Review on Energy Consumption Optimization Methods of Typical Discrete Manufacturing Equipment

Ming Yao[1,2], Zhufeng Shao[1,2](✉), and Yanling Zhao[3]

[1] State Key Laboratory of Tribology and Institute of Manufacturing Engineering, Tsinghua University, Beijing 100084, China
shaozf@mail.tsinghua.edu.cn

[2] Beijing Key Lab of Precision/Ultra-precision Manufacturing Equipments and Control, Tsinghua University, Beijing 100084, China

[3] Instrumentation Technology and Economy Institute, Beijing 100055, China

Abstract. With China's commitments on "carbon peak" and "carbon neutral", energy consumption optimization for discrete manufacturing has become an important hot issue. By reviewing and analyzing related researches on energy consumption of typical discrete manufacturing equipment such as machine tools and industrial robots, this paper summarizes energy consumption optimization methods for the discrete manufacturing, especially focusing on the promising intelligent optimization technology. The intelligent optimization for multi parameters in complex and variable working conditions is the trends of the energy consumption, which requires the combination of software and hardware.

Keywords: Discrete manufacturing · Energy consumption optimization · Machine tool · Industrial robot · Intelligent algorithm

1 Introduction

The global manufacturing industry is a big contributor to greenhouse gas emissions and energy consumption, consuming 33% of the total energy and accounting for 38% of direct or indirect CO_2 emissions [1], which has become the focus of energy conservation and emission reduction. Facing the demand of global sustainable development, the research related to reducing energy consumption in manufacturing industry has gradually become a hot spot, and low-carbon manufacturing has attracted more and more attention [2].

As core equipment of the discrete manufacturing system, machine tools and industrial robots are the main energy consumers. At the same time, a large number of survey statistics show that the energy utilization of machine tool and industrial robot is low [3]. Research on energy consumption optimization for typical equipment, is of great significance for improving the energy utilization efficiency of discrete manufacturing and fulfilling China's commitment of "carbon peak" and "carbon neutral". This article will focus on the energy consumption optimization of machine tools and industrial robots, discuss the existing researches, and explore potential research directions in the future.

X.-J. Liu et al. (Eds.): ICIRA 2021, LNAI 13015, pp. 48–58, 2021.
https://doi.org/10.1007/978-3-030-89134-3_5

2 Typical Equipment Energy Consumption Optimization Method

Machine tools and industrial robots are the main body of energy consumption in discrete manufacturing [4]. The energy consumption optimization methods of these two typical equipment can be divided into three categories: hardware approaches, software approaches and hybrid approaches, as shown in Fig. 1.

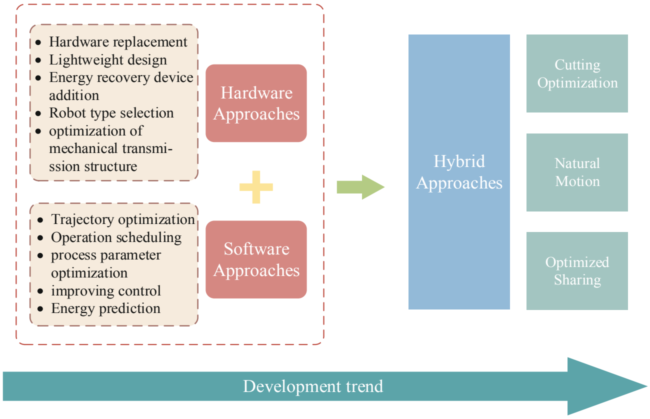

Fig. 1. Development of the energy consumption optimization

2.1 Hardware Approaches

The hardware approaches to lower the energy consumption is mainly concentrated in the design and manufacturing stage of the equipment [5]. Common solutions include adopting lightweight design and adding energy recovery units.

Industrial robot hardware solutions include methods such as lightweight design [6, 7], adding energy recovery units [8] and robot type selection [9]. The lightweight design of industrial robot mainly adopts the methods of sub-component redesign, optimization and replacement. Using more efficient or lighter components to reduce weight and arm inertia, so the robot movement consumes less energy, which is the main hardware optimization method.

