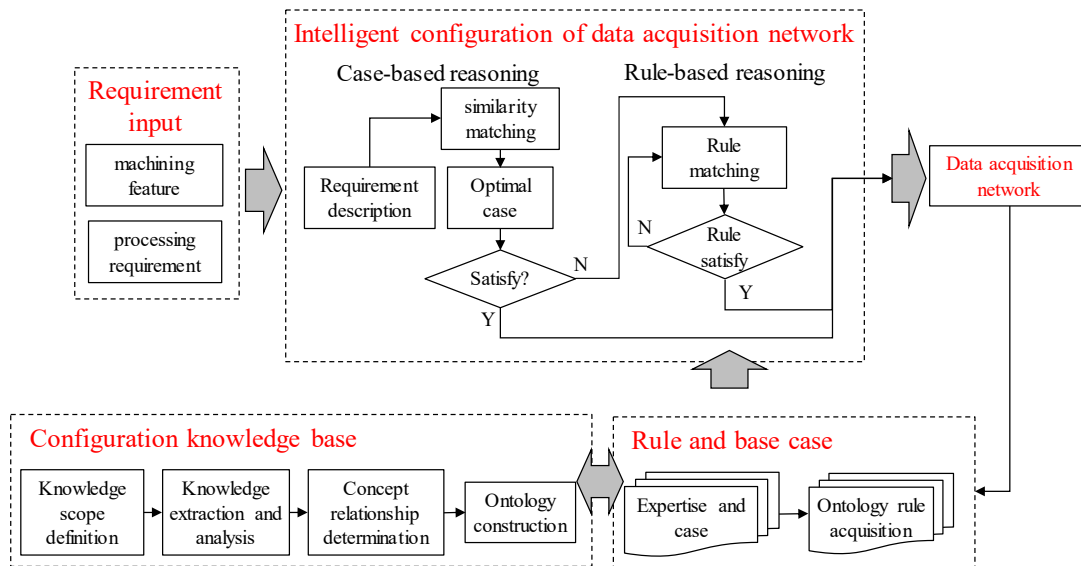


Figure 2. Intelligent configuration of manufacturing data acquisition network.

### 3.2.2. Dynamic Network Construction for a Certain Production Task

To improve the efficiency of configuration reasoning, case-based reasoning (CBR) is used to configure the data acquisition subnetwork, which is used to search for similar cases based on the matching of the above-mentioned processing-task attributes. The matching steps of CBR are described as follows: (1) define the processing task, including its characteristics or attributes; (2) search the instance database and find the highest similarity instance in the sample database according to the processing task’s characteristic data; (3) constitute a data acquisition network configuration scheme for the processing tasks to serve as a new paradigm; and (4) save the valuable new configuration examples obtained in the instance database for future energy data acquisition subnetwork configuration reference. Owing to the different attribute categories of machining tasks, the machining type is text data, the machining size is continuous numerical data and the machining accuracy is discrete numerical data. Therefore, the similarity ( $SIM_{i,j}$ ) calculation is an integration of the similarities of different types of data as follows:

$$SIM_{i,j} = \prod_a Sim_{i,j}^a \cdot \sum_b w_b \cdot Sim_{i,j}^b \tag{1}$$

$$Sim_{i,j}^a = \begin{cases} 1, & \text{if } mta_i^a \text{ is the same to } mta_j^a \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$Sim_{i,j}^b = 1 - \frac{\sqrt{(mta_i^b - mta_j^b)^2}}{\sqrt{(\max_i mta_i^b - \min_j mta_j^b)^2}} \tag{3}$$

$$\sum_b w_b = 1 \quad (4)$$

where  $SIM_{i,j}$  denotes the total similarity of the  $i$ th and  $j$ th manufacturing tasks.  $Sim_{i,j}^a$  and  $Sim_{i,j}^b$  represent the similarity of the text-type property and the value-type property, respectively, and  $a$  and  $b$  represent the indexes of these two similarities.  $mta_i^a$  and  $mta_j^a$  represent the  $a$ th text-type property of the  $i$ th and  $j$ th manufacturing tasks, respectively.  $mta_i^b$  and  $mta_j^b$  represent the  $b$ th value-type property of the  $i$ th and  $j$ th manufacturing tasks, respectively.  $w_b$  denotes the weight of the  $b$ th value-type property.

