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Variation of Production Line Energy Consumption: Stochastic Process Models for Single and Multiple Machine Systems

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Abstract

The energy consumption of production lines can vary across different machines due to diverse factors such as varying processing rates, machine conditions, product characteristics, and the compatibility between products and machines. Additionally, identical products on the same type of machine may experience temporal variations in energy consumption due to real-time equipment status and operational activities. Accurately understanding these influencing factors can aid in developing more efficient energy management strategies. This study first analyzes the energy consumption of single machines processing single products, establishing a probabilistic model for the stochastic process of single-machine energy consumption over time. Mathematical tools, including convolution, are then employed to develop a stochastic process model for energy consumption across multiple machines and products within the entire plant. The overall stochastic process model is optimized, leading to the creation of a "Peak Energy Consumption Alert" and an "Energy Efficiency Alert" system to mitigate the risks of peak energy consumption and overall energy inefficiency. By utilizing the proposed optimization model for machine component energy consumption and the production scheduling module, the likelihood of exceeding contracted power capacity is significantly reduced. This approach also enhances the energy efficiency of production scheduling, thereby reducing the total energy consumption of the entire plant. Furthermore, while meeting energy planning goals, the model considers non-energy-related production indicators (e.g., completion time, order delivery dates), ultimately improving the operational efficiency of production lines.

Keywords: energy consumption, non-energy-related, production indicators

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1. Introduction

In response to the inclusion of future mechanical equipment in global energy policy regulation projects, it is essential to effectively guide domestic industries to promptly react to market changes and to establish the energy management capabilities of domestic companies. Energy management issues will become one of the key considerations in the industry in the future [1]. However, currently, there are of the power consumption of various operations of the machine tools. Therefore, it is not possible to develop more value-added application services. If the power consumption during the operation of machine tools can be used to establish various power consumption histories to differentiate between different processing states and their corresponding processing conditions, it will help in the management of power consumption histories and related application services, including monitoring services, warning services, etc.

In recent years, with rising electricity prices and increased emphasis on environmental protection, the power energy consumption of machines has begun to be

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incorporated into production scheduling systems, exploring the influence of energy consumption (Bougain, Gerhard, Nigischer, & Uĝurlu, 2015) [2]. From a technological and economic perspective, using models to predict and control short-term energy consumption is also an important issue (Filimonova, Kazarinov, & Barbasova, 2015) [3]. For electricity efficiency, the prediction of short-term power load can be used to manage production capacity and power distribution (Soares, Medeiros, 2008) [4]. In the past, scholars have also used different forecasting models to predict power load (Al-Hamadi & Soliman, 2004; Amjady, 2001) [5][6]. Additionally, accurately predicting daily peak power load demand can help power plants maintain stability during peak periods (Sigauke & Chijobvu, 2011) [7]. By monitoring energy consumption, the transparency of the energy use process can be increased, reducing machine waste and thereby lowering manufacturing costs. Furthermore, by installing sensors on the machines, machine data can be transmitted to the central system through networks [8] for storage, calculation, and analysis of energy consumption (Tristo, Bissacco, Lebar, & Valentinčič, 2015) [9].

In terms of energy consumption management, combining intelligent energy monitoring systems with wireless transceiver smart sockets (ZigBee-Equipped) and using portable devices on the Internet, the usage status of the equipment and energy anomalies can be monitored to save users' energy consumption and achieve real-time monitoring (Shie, Lin, Su, Chem, & Hutahaean, 2014) [10]. In the circuit board manufacturing process, an ERM system is provided to monitor energy consumption analysis to manage and improve energy use efficiency in the manufacturing process (Lee, Ko, & Ku, 2012) [11]. Retailers have set up sensors connected to the SMS system to detect external temperature, humidity, and other related data for real-time monitoring to achieve effective energy control and understand energy waste (Singh, Saini, Sharma, & Trivedi, 2015) [12].

2. Related Work

2.1. Contract Capacity and Excess Contract Additional Fees

Due to the inability to store electricity, in order to meet the electricity demands of users at any time, Tai power must plan sufficient power generation and supply equipment based on the "contract capacity" applied for by users. To prevent users from exceeding the originally applied capacity, which could lead to insufficient supply capacity or line damage, affecting the safety of power supply, a regulation of "excess contract additional fees" has been established to ensure the quality of power usage for all users. For large electricity users, Tai power calculates the average power consumption of users every 15 minutes. If this average exceeds the contract capacity, an additional fee must be paid.

