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Research on the Energy Efficiency Optimization Scheduling Method of Multi-Load Trolleys in Workshops

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Abstract: With the shift of China's industrial structure toward green and intelligent manufacturing, energy-efficient and flexible production scheduling has become an essential research focus. In response to increasing complexity in mixed-flow assembly environments—such as the diversification of products, compressed delivery cycles, and growing energy consumption—this study reviews recent developments in the scheduling optimization of workshop material handling systems, especially those involving multi-load AGVs. The literature reveals a clear evolution from static scheduling models based on fixed plans to dynamic, real-time strategies that address uncertainties in production rhythms and resource availability. In particular, energy-aware scheduling has gained prominence, emphasizing the need to jointly optimize delivery timeliness, path planning, and energy efficiency. Deep reinforcement learning (DRL) has emerged as a promising solution, offering strong capabilities in modeling high-dimensional states, capturing temporal dependencies, and making adaptive decisions. However, challenges remain in sparse rewards, action feasibility, and decision interpretability. This review highlights the need for DRL frameworks that incorporate energy consumption modeling, action masking, and semantic state encoding to achieve robust, efficient, and sustainable AGV scheduling under dynamic manufacturing scenarios.

Keywords: Workshop material handling system; Multi-load AGV; Solution method; Energy Optimization.

1. Introduction

At present, China's industrial structure is at a crucial stage of transitioning from traditional manufacturing to green and intelligent manufacturing. In 2022, the National Development and Reform Commission and other departments jointly issued the "Implementation Plan for Carbon Peaking in the Industrial Sector", which pointed out that efforts should be accelerated to promote the green and low-carbon transformation of key industries, enhance energy efficiency, implement intelligent process control, and optimize the entire process of carbon emissions. It particularly emphasized the systematic improvement of "production scheduling optimization and energy consumption coordinated control" through intelligent manufacturing means. By 2025, The energy consumption per unit of added value of industrial enterprises above designated size decreased by 13.5% compared with 2020, and the decline in carbon dioxide emissions per unit of industrial added value was greater than that of the whole society. Under the guidance of this strategy, manufacturing enterprises are no longer confronted with merely the expansion of production capacity, but rather a full-process redesign centered on "optimal energy efficiency", "intelligent scheduling" and "green operation". Take the automotive manufacturing industry as an example. As can be seen from Figure 1.1, the total energy consumption of China's automotive manufacturing industry has been on a continuous upward trend from 2005 to 2022. Although the growth rate fluctuates annually, the total energy consumption has far exceeded the level of ten years ago, indicating that the overall energy consumption pressure on the industry is still increasing. Especially after 2013, with the expansion of production capacity and the advancement of vehicle model diversification, the energy usage in the manufacturing process failed to effectively curb the growth trend. Meanwhile, the year-on-year growth rate of energy consumption reflected in the chart fluctuates significantly, and the growth rate rebounds notably in some years, indicating that energy conservation and consumption reduction still face multiple challenges such as complex raw material structure, lengthy process paths, and low efficiency in dispatching and organization at present. This current situation reflects that although certain progress has been made in energy efficiency management in China's automotive manufacturing sector, on the whole, the energy consumption level remains at a high level and there is significant room for optimization. Especially in the material handling stage at the workshop level, as a key node running through the entire production process, its operational efficiency directly affects the energy consumption level per unit output, making it a key breakthrough direction for the green transformation of the manufacturing system. In a typical discrete manufacturing environment, material flow often occurs in the form of batch, uneven and multi-path. Especially in the mixed-flow assembly scenario, the growth of part types, the fragmentation of order structures and the differences in workstation rhythms significantly increase the complexity of the internal logistics system. This nonlinear and dynamic logistics structure not only challenges the traditional rule-based scheduling methods, but also exposes the uneconomy in energy use - excessive empty routes, waiting and non-optimal transportation routes directly translate into an increase in energy consumption per unit of output.