The hardware optimization methods of machine tools mainly include the use of high-efficiency components, optimization of mechanical transmission structure, lightweight design, adding energy recovery units and reducing auxiliary system energy consumption [10]. The use of high-efficiency components is mainly to reduce the energy consumption of the system by using high-efficiency drive components. For the lightweight design of machine tools, researchers have proposed three types of lightweight design methods: structural lightweight design, material lightweight design and system lightweight design [11].

Hardware approaches can reduce the energy consumption of equipment. But it is mainly applicable to the design phase of the equipment. At the same time, it's hardware changes are relatively large, and the modification cost is relatively high [5]. For equipment that has already been put into the production cycle, more consideration should be given to software solutions.

2.2 Software Approaches

Software approach can reduce the energy consumption without making a lot of hardware modifications. Compared with the hardware approach, it has the advantages of low cost and good applicability. Energy optimization methods at software level generally involve parameter modification, trajectory optimization and operation scheduling.

Software solutions for industrial robots can be divided into two categories: trajectory optimization [12, 13] and operation scheduling [14, 15]. Trajectory optimization refers to the trajectory planning with minimum energy consumption to complete the same task, while the operation scheduling generally considers the time scale and sequence arrangement of the robot cell or the robot production line.

Software optimization methods for machine tools mainly include process parameter optimization, reducing waiting time and improving control. Optimization of process parameters, including tool paths, minimum machine tool standby time and scheduling, etc. Using the constructed energy consumption model to optimize the process parameters can reduce the energy consumption of the machine tool and does not require major hardware transformation [16].

The software method does not need to modify or redesign hardware, which is an ideal solution to reduce energy consumption for equipment that is already in the mature production cycle. However, due to the high dimension of the relevant parameters of the discrete manufacturing equipment and the complex working conditions, the optimization algorithm is difficult to achieve global optimization and rapid planning, and fail to meet the actual production needs.

2.3 Hybrid Approaches

The hybrid energy consumption optimization method is a comprehensive optimization scheme that takes into account both hardware and software approaches. Scholars have proposed various optimization methods.

As for industrial robots, literature [17] divides hybrid approaches into two categories: natural motion [18] and optimized sharing [19]. Natural motion transforms the hardware system by adding elastic elements to the actuator, and carries out corresponding motion planning accordingly. Optimal sharing is to comprehensively consider the impact of motion optimization, energy storage and sharing devices on the energy consumption of the robot, so as to jointly optimize the energy consumption of the robot.

The hybrid energy consumption optimization method of machine tools is focusing on the cutting process, which is the effective and kernel action. Since the energy consumption of cutting process is attributed to the cutting load in the process, the energy consumption of machine tools can be reduced by optimizing the cutting parameters and using advanced cutting technologies, such as using high-efficiency lubrication systems [20] and auxiliary processing technology [21].

The hybrid optimization method can comprehensively consider the constraints of hardware and software to optimize energy consumption of the equipment, which has the best optimization result. However, because it is necessary to modify the equipment at both the hardware and software levels at the same time, the hybrid optimization method is complex and difficult, and the robustness and stability in the actual production environment are not desirable.

In addition to hybrid approaches, the optimization technology based on intelligent algorithm has also emerged in recent years, which has achieved good results in dealing with complex nonlinear energy consumption modeling and prediction problems. The intelligent energy consumption optimization method is introduced in the following.

3 Intelligent Optimization Method

Energy consumption modeling and forecasting are the key to optimization. However, the energy consumption modeling and prediction of manufacturing equipment is a highly nonlinear problem with many influencing factors, and traditional mathematical modeling methods are difficult to solve well. In recent years, intelligent algorithms have been developing rapidly and show advantages in dealing with nonlinear problems, which have achieved good results in the energy consumption modeling and prediction of industrial robots and machine tools.

3.1 Industrial Robots

The intelligent optimization method on energy consumption of industrial robots is to realize data-driven optimization, and the existing research will be discussed below.

Researches on energy consumption optimization of industrial robots mainly focused on the trajectory optimization with intelligent algorithms such as genetic algorithm and cloning algorithm. For example, Biswas A et al. [22] used a genetic algorithm to determine the trajectory that minimizes energy consumption when studying the collision-free trajectory planning problem of a 3 DOFs space manipulator. Because dynamic models are difficult to discover the precise relation-ship between robot motion parameters and energy consumption, algorithms such as neural network have been applied to the energy consumption optimization of industrial robots. Yin S et al. [23] proposed a trajectory planning method that combines artificial neural network (ANN) with evolution-based/swarm intelligent algorithms. The model after neural network training can provide a fitness function for evolutionary algorithms, and provide powerful optimization capabilities on achieving energy efficiency goals.

