

Retraction

Retracted: Automatic Control of Mobile Industrial Robot Based on Multiobjective Optimization Strategy

Journal of Electrical and Computer Engineering

Received 22 November 2022; Accepted 22 November 2022; Published 18 December 2022

Copyright © 2022 Journal of Electrical and Computer Engineering. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Journal of Electrical and Computer Engineering has retracted the article titled “Automatic Control of Mobile Industrial Robot Based on Multiobjective Optimization Strategy” [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the editorial board.

References

- [1] Y. H. Zhu and J. Jiao, “Automatic Control of Mobile Industrial Robot Based on Multiobjective Optimization Strategy,” *Journal of Electrical and Computer Engineering*, vol. 2022, Article ID 7825906, 7 pages, 2022.
- [2] L. Ferguson, “Advancing Research Integrity Collaboratively and with Vigour,” 2022, <https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/>.

Research Article

Automatic Control of Mobile Industrial Robot Based on Multiobjective Optimization Strategy

Ya-Hong Zhu¹ and Jian Jiao² 

¹Chongqing Creation Vocational College, Chongqing 402160, China

²Chongqing Water Resources and Electric Engineering College, Chongqing 402160, China

Correspondence should be addressed to Jian Jiao; jiaojian@st.btbu.edu.cn

Received 10 February 2022; Revised 24 February 2022; Accepted 2 March 2022; Published 27 March 2022

Academic Editor: Wei Liu

Copyright © 2022 Ya-Hong Zhu and Jian Jiao. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In order to solve the optimal cascade mobile path selection problem when mobile industrial robots repair network coverage holes, a cascade mobile path selection optimization method considering the number and energy of intermediate cascade nodes is proposed. By calculating the energy availability of intermediate cascade nodes, this method further obtains the energy availability and decisive energy of each path, selects the optimal cascade mobile path from the perspective of multiobjective optimization, effectively balances the energy consumption of each mobile industrial robot, makes full use of the energy of the whole network, and prolongs the survival time of the network. Simulation results show that the optimization method has higher network energy efficiency than the standard cascaded mobile method.

1. Introduction

In the late 1950s, industrial robots were put into use for the first time. Joseph F. Engleberger used the relevant inspiration of servo system to jointly develop the industrial robot “unimate” with George DeVol, which was first used in GM’s production workshop in 1961. The original industrial robot structure was relatively simple, and its function was to pick up automobile parts and place them on the conveyor belt. It cannot interact with other working environments; that is, it accurately completes the same repetitive actions according to the predetermined basic program. Although the application of “unimat” is a simple and repeated operation, it not only shows the bright prospect of industrial mechanization but also opens the prelude to the vigorous development of industrial robots. Since then, in the field of industrial production, many heavy, repetitive, or meaningless process operations could be completed by industrial robots instead of humans.

In the 1960s, the development of industrial robots ushered in the dawn, and the simple functions of robots have been further developed. The application of robot sensors

improves the operability of the robot, including Ernst’s tactile sensor; Tomovich and Boni used pressure sensors in the world’s earliest “dexterous hand”; McCarthy improved the robot, added a visual sensing system, and helped MIT launch the world’s first robot system with visual sensors, which can identify and locate building blocks. In addition, using sonar system, photocell, and other technologies, industrial robots can correct their accurate position through environmental recognition.

Since the mid-1960s, robotics laboratories have been established at MIT, Stanford University, and the University of Edinburgh. The research on the second-generation “sensory” robot with sensors is rising in the United States and is developing in the direction of artificial intelligence.

In the 1970s, with the development of computer and artificial intelligence technology, robots entered a practical era. Like Hitachi’s robot with tactile and pressure sensors and 7-axis AC motor drive, the world’s first small computer-controlled robot launched by Milacron company of the United States, driven by electrohydraulic servo, can track moving objects for assembly and multifunctional operation. There are also robots suitable for assembly work, such as

SCARA plane joint robot invented by Yamanashi University in Japan.

