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A digital twin-driven approach to the design of energy consumption optimization control strategies for industrial production processes

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SUMMARY: *The current research proposes an energy optimization model to the production systems in reaction to the increased levels of demand concerning enhanced energy management in real-time in the industrial sector of manufacturing. The proposed framework is based on digital twin technology, which plays the role of the core enabling mechanism in the methodology. First, a simulation architecture of production lines is created, then a thorough explanation is given on how the digital twin model is designed along four different dimensions, namely geometry, physics, production behavior, and simulation rules. BP neural networks are used to create specific energy consumption models of each device to represent the energy properties of each piece of equipment. Then a method of optimization is created that targets workshop-level production processes and combines a multi-objective objective function based on several assessment criteria. They are tool life, robot motion smoothness and production time. This dynamic model is fed directly into this optimization process using energy consumption data extracted out of the digital twin model. When dealing with the collaborative adjustment of machining parameters between several machines when producing low carbon products, the artificial bee colony algorithm is applied, providing a strong global search capability, which is well suited to the complexity of this optimization problem. The proposed strategy is verified using a case study focusing on the production process of a particular workpiece. During normal operating conditions, the optimization of both workshop energy consumption and production time reduces energy use by 29.71 percent compared to the traditional approach. In rework situations, more emphasis on tool life and robot motion smoothness results in a 12.63 percent lower plant energy consumption than the current baseline. These findings indicate that the framework is effective in supporting energy monitoring and optimization in all aspects of shop floor production activities.*

KEYWORDS: *BP neural network; artificial bee colony algorithm; digital twin; energy consumption optimization*

1 Introduction

The Industrial Revolution has been a shift in the use of energy by humans. Since then, fossil fuels have been combusted increasingly rapidly to support industrial production, which has essentially transformed the nature of the worlds energy supplies [1]. The ecological effects have been disastrous. The uncontrolled burning of fossil fuels has resulted in massive pollution and

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a constant increase in the overall temperature of the earth, which has alarmed many governments as well as scientists [2]. World leaders officially backed the aim of restricting global warming to 2 degrees Celsius at the 2009 G8 Summit. It was restated in the 2015 Paris Agreement where signatory states undertook to ensure that warming does not exceed 2.0 degrees beyond pre-industrial levels, and further action should be taken to limit it to the more ambitious target of 1.5 degrees [3, 4]. China is especially significant in this global endeavor. Because it is the largest developing economy in the world, the extensive use of high-carbon energy resources has given the country the highest position in the list of world carbon emissions. To acknowledge its obligations, China has pledged particular goals in terms of carbon peaking and carbon neutrality, steps that are predicted to have a significant impact on the reduction of carbon emissions around the world [5]. This would need action in two directions. Increasing the share of clean and non-fossil energy in the total mix can directly reduce greenhouse gas emissions, and increasing the efficiency of energy conversion into economic activity can ensure that less fuel is used to produce similar effects [6, 7]. In this larger picture, industrial production of energy consumption optimization has become one of the most pragmatic and effective ways to increased energy efficiency. It can be seen as a natural path to take in the next generation of energy saving and emission reduction. The energy supply to industry is becoming an increasingly tight fit, and the importance of conservation has now become a challenge to face the world [8]. In the face of decelerating economic progress, the traditional model of energy intensive energy expenditure is being replaced by more calculated actions. Producers are beginning to focus more on the expenditure of energy at each step of production [9, 10].

The introduction of the concept of the so-called "Industry 4.0" brought about a novel outlook on manufacturing, i.e., one where production technologies, business activities, and customer experience will be interwoven into smart factories that can react to changes and exploit resources much more efficiently. This vision has gradually become the central theme of what the future industrial development will be like. At its technical heart is the intersection of intelligent integrated sensing and control systems with Internet of Things infrastructure [11-13]. The factory has made significant improvements in automation and information management as smart manufacturing under the banner of Industry 4.0 has continued to make strides. Such advances have resulted in favorable environments to perform the systematic analysis of the energy usage. The mass application of sensing, measurement, communication, and control technologies brought about the emergence of densely connected industrial information networks and huge pools of operation data [14-16]. Amongst other technologies in this technological ecosystem, digital twin technology is exceptional because it has the potential to produce high-value insights based on data, making it one of the core pillars of future energy management [17].

The digital twin technology essentially aims at creating a virtual replica of the physical world that reflects its actual-world subject with the level of fidelity akin to a holographic projection. Their relationship is not fixed. It is constantly recording and replicating the present state and changing behaviors of physical systems because of the continuous flow of both virtual and real information. It creates a feasible space of analytical work and experimentation that would otherwise have been precluded by physical limitations, and provides the foundation of implementing a wide range of advanced engineering systems [18-21]. In the case where this ability to unify data is applied to the manufacturing environment, the bringing together of disparate data including past production records and real-time data kept up to date, the twin model could be based on live operational data instead of static assumptions. The outcome is a simulation model that is able to provide information and implement the optimal and accurate regulation of energy usage throughout the entire length of the production process.

The academic interest in energy consumption optimization has increased significantly over the last few years, covering a large variety of industrial applications. The literature can be roughly divided into two major themes that recur throughout the corpus: process modeling and the optimization of process parameters. As an example, Basem et al. considered the energy performance of refrigerator freezers and used analysis of variance to determine the best combination of evaporator volume, capillary tube length, and refrigerant amount. The final parameters settings have provided significant 20 percent energy consumption reduction [22]. Torayev et al. paid their focus to industrial robots and suggested an optimization framework based on black-box models, which they tested on two FANUC robots working in different industrial settings. Their solution was successful in alleviating the energy burden that is traditionally heavy in the case of robot operation[23]. Kurbonov et al. adopted a different approach where they referred to the Energy Balance Reporting Tool to bring reason to the energy consumption norms in industrial facilities. It gauges, compares, and evaluates the energy-related indicators in the manufacturing process, and with the help of scientific algorithms it creates specific optimization solutions, allowing companies to track and control their energy usage much more accurately [24]. Zhong et al. have created an analysis approach to energy consumption based on multi-parameter properties and created a model that will encode features, states, and operations of the production process. Integrating standby energy ratio, production sensitivity, temperature impact factor, and equipment efficiency within the computational framework, their approach can provide a consistent estimate of energy consumption and provide the data needed to make informed optimization choices [25]. Yang studied silicone rubber manufacturing and determined that the most energy-intensive steps are mixing, molding, vulcanization, and post-treatment. In these terms, a group of optimization actions were suggested, including the upgrade of the equipment, the adjustment of the process parameters, energy management system introduction, and renewable energy sources integration. The combination of these interventions produced significant savings of energy in practice [26]. Chang solved the problem by mathematically modeling the refrigeration unit operation parameters, building an energy consumption model as the analytical base. It was then optimized with the help of the Lagrangian method and the obtained control scheme proved effective in the overall reduction of energy usage of the entire refrigeration system [27].