Different from the traditional energy consumption modeling that takes the dynamic behavior of industrial robots as the main research object, Zhang M et al. [24] proposed a data-driven energy consumption optimization method, using back propagation neural network (BPNN) to accurately reveal the quantitative relationship between operating parameters and energy consumption, and used genetic algorithms to optimize the parameters. In addition, some scholars apply BPNN to the energy consumption prediction of the articulated manipulator under unknown angular displacement and load [25]. Apart from neural network, Efimov A et al. [26] applied the neuro-fuzzy inference system to the energy consumption prediction of industrial robots to provide support for finding the trajectory with the least energy consumption in the robot workspace.

At present, there are few studies on intelligent energy consumption optimization of industrial robots, and the actual application in industrial field is relatively few. Therefore, it needs more further studies.

3.2 Machine Tools

The energy consumption of machine tools is a multi-component and multi-level system problem. There are many energy-consuming components with the characteristics of multi-source energy consumption [27]. During the operation of the machine tool, there are various energy interactions and mutual influences among various components, which makes the research on energy consumption optimization more complicated. This also brings great difficulties to the energy consumption modeling, prediction and optimization of machine tools.

Table 1. Machine learning algorithms for machine tool energy consumption optimization.

Algorithm	Literature	Year
Neural Network	Xie D et al. [28]	2012
	Garg A et al. [31]	2015
	Kant G et al. [29]	2015
	Li L et al. [34]	2015
	Ak R et al. [35]	2015
	Long Z et al. [32]	2018
	Shin et al. [33]	2018
	Shin S J et al. [37]	2019
	CHEN Shiping et al. [36]	2020
Support Vector Machine	Chen W W et al. [40]	2014
Ensemble Learning	Ak R et al. [35]	2015
	Liu Z et al. [42]	2018
	Chen T et al. [43]	2019
	CHEN Shiping et al. [36]	2020
Transfer Learning	Shin S J et al. [37]	2019
	Chaoyang Zhang et al. [38]	2020
k-Nearest Neighbor	Ak R et al. [35]	2015
	Komoto H et al. [41]	2020
Gaussian Process Regression	Bhinge R et al. [44, 45]	2015, 2017
Deep Learning	Y He et al. [39]	2020

At present, most researches based on machine learning algorithms include at least three types of input data: spindle speed, feed rate and depth of cut. Table 1 lists the common machine learning algorithms in the research on energy consumption optimization of machine tools. It can be seen that many researches are based on neural network models.

Neural Network. BPNN is an artificial neural network based on error back propagation algorithm. Xie D et al. [28] built the cutting parameters-based energy consumption model for machine tool with BPNN, and used genetic algorithms to optimize the cutting parameters. The energy consumption prediction accuracy reached 92%. In order to choose the optimal processing parameters, Kant G et al. [29] used ANN to establish a prediction model for the milling process, with an average relative error of 1.50%. The relevant data set can be found in literature [30]. In addition, Garg A et al. [31] added a variety of intelligent algorithms such as ANN, Bayesian models and genetic algorithms to the energy consumption modeling of machine tools. Long Z et al. [32] proposed a method for predicting energy consumption using Elman neural network. These energy consumption optimization researches have achieved good results.

The above studies only considered relatively simple working conditions, and established a coarse-grained model for the cutting process of machine tools, which is not for actual manufacturing. In response to the above problems, Shin et al. [33] used ANN to propose a predictive modeling method based on historical data of machine tool operation, and created multiple fine-grained power consumption prediction models, which are suitable for predicting energy consumption of machine tools under different processes. Professor Fei L from Chongqing University also carried out researches on the application of BPNN in energy consumption optimization, and proposed a multi-objective optimization method based on neural network to optimize cutting parameters [34].