In the late 1970s, Puma series robots launched by union company of the United States adopted multijoint, multi-CPU two-level computer control, all electric, special Val language, vision, and force sensors, marking the complete maturity of industrial robot technology. Puma still works in the front line of the factory.

In the 1980s, robots entered a period of popularization. With the development of manufacturing industry, industrial robots have been popularized in developed countries and are developing in the direction of high speed, high precision, lightweight, complete set, serialization, and intelligence, to meet the needs of more varieties and less batches.

In the 1990s, with the progress and development of computer technology and intelligent technology, the second-generation robot with certain sensory function was applied and began to be popularized. The third generation of intelligent robots with vision, touch, high dexterous fingers, and walking ability has emerged and began to be applied.

Coverage problem is the basic problem of wireless industrial robot network. It reflects the perceived service capability provided by the monitored area or target. Wireless industrial robot network usually adopts random deployment mode when deploying industrial robots, so the occurrence of coverage holes cannot be avoided. This will end the network lifetime in advance; many unused energy resources will be left in the network. Therefore, based on maintaining the original coverage level of the network, effective energy saving is very important for industrial robot network [1].

In the wireless industrial robot network, the goal of coverage problem is to effectively distribute the state of each node without reducing the original coverage level, minimize the energy consumption of each round of the network, and make each node share the network energy consumption equally [2]. Therefore, when the mobile industrial robot repairs the coverage hole, after determining the final position of the mobile industrial robot, we need to decide how to move the industrial robot to the target position to achieve better network coverage. In literature [3], the basic bidding protocol adopts direct movement (DM), but it generally fails to meet the application requirements of the network and wastes more time. Cascaded movement (CM) is proposed to optimize this problem in document [4]. The method of selecting intermediate cascaded nodes is described in detail, but only the total energy consumption of the path is considered when selecting the cascaded mobile path. The energy consumption of each mobile industrial robot cannot be better balanced. How to determine the optimal cascade moving path is a problem worth considering. The optimal cascade moving path should not only balance the energy consumption of each industrial robot but also reduce the total energy consumption of the path.

Aiming at the abovementioned problem, this paper improves the cascade movement in document [5]. When selecting the optimal cascade movement path, the multi-objective optimization method is used to fully consider the energy consumption balance among industrial machines. It balances the energy of industrial robots in the network by

reducing the energy consumption of a single industrial robot and improves the energy use efficiency of the network.

2. Related Works

Industrial robot consists of three parts and six subsystems.

The three parts are the mechanical part, the sensing part, and the control part.

The six subsystems are the mechanical structure system, driving system, perception system, robot environment interaction system, human-computer interaction system, and control system.

2.1. Mechanical Structure System. In terms of mechanical structure, industrial robots are generally divided into series robots and parallel robots. The characteristic of series robot is that the motion of one axis will change the coordinate origin of the other axis, while the motion of one axis of parallel robot will not change the coordinate origin of the other axis. Early industrial robots used series mechanisms. Parallel mechanism refers to a closed-loop mechanism in which the moving platform and the fixed platform are connected through at least two independent kinematic chains. The mechanism has two or more degrees of freedom and is driven in parallel. The parallel mechanism has two parts: wrist and arm. The active area of the arm has a great impact on the active space. The wrist is the connecting part between the tool and the main body. Compared with series robot, parallel robot has the advantages of large stiffness, stable structure, large bearing capacity, high fretting accuracy, and small motion load. In the position solution, the forward solution of the series robot is easy and the inverse solution is difficult. On the contrary, the forward solution of parallel robot is difficult and the inverse solution is easy.