Intelligent optimization algorithms have been used to resolve energy consumption issues which has become an area of research that has received significant attention over the years by both industry experts and academic scholars [28].Yao et al. analyzed the power usage of discrete manufacturing machinery, which included a machine tool and an industrial robot, and arrived at a conclusion that multi-parameter intelligent optimization algorithms can be widely used in the field of energy. They indicated that this kind of approach could be seen as the next frontier of further development in the field of energy consumption optimization [29]. Wen et al. dealt with energy issues of automated assembly lines by integrating an enhanced reinforcement learning algorithm with a multi-objective harmony search algorithm. The combination of the two methodologies had a very positive impact on the adaptive choice of search strategies and improved the local search performance of the population, ultimately providing several feasible improvement options to assembly line energy management [30]. Yang, D et al. solved the issue of energy consumption related to the trajectory of the robotic system by developing an NSGA-II model based on the energy mapping concepts. The objective functions that aimed to minimize energy consumption and minimize cycle time were developed and the algorithm was implemented to calculate the Pareto-optimal solution set. This approach resulted in the reduction of robot energy consumption by over 10 percent [31]. The problem of production line energy consumption was formulated as a nonlinear programming problem by Chen et al., who constructed two nonlinear equations to find a solution that minimizes the consumption of resources, thus framing the problem of production line energy consumption.

The optimization calculation was performed using a binary search algorithm, and the obtained strategy demonstrated significant energy savings in numerical experiments [32]. Lu et al. have developed a dynamic flow model of coal flows and then implemented the NSGA-II-ARSBX algorithm to solve a multi-objective optimization problem that regulates energy use during the transportation of coal. Their findings indicated that smaller coal block-size and higher hauling-speed and decreasing the speeds of the scraper-chain and drum-speed are useful leverage points in reducing energy use [33]. The work of Lee et al. explored the issue of load distribution between refrigeration units thoroughly, based on actual engineering examples to create control schemes of optimal load distribution with three different algorithms. The optimized schemes all demonstrated significant energy saving compared to the original control scheme, where the particle swarm algorithm proved to be the most effective of the three [34]. The study by Ding et al. analyzed the interaction between energy constraints of devices that worked under the framework of an Internet of Things environment and came up with a multi-objective fuzzy algorithm to optimize the scheduling of the devices. It was found that their strategy enhanced the effectiveness of energy usage and reduced the amount of total energy used in the entire IoT system [35].

Machine learning and deep learning algorithms have proven to be strongly capable of precise predictions of energy consumption, and this has opened up new opportunities in the field of optimization studies that were not accessible before [36, 37]. Surya et al. explored the application of machine learning methods to energy optimization in mining, their value in three different areas of functionality: predictive modeling of energy use, anomaly detection and adaptive control. The regression algorithms, random forests, and models of XGBoost were found to be able to predict the level of energy consumption within acceptable limits and long short-term memory networks and convolutional neural networks were especially effective in detecting equipment failures and enhancing the general efficiency of energy consumption [38]. Tang stressed the importance of intelligent energy optimization and scheduling to reduce the burden of energy resource scarcity and thus came up with an adaptive dynamic programming collaborative reinforcement learning algorithm. The suggested approach was tested on a simulated setting developed to simulate various conditions of the task load and minimized energy consumption by 25.3 per cent as compared to traditional algorithms [39]. Wang et al. focused on robotic systems, creating deep learning hybrid models especially designed to forecast and optimize energy consumption of the industrial robots. Tests performed on Kuka KR210 and KR60 robots produced accuracies greater than 95% which indicates the applicability of the proposed models in typical industrial settings [40]. Ye et al. studied the implementation of machine learning in energy optimization of compressors, using an optimization model to conduct global optimal energy usage analysis of 1000 simulation samples. The results indicated that both the feasibility and efficacy of machine learning-based methods in this field are achieved [41].

The accelerated development of cyber-physical systems, artificial intelligence, and big data analytics and the Internet of Things has made the study of digital twins an area of interest to scholars in many fields, leading to a surge in theoretical and practical studies related to the topic [42]. Within the field of energy consumption optimization, Nozari et al. were among the earliest to confirm that digital twin technology could be applied to this task. They demonstrated that factories that are equipped with the digital twin infrastructure are capable of analyzing data on energy consumption in real-time, implementing smart algorithms to predict and understand the trends of consumption, and using IoT monitoring systems to obtain detailed insight into the pattern of energy usage and eventually reduce the consumption rate without affecting the level of operational efficiency [43]. The team of Hosamo et al. focused its attention on heating, ventilation and air conditioning systems, developing a digital twin model which was aimed at decreasing the energy use of air conditioning systems but preserving thermal comfort. The feasibility of the framework was assessed using the energy consumption information gathered by a Norwegian office building during the period between August 2019 and October 2021 as a test basis [44]. The approach proposed by Zhang et al. was based on the view of production workshops, considering the interaction between the fluctuation of equipment energy consumption and the overall equipment network in the shop floor. To measure and reproduce the dynamic changes of these fluctuations, a digital twin workshop energy footprint model was created. Upon such basis, a workshop-level objective function to minimize energy use was derived and optimized to obtain the optimal value of the method, which showed significant reductions in the energy use of production units[45]. The agent decision-making driven digital twin strategy of Vatankhah Barenji et al. was developed as a way to optimize the planning of robot trajectories as a way to reduce energy use. Both the qualitative and the quantitative analyses proved that the proposed method could provide tangible enhancements in the results of robotic path planning [46]. Digital twin technology was applied to the problem of production line energy optimization by Xia et al., who built a real-time simulation platform incorporating geometric, physical, and production behavior dimensions. Next, a genetic algorithm was used in this setting to find the minimum energy configuration and translate the simulation results into practical solutions of optimization [47]. Production system-level energy consumption was considered by Sun et al., who used digital twin technology to aggregate flows of energy data and establish optimal buffer levels of online energy management. The application of the method to the battery module manufacturing line of a new energy vehicle factory demonstrated the presence of positive results in real-life energy optimization [48].