#### 4. Energy Consumption Characteristic Analysis Based on Process Time Window

##### 4.1. Data Modeling of Discrete Manufacturing Processes

Different kinds of data can be obtained after the manufacturing data acquisition network configuration. To realize data processing and data storage, data modeling is conducted first. The discrete manufacturing processes mainly include three types of data related to energy conservation: process data, energy consumption data and supporting-material data.

Process data model:

The process data involve the information of each machining process, for example, the process name, machine tool and process time. Because all the manufacturing activities are carried out according to process planning, process data are the core data for the discrete manufacturing workshop. The process data are modeled in Equation (5), and these data can be obtained from process planning and the WIP state.

$$PD = \langle PDID, WID, PID, PName, MID, STime, ETime \rangle \quad (5)$$

where  $PDID$  is the index of the process data, and  $WID$ ,  $PID$  and  $MID$  are the indexes of the workpiece, process and machine tool, respectively.  $PName$  denotes the process name.  $STime$  and  $ETime$  represent the starting and ending time of the process, respectively.

Energy consumption data model:

For a manufacturing workshop, the energy consumption mainly comes from machine tools; thus, the energy consumption data can be modeled by Equation (6).

$$ECD = \langle ECDID, MID, EData, T \rangle \quad (6)$$

where  $ECDID$  is the index of the energy consumption data, and  $EData$  represents the real-time power of a machine tool at time  $T$ .

Supporting-material data model

In addition to the energy consumption, a machining process also consumes some supporting materials that may be related to energy consumption, such as compressed air and cooling liquid. Thus, the supporting-material data can be expressed by Equation (7).

$$SMD = \langle SMDID, MID, SType, SMDData, T \rangle \quad (7)$$

where  $SMDID$  is the index of the supporting-material data, and  $SType$  represents the type of supporting material.  $SMDData$  is the real-time usage amount of the supporting material.

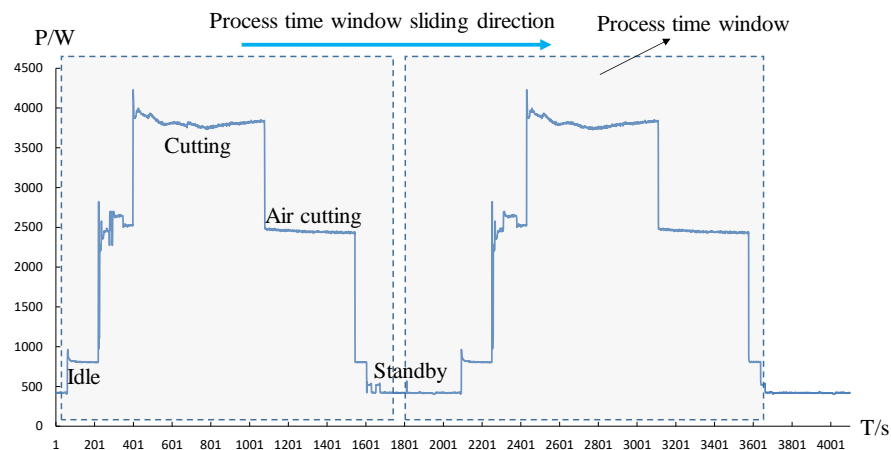
##### 4.2. Energy Consumption Data-Partition Method Based on Process Time Window

For a manufacturing process, the process data are discrete, whereas the data on energy consumption are continuous. To relate the energy consumption data with process data, the former needs to be divided according to machining processes or feeds. Thus, an energy consumption data-partition method is proposed based on the process time window. The time window method can divide time series into segments, and has been used in many applications [46]. Because the traditional time window moves forward in succession over a fixed or variable time, it is not suitable for discrete manufacturing processes. The concept of



the process time window is defined, which means that the interval time of the time window is determined on the basis of the processing stages, as shown in Figure 3.