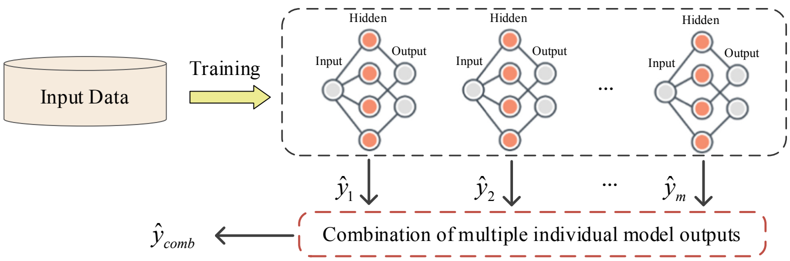

Fig. 2. Basic scheme of neural network ensemble [35]

Some scholars found that the generalization performance of a single neural network model in actual applications is not good for the energy consumption optimization. Therefore, they introduced ensemble learning into energy consumption optimization. Through the combination of multiple learners, ensemble learning can often obtain more significantly superior generalization performance than a single learner. By using neural network as the basic learner, they built a neural network ensemble learning model to predict machine tool energy consumption [35], which is shown in Fig. 2. Then, CHEN

Shiping et al. [36] integrated BPNN through the Adaboost algorithm to obtain a strong predictor, which improved the prediction accuracy for the CNC machine tool.

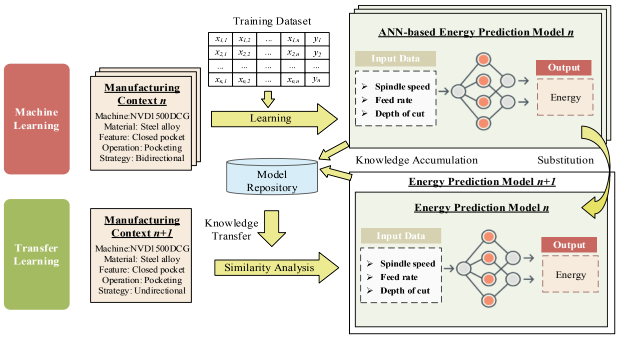

Fig. 3. Transfer learning in machine tool energy consumption prediction [37]

In addition, another important reason that affects the generalization of intelligent algorithms is lack of data and insufficient sample data quality in the complex cutting environment. Transfer learning can reuse a pre-trained model in another task, and can be used to solve the above problems. Shin S J et al. [37] proposed a self-learning factory mechanism based on transfer learning, as shown in Fig. 3. When the training data set exists, the energy consumption prediction model is established based on ANN. When the training data set is not available, the transfer learning algorithm creates an alternative model by transferring the learned knowledge. Using this method, the energy consumption can be reduced by 9.70%. In addition, some scholars have established a machine tool energy saving decision-making method that integrates deep belief networks and transfer learning [38], which reduces the energy consumption of waiting process.

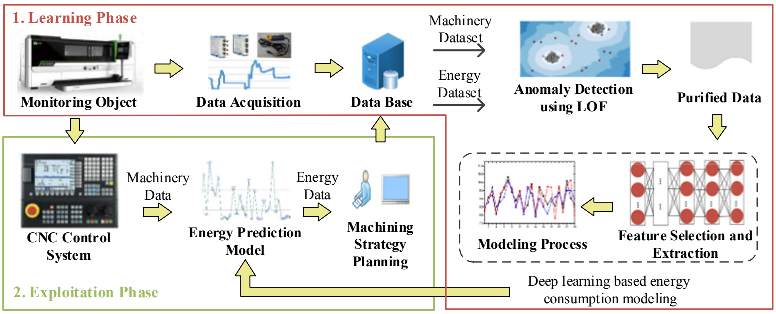

Fig. 4. General framework of the energy prediction method based on deep learning [39]

The existing data-driven researches mainly focus on the use of manual feature learning methods, which are low in efficiency and poor in generalization. To solve this problem, Yan He et al. [39] proposed a data-driven energy prediction method, which used deep learning to extract sensitive energy consumption features from raw data in an unsupervised manner, and developed and extracted them in a supervised manner, as shown in Fig. 4. The results show that it can improve the energy prediction performance, which is superior to the traditional method in terms of effectiveness and versatility.

The unique advantage of deep learning is that it can spend little effort and expert knowledge to extract energy consumption characteristics, which has great potential in practical applications. But the shortcomings are higher requirements for computing resources, longer model training time and the risk of overfitting.