The presented work describes a systematic way of creating a digital twin model of industrial production processes with the aim of lowering energy use at the level of the workshop. In addition to this modeling system, a cooperative optimization process is designed to simultaneously optimize the machining parameters on several machines. The approach considers the overall performance of workshops, including energy usage, tool life, the smoothness of robot movements, and time taken to complete the production process in an integrated optimization architecture. The artificial bee colony algorithm acts as the computational engine that can be used to determine the optimal machining parameter set up of the entire workshop equipment. In order to evaluate the utility of the suggested approach, simulation experiments are planned that will consider both normal production operations and rework situations. The data on the optimization index are gathered at different weights of every case and the numerical results are employed to test the validity of the method suggested in this paper.

2 Construction of digital twin models of industrial production processes

2.1 Production Line Simulation System Component Architecture

The simulation of production line is the concept of physical objects that can be significantly different in types and functions. To cope with such variety in a consistent context, the model needs to have a single logical organization, able to represent any of the mentioned entities in the digital world in a uniform and non-ambiguous manner.

The building technique used in this paper relies on a multi-dimensional modeling approach based on four components, which include geometry, physics, behavior, and rules. In this context, digital twin technology can be applied to create virtual models of actual equipment, obtaining a systematic, multi-dimensional relationship between manufacturing assets in the material world and their equivalents in the digital world. The correspondence works on multiple different levels. Geometric and physical mapping converts the spatial arrangements and material attributes of manufacturing equipment into corresponding geometric information and physical characteristics in the model. Behavioral mapping will focus on the dynamic aspect of production, representing the state changes in manufacturing equipment and changes in the form of products and other process-related events. In turn, rule mapping codifies the operational logic and evolutionary trends that control the functioning and evolution of physical devices over time. All these four layers form a digital twin logic model that describes the manufacturing resources in digital space by coordinating the description of geometric parameters, physical properties, production behaviors and simulation rules.

2.2 Construction of the digital twin model

The process of building the digital twin logic model to simulate the production line is conducted in three consecutive steps.

The initial phase is based on the physical manufacturing line. The relevant production details are obtained on the basis of the actual entities existing on the floor, including the dimensional information, layout design of the workshop, and processing types related to each entity. It is this information that constitutes the geometric parameters and physical characteristics which provide the digital twin logic model with a connection to its real world referent. The second phase refers to the aspect of the model that is behavioral. According to the type of production behavior a physical entity can demonstrate in real-life operation, an event-driven finite state transfer model is built. This mechanism provides the digital twin logic model with an ability to react to operational triggers, to display inherent behaviors, and to conduct state transitions in the same way as physical equipment does on the production line. In the third stage, the geometric, physical, and behavioral bases laid down in previous stages are developed further. At this point, the rules of simulation of the physical production entities are defined, especially synchronous advancement rules and mutual exclusion priority rules that regulate the interactions between the models. Behavioral information produced during the simulation is routed to the relevant associated models by using a logic pipeline so each category of modeled device is able to develop and act in line with the dynamics of the overall production system.

Digital twin logic model of production line simulation can be used as the process of representing the attributes, methods, behaviors and other properties of physical objects and processes in the digital form of a virtual space. This representation is obtained through the combination of four constituent elements. The geometric properties (GP) encode the dimensions and spatial positions of the physical entities that occupy the production workshop, including personnel, equipment, materials, and the surrounding environment as they are during real production. The physical properties (PP) depict the modes of processing and operational conditions of the equipment, giving a dynamic view of how the machines behave at any particular time. The behavior of production (PB) considers the fact that the activities taking place in the workshop occur in sequence, which is an indication of the sequence of events that define the actual manufacturing processes. The rules of simulation (SR) are inferred through the operational logic and the trends of evolution in the workshop practice and set the conditions under which the model evolves and reacts over time. Using these four elements, the digital twin logic model of the production line simulation is formally stated as:

$$TLM = \{GP, PP, PB, SR\} \tag{1}$$

In the context of the digital twin logic model to simulate a production line, physical attributes are used to verify the identity of a given production element logic model in the logical space and to re-create critical processing parameters relative to the real-life production elements. Physical attributes encode information in four major categories, namely, type number, element name, physical parameter, and production and processing state. Type number acts as a unique identifier of each digital twin logic model of production elements in the system. The names of elements make it possible to distinguish among various digital twin logic models based on the same abstract manufacturing equipment model. Physical parameters contain equipment-based data like transmission speed, cutting force, maximum capacity, and the exact values differ between the different logic models. The production and processing state reflects the status of a particular piece of equipment at a specific time in its operation. Physical properties are defined as:

$$GP = \{GS, GSA, GPT, PMS, BMS\} \tag{2}$$

where: GS is the geometry. GSA is the geometric shape. GPT is the geometric position. PMS is the precursor model set. BMS is the subsequent model set.

In the context of a digital twin logic model of a production line simulation, production behavior stands as an abstract depiction of what production resources produce in response to external instructions. The extent of production behavior includes time information related to the abstract representation of manufacturing equipment as well as event messages, including the end of a processing operation or the achievement of maximum loading capacity. Timer information logs when every digital twin logic model enters and leaves the simulation, as well as the length of time it spends inside the simulation. Events are the triggering events that cause state transitions throughout the simulation under the production behavior model. Production behavior is defined as:

$$PP = \{TPID, Name, PPS_{Eq}, MSS\} \tag{3}$$

where: $TPID$ is the type number. $Name$ is the name of the digital twin logic model. PPS_{Eq} is the physical parameters of different types of production factors. MSS is the set of model states.

In the digital twin logic model for production line simulation, the production behavior refers to the abstraction of the corresponding actions generated by the production resources under the stimulation of external commands, which mainly includes the timer information of the abstract model of the manufacturing equipment, as well as the relevant messages such as completing processing and reaching the maximum loading capacity. Among them: timer information records the moment when each digital twin logic model enters simulation and ends simulation, as well as the time during simulation. Events are triggering conditions, which are used to trigger the state transfer of the production behavior during the simulation process. The production behavior is described as:

$$PB = \{IST, OST, CST, PDS, MES_{Eq}\} \tag{4}$$

where: IST is the moment of entering the simulation. OST is the moment of ending simulation. CST is the current simulation time. PDS is the current processing state of the manufacturing equipment. MES_{Eq} is the related messages of different digital twin logic models.