2.2. Drive System. The driving system is a device that provides power for the mechanical structure system. According to the different power sources, the transmission mode of the transmission system is divided into hydraulic, pneumatic, electrical, and mechanical. Early industrial robots were hydraulically driven. Due to the problems of leakage, noise, and low-speed instability in the hydraulic system, as well as the heavy and expensive power plant, large heavy robots, parallel processing robots, and hydraulically driven industrial robots are only used in some special applications. Pneumatic device has the advantages of high speed, simple system structure, convenient maintenance, and low price. However, the working pressure of the pneumatic device is low and it is not easy to locate accurately. Generally, it is only used to drive the end effector of industrial robot. Pneumatic grasping, rotating cylinder, and pneumatic suction cup are used as end actuators for grasping and assembly of medium and small load work pieces. Electric drive is one of the most widely used driving methods at present. It has the characteristics of convenient power access, fast response speed, large driving force, and convenient signal detection, transmission, and processing and can adopt a variety of

flexible control modes. The driving motor generally adopts stepping motor or servo motor. At present, there are also direct drive motors, but the cost is high and the control is complex. The reducer matched with the motor generally adopts harmonic reducer, cycloidal pinwheel reducer, or planetary gear reducer. Due to the great demand for linear drive of parallel robot, linear motor has been widely used in the field of parallel robot.

2.3. Perception System. The robot perception system converts various internal state information and environmental information of the robot from signals to data and information that can be understood and applied by the robot itself or between robots. In addition to sensing the mechanical quantities related to their working state, such as displacement, speed, and force, visual perception technology is an important aspect of industrial robot perception. Visual servo system takes visual information as feedback signal to control and adjust the position and attitude of robot. Machine vision system is also widely used in quality inspection, work piece recognition, and food classification and packaging. The sensing system consists of an internal sensor module and an external sensor module. The use of intelligent sensors improves the mobility, adaptability, and intelligence of the robot.

2.4. Robot Environment Interaction System. Robot environment interaction system is a system that realizes the interaction and coordination between robot and equipment in the external environment. The robot and external equipment are integrated into a functional unit, such as processing and manufacturing unit, welding unit, and assembly unit. Of course, multiple robots can also be integrated into a functional unit to perform complex tasks.

2.5. Human-Computer Interaction System. Human-computer interaction system is a device through which people contact with robots and participate in robot control, for example, computer standard terminal, command console, information display board, and danger signal alarm.

2.6. Control System. The task of the control system is to control the robot actuator to complete the specified motion and function according to the robot operation instructions and sensor feedback signals. If the robot has no information feedback characteristics, it is an open-loop control system. With information feedback characteristics, it is a closed-loop control system. According to the control principle, it can be divided into program control system, adaptive control system, and artificial intelligence control system. According to the form of control motion, it can be divided into point control and continuous trajectory control.

Compared with traditional industrial equipment, industrial robot has many advantages. For example, the robot has the characteristics of ease of use, high intelligence, high production efficiency, high safety, easy management, and

remarkable economic benefits. It can run in a high-risk environment.

2.7. Ease of Use of Robot. In China, industrial robots are widely used in manufacturing, not only in automobile manufacturing but also in space shuttle production, military equipment, high-speed railway development, and ball point pen production. It has been extended from more mature industries to food, medicine, and other fields. Due to the rapid development of robot technology, compared with traditional industrial equipment, not only is the price gap of products become smaller and smaller, but also the degree of personalization of products becomes higher and higher. Therefore, in some technologically complex product manufacturing processes, industrial robots can replace traditional equipment and improve economic benefits to a great extent. According to statistics, from 2016 to 2017, the total sales of global industrial robots increased from 294000 to 346000. Industrial robots have a wide range of applications.

2.8. High Level of Intelligence. With the continuous progress of computer control technology, industrial robots will gradually be able to understand human language. At the same time, industrial robots can complete the components of products, so that workers can avoid complex operations. In industrial production, the welding robot system can not only realize the automatic real-time tracking of space weld but also realize the online adjustment of welding parameters and real-time control of weld quality. It can meet the urgent requirements of complex welding process, welding quality, and technical product efficiency. In addition, with the expansion of human space exploration, industrial robots can also use their intelligence to successfully complete tasks in extreme environments such as space, deep water, and nuclear environment.

2.9. Efficient and Safe Production. Manipulator, as the name suggests, is a one made by imitating human hands. It takes a fixed time to produce a product. In the same life cycle, the output of the manipulator is fixed and will not be high or low. Moreover, the time of the first mock test is fixed, and the test report card is also very high. The production of robots is more in the interests of the boss.