Other Machine Learning Algorithms. In addition to neural network, other machine learning algorithms such as support vector machine and k-nearest neighbor algorithm have also been used in the research of machine tool energy optimization.

Support Vector Machine (SVM). SVM can solve practical problems such as small samples, nonlinearity and local minima. Some scholars verified the feasibility of energy consumption prediction methods based on SVM [40]. However, SVM cannot handle the complex nonlinear relationship between the cutting parameters of the machine tool well, and the effect in the application of the energy consumption optimization of the machine tool is not as good as the neural network. Therefore, SVM has not received much attention in the following research.

K Nearest Neighbor (KNN). KNN is a non-parametric machine learning algorithm in which the value of each sample can be represented by its nearest K neighboring values. Some scholars have applied the KNN algorithm, and proposed a behavioral model that characterizes the five-axis machining center during the finishing process of the test piece. This behavior model predicts the behavior and energy consumption in the finishing process from multiple technological perspectives such as production, processing and cutting [41], and can accurately predict the energy usage of machine tools.

Ensemble Learning Based on Tree Model. Except from using neural network as the basic learner, a number of scholars construct an ensemble learning model based on the tree model. Liu Z et al. [42] proposed a cutting energy prediction model based on a tree-based gradient boosting method, which improved the prediction accuracy of milling energy and provided a new method for energy optimization in the milling process. Later, Chen T et al. [43] conducted related research and proposed a milling energy consumption prediction model based on the gradient advance regression tree algorithm, which achieved the prediction accuracy of 94%.

Gaussian Process Regression. Gaussian process regression is also a non-parametric machine learning algorithm. The team of Professor Bhinge R from the University of California has been studying the application of this algorithm to the energy optimization of machine tools. They used gaussian process regression to establish an energy prediction model for CNC machine tools and modeled the complex relationship between processing parameters and energy consumption. The accuracy of the total predicted energy is above 95% [44]. Moreover, they also extended the energy prediction model to multiple process parameters and operations for process planning to optimize the energy efficiency of the machining process [45].

4 Conclusions

In this paper, the energy consumption optimization of two typical equipment of discrete manufacturing system is reviewed. Firstly, it summarizes the energy consumption optimization methods of machine tools and industrial robots, which are divided into three categories: hardware approaches, software approaches and hybrid approaches. Then, it focuses on the data-driven intelligent optimization technology on the energy consumption, summarizes the existing researches and analyzes their application effects. Conclusions are drawn as follows.

1. Hybrid optimization method of energy consumption. At present, most researches focus on a single level, hardware or software. However, the overall energy consumption optimization combining hardware and software deserves further attention. In addition, many researches only focus on single device without considering factors such as the environment in which the device is located. The hybrid energy consumption optimization technology that integrates multiple factors such as environment and production requirements is a worth direction.
2. Self-learning, adaptive real-time energy consumption optimization. Discrete manufacturing production tasks continue change. It is a new challenge that how to adapt quickly to the working conditions, learn independently and make real-time response in the face of unfamiliar tasks and uncertainty of production data. In the future, the latest artificial intelligence technologies such as transfer learning will be adopted to improve self-learning capabilities. According to different environments and tasks, it can independently select the most suitable energy consumption plan in real time.
3. Intelligent optimization technology that considers multiple parameters and complex working conditions. The equipment energy consumption process is highly nonlinear, while the discrete manufacturing system is random and dynamic in production process with many influencing factors. Therefore, pure mathematical models and traditional machine learning methods are difficult to accurately model the energy consumption process of the manufacturing system and its equipment. Instead, it is the key to solving the above problems that combining deep learning to learn deep-level feature representations and research energy consumption modeling and prediction.

Acknowledgement. This work is supported by the National Key R&D Program of China (Grant No. 2020YFB1710700).