In the digital twin logic model, which simulates production lines, simulation rules are a detailed abstract encapsulation of all the events that can be experienced during the production processing of the given production factors. When a message is received, an instantiated model will refer to its logical event response list and pick the suitable event response to execute. Interaction between twin models can only be achieved through simulation rules. These are the adhesive agents connecting different models on the production line and they are the basic mechanisms responsible in facilitating the dynamic functioning of the entire digital twin logic model. In content, simulation rules include all the production behavior abstractions of the production elements as well as the auxiliary event responses needed to maintain logical simulation. The simulation rules are defined as:

$$SR = \left\{ LBE_{Eq}, AER \right\} \tag{5}$$

where: LBE_{Eq} is the event response abstraction for different manufacturing equipment. AER is the auxiliary event response.

3 Modeling of energy flow patterns in workshop production processes

This chapter deals with two types of production equipment commonly available in manufacturing settings which are CNC machine tools and industrial robots, which are used to discuss the primary objects of energy usage modeling. The principal energy-consuming equipment inside the physical production shop is sensor-based data collected on the main energy consuming equipment, which forms the empirical basis of further analysis. The structure of energy consumption is studied in depth and the interaction between energy consumption of the equipment and machining parameters are characterized using a BP neural network, giving the resultant energy consumption structure per equipment type. Interaction logic is incorporated in the energy consumption models such that with a given set of machining parameters as inputs, each model can produce estimated energy consumption outputs. This functionality allows simulating energy consumption of the overall production process at the workshop level. The energy consumption model developed to represent the production workshop is depicted in Figure 1.

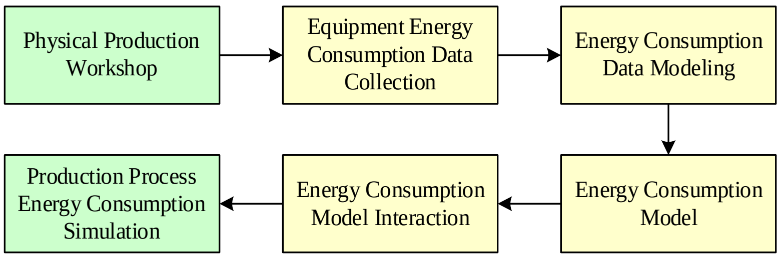

Figure 1: The energy consumption model of the production workshop

3.1 Artificial Neural Network Modeling Approach

The conceptual foundation of artificial neural networks lies in the abstraction and computational modeling of basic properties of biological neural systems, such as the human brain. It consists of many neurons and with the help of the emulation of biological neuronal behavior it can approximate highly complicated non-linear functions relating inputs to outputs.

Of all the architectures that have been proposed, the BP neural network has been the most widely used in practice.

Figure 2 illustrates the algorithmic procedure of the BP neural network. The first step is to initialize the network whereby connection weights and thresholds are given small random values. Then a set of input-output data samples are presented to the network and output at each layer node is calculated by forward propagation. Discrepancy between computed output and target value is measured and connection weights are changed in such a way that minimizes this error. This loop of forward computation and weight adjustment is executed repeatedly until all the error related to all input-output sample pair is in the allowable tolerance.

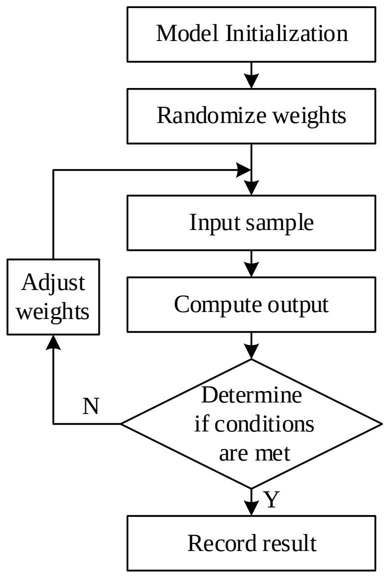

Figure 2: Flow chart of the BP neural network algorithm

3.2 Modeling energy consumption in the production plant

The energy consumption model of the production workshop is developed based on the BP neural network approach explained above. Careful observation of the machine tool production process shows that it requires different levels of energy at different stages of its operation. Standby power consumption is used to maintain auxiliary systems, including lighting and numerical control functions, of the machine tool when standby. After being activated, extra power is taken over with spindle cutting and axis feed actions, which are overlaid on the original stand-by load. The total energy requirement of spindle cutting and feed movement is referred to as the machining energy use of the machine tool. On these grounds, the total energy consumption model W_{m1} of the machine tool is written as follows:

$$W_m = \int_0^{t_m} P_{m1} dt + \int_0^{t_m+2t_f+t_s} P_{m2} dt \tag{6}$$

where: P_{m1} is the machining power of the machine. P_{m2} is the other system power of the machine. t_m is the machining time of the machine. t_f is the loading time of the machine. Since the loading and unloading time of the machine is the same, the total loading and unloading time is taken as $2t_f$. t_s is the remaining standby time of the machine.

The machining energy consumption model of the machine tool is derived with a BP neural network. Five machining parameters are chosen as model inputs, which are spindle speed, feed rate, depth of cut, width of cut, and tool machining time. All these variables are a measure of the main causes of energy spending when active cutting occurs. The obtained machining energy consumption model of the machine tool is

$$W_{m1} = \int_0^{t_m} P_{m1} dt = F\left(n, f, a_p, a_e, t_f\right) \tag{7}$$

where: n is the spindle speed. f is the feed rate. a_p is the depth of cut. a_e is the cutting width. t_f is the tool machined time.

The energy consumption of the residual auxiliary systems of the machine tool is considered to be a fixed constant and the related energy consumption model is formulated through the measurement of the power of such systems. The overall energy consumption model of the machine tool is then achieved by adding together the machining energy consumption model and the auxiliary system energy consumption model using equation (6).

The energy consumption of the robot also changes during different operating conditions. Standby mode causes the robot to use energy due to motor idling and operating control system. When working actively, the energy requirement changes to cover the total working load of the motor and the control system. The complete energy consumption model W_r of the robot is given by the equation:

$$W_r = \int_0^{2t_r} P_{r1} dt + \int_0^{t_m + t_r} P_{r2} dt \tag{8}$$

where: P_{r1} is the transportation power of the robot. P_{r2} is the standby power of the robot.

Transportation energy consumption in the model of the robot is calculated through the use of a BP neural network. Considering all the parameters that define robot operation, the Tool Center Point speed is chosen to serve as the model input because it is easy to adjust and its relationship with overall energy consumption is very strong. The transportation energy consumption model of the robot is the following:

$$W_{r1} = \int_0^{2t_r} P_{r1} dt = F\left(v_T\right) \tag{9}$$

where v_T is the TCP speed of the robot.

Standby power of the robot is considered to be a constant, and the energy consumption model is built based on the direct measurement of standby power. The full energy consumption model of the robot can be then acquired by substitution of both, the transportation energy model and the standby energy model into equation (8).