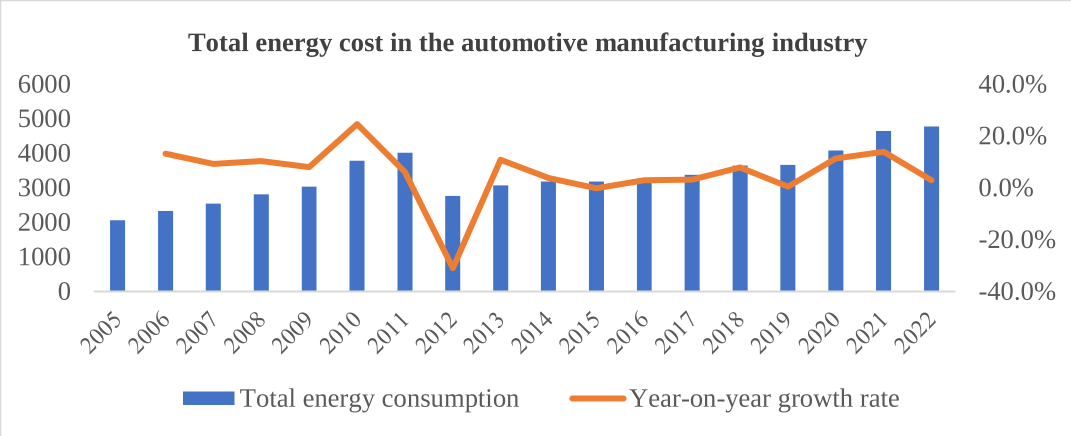

Figure 1. Total energy cost in the automotive manufacturing industry

Meanwhile, the research on intelligent scheduling systems mostly focuses on shortening task execution time or reducing inventory costs. However, the modeling and evaluation of energy conversion efficiency and carbon emission costs associated with system operation remain weak. Especially in today's emerging industrial chains represented by new energy vehicles and green manufacturing, factory operations have shifted from focusing on "cost minimization" to the dual goals of "optimal energy efficiency" and "cost constraints", reflecting the structural transformation of the optimization objective function of industrial systems. This trend also calls for more research on energy-aware scheduling methods, which can integrate energy consumption distribution modeling and path-level energy assessment while meeting timeliness and flexibility. Therefore, starting from the "multi-objective scheduling problem in the intelligent manufacturing environment", this paper focuses on the material handling system within the mixed-flow assembly workshop to summarize the existing research.

2. Research Objectives and Significance

Against the backdrop of the manufacturing industry accelerating towards high-end, intelligent and green development, while enterprises are pursuing production efficiency, they are also confronted with multiple challenges such as diversified orders, complex products and compressed delivery cycles. As an important organizational model to meet the demands of flexible production, the mixed-flow assembly line has advantages in flexibility and resource coordination. However, it poses higher requirements for the response speed, scheduling efficiency and energy consumption control of the workshop logistics system. Most traditional material distribution systems adopt static rules or periodic replenishment strategies, which are difficult to adapt to the actual operational requirements of the dynamic state of the workshop and the variable task rhythms. This often leads to problems such as shortages of key parts, overstocking of line-side inventory, and uneconomical energy consumption, affecting the stability of the production rhythm and cost control.

To break through the above-mentioned bottlenecks, intelligent material handling systems based on multi-load AGVs have been widely applied in workshop distribution tasks. Compared with single-vehicle scheduling, multi-vehicle systems face more complex multi-objective optimization problems such as task allocation, path conflicts and energy constraints, which belong to NP-Hard level scheduling challenges and are difficult to be effectively solved by traditional precise algorithms. In recent years, deep reinforcement learning has become an important means to solve high-dimensional dynamic scheduling problems by virtue of its advantages in state representation, autonomous decision-making and dynamic adaptation. This paper focuses on the workshop rechargeable multi-load AGV system and designs a scheduling strategy framework integrating the GRU network, Double DQN structure and contrastive learning module. Combined with the simulation linkage mechanism, it realizes the autonomous learning and closed-loop optimization of the scheduling process. This strategy not only enhances the model's perception ability of temporal state changes, but also optimizes the discriminability of state expression through the semantic comparison mechanism, overcoming the limitations of traditional algorithms in aspects such as sparse rewards and processing of infeasibility of actions. In conclusion, the reinforcement learning scheduling method proposed in this paper not only responds to the actual demands for the efficiency and greenness of material handling systems in the intelligent manufacturing environment, but also provides theoretical and methodological support for the engineering implementation of deep reinforcement learning in the field of industrial scheduling. It has significant academic research value and practical promotion significance.