The factory uses industrial robots to produce, which can solve many safety production problems. Due to personal reasons, such as being unfamiliar with the work process, work negligence, and fatigue work, all potential safety hazards can be avoided.

2.10. Simple Management and Remarkable Economic Benefits. Enterprises can clearly understand their daily production and receive orders and produce goods according to their ability. It will not blindly estimate the output or produce too many products, resulting in waste. The daily management of industrial robots in factories will be much simpler than managing employees.

Industrial robots can work in a 24-hour cycle, which can achieve the maximum output of the production line without paying overtime. For enterprises, it can also avoid the fatigue of employees after long-term and high-intensity work and the delay of asking for leave due to illness. After the production line is replaced with industrial robots, the enterprise only needs to leave a few employees who can operate and maintain industrial robots. The economic benefit is very remarkable.

According to the intelligent manufacturing development plan formulated by the state [6], developing intelligent manufacturing will become a long-term strategic task in China; the action program of made in China 2025 [7] specifies that green manufacturing is one of the future development policies of China's manufacturing industry. China's manufacturing industry will continue to deepen its development in the direction of intelligence and energy saving. As the main production force of the future manufacturing industry, energy saving of industrial robots based on trajectory planning can be realized.

In the manufacturing environment, there are two problems in the application of industrial robot trajectory planning technology: (1) the robot dynamic parameters are unknown; (2) the existing energy-saving trajectory planning cannot guarantee the solution stability. The trajectory planning of industrial robot needs to use the dynamic model to calculate the motion energy consumption [8]. Aiming at the problem of unknown robot dynamic parameters in the manufacturing environment, researchers have proposed dynamic identification. The traditional methods used in dynamic parameter estimation are least square method [9], Kalman filter method [10], and instrumental variable method [11]. In recent years, there have also been dynamic identification methods based on intelligent algorithms, such as particle swarm optimization algorithm [12], Hopfield neural network [13], and cyclic neural network [14]. However, both parameter estimation method and intelligent identification method can only obtain the dynamic model in linear form or specific neural network structure [15]. In conclusion, it is necessary to improve the dynamic identification method so that the identification results can be applied to energy-saving trajectory planning.

The solution methods of energy-saving trajectory planning include parametric trajectory [16], dynamic programming [17], and convex optimization [18]; the parametric trajectory method can ensure the high-order continuity of the robot trajectory, and the dynamic programming method can arbitrarily specify the objective function and constraints. The implementation steps of parametric trajectory and dynamic programming are simple and flexible, but only the approximate optimal solution results can be obtained, and it is difficult to obtain a stable robot trajectory; the convex optimization method transforms the trajectory planning problem into a convex optimization problem and then solves the trajectory with the optimal index. In the past, the convex optimization method was mostly used to solve the trajectory planning problem with the optimal time. Its advantage is that it can ensure the

global optimality of the solution results. In the manufacturing environment, the motion trajectory is obtained through off-line planning; the industrial robot will work for a long time according to the corresponding control program and will not easily adjust the motion trajectory before the end of production.

Obviously, considering the industrial robot in the actual manufacturing environment, the energy-saving effect of the trajectory and the stability of the solution result of the planning algorithm are the main influencing factors for the production line manager to select the planning algorithm; the energy-saving trajectory planning based on convex optimization is more in line with the requirements of manufacturing environment. However, because the convex optimization method needs to maintain the convexity of the trajectory planning problem in the process of problem construction, transformation, and solution and the implementation steps are strict and cumbersome, most of the current trajectory planning research uses the parametric trajectory method. There is little energy-saving trajectory planning based on convex optimization [19].

3. Optimization of Mobile Path

3.1. Basic Assumptions. This paper is based on the following assumptions: (1) Once the industrial robot is deployed, it will work independently, and the energy of each industrial robot cannot be supplemented; that is, when the industrial robot's energy is exhausted, it cannot work, and the initial energy of each industrial robot is $E > 0$. (2) The sensing radius and communication radius of all industrial robot nodes are equal and are disk-shaped. (3) The moving speed of all mobile industrial robots is equal, which is expressed by speed. In the improved cascaded movement (ICM) proposed in this paper, firstly, the method of literature [20] is used to select the intermediate cascaded mobile node, and then the following method is used to select the optimal cascaded mobile path.