The energy consumption model W of the production plant is:

$$W = \sum_{i=1}^{x_m} W_{mi} + \sum_{i=1}^{x_r} W_{ri} + W_o \tag{10}$$

where: W_{mi} is the energy consumption of the i th machine tool in the production plant. W_{ri} is the energy consumption of the i th robot in the production plant. W_o is the other fixed energy consumption of the production plant. x_m is the number of machine tools in the shop floor. x_r is the number of robots in the workshop.

The workshop-level energy consumption model is derived by replacing the machine tool energy consumption model and the robot transportation energy consumption model into equation (10).

4 Energy model optimization methods for workshop production processes

The multi-objective optimization function is formulated in this chapter based on the energy consumption models developed in the previous section. The Artificial Bee Colony algorithm is subsequently used as the computational solver to perform optimization of the energy usage throughout the workshop manufacturing.

4.1 Establishment of multi-objective optimization function

A sound optimization model should not be based on energy usage only. The optimization of parameters with regard to more than one viewpoint requires that other indicators of production significance (besides energy use in the workshop) be added to the objective function. The three supplementary optimization indexes of tool life, robot motion smoothness, and production time are thus accepted as bases of the multi-objective optimization function.

The amount of workpieces to be worked on before a tool becomes unserviceable is used to measure the tool life. This index and the machining parameters of the machine tool are characterized by means of a neural network, which is given by:

$$C = F\left(n, f, a_p, a_e\right) \tag{11}$$

Smoothness of robot motion is the inverse of the maximum power used in one transportation cycle. On this index, a larger value implies that the movement profile is smoother and more consistent. The connection between robot motion smoothness and the corresponding robot processing parameters are made using a neural network, which can be written as:

$$S = F\left(v_T\right) \tag{12}$$

The measurement of production time is the total time it takes to finish the processing of one workpiece. In a production cell having only one machine tool and one robot, the time to process one workpiece is stated as:

$$t = t_m + 2t_f + t_s \tag{13}$$

The four optimization indexes discussed above are combined into a single multi-objective optimization function. Energy consumption in workshops and time spent on production are normalized to put them on the same scale. Indexes of tool life and robot motion smoothness, the larger values of which are good, are first inverted and then normalized and included. The resulting multi-objective optimization function is:

$$F = \omega_1 W_n + \omega_2 C_n + \omega_3 S_n + \omega_4 t_n \tag{14}$$

where: W_n, t_n are the energy consumption model and production time index of the production plant after normalization. C_n, S_n are the normalized tool life index and robot motion smoothness index after taking the reciprocal. ω_1, ω_2, ω_3, ω_4 are the weights of different optimization objectives, which are determined according to different optimization focuses.

4.2 Optimization of energy consumption in workshop production processes

The algorithm of Artificial Bee Colony is based on the operations of natural bee colonies in their process of foraging. Its foundations are simple and the algorithm can find optimal solutions with great efficiency and at the same time react to the changes in the problem environment. These features have brought it into being a popular device in multi-objective optimization and in the area of combinatorial optimization.

The basic ABC algorithm optimization search process is divided into four stages:

Initialization phase: set the parameter values, set the population size to, the dimension of the solution to D, and limit the maximum number of times the nectar source has not been updated to $Limit$. The formula for generating the initial nectar source is as follows:

$$X_i^j = X_{\min}^j + rand\left(0,1\right)\left(X_{\max}^j - X_{\min}^j\right) \tag{15}$$

where i is the serial number of the nectar source, j is the dimension of the bee colony, and $X_{\min}$ and $X_{\max}$ are the lower and upper limits of the nectar source location taking values, respectively.

The honey harvesting stage: The honey harvesting bees start the activity by exploring the search space and utilizing the discovered nectar sources. This action helps them gather data on the position of every nectar source and the amount of nectar present at these locations, which is then passed to the rest of the colony. Exploitation of nectar sources by the honey harvesting bees is described by the update formula:

$$new\_x_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \tag{16}$$

where new_x_{ij} is the updated nectar position, x_{ij} is the original un-updated nectar position, φ_{ij} is a random number between $\left[-1,1\right]$ and x_{ij} and x_{kj} are nectar positions that are not identical to each other. The fitness function values of x_{ij} and new_x_{ij} are computed separately with the formula:

$$fit_i = \begin{cases} 1/(1+f(x_i)) & if\,(f(x_i)\geq 0) \\ 1+abs(f(x_i)) & otherwise \end{cases} \tag{17}$$

If the new nectar source mined by the honey harvesting bee is of better quality than the original one, i.e., $fit(new\_x_{ij}) > fit(x_{ij})$, then the original nectar source will be replaced by the new one, otherwise, the original nectar source will be kept.

Observer bee stage: The role of the observer bees is that they are selective instead of explorative in the algorithm. They evaluate the candidate sources based on the information about the nectar source given by the honey harvesting bees and decide on which sources they can select following the greedy selection strategy described in equation (18). When a nectar source has been chosen, the observer bees go on to perform additional nectar search in the area surrounding the source with equation (16):

$$p_i = \frac{fit(i)}{\sum_{i=1}^{NN} fit(i)} \tag{18}$$

Scout bee stage: If a particular nectar source does not improve after $Limit$ a specified amount of consecutive search attempts have been made, it is considered exhausted and is subsequently abandoned. The observer bees related to that source are then reorganized into scout bees and assigned to perform random searches in the solution space in order to find new and better quality nectar sources to replace them. Equation (15) forms the basis of the positional update controlling the random search of the scout bees.

The overall optimization search procedure of the Artificial Bee Colony algorithm, according to the analysis presented above, is depicted in Fig. 3. The working of the algorithm is based on the cyclic change between three separate stages, such as honey harvesting bee stage, observer bee stage and scout bee stage, and this iterative process is repeated until the maximum number of iterations has been achieved, or the accuracy in the solution is less than the required minimum threshold level at which the search stops.