References

1. Wang, J.: A survey on energy efficient discrete manufacturing system. J. Mech. Eng. (2013)
2. Duflou, J.R., Sutherland, J.W., Dornfeld, D., et al.: Towards energy and resource efficient manufacturing: a processes and systems approach. CIRP Ann. Manuf. Technol. **61**(2), 587–609 (2012)

3. Fei, L.: Content architecture and future trends of energy efficiency research on machining systems. J. Mech. Eng. **49**(19), 87 (2013)
4. Zhao, G.Y., Liu, Z.Y., He, Y., et al.: Energy consumption in machining: Classification, prediction, and reduction strategy. Energy **133**(Aug 15), 142–157 (2017)
5. Hou, Q., Yang, D., Guo, S.: Review on energy consumption optimization methods of industrial robots. Comput. Eng. Appl. **54**(22), 1–9 (2018)
6. Albuschäffer, A., Haddadin, S., Ott, C., et al.: The DLR lightweight robot: design and control concepts for robots in human environments. Ind. Robot **34**(5), 376–385 (2007)
7. Aziz, M., Zanibek, M., Elsayed, A., et al.: Design and analysis of a proposed light weight three DOF planar industrial manipulator. In: 2016 IEEE Industry Applications Society Annual Meeting. IEEE (2016)
8. Gale, S., Eielsen, A.A., Gravdahl, J.T.: Modelling and simulation of a flywheel based energy storage system for an industrial manipulator. In: IEEE International Conference on Industrial Technology. IEEE (2015)
9. Li, Y., Bone, G.M.: Are parallel manipulators more energy efficient? In: Proceedings of 2001 IEEE International Symposium on Computational Intelligence in Robotics and Automation. IEEE (2001)
10. Yue-Jiang, W.U., He-Jian, O.U., Zhang, C.: Review and application of energy consumption model for cutting machine. J. New Ind. (2016)
11. Kroll, L., Blau, P., Wabner, M., et al.: Lightweight components for energy-efficient machine tools. CIRP J. Manuf. Sci. Technol. **4**(2), 148–160 (2011)
12. Liu, S., Wang, Y., et al.: Energy-efficient trajectory planning for an industrial robot using a multi-objective optimisation approach. Procedia Manuf. **25**, 517–525 (2018)
13. Wang, Q., Cheng, X., et al.: Inverse solution optimization and research on Trajectory Planning of cleaning manipulator for insulator. In: IOP Conference Series: Materials Science and Engineering, vol. 493, no. 1, pp. 12060–12060 (2019)
14. Pellicciari, M., Berselli, G., Leali, F., et al.: A method for reducing the energy consumption of pick-and-place industrial robots. Mechatronics **23**(3), 326–334 (2013)
15. Brossog, M., Bornschlegl, M., Franke, J.: Reducing the energy consumption of industrial robots in manufacturing systems. Int. J. Adv. Manuf. Technol. **78**(5–8), 1315–1328 (2015)
16. Yoon, H.S., Kim, E.S., Kim, M.S., et al.: Towards greener machine tools – a review on energy saving strategies and technologies. Renew. Sustain. Energy Rev. (2015)
17. Giovanni, C., Erich, W., Renato, V.: A review on energy-saving optimization methods for robotic and automatic systems. Robotics **6**(4), 39 (2017)
18. Iwamura, M., Imafuku, S., Kawamoto, T., Schiehlen, W.: Design and control of an energy-saving robot using storage elements and reaction wheels. In: Font-Llagunes, J.M. (ed.) Multi-body Dynamics. CMAS, vol. 42, pp. 277–297. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-30614-8_13
19. Boscariol, P., Richiedei, D.: Energy-efficient design of multipoint trajectories for Cartesian robots. Int. J. Adv. Manuf. Technol. (2019)
20. Reddy, N.S.K., Nouari, M., Yang, M.: Development of electrostatic solid lubrication system for improvement in machining process performance. Int. J. Mach. Tools Manuf. **50**(9), 789–797 (2010). https://doi.org/10.1016/j.ijmachtools.2010.05.007
21. Germain, G., et al.: Comprehension of chip formation in laser assisted machining. Int. J. Mach. Tools Manuf. **51**(3), 230–238 (2011). https://doi.org/10.1016/j.ijmachtools.2010.11.006
22. Biswas, A., Deekshatulu, B.L., Roy, S.S.: Energy Optimal Trajectory Planning of a Robotic Manipulator Using Genetic Algorithm. American Institute of Physics (2010)
23. Yin, S., Ji, W., et al.: A machine learning based energy efficient trajectory planning approach for industrial robots. In: The 52nd CIRP Conference on Manufacturing Systems (2019)
24. Zhang, M., Yan, J.: A data-driven method for optimizing the energy consumption of industrial robots. J. Cleaner Prod. **285** (2020)