For a single process, the time window can be obtained from the enterprise resource planning system, that is, the starting and ending times of the process. However, this process may contain several steps. For example, a turning process may include cylindrical turning, face cutting and internal cylindrical turning. Meanwhile, a step contains different states, such as standby, idle, air cutting and cutting, as shown in Figure 3. The power of different processes and states shows a high variation due to different cutting parameters [47,48].



**Figure 3.** Energy consumption data partition based on process time window.

To analyze the energy characteristics of different steps or cutting states, the continuous energy data belonging to different steps are divided based on the process time window. The power of the air-cutting state is used to judge whether a machine tool is in a cutting state, and the power of the cutting state is for identifying different processes or cutting steps. Here, ten real-time energy data are analyzed every time, that is,  $P^t = \{p_i^t\}, i = 1 \dots 10$ . Then, the maximum and minimum values of these data are deleted to exclude the influence of chance factors. The average value of the remaining data  $P^{t'} = \{p_i^{t'}\}, i = 1 \dots 8$  is used as the judgment standard, as denoted in Equation (8).

$$MeanCE_t = \frac{1}{8} \sum_{i=1}^8 p_i^{t'} \quad (8)$$

The algorithm flow of the entire energy data-partition method based on the process time window is shown in Algorithm 1.

#### 4.3. Real-Time Energy Consumption Characteristic Analysis

For a machining process, the original energy consumption data cannot be directly used to evaluate or optimize the machining processes. Important characteristic values must be derived. In this study, these characteristic values mainly fall into two categories: instantaneous and cumulative.

The instantaneous characteristics mainly reflect the variation law of cutting power, such as the maximum, minimum and mean power of a process or feed, as follows:

$$MaxP_i = \max_{t \in [s_i, e_i]} p_t \quad (9)$$

$$MinP_i = \min_{t \in [s_i, e_i]} p_t \quad (10)$$

$$MeanP_i = \frac{1}{N_i} \sum_{t \in [s_i, e_i]} p_t \quad (11)$$

where  $p_t$  denotes the power at time  $t$ , and  $MaxP_i$ ,  $MinP_i$  and  $MeanP_i$  represent the maximum, minimum and mean of the energy consumption values, respectively.  $s_i$  and  $e_i$  denote the starting and ending times of a process time window, respectively.  $N_i$  is the number of cutting-power data points during the process time window.

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**Algorithm 1:** Energy Data Partition Method
 

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**Input:** the power of air cutting  $P_{aricutting}$

**Output:** the time window node of each steps  $s_{i,j}$  and  $e_{i,j}$

**Algorithm flow:**

1. According to process planning, obtain the starting time  $s_i$  and ending time  $e_i$
  2. **For** each process
  3.   **For** each energy data of this process
  4.     The starting time of the first step is  $s_i$ , obtain the mean value  $MeanCE_t = \frac{1}{8} \sum_{i=1}^8 p_i'$
  5.     **If**  $\frac{MeanCE_t - P_{aricutting}}{P_{aricutting}} > 0.05$
  6.       The step is in cutting state, and obtain the mean power value  $P_{cutting}^1$
  7.     **Else**
  8.       Obtain the time point  $e_{i,1}$
  9.     **End if**
  10.    **If**  $\frac{|P_{cutting}^2 - P_{cutting}^1|}{P_{cutting}^1} > 0.05$
  11.      This is the next step, and the above  $e_{i,1}$  is the starting time of the next step  $s_{i,2}$
  12.    **End if**
  13.    **End For**
  14. **End For**
  15. **Return**  $s_{i,j}$  and  $e_{i,j}$
- 

These instantaneous characteristics can reflect the operating state of a manufacturing system and have been used to detect recessive production anomalies [49].

On the other hand, the cumulative characteristics mainly show the overall energy consumption and energy efficiency of a process. These characteristics can be obtained as follows:

$$TotalE_i = \sum_{t \in [s_i, e_i]} p_t * \Delta t \quad (12)$$

$$EnergyEff_i = \frac{\sum_{t \in [s_i, e_i] \cap [ms_i, me_i]} p_t * \Delta t}{TotalE_i} \quad (13)$$

$$ProcessEff_i = \frac{V_i}{TotalE_i} \quad (14)$$

where  $TotalE_i$  denotes the total energy consumption during the process time window.  $\Delta t$  is the energy consumption data-sampling interval.  $EnergyEff_i$  denotes the energy efficiency, which is the ratio of the material-removal energy consumption to the total energy consumption during the process time window.  $ProcessEff_i$  is the material-removal volume of each energy consumption.  $V_i$  denotes the material-removal volume during this process time window.  $ms_i$  and  $me_i$  mean the starting time and ending time of the material-removal process.