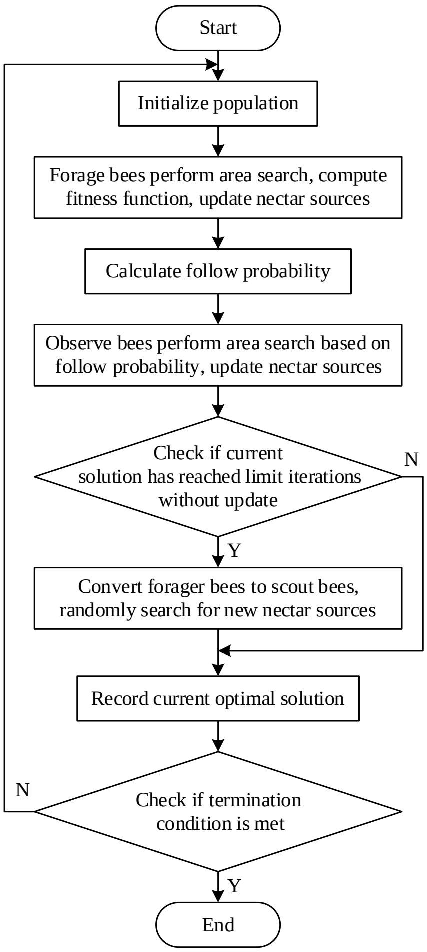

Figure 3: ABC algorithm flow chart

The implementation of the Artificial Bee Colony algorithm in the process of workshop production process energy optimization is based on the following principle. The main bee would then perform random search on the parameter space with the help of a roulette algorithm, which would produce an initial set of machining parameters and the calculation of the multi-objective optimization function values. The next group of follower bees would conduct local searches in the vicinity of the position of the leader bee, with each producing their own set of machining parameters and their respective function values. These function values are then compared between all candidates, and the greedy selection rule is used to select the best parameter configuration out of these candidates. A new generation of bees is then sent to search locally in the vicinity of this optimal solution and follow-on bees also perform random searches in neighboring parameter space. The operation sequence is repeated over subsequent iterations. The machining parameters that are obtained at the end of this iterative step are the solution to the multi-objective optimization function problem. By following such steps, the Artificial Bee Colony algorithm comes up with the optimal machining parameters of the machine being considered.

5 Analysis of examples

After defining the multi-equipment collaborative energy consumption optimization approach to the production workshop, it is necessary to test it experimentally to verify its practical applicability. To select a workpiece with a well-defined structural specification as the machining object, select a production workshop setting that contains machine tools and robots to perform the entire cycle of workpiece processing and transportation. Controlled experiments are performed prior to and following the application of the optimization method in order to obtain energy consumption data of machine tools and robotics. The empirical foundation of assessing the energy consumption optimization effect attained through the proposed method can be obtained through the comparison of these datasets.

5.1 Experimental setup

Considering the diversity of product structures in the actual production process, the dimensions of the experimental workpiece for machining parameter optimization are shown in Figure 4. The workpiece contains four structures: plane, fillet, slot and hole, and the same tool is used to complete the machining of all structures.

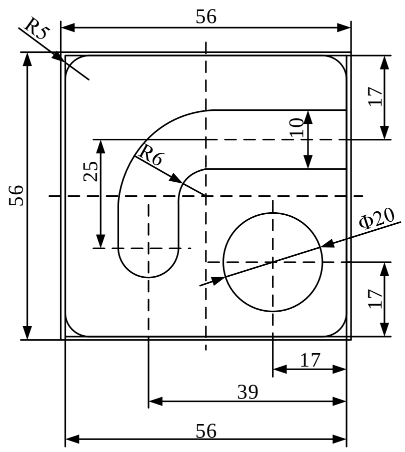

Figure 4: The size of the processing parameter optimization experiment

The machining process of this workpiece is accomplished by a CNC machine and an industrial robot, and the machining route of the workpiece is shown in Figure 5. The workpiece contains several structures, so it needs to be machined by several processes.

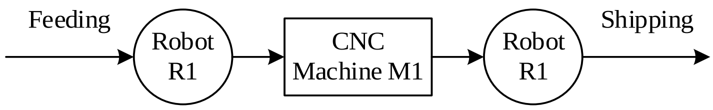

Figure 5: Processing parameters of processing parameters

Table 1 demonstrates the proportion coefficients that have been allocated to each machining process of the experimental workpiece. The surface milling has the highest percentage in terms of machine tool energy usage among all the processes considered and is thus identified as the main area of optimization. The machining parameters of the three remaining processes i.e. milling the fillet, milling the slot and milling the hole are obtained by multiplying the optimized machining parameters of the milling surface process by the corresponding proportion coefficients as given in the table under each of the processes.

Table 1: The ratio of the process ratio of the experimental workpiece

Processing process	Spindle speed (r/min)	Feed speed (mm/r)	Cutting depth (mm)	Cutting width (mm)
Milling surface	n	f	a_p	a_e
Milling circle Angle	$1.12\times n$	$0.82\times f$	$0.13\times a_p$	Variation
Milling tank	$0.82\times n$	$0.82\times f$	$0.13\times a_p$	13
Milling hole	$1.12\times n$	$1.12\times f$	$0.05\times a_p$	13

In order to show that the multi-objective optimization function may satisfy various optimization needs with different weight configurations, two different sets of weight values are chosen to optimize machining parameters. In the first set, referred to as Group A, workshop energy consumption and production time are given more importance than the other factors. The second set, labeled as Group B, focuses more on the tool life and robot motion stability. The two sets of weight values are both determined empirically and recorded in Table 2. It is interesting to note that the energy consumption weights in the two groups are not the same, whereas Group A has a weight of 1.66, and Group B has a weight of 0.83.

Table 2: Workshop optimization weight value

Group	Energy consumption weight (ω_1)	Life weight (ω_2)	Stability weight (ω_3)	Time weight (ω_4)
A	1.66	5.24	0.16	0.83
B	1.66	10.23	0.25	0.83

The optimized range of machining parameters is determined by production experience and is shown in Table 3.

Table 3: Optimization range of machining parameters in workshop

Processing parameter	Spindle speed (r/min)	Feed speed (mm/r)	Cutting depth (mm)	Cutting width (mm)
Optimized range	1050~1250	0.11~0.14	0.8~1.5	0.42~0.68

5.2 Analysis of energy consumption optimization results for normal scenario

The steady-state tool wear period is used as the first optimization window where both multi-objective optimization functions and their corresponding weight structures are solved with the Artificial Bee Colony algorithm. Every optimization run consists of 200 colony searches done in total over six rounds. Figure 6 shows the optimization trajectory of energy consumption Group A. The objective function value is stabilized after roughly the 90th colony search, which indicates that convergence is reached much earlier than the search budget allotted.

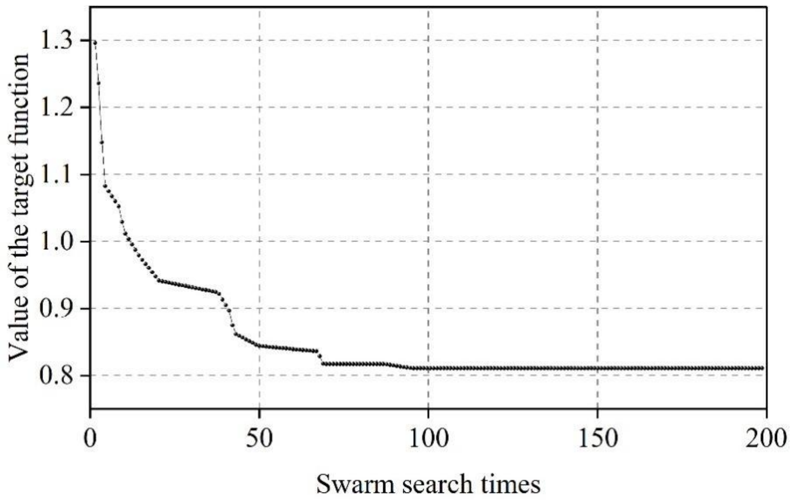

Figure 6: Optimization process of Artificial Bee Colony algorithm

In order to compare the changes of various production data in the production workshop before and after optimization, group S is set as the control group, and the control group adopts the existing energy consumption optimization strategy-energy management system (EMS), and takes the values of its machining parameters to the commonly used parameters in industry, and the specific values are shown in Table 4. The TCP speed of the robot in the energy consumption group reaches 354 mm/s, which is much faster than that of the lifetime group (209 mm/s).

Table 4: Optimization results of machining parameters in workshop

Processing parameter	Spindle speed (r/min)	Feed speed (mm/r)	Cutting depth (mm)	Cutting width (mm)	TCP velocity (mm/s)
A	1090	0.144	1.1	0.59	354
B	1055	0.146	1.1	0.59	209
S	1230	0.13	1.1	0.52	257

The study explores the results of energy optimization for the normal case in terms of energy savings, tool life extension, robot maximum power reduction, and production time savings, respectively.

(1) Denote the energy saving rate E_W of the optimized equipment as:

$$E_W = \frac{W_S - W_A}{W_S} \tag{19}$$

where W_S is the average energy consumption of the equipment in the control group and W_A

is the average energy consumption of the equipment in the energy consumption group.

(2) Denote the optimized tool life extension rate E_N as:

$$E_N = \frac{N_{nB} - N_{nS}}{N_{nS}} \tag{20}$$

where N_{nB} is the number of workpieces cut during the tool life of the life group and N_{nS} is the number of workpieces cut during the tool life of the control group.

(3) Denote the optimized maximum power reduction of the robot E_P as:

$$E_P = \frac{P_{S\max} - P_{B\max}}{P_{S\max}} \tag{21}$$

where $P_{S\max}$ is the maximum power of the robot in the control group and $P_{B\max}$ is the maximum power of the robot in the lifetime group.

(4) Denote the optimized production time saving rate E_t as:

$$E_t = \frac{t_S - t_A}{t_S} \tag{22}$$

where t_S is the production time of the control group workpieces and t_A is the production time of the energy consumption group workpieces.

Figure 7 shows the dynamic energy consumption of the machine tool to machine a single workpiece as it changes with the cumulative number of machined pieces on the three optimization schemes. The comparison between all three groups shows a clear and steady order: the control group has the highest energy consumption per workpiece, then the tool life group, and finally, the energy consumption group is the lowest of them all during the entire machining process.

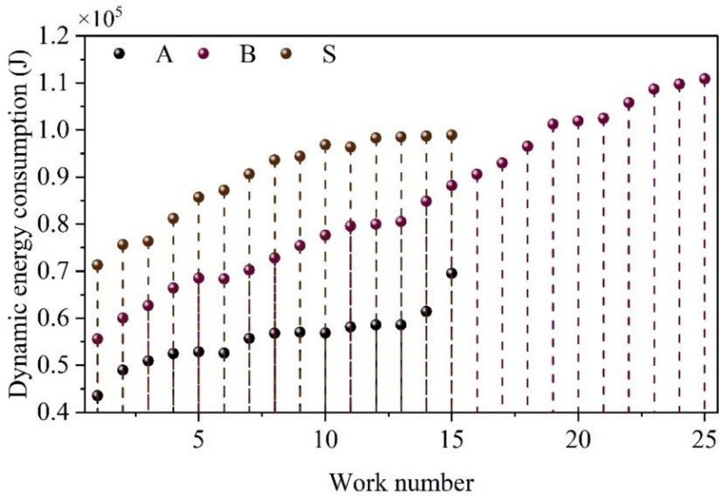

Figure 7: Dynamic energy consumption of different optimization schemes

The machining parameters obtained based on the optimization process are used to finish the machining of the workpiece as depicted in Fig. 7. The production data that can be associated with every optimization index are gathered during the entire machining process and the summary of the collected data is presented in Table 5. According to the previously formulated formulas, a quantitative comparison with the control group S gives the following results. In the case of the energy consumption Group A configuration, machine tool energy consumption per workpiece is decreased by an average of 29.71 percent and energy used in one robot transportation cycle goes down by an average of 23.35 percent. The duration of production is reduced by 23.26 percent compared with the baseline. With the tool life Group B configuration, the serviceable life of a single tool increases by 66.67 percent and the maximum power measured during the robot transportation is reduced by 13.8 percent.

Table 5: The production workshop is optimized before and after the indexes

Group	Dynamic energy consumption of machine tool (J)	Robot dynamic energy consumption (J)	The number of pieces in the tool life	Robot maximum power (W)	Production time (s)
A	69523	4163.4	15	354.1	739
B	110863	4961.4	25	393.4	745
S	98914	5431.5	15	456.4	963

In summary, if we choose to increase ω_1 and ω_4 (Group A strategy) in the industrial production process, the average energy saving per workpiece is the largest, but the tool life will be shorter compared to the choice of increasing ω_2 and ω_3 (Group B optimization strategy). Both strategies in this paper have a great advantage over the existing energy optimization strategies.

5.3 Analysis of energy consumption optimization results considering rework scenarios

The rework scenario presents a different list of challenges in the production system. The composition of the equipment changes significantly, the time spent on idle machines increases, and it is becoming harder to optimize the energy usage with online methods. The control strategy of optimizing energy consumption proposed in the present paper will overcome these issues as it assesses the efficiency of the optimization in the rework scenario using four cost indicators, namely, running energy cost, state transition energy cost, forced abandonment cost, and delayed production cost.

(1) Running energy cost

The concept of running energy cost is the energy expenses used by processing modules and quality control stations when they are actively working. The processing modules and quality control stations work in one of two conditions: on and off. Off state energy consumption is assumed to be insignificant and given a value of zero. In the on state, a further sub-categorization is made into active processing and standby. Manual processing stations consume little energy during operation that can be ignored. Based on this, the overall running energy cost of the system can be written as:

$$U_i^P(t) = \begin{cases} 1, & P_i \text{ is in the powered-on state during time period } t \\ 0, & P_i \text{ is in the powered-off state during time period } t \end{cases} \tag{23}$$

$$O_i^P(t) = \begin{cases} 1, & P_i \text{ is in the machining state during time period } t \\ 0, & P_i \text{ is in the standby state during time period } t \end{cases} \tag{24}$$

$$C_e = \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{P=\{M,I\}} c_e U_i^P(t)\left\{E_{p,i}^P O_i^P(t) + E_{w,i}^P\left[1-O_i^P(t)\right]\right\} \tag{25}$$

where: $E_{p,i}^P, E_{w,i}^P$ is the energy consumption per unit time of operation and standby energy consumption of the process module. c_e is the price per unit time consumption. T is the total number of discrete time periods of the simulation.

(2) State transition energy cost

The energy cost of state transition indicates extra energy consumption during changes of modules and quality control stations between operational modes. Every state-to-state transition comes with its own energy penalty which is different than the energy cost of a steady-state run. Let $S_i^P(t) = \left|U_i^P(t) - U_i^P(t-1)\right|$ and let $U_i^P(0) = 0$ hold for all i and P, then the state transition cost is:

$$C_s = \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{P=\{M,I\}} c_e E_{s,i}^P S_i^P(t) \tag{26}$$

$E_{s,i}^P$ in this expression represents the energy used in one process module state transition that is associated with the ith rework inspection group.

(3) Forced Discard Cost

Forced discard cost is the cost brought about by the forced removal of work-in-process from the buffer B_i^H to avoid ring jamming:

$$C_d = \sum_{t=1}^{T}\sum_{i=1}^{n} c_d d_i(t) \tag{27}$$

where: c_d is the unit discard cost of each cache, and $d_i(t)$ is the amount of work-in-process moved out of the production system by the cache B_i^H at time t.

(4) Delayed Production Cost

Delayed production cost is in the specified production time limit T_L, because the output does not meet the requirements of the production plan to extend the production time, the additional non-production energy costs (lighting, air conditioning, electricity, etc.) and processing fee costs and other economic losses, c_j for the unit cost of delayed production, then there are:

$$C_j = c_j \cdot \max\left(T - T_L, 0\right) \tag{28}$$

The total energy cost of the production system model is the sum of the above 4 components of energy cost:

$$C_{es} = C_e + C_s + C_d + C_j \tag{29}$$

The energy consumption of the rework production system was optimized. The comparison between the final energy consumption cost and the algorithm efficiency is shown in Table 6. The final energy consumption cost of Group B was 2,239.99 yuan less than that of Group A.

Compared with the existing energy consumption optimization strategies, Group A saved 9.41% of the workshop energy consumption, and Group B saved 12.63%. Therefore, when the workpiece undergoes rework, choosing to increase the weight of tool life and robot motion stability will lead to better energy consumption optimization effects.

Table 6: Final cost of energy consumption compared with algorithm efficiency

	Target value/Yuan	More existing strategy optimization results/%
A	71652.32	9.41
B	69412.33	12.63
Difference value	2239.99	3.22

The results of the energy optimization of the rework-based production system are evaluated from four cost indicators, and the statistical results are shown in Figure 8. After adopting the Group B strategy, the system operation energy cost has been significantly improved, compared with the Group A strategy and the existing strategy, the reduction ratio is 9.4% and 15.7% respectively. At the same time, the occurrence of ring jamming in the production system is reduced, and the cost of forced parts disposal is reduced. For individual machines, the Group B strategy reduces the operating costs of these machines.

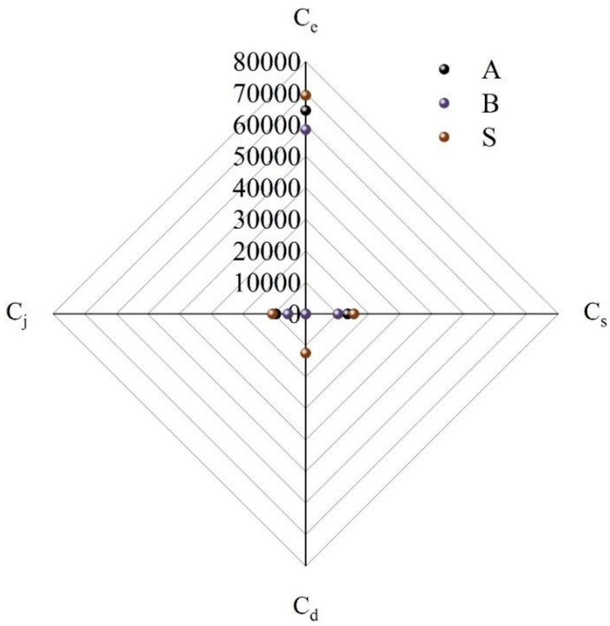

Figure 8: Energy consumption optimization results of the rework production system

In summary, when the workpiece needs to be reworked, adding ω_2 and ω_3 minimizes the energy consumption and significantly reduces the operational energy cost.

6 Conclusion

The present research explores the digital twin model of industrial production processes and develops energy consumption models based on the BP neural network approach. To optimize workshop energy consumption, tool life, robot motion smoothness, and production time at the same time, a multi-objective optimization function is formulated, and the Artificial Bee Colony algorithm is used to compute the best machining parameters of the workshop equipment. The simulation experiments are carried out on two different scenarios. With normal production conditions, emphasis has been given to the workshop energy consumption and production time in the optimization function. As opposed to the current EMS strategy, the optimized machining parameters have a 29.71 percent saving in workshop energy consumption on the processing of a single workpiece, which can be described as significant and well quantifiable. When the reworked scenario is considered, the weights are distributed to tool life and robot motion smoothness. In comparison to the current energy optimization strategy, this configuration gives a 12.63 percent decrease in workshop energy consumption, but the end energy cost on this scheme is 2239.99 yuan higher than the combined energy consumption and production time weighted scheme. The results of the present research provide an insight to practitioners and researchers attempting to implement the concept of digital twins into the energy consumption optimization of the manufacturing facilities in the shop floor. In future, further research will expand the range of study to include digital twin-based energy optimization in rework-based production systems, and it will add other constraints such as detection errors in quality control modules of production lines and energy use due to the operation of workshop logistics equipment.

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