3.2. Selection of Optimal Path. In order to balance the energy consumption of each industrial robot in the network, the moving distance of each mobile industrial robot should be approximately equal, so it is assumed that all mobile industrial robots in the cascade moving path move at the same time [21].

Definition 1. In the cascaded moving path, the time spent from any mobile industrial robot (including the destination mobile industrial robot and all intermediate cascaded industrial robots) to the completion of covering cavity repair is called the moving time of the path. Suppose that there are n intermediate cascade nodes in an effective cascade moving path m and the moving distance of node i is $d_{m,i}$. Then the moving time of path m is

$$T_m = \frac{\max(d_{m,i})}{\text{Speed}}. \quad (1)$$

In the above equation, $T_m \leq T$. Only when $d_{m,i}$ is smaller will the movement time of path m be smaller, to shorten the recovery time of the network.

Total moving length of path m is

$$d_m = d_{m,0} + d_{m,1} + \dots + d_{m,n}. \quad (2)$$

On path m , the energy consumed by the movement of industrial robot node i is

$$EC_{m,i} = e \times d_{m,i}, \quad (3)$$

where e represents the energy consumed by the mobile industrial robot per unit distance. Then the residual energy of node i is

$$ER_{m,i} = E - EC_{m,i}. \quad (4)$$

Energy availability of mobile industrial robot node i is

$$\eta_{m,i} = \frac{ER_{m,i}}{E}. \quad (5)$$

Energy availability of path m is

$$\eta_m = \prod_{i=0}^n \eta_{m,i}. \quad (6)$$

Definition 2. Decisive energy refers to the minimum energy availability of all nodes on an available cascade mobile path m , which is recorded as DE_m :

$$DE_m = \min(\eta_{m,i}), \quad (7)$$

where i represents the i th node S_i on path m .

There are many available cascaded moving paths from the target mobile industrial robot to the target location, and it is necessary to select an optimal moving path. Then select a path with the highest energy availability from P .

$$R = \max_{m \in P} (\eta_m). \quad (8)$$

Otherwise, select a path with the largest decisive energy DE_m from set M .

$$R = \max_{m \in M} (DE_m). \quad (9)$$

According to (7) and (8), the decisive energy greater than the threshold can be selected from all available path sets M . The path with the maximum energy availability or the maximum decisive energy is regarded as the optimal cascade moving path λ , the size of which can be determined by the user according to the actual application, which is generally set to 0.3.

To solve the cascade mobile path problem of mobile industrial robots and improve the use efficiency of network energy is to maximize the energy availability or decisive energy of the path. According to (6), the energy availability η_m of the path is determined by the number n of intermediate cascade nodes and the energy availability $\eta_{m,i}$ of each node. Moreover, when the energy availability of nodes is relatively equal, the more intermediate cascade nodes on

the path, the smaller the value of η_m . According to (7), the decisive energy DE_m is also determined by the energy availability $\eta_{m,i}$ of each node. According to equations (3), (4), and (5), the energy availability $\eta_{m,i}$ of each node is finally determined by the moving distance $d_{m,i}$ of node i in the final analysis; the root of the problem is to minimize the number of intermediate cascade nodes n . As can be seen from (1) and (2), this is a multiobjective optimization problem.

Using the multiobjective optimization method, it is assumed that there are three available cascade moving paths from the target mobile industrial robot S_0 to the target position s , and the target mobile industrial robot can move to the target position along any path.

As can be seen from Figure 1, according to the path selection rules of (8) and (9), since the decisive energy of path 2 and path 3 is greater than λ , the optimal cascade movement path will be generated in path 2 and path 3, η_2 greater than η_3 . Therefore, path 2 becomes the optimal path for the industrial robot to move and repair the covered hole. From the above calculation, it can be seen that η_m of path 1 is the largest, but because DE_m is not greater than λ , path 1 is excluded. Although $\eta_{m,i}$ of nodes on path 3 is greater than or equal to that on path 2, due to the large number of intermediate cascaded nodes, the last is η_3 less than η_2 .