The cumulative characteristic values can reveal the energy consumption feature at the process level, which can support process improvement and parameter optimization.

## 5. Case Study

### 5.1. Case Description

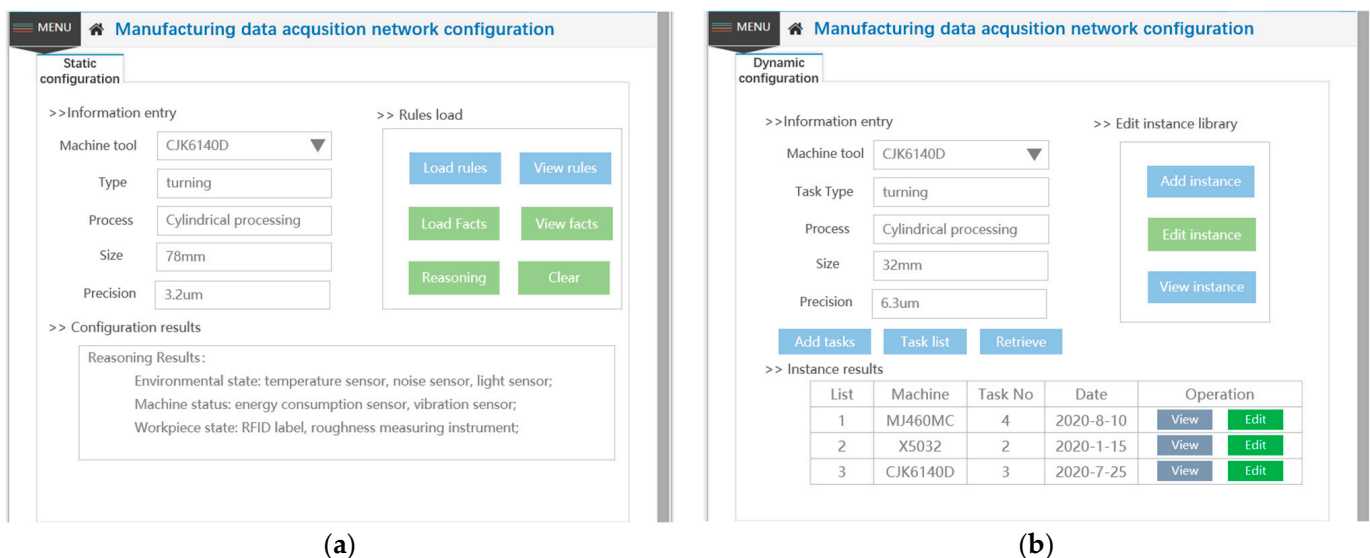
To verify the proposed method, a case of a discrete manufacturing workshop that mainly produces coupling parts for different customers is studied. This workshop contains three types of machine tools from different equipment providers: a CNC lathe, milling center and drilling machine. There are four machining processes for a coupling part: cylindrical lathe cutting, milling flat, drilling hole and tapping. The relationship between

the machining processes and machine tools is presented in Table 1. The power of the air-cutting state of each machine tool is also listed in the table.

**Table 1.** The machining processes of a coupling part.

No.	Processes	Machine Tool	Machine No.	Power of Air Cutting (W)
1	Cylindrical lathe cutting	CNC lathe	M1	2411
2	Milling flat	Milling center	M2	2941
3	Drilling hole			
4	Tapping	Drilling machine	M3	2182

To realize the monitoring of machining states, a static data acquisition network is first configured for each machining system in the manufacturing workshop, as shown in Figure 4a. The processing characteristics, accuracy, optional sensing-equipment set and measuring-equipment set of the machining system are input to build the rule-reasoning library. A feasible sensing-equipment recommended list is obtained according to the specific process system information. Then, the appropriate configuration instances for a specific processing task are retrieved from the instance database through similarity calculation. According to a specific instance, the operator selects and modifies sensing devices from the static data acquisition network, and then a dynamic data acquisition subnetwork is formed for the current task, as shown in Figure 4b.

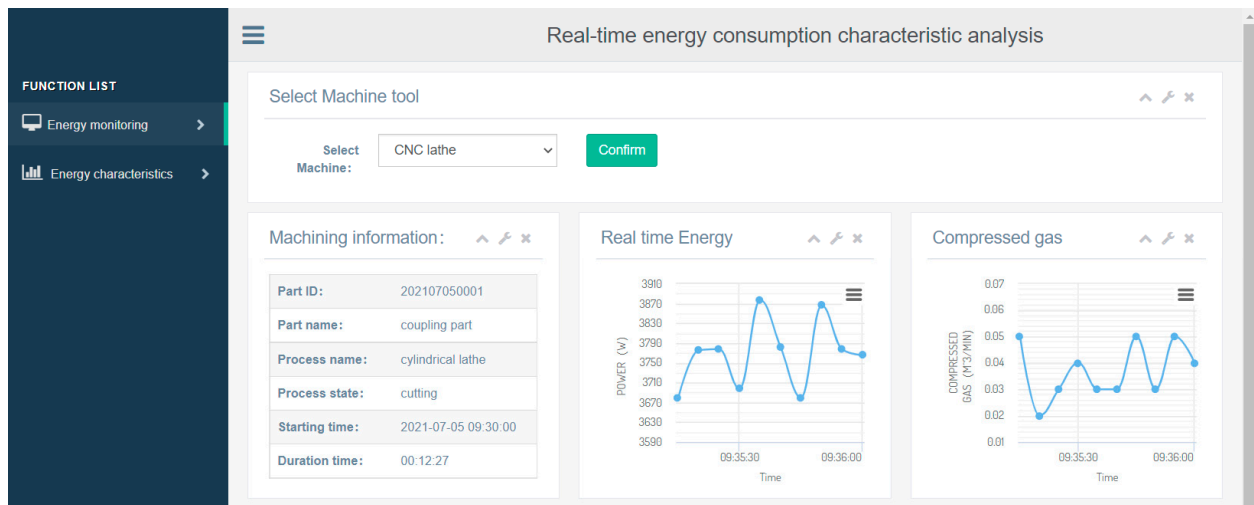


**Figure 4.** Configuration of manufacturing data acquisition network; (a) static data acquisition network configuration; (b) dynamic data acquisition network configuration.

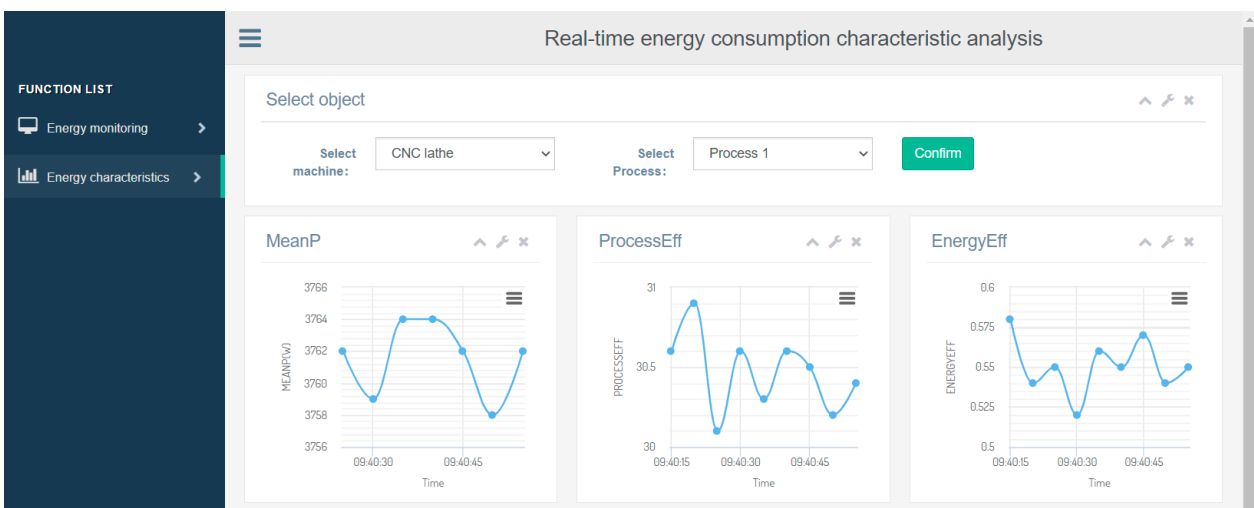
### 5.2. Energy Consumption Monitoring and Characteristic Analysis