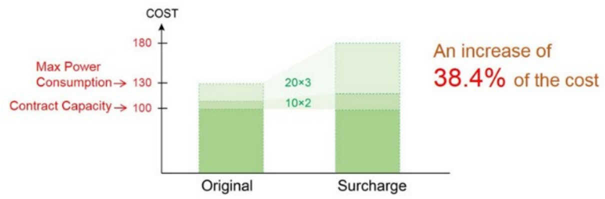

Figure 1. The method for calculating excess contract additional

The method for calculating excess contract additional fees (illustrated in Figure 1) is as follows:

(i) For the portion exceeding up to 10%, an additional fee is charged at twice the rate.
(ii) For the portion exceeding beyond 10%, an additional fee is charged at three times the rate

2.2. Optimization of Energy Consumption for Machine Tool Components and Production Scheduling Module

The energy consumption required for producing different products on different machines varies, and even the energy consumption required for producing the same product on the same machine is not always consistent. If we can more accurately grasp the energy consumption characteristics of different product and machine combinations, it will enable more effective energy management, reduce the risk of electricity usage exceeding the contract capacity, and improve energy use efficiency.

2.3. Current Issues in Energy Efficiency Analysis Cases

Due to factors such as machine conditions, operator status, and other variables, the energy consumption required to produce the same product on different machines may not be the same, and consequently, the energy efficiency will also vary. As shown in Figure 2, assume that Product A can be produced on Machine 1 and Machine 2. The energy consumption for each is represented by the peak value curves on the right. The red shaded area under each curve represents the expected energy consumption required to produce the product on that machine.

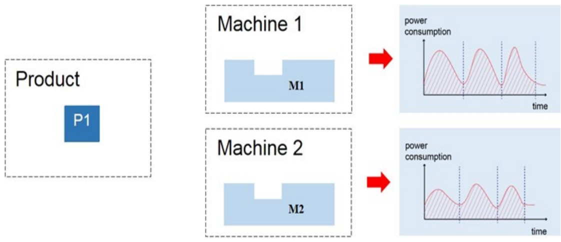

Figure 2. Energy Consumption of the Same Product on Different Machines

Considering the ratio of "energy consumption/production output" per unit time as a Key Performance Indicator (KPI) for evaluating energy efficiency, this KPI can be used to assess the energy usage efficiency of products on different machine combinations. This provides decision-makers with a basis for adjusting schedules to improve the energy efficiency of the production line.

3. Research Objectives and Methods

3.1. Research Objectives

The energy consumption required for producing different products on different machines varies, and even the energy consumption required for producing the same product on the same machine is not always consistent. If we can more accurately grasp the energy consumption characteristics of different product and machine combinations, it will enable more effective energy management, reduce the risk of electricity usage exceeding the contract capacity, and improve energy use efficiency.

To incorporate mechanical processing devices into the scope of energy control and enhance the management capabilities of energy efficiency, this collaborative research will develop a "Tool Component Energy Optimization and Production Scheduling Module" technology. Through this project, we aim to achieve the following objectives:

- Analyze the stochastic characteristics of energy demand for product and equipment combinations and establish a stochastic process model for energy demand based on this randomness.
- Use the stochastic energy consumption model to generate scheduling energy consumption warnings and improvement suggestions.
- Identify the probability distribution of peak energy consumption for different schedules and the occurrence time of peak energy consumption.
- Through the "Peak Energy Consumption Warning Function," quickly screen high-risk time points that violate energy consumption limits, significantly reducing the probability and frequency of violating maximum energy consumption limits.

3.2 Research and Development Technical Framework

This project will gather energy consumption data by installing meters and constructing energy consumption stochastic process models. The aim is to understand the energy consumption information for different products produced on different machines. A system will be established to analyze the relationship between the electricity consumption of processing machines and production products, achieving the objectives of "Peak Energy Consumption Warning" and "Energy Efficiency Warning.

The IDEF0 (ICAM DEFinition method) uses graphical and structured approaches to clearly and rigorously represent the functions within a system, as well as the constraints, relationships, and interactions between these functions. Based on IDEF0, this project designs the research and development technical framework as shown in Figure 3.

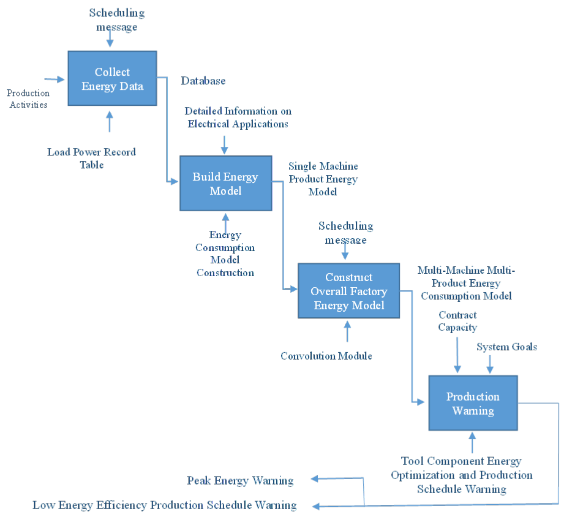

Figure 3. Research and Development Technical Framework

3.3 Collecting Machine Energy Consumption Information

In this research project, the "PA310 Load Record Power Meter" (specifications summarized in Table 1 below) will be installed on the machines. The PA310 is designed for power monitoring and load investigation in general single-phase and three-phase systems. Its wide measurement range (up to 200A) makes it suitable for general low-voltage single-phase and three-phase systems. Additionally, it maintains an accuracy of better than 0.5% even at low currents (below 5A), allowing it to be used in medium and high-voltage systems as well. By using the load record power meter, the project will record the energy consumption information of products and machines in different combinations and understand the energy consumption characteristics of different products in various machine production environments

Table 1. Product Specifications

Input Voltage	phase voltage 96-418V
Input Current	CTØ10(60A), Optional CTØ16(100A) CTØ24(200A)
Auxiliary Power Supply	AC~110V/220V
Rated	<0.001 lb
Frequency	50/60Hz
Output	Wh
Bidirectional Measurement	kW, kWh, kVAR, kVARh
kWh Accuracy	kWh Accuracy

In this research project, the PA310 Load Record Power Meter was used to preliminarily collect energy consumption information from "June 1, 2023, to June 10, 2023 (a total of 4 working days), from 08:00 to 23:59 each day." The electric load curve graph is shown in Figure 4 below.

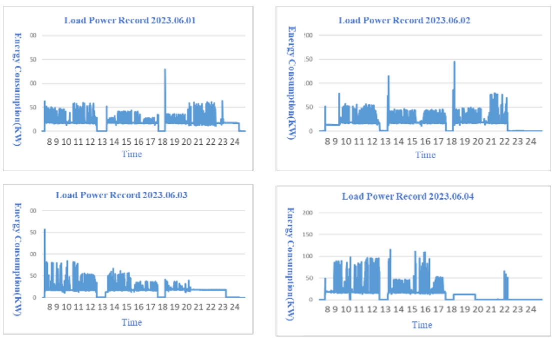

Figure 4. Electric Load Curve Graph (June 1-4, 2023)

3.4 Energy Consumption Model Construction Module

Matching Power Load Data with Work Order Data

To further analyze the energy consumption status of various products produced on different machines, it is necessary to match "power load data" with "work order data." This study classifies energy consumption information based on products and production lines to construct a single-machine single-product energy consumption model that matches products with machines. $E_{i.j}$ represents the energy consumption model for production line i producing product j.(see fig.5)

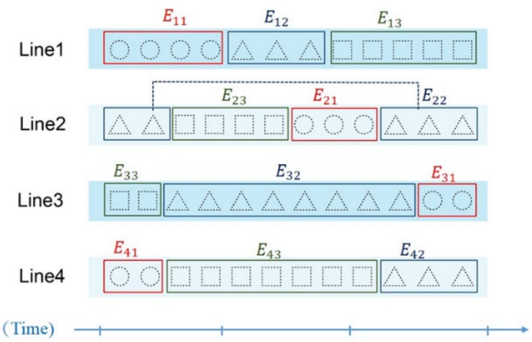

Figure 5. Matching Power Load Data with Work Order Data

Steps for Constructing the Energy Consumption Model

Step 1: Extract the electricity usage data for a specific product produced on a specific machine.
Step 2: Calculate the average electricity usage every fifteen minutes.
Step 3: Count the number of occurrences of all averages falling within each energy consumption interval.
Step 4: Calculate the probability (PDF) of all averages falling within each energy consumption interval.
Step 5: Sequentially accumulate the PDF to calculate the cumulative probability (CDF).

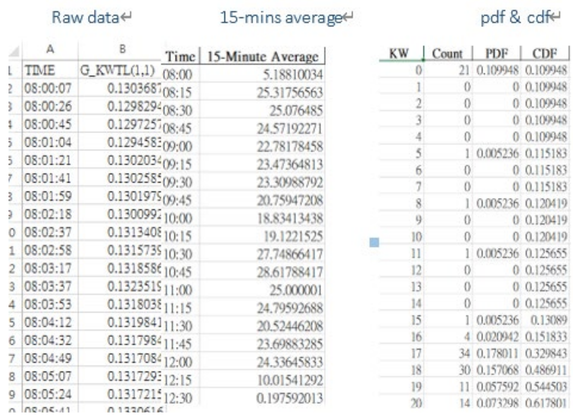

Figure 5. Flowchart for Constructing the Energy Consumption Model

Energy Consumption Probability Density Function

The "Probability Density Function" (PDF) is a function that describes the likelihood of a random variable's output value falling within a specific range around a certain point. As shown by the red dots in Figure 7, this can be expressed as Prob{18(kw)<Energy Consumption<19(kw)} =0.17.

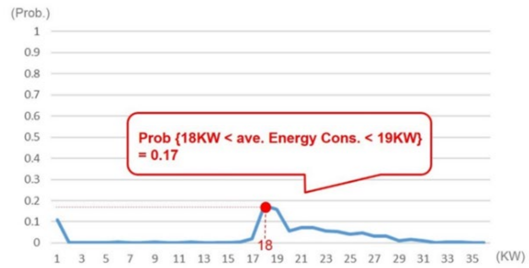

Figure 7. Energy Consumption Probability Density Function Graph

Energy Consumption Cumulative Distribution Function

The "Cumulative Distribution Function" (CDF) is a function that describes the cumulative probability of a random variable's output value being less than or equal to a specific point. As shown by the red dots in Figure 8, this can be expressed as Prob{Energy Consumption < 26(kw)} = 0.9.

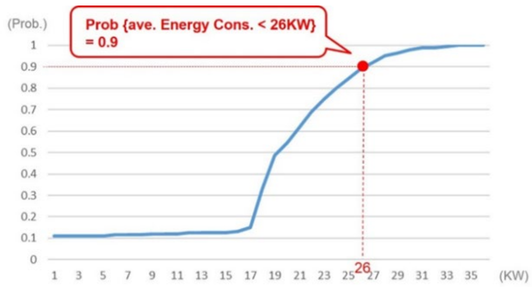

Figure 8. Energy Consumption Cumulative Distribution Function Graph

Using the electricity consumption data from June 1, 2023, to June 10, 2023, the machine energy consumption probability density function model is constructed as shown in Figure 9.

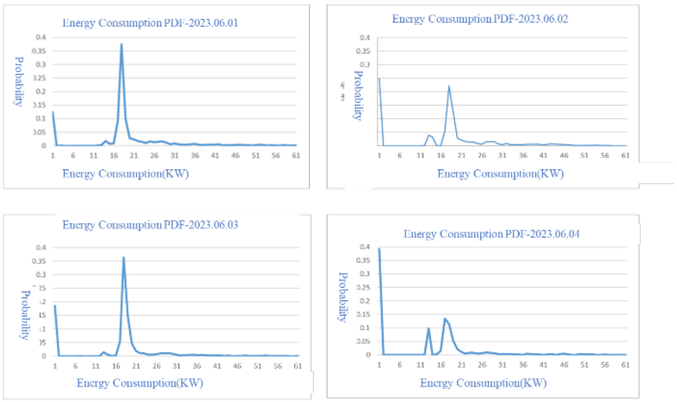

Figure 9. Energy Consumption PDF(2023.06.01-06.04)

Using the electricity consumption data from June 1, 2023, to June 4, 2024, the machine energy consumption probability density function model is constructed as shown in Figure 10.

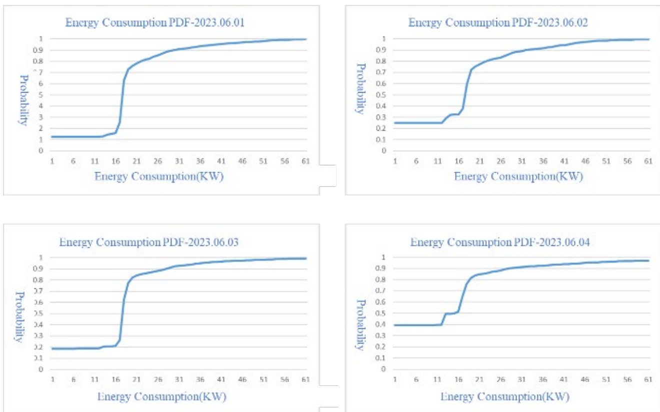

Figure 10. Energy Consumption CDF(2023.06.01-06.04)

From Figures 9 and 10, we can observe that:

- Energy consumption is indeed highly correlated with production activities, and there are significant differences in energy consumption for different production activities.
- There is a high risk of peak energy consumption exceeding the standard each day. Therefore, if efficient management rules can be established, the risk of exceeding the standard can be greatly reduced.
- Although the proportion of energy consumption exceeding 50KW is less than 3%, it results in very high excess additional fees. By utilizing a peak energy consumption warning system, it is possible to more efficiently identify schedules with a high risk of exceeding the standard.

Convolution

Convolution has numerous applications in both engineering and mathematics. In statistics, a weighted moving average is a type of convolution. In probability theory, the probability density function of the sum of two independent variables, X and Y, is the convolution of the probability density functions of X and Y. In electrical engineering and signal processing, the output of any linear system can be obtained by convolving the input signal with the system's function. In physics, any linear system that follows the principle of superposition involves convolution.

Let X and Y be two independent continuous random variables, with $f_X(x)$ and $f_Y(y)$ representing the probability density functions of X and Y, respectively, and$F_X(x)$ and $F_Y(y)$ representing the cumulative distribution functions of X and Y, respectively. Assuming $Z = X + Y$, we have:

$$F_Z(t) = F_{X+Y}(t) = p(X + Y \leq t)$$

$$= \iint_{x+y\leq t} f_X(x) f_Y(y) dxdy. \quad (1)$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{t-y} f_X(x) dx f_Y(y) dy$$

$$= \int_{-\infty}^{\infty} F_X(t-y) f(y) dy$$

It can be proven that for all $t \in (-\infty, \infty)$, the above integral exists. As t takes different values, this integral defines the cumulative distribution function $F_Z(t)$ of Z, which is the convolution of the two independent random variables X and Y.

Using convolution, multiple single-machine single-product energy consumption stochastic process models can be summed to obtain the overall total energy consumption stochastic process model. An illustration is shown in Figure 11.

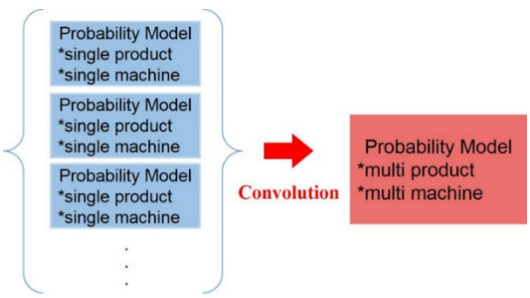

Figure 11. Illustration of Convolution

4. Simulation

4.1 Simulation Scheduling

Based on the electricity load data collected from June 1, 2023, to June 4, 2023, it can be observed that the continuous production time for each product on the same machine ranges from 1 to 4.5 hours. Additionally, it is known that this electricity data includes the electricity usage records of three products on four production lines. Therefore, this study defines two variables, T and P, to generate "simulation scheduling" data in a random manner.

T~$Uniform(4,18)$: The continuous production time for each product on the same machine

P~$Uniform(1,3)$: Product Number to be Produced

The system will simultaneously consider the output values generated by the two random variables, T and P, to produce the simulation scheduling. For example, if T=10 and P=2, it represents "continuously producing product 2 for ten intervals," and so on, until all time slots are scheduled. The illustration is shown in Figure 12.

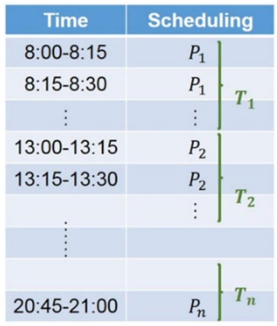

Figure 12. Simulation Scheduling Illustration

4.2 Verification Method

Using the energy consumption stochastic process model constructed from the electricity load data collected from June 1, 2023, to June 4, 2023, the probability of total energy consumption exceeding the contract capacity for each simulation schedule in every fifteen-minute interval is predicted. The simulation results are further analyzed to verify the effectiveness of this energy warning system. The structure is shown in Figure 13.

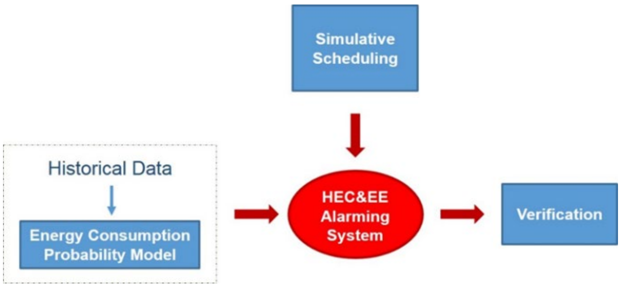

Figure 13. Verification Method Structure Diagram

4.3 Simulation Results

Under the conditions of a contract capacity of 110 KW and a critical probability of 0.99 (the probability that the total energy consumption does not exceed the contract capacity), the statistical results of 20 repeated simulations are shown in Table 2:

Table 2. Simulation Results Statistical

Frequency	Frequency	Probability of Exceedances	Accuracy of Warnings	Type I Error	Type II Error
1	3	0.00115	1.0	0	0.333
2	4	0.00154	1.0	0	0.284
3	7	0.00269	0.714	0.286	0.239
4	8	0.00308	0.875	0.125	0.266
5	3	0.00115	1.0	0	0.32
6	6	0.00231	0.667	0.333	0.293
7	1	0.00038	1.0	0	0.315
8	8	0.00308	0.75	0.25	0.982
9	2	0.00077	1.0	0	0.328
10	4	0.00154	1.0	0	0.323
11	8	0.00308	0.75	0.25	0.295
12	3	0.00115	0.667	0.333	0.309
13	6	0.00231	0.667	0.333	0.303
14	5	0.00192	1.0	0	0.23
15	4	0.00154	0.5	0.5	0.177
16	6	0.00231	0.833	0.167	0.256
17	5	0.00192	1.0	0	0.309
18	6	0.00231	1.0	0	0.229
19	9	0.00346	0.667	0.333	0.248
20	3	0.00115	0.667	0.333	0.289
Average	5.05	0.00194	0.83785	0.16215	0.3164

Among them:

- **Accuracy of Warnings**: The probability that the system provides a warning when the contract capacity is exceeded.
- **Type I Error**: The probability that the contract capacity is exceeded, but the system does not provide a warning.
- **Type II Error**: The probability that the contract capacity is not exceeded, but the system provides a warning.

Each simulation includes the results of "50 working days, from 08:00 to 21:00 each day." Among the 20 simulation results, the average percentage of exceeding the contract capacity is approximately 0.0019. The probability that the system correctly provides a warning when the contract capacity is exceeded is 0.838, while the average Type I and Type II errors are 0.162 and 0.316, respectively.

The simulation results indicate that the peak energy consumption warning system can correctly predict more than 80% of production activities where the machine exceeds the contract capacity. It generates warnings for production schedules with peak energy consumption, providing a basis for improving the schedule and thus reducing the probability that the total energy consumption of the production system exceeds the contract capacity. This verifies the project's goal of "achieving an 80% reduction in the risk of machine tools exceeding the contract capacity.

5. Conclusion

Currently, the technology for capturing the electricity consumption of machine tools only considers total electricity usage data without further analyzing the energy consumption of each operation of the machine tool. As a result, it is challenging to develop more value-added application services. To overcome the issue of frequent line changes in the stamping machine manufacturing industry due to small batch production with various products, this project aims to establish various energy consumption histories based on the electricity usage content of machine tool operations and work order data. This approach will analyze the energy consumption status of the same product produced on different machines, assisting decision-makers in formulating more effective energy management strategies. By analyzing the electricity consumption histories and the electricity usage content of machine tools, it can be confirmed that energy consumption is indeed highly correlated with production activities, and there are significant differences in energy consumption for different production activities. If the electricity consumption history of each product can be understood in advance, it can provide decision-makers with references for scheduling planning, allowing high-energy-consuming production activities to be distributed across different time periods. This approach can reduce the overall energy consumption demand of the production system, lower the contract capacity signed with Taipower, save fixed electricity costs, and reduce variable electricity costs, ultimately reducing the carbon footprint.

The tool component energy optimization and production scheduling module developed in this project includes the "Peak Energy Consumption Warning System" and the "Energy Efficiency Warning System." These systems can generate warnings for schedules with a high risk of exceeding the total energy consumption contract capacity and low power usage efficiency. The peak energy consumption warning system can accurately predict more than 80% of production activities where the machine tools exceed the contract capacity. This significantly reduces the chances of exceeding the contract capacity, improves the energy efficiency of production activities, and reduces the total energy consumption of the entire plant.

Acknowledgment

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