Therefore, the cascade mobility strategy not only protects the low-energy nodes on the path but also considers the feasibility of selecting the average residual energy of the node and the small number of intermediate cascade nodes as the path. Therefore, when the mobile industrial robot moves, it can balance the energy consumption in the current network, reduce the energy consumption of the mobile industrial robot, and prolong the service time of the industrial robot network [22].

4. Simulation Experiment

The target area is a 30m \times 30m rectangle; a certain number of mobile nodes and static nodes are randomly deployed in the area. Assuming that the total number of industrial robot nodes is 50, the percentage of mobile industrial robots changes from 10% to 50%.

The experiment randomly generates closed cover holes of different sizes in the target area.

The performances of CM and ICM in energy efficiency are compared through simulation and are shown in Tables 1–3.

In the wireless industrial robot network, the network energy consumption is mainly caused by the movement and communication of industrial robots. Figure 2 compares the average moving distances of CMI and CM. CM only selects the cascade moving path in terms of total energy consumption; the average energy consumption of mobile industrial robots involved cannot be optimized. The average energy consumption of mobile industrial robots is mainly determined by their average moving distance. In addition, ICM needs to clearly calculate the energy of cascade moving path, so its message complexity is significantly increased

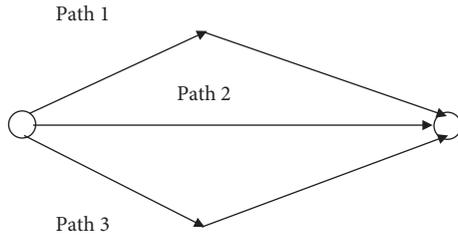


FIGURE 1: Robot motion path selection.

TABLE 1: Average moving distance of CM and ICM compared through simulation.

	0.1	0.2	0.3	0.4	0.5
CM	45	35	28	25	21
ICM	36	32	22	15	12

TABLE 2: Message complexity of CM and ICM compared through simulation.

	0.1	0.2	0.3	0.4	0.5
CM	45	53	66	76	87
ICM	36	41	57	63	72

TABLE 3: Energy consumption ratio of CM and ICM compared through simulation.

	0.1	0.2	0.3	0.4	0.5
CM	0.41	0.48	0.54	0.63	0.74
ICM	0.34	0.44	0.47	0.54	0.64

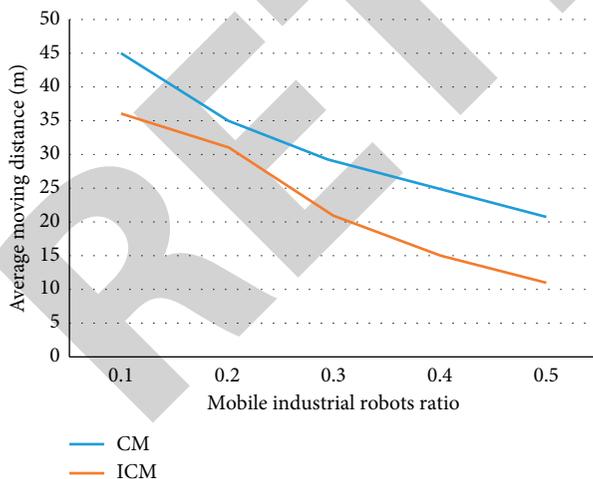


FIGURE 2: Average moving distance.

compared with direct moving, as shown in Figure 3. However, mobile industrial robots consume 30J energy when moving 1 m; sending a 1-byte message consumes only 0.1 J of energy. That is, the energy consumed by a mobile industrial robot moving 1 m is 300 times that consumed by sending a 1-byte message. Therefore, in a wireless industrial