Based on the above data acquisition network, the machining state and energy consumption data are obtained. Meanwhile, a prototype system of energy consumption monitoring and characteristic analysis is developed, as shown in Figure 5. This system is designed based on the browser/server (B/S) architecture. On the server side, the Java web-programming language is adopted, whereas HTML5/CSS/JavaScript is used to develop the browser side. This system can be conveniently visited by networked computers or remote handheld terminals. The prototype system mainly contains two functions: energy consumption monitoring and energy characteristic analysis. Figure 5a shows the real-time energy consumption monitoring module, which contains the machine tool, the current process and real-time energy. Figure 5b shows the energy consumption characteristic

analysis module, which includes the mean energy consumption value, energy efficiency and material-removal volume of each energy consumption.



(a)



(b)

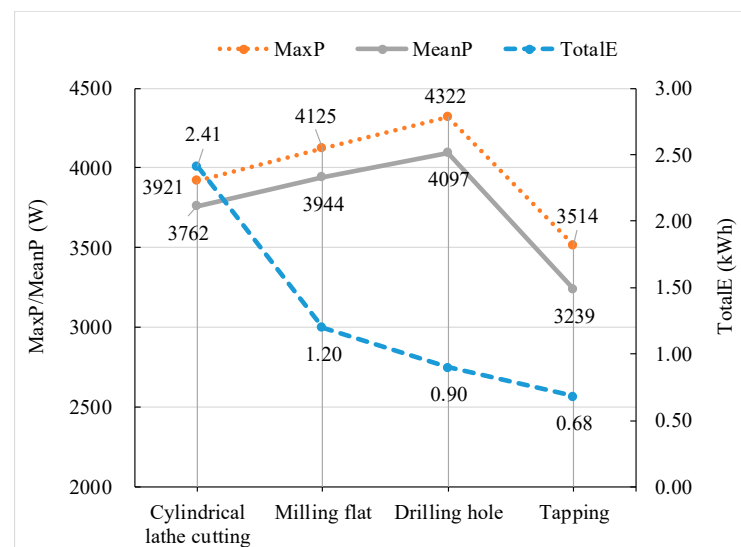
**Figure 5.** A prototype system of energy consumption monitoring and characteristic analysis; (a) real-time energy consumption monitoring; (b) energy consumption characteristic analysis.

To analyze the accuracy of the proposed energy data-partition method, three tests with different machining times and sample sizes are chosen for comparison, as shown in Table 2. The sample sizes are 2700, 5400 and 8100. The partition accuracy is calculated by the ratio of properly segmented data and total energy consumption data. The results show that the partition accuracies of these three tests are all more than 98%, and it reaches 99.5% for Test No. 1. Moreover, clustering approaches were often used in the data-partition process [50]. In order to evaluate the validity of the proposed method, the clustering approach is used as a contrast in Table 2. The results show that the accuracy of the clustering approach for Test No. 1 is 98.7%, and the results for the other two tests are 97.8% and 97.1%. In summary, the proposed method has a high partition precision for manufacturing energy consumption data. The partitioned energy consumption data can then be used to analyze the characteristics of energy efficiency.

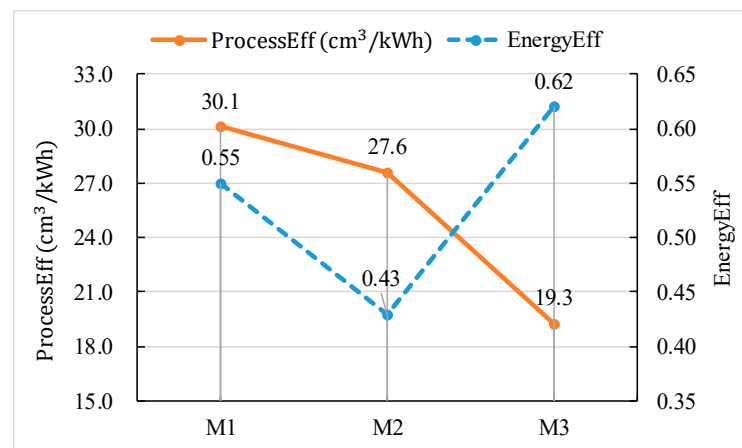
**Table 2.** The accuracy of the energy data-partition method.

Test No.	1	2	3
Machining time (min)	15	30	45
Sample size	2700	5400	8100
Partition accuracy (%)	99.5	98.6	98.4
Accuracy of clustering approach (%)	98.7	97.8	97.1

According to the proposed energy analysis method, some energy characteristic values of each process and machine tool can be obtained. The instantaneous energy characteristics of different processes are shown in Figure 6. It can be seen that the total energy of the four processes is descending, and the cylindrical lathe-cutting process consumes the most energy, which reaches 2.41 kWh. Therefore, this lathe process needs more attention, and some adjustment strategies can be implemented by equipment providers to realize energy conservation, such as process route modification or process parameter optimization. Moreover, the maximum power and mean power of the cutting state of the different processes are consistent. The power of the drilling hole on M2 is the highest, which is 4097 kW. The differentiation of mean power over time can be used to detect abnormal production conditions, for example, machine tool performance degradation and cutting tool wear. Additionally, the whole energy consumption of coupling parts can be obtained, which can be used by customers to optimize their product design.

**Figure 6.** The energy characteristic analysis of different processes.

The energy characteristic values of different machine tools are shown in Figure 7. This shows that the energy efficiency of M3 is the highest, reaching 0.62, which means that most of the energy consumption of M3 is used to conduct the material-removal process. That of M2 is the lowest, and more energy is wasted in standby or air-cutting states. For this problem, the NC code on M2 can be improved to increase its energy efficiency. For the process efficiency, M1 is the best, whereas M3 has the lowest process efficiency. This characteristic value can be used by manufacturers to select the appropriate machine tool with the highest processing efficiency, especially for roughing processes.



**Figure 7.** The energy characteristic analysis of different machine tools.

## 6. Conclusions and Future Work

To realize energy conservation and carbon emission reduction of manufacturing processes, one important step is to calculate and analyze the energy consumption and energy efficiency of machining processes. In this paper, a real-time energy consumption characteristic analysis method for IM workshops is established. First, an energy-conservation production architecture for IM processes is introduced, and the configuration of the data acquisition network is described to create a ubiquitous manufacturing environment. After the dynamic network construction, the required data can be acquired and the usage effectiveness of the sensor network can be improved. Then, an energy consumption data-partition and characteristic analysis method is proposed based on the process time window. The results show that the partition accuracies of these three tests are all more than 98%. Thus, the proposed method has a high partition precision for manufacturing energy consumption data. The energy characteristic values of different processes and machine tools can be obtained, which can be used by manufacturers to select the appropriate machine tool with the highest processing efficiency. The obtained energy characteristics can be used by different SM participants. This method realizes a combination of SM and real-time energy characteristic analysis.

In addition, there are also some limitations in the proposed methods which need to be researched in future works. First, in this study, only the energy consumption data of machine tools are analyzed, and many other important production data are neglected, such as energy consumption data of logistic processes and the workshop environment, the production capacity, and the utilization rate of equipment. Thus, more aggregative indicators are necessary for the overall assessment of manufacturing processes. Second, the actual manufacturing processes may be more complex, and include machine fault and cutting tool wear. Manufacturing data are dynamic and present uncertainties, and an intelligent processing method for complex data is required. Third, an energy consumption characteristic analysis cannot directly reduce the energy consumption of manufacturing systems. It is necessary to combine the energy characteristic analysis with some energy-saving strategies, such as multicriteria decision making about the selection of appropriate machine tools, process planning and production scheduling.

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