25. Ding, Y., Zhu, X., Sun, X., et al.: Soft sensor simulation of minimum energy consumption of joint manipulator drive system based on improved BP neural network. In: Journal of Physics: Conference Series, vol. 1626, no. 1, p. 012020 (16pp) (2020)
26. Efimov, A., Gorkavyy, M., Gorkavyy, A.: Predicting power consumption of robotic complex based on neuro-fuzzy system. In: 2020 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM) (2020)
27. Wang, Q.: Mathematical model of multi-source energy flows for CNC machine tools. J. Mech. Eng. **49**(7), 5 (2013)
28. Xie, D., Chen, G.R., Wang, F., et al.: Modeling of CNC machine tool energy consumption and optimization study based on neural network and genetic algorithm. Appl. Mech. Mater. **195–196**, 770–776 (2012)
29. Kant, G., Sangwan, K.S.: Predictive modelling for energy consumption in machining using artificial neural network. Procedia CIRP **37**, 205–210 (2015)
30. Yan, J., Lin, L.: Multi-objective optimization of milling parameters - the trade-offs between energy, production rate and cutting quality. J. Clean. Prod. **52**, 462–471 (2013)
31. Garg, A., Lam, J., Gao, L.: Energy conservation in manufacturing operations: modelling the milling process by a new complexity-based evolutionary approach. J. Cleaner Prod. **108**(DEC.1PT.A), 34–45 (2015)
32. Long, Z., Zhang, J., Fan, Q., et al.: Energy prediction for rotating ultrasonic machining based on neural network model. In: 2018 IEEE International Conference on Information and Automation (ICIA). IEEE (2018)
33. Shin, S.-J., et al.: Standard data-based predictive modeling for power consumption in turning machining. Sustainability **10**(3), 598 (2018)
34. Li, L., Fei, L., et al.: Multi-objective optimization of cutting parameters in sculptured parts machining based on neural network. J. Intell. Manuf. **26**(5) (2015)
35. Ak, R., Helu, M.M., Rachuri, S.: Ensemble neural network model for predicting the energy consumption of a milling machine. In: ASME International Design Engineering Technical Conferences & Computers & Information in Engineering Conference (2015)
36. Chen, S., Xie, J., Luo, X.: Study on material cutting energy consumption prediction of CNC machine tool based on BP-Adaboost algorithm. Green Manuf. **12**, 20–24 (2020)
37. Shin, S.J., Kim, Y.M., Meilanitasari, P.: A holonic-based self-learning mechanism for energy-predictive planning in machining processes. Processes **7**(10), 739 (2019)
38. Zhang, C., Ji, W., Peng, W.: Decision-making method for energy-saving control of CNC machine tools based on transfer learning. China Mech. Eng. **31**(23), 2855 (2020)
39. He, Y., Wu, P., Li, Y., et al.: A generic energy prediction model of machine tools using deep learning algorithms. Appl. Energy **275**, 115402 (2020)
40. Chen, W.W., Zhang, H., et al.: Research on CNC machine tool cutting energy consumption prediction based on support vector machine. Mach. Des. Manuf. (2014)
41. Komoto, H., Herrera, G., Herwan, J.: An evolvable model of machine tool behavior applied to energy usage prediction. CIRP Ann. Manuf. Technol. **69**(1) (2020)
42. Liu, Z., Guo, Y.: A hybrid approach to integrate machine learning and process mechanics for the prediction of specific cutting energy. CIRP Ann. Manuf. Technol. (2018). S0007850618300155
43. Chen, T., Shang, H., Bi, Q.: A prediction method of five-axis machine tool energy consumption with GBRT algorithm. In: International Conference on Mechatronics System and Robots (2019)
44. Bhinge, R., Biswas, N., Dornfeld, D., et al.: An intelligent machine monitoring system for energy prediction using a Gaussian Process regression. In: 2014 IEEE International Conference on Big Data (Big Data). IEEE (2015)
45. Rachuri, S., Bhinge, R., et al.: Toward a generalized energy prediction model for machine tools. J. Manuf. Sci. Eng. Trans. ASME (2017)