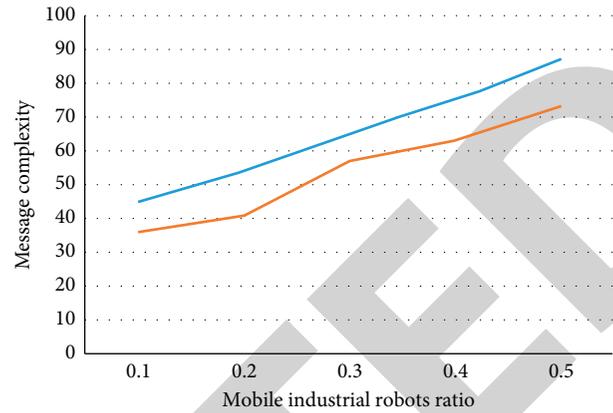


FIGURE 3: Message complexity.

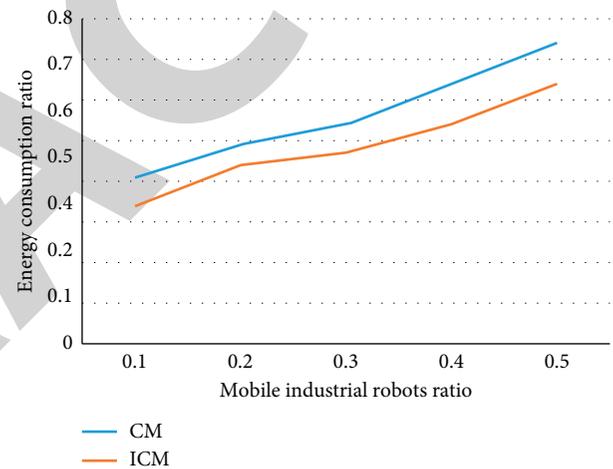


FIGURE 4: Energy consumption ratios.

robot network, the impact of message complexity on network energy consumption is minimal; it cannot be considered. Figure 4 shows the change of the energy use efficiency of the wireless industrial robot network with the proportion of mobile industrial robots under the two mobile modes. The energy use efficiency in the wireless industrial robot network is closely related to the network survival time. Therefore, the cascade mobile greatly prolongs the network survival time.

5. Conclusions

Aiming at the problem of repairing the coverage hole of wireless industrial robot network by mobile industrial robot, the cascade motion is further improved. When selecting the cascade motion path, the energy utilization of the path is accurately calculated through the node residual energy, the concept of path decisive energy is introduced, and the energy consumption balance between mobile industrial machines is fully considered combined with the idea of multiobjective optimization. It reduces the energy consumption of a single

mobile industrial robot, balances the energy of industrial robots in the network, and improves the energy utilization efficiency of the network. Finally, simulation experiments verify the effectiveness and superiority of the improved method significantly improve the energy utilization efficiency of the network and prolong the survival time of industrial robots.

Data Availability

The labeled datasets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This study was sponsored by the Natural Science Foundation of Chongqing, China (no. cstc2021jcyj-msxmX1113).