3. Review of Domestic and International Research

In recent years, the research on the scheduling optimization of workshop material handling systems has gradually shifted from static planning to dynamic response, and the scheduling goals have also expanded from task completion efficiency to multi-dimensional indicators such as path optimization, cost control, and energy consumption perception. Early studies mostly focused on static scheduling as the core, relying on predefined production plans and fixed input conditions. By optimizing AGV paths and material distribution sequences through methods such as integer programming and tabu search, the resource utilization rate and line-side inventory control ability were improved to a certain extent. However, the static scheduling method faces uncertain factors such as fluctuations in production rhythm and changes in equipment status in practical applications, and it is difficult to meet the dynamic requirements of strong real-time performance and variable tasks of the mixed-flow assembly line. Therefore, research has gradually shifted to dynamic scheduling strategies that are more adaptable and have real-time response capabilities. Especially in multi-load AGV systems, researchers have constructed various task allocation and path selection mechanisms around scheduling rule optimization, heuristic search and intelligent algorithms, enhancing the system's processing ability for complex events and the flexibility of scheduling strategies. With the development of deep learning and reinforcement learning technologies, more and more studies have introduced reinforcement learning into the dynamic AGV scheduling problem. Through state awareness, autonomous learning and feedback optimization, the intelligent decision-making ability of the scheduling system has been significantly enhanced. In terms of considering energy consumption factors, existing studies have also initially explored the introduction of energy consumption indicators into the modeling of reward functions, and achieved the joint optimization of transportation routes, power consumption states and distribution tasks through deep reinforcement learning algorithms. It can be seen from this that the scheduling method based on deep reinforcement learning has become an important direction for dealing with the multi-objective scheduling problem of AGVs in the dynamic workshop environment. Especially in the scenario of multi-load and rechargeable AGV systems, it is even more urgent to build a scheduling model that takes into account both timeliness and energy consumption control to adapt to the development needs of complex production rhythms and green manufacturing. Therefore, based on integrating the existing research results, further exploring the deep reinforcement learning scheduling method with the ability of time series modeling and state expression optimization has important research value and practical significance.

3.1. Static Scheduling

The static scheduling method regards the scheduling problem of the workshop material handling system as a deterministic problem. The input information of scheduling usually includes the production status of the system at a certain moment and the predetermined production task plan, and this information is determined before scheduling. Based on these fixed information, the scheduling algorithm is solved by applying operational research methods such as integer programming and dynamic programming, thereby outputting the optimized scheduling scheme under certain constraints.

Aiming at the problem of on-time material delivery in the automotive mixed-flow assembly line, Emde [1] proposed a scheduling method based on workstation and trolley path optimization, aiming to minimize the cost of line-side inventory and handling equipment. In order to improve the distribution efficiency, Emde [2] further introduced the Tabu search algorithm and achieved the optimization of the trolley distribution path and parts loading through path selection optimization. With the increase in the complexity of the problem, Emde [3] considered the uncertainty of the path and, on the basis of ensuring the minimum service frequency, minimized the number of vehicles and the total route duration as much as possible. Maurizio and Mauro [4] carried out optimizations on the mixed-flow assembly line based on the Signboard system. They managed the scale of distribution vehicles through long-term and short-term optimization schemes and achieved scheduling optimization based on actual demand in the Signboard system.

3.2. Dynamic Scheduling

Compared with static scheduling, dynamic scheduling has stronger responsiveness and flexibility. Its core lies in adjusting the handling strategy and operation plan in real time based on the current status information during the operation of the production system. This type of method remains effective during the system's operation. It can dynamically generate scheduling plans based on real-time changing information such as the operation status of manufacturing equipment, the scheduling status of AGV carts, and the rhythm of task generation, without the need to obtain complete order or task data in advance. The dynamic scheduling mechanism is usually initiated through two types of triggering methods: One is to periodically perform scheduling calculations at fixed time intervals [5]; The other type is triggered when critical changes occur in the system status, such as the generation of new distribution tasks or changes in the status of handling equipment [6]. In the process of decision generation, the scheduling system, based on the currently known information, outputs feasible handling decisions through intelligent methods such as heuristic search, evolutionary algorithms or reinforcement learning, thereby effectively dealing with system uncertainties. In related studies, Choi [7] focused on the scheduling problem in dynamic feeding earlier. They conducted dynamic prediction of part consumption by introducing real-time production progress and established an optimization model to determine the replenishment sequence that meets the minimum delay penalty. Subsequently, many studies have been carried out around the dynamic scheduling problem of multi-load handling equipment. From the modeling method, scheduling goals to the algorithm framework, they have been continuously expanded, promoting the transformation process of workshop material handling scheduling research from static planning to real-time response.

3.2.1. Scheduling rule method

For the scheduling optimization problem in multi-load handling systems, researchers have proposed a variety of rule-based methods. Liu and Hung [8] proposed a control strategy for a single multi-load AGV suitable for unmanned operation workshops. By collecting the information of the entire workshop in real time, the deadlock phenomenon in the operation flow process was effectively avoided, and the timely completion of transportation tasks was guaranteed at the same time. Grunow [9] systematically evaluated the performance of different scheduling strategies in a dynamic environment based on an extensible simulation model. The results show that the offline heuristic algorithm based on pattern recognition outperforms the traditional online scheduling method in overall performance. Azimi [10] aimed at the problem of task selection and distribution scheduling in multi-load AGV systems, proposed to generate an alternative control strategy set by combining different job selection rules to improve the adaptability and flexibility of the scheduling strategy. Chawla [11] compared the applicability of various real-time scheduling rules at different scales in the context of flexible manufacturing systems. The research shows that the scheduling method based on the similarity of production targets exhibits better scheduling effects in most scenarios.

3.2.2. Intelligent optimization algorithm

With the increase in the complexity of manufacturing workshop scheduling, intelligent optimization algorithms have gradually become an important research direction for AGV scheduling and path optimization. Buyurgan [12] proposed a real-time path selection architecture based on evolutionary algorithms, aiming to maximize the overall output of flexible manufacturing systems. Tabatabaei [13] generated the scheduling schedule by defining a certain time range in the MATLAB software, thereby executing a new dynamic scheduling. Aiming at the problem of simultaneously optimizing the scheduling machine and the handling trolley, a heuristic scheduling program was designed to solve the flexible scheduling scheme. Klerides [14] studied the scheduling problem of dual-load AGVs in the container terminal scenario and verified the efficiency of the rolling planning method under different layout and load conditions.

3.2.3. Machine learning

In recent years, with the continuous intensification of the complexity and dynamic change characteristics of manufacturing systems, traditional scheduling methods have gradually exposed problems of insufficient adaptability and excessively high computational complexity. To address these challenges, researchers have introduced machine learning and intelligent optimization technologies to drive the workshop scheduling system towards a more efficient and intelligent direction.

Yu [15] proposed a location-dependent total load minimization scheduling model around the deterioration of processing time. They improved the solution effect of the multi-machine scheduling problem through mathematical optimization methods and introduced the consideration of dynamic processing characteristics for scheduling modeling. Zhang and Dietterich [16] aimed at minimizing the production cycle and applied the reinforcement learning method to solve the dynamic scheduling problem of workshop installation and inspection operations, verifying the application value of autonomous strategy learning in complex production processes. Aydin and Ozrtemels [17] proposed the Q-III learning algorithm. The agent dynamically selects the allocation rules based on real-time information such as the average relaxation time of the system and the queue length, achieving the online optimization of the scheduling strategy. In the field of AGV dispatch and path optimization, Li [18] comprehensively considered the location, idle state and material distribution requirements of AGVs, and formulated the trolley scheduling scheme based on Markov game and reinforcement learning methods, which improved the overall response speed and resource utilization rate of the material handling system. Jeon [19] optimized the path planning of AGVs in container terminals based on Q-learning, effectively shortening the transportation time and improving the throughput efficiency of the system. Xue [20] focused on the multi-trolley scheduling problem and adopted the reinforcement learning method to minimize the average operation delay and the total construction period, achieving the adaptive optimization of the handling task under multiple objectives. With the development of Deep Learning and Reinforcement learning technologies, Deep Reinforcement Learning (DRL) has shown broad application prospects in the field of dynamic scheduling. Ren [21] proposed a method combining the MachineRank algorithm with the Dueling Double Deep Q Network structure to model the uncertain factors such as dynamic order placement, equipment failure and changes in AGV transportation time in the flexible operation workshop. By introducing the ranking mechanism of machine comprehensive utilization rate and the composite scheduling rules, the robustness and adaptability of the scheduling system in the dynamic event environment have been significantly improved. Zhang [22] designed a multi-head attention map convolutional network model integrating spatial-temporal features around the problem of buffer resource optimization in flexible production workshops. By extracting the topological information of production layout and the temporal characteristics of logistics, the intelligent level of material flow prediction and resource allocation was improved. Li [23] aimed at the dynamic workshop scheduling problem with AGV systems and constructed a scheduling optimization framework based on the deep Q-network, taking into account both the material handling path planning and the goal of minimizing the operation completion time.

3.3. Research Related to Assembly Lines Considering Energy Consumption

With the increasing emphasis on energy consumption control and the concept of green manufacturing in production and manufacturing, research on energy consumption optimization in AGV systems has gradually emerged. Early studies mostly focused on energy consumption modeling and optimization in a static scheduling environment. Emde [24] constructed an AGV static distribution optimization model for parallel mixed-flow assembly lines, reducing the total energy consumption of the system by reasonably arranging distribution tasks. Rashid [25] considered the energy utilization of equipment in idle mode in the energy-sensitive Assembly Line balancing Problem and designed an assembly task allocation method for minimizing energy consumption. Fratczak [26] established an energy consumption measurement and modeling method for individual assembly components, providing a basic tool for energy consumption assessment in the static scheduling stage. Fysikopoulos [27] modeled and analyzed the energy consumption of the automotive body assembly process through simulation technology, emphasizing the close relationship between the material handling path and energy efficiency in the static scheduling stage. Oumer [28] systematically evaluated the energy efficiency performance of traditional