References

- [1] X. Lai, C. Li, J. Zhou, Y. Zhang, and Y. Li, "A multi-objective optimization strategy for the optimal control scheme of pumped hydropower systems under successive load rejections," *Applied Energy*, vol. 261, Article ID 114474, 2020.
- [2] Q. Li, J. Zou, S. Yang, and R. Gan, "A Predictive Strategy Based on Special Points for Evolutionary Dynamic Multi-Objective Optimization," *Soft Computing*, vol. 23, 2018.
- [3] C. Zhang, Z. Tang, K. Li, J. Yang, and L. Yang, "A polishing robot force control system based on time series data in industrial internet of things," *ACM Transactions on Internet Technology*, vol. 21, no. 2, pp. 1–22, 2021.
- [4] Y. Wang, M. Zhang, and X. Tang, "A kMap optimized VMD-SVM model for milling chatter detection with an industrial robot," *Journal of Intelligent Manufacturing*, no. 3, 2021.
- [5] S. Wenjing, W. Weiwen, and D. Dao-Qing, "Subtype-Weslr: Identifying Cancer Subtype with Weighted Ensemble Sparse Latent Representation of Multi-View Data," *Briefings in Bioinformatics*, vol. 23, 2021.
- [6] X. Wang, X. Zhou, and Z. Xia, "A survey of welding robot intelligent path optimization," *Journal of Manufacturing Processes*, vol. 63, 2020.
- [7] T. Pathmakumar, M. M. Rayguru, S. Ghanta, M. Kalimuthu, and M. R. Elara, "An optimal footprint based coverage planning for hydro blasting robots," *Sensors*, vol. 21, no. 4, p. 1194, 2021.
- [8] Y. Hu, H. Su, and J. Fu, "Nonlinear model predictive control for mobile medical robot using neural optimization," *IEEE Transactions on Industrial Electronics*, vol. 68, no. 99, 1 page, 2020.
- [9] M. Shi, X. Qin, and H. Li, "Cutting force and chatter stability analysis for PKM-based helical milling operation," *International Journal of Advanced Manufacturing Technology*, vol. 111, no. 11–12, pp. 1–18, 2020.
- [10] K. Li, J. Luo, Y. Hu, and S. Li, "A novel multi-strategy DE algorithm for parameter optimization in support vector machine," *Journal of Intelligent Information Systems*, vol. 54, no. 3, pp. 527–543, 2020.
- [11] M. Nell, A. Kubin, and K. Hameyer, "Multi-stage optimization of induction machines using methods for model and parameter selection," *Energies*, vol. 14, 2021.
- [12] J. S. Almeida, L. A. Meira, A. D. S. Nascimento, G. L. Santos, V. A. Lemos, and L. S. G. Teixeira, "Ultrasound-assisted dispersive liquid-liquid microextraction based on melting of the donor phase: a new approach for the determination of trace elements in solid samples," *Food Analytical Methods*, vol. 14, no. 3, pp. 596–605, 2021.
- [13] Z. R. Wani, M. Tantray, and E. Noroozinejad Farsangi, "Investigation of proposed integrated control strategies based on performance and positioning of MR dampers on shaking table," *Smart Materials and Structures*, vol. 30, no. 11, Article ID 115009, 2021.
- [14] M. Roayaei, "On the binarization of Grey Wolf optimizer: a novel binary optimizer algorithm," *Soft Computing*, vol. 25, no. 23, Article ID 14715, 14728 pages, 2021.
- [15] Z. Lv, R. Lou, and A. K. Singh, "Transfer Learning-Powered Resource Optimization for Green Computing in 5G-Aided Industrial Internet of Things," *ACM Transactions on Internet Technology (TOIT)*, vol. 22, 2021.
- [16] P. Liu and H. Zhang, "A mathematical theory of computational resolution limit in multi-dimensional spaces," *Inverse Problems*, vol. 37, no. 10, Article ID 104001, 2021.
- [17] V. F. Yu, T. H. A. Le, and T. S. Su, "Optimal maintenance policy for offshore wind systems," *Energies*, vol. 14, 2021.
- [18] G. Liao, Z. Li, and F. Zhang, "A review on the thermal-hydraulic performance and optimization of compact heat exchangers," *Energies*, vol. 14, 2021.
- [19] C. Miao, G. Chen, C. Yan, and Y. Wu, "Path planning optimization of indoor mobile robot based on adaptive ant colony algorithm," *Computers & Industrial Engineering*, vol. 156, Article ID 107230, 2021.
- [20] G. Fu, T. Gu, H. Gao, and C. Lu, "A postprocessing and path optimization based on nonlinear error for multijoint industrial robot-based 3D printing," *International Journal of Advanced Robotic Systems*, vol. 17, no. 5, Article ID 172988142095224, 2020.
- [21] X. Liu, F. Zhang, and Q. Sun, "Multi-objective optimization strategy of integrated electric-heat system based on energy storage situation division," *IEEE Access*, vol. 9, no. 99, 1 page, 2021.
- [22] Y. Chen, C. Chen, J. Ma et al., "Multi-objective optimization strategy of multi-sources power system operation based on fuzzy chance constraint programming and improved analytic hierarchy process," *Energy Reports*, vol. 7, no. 5, pp. 268–274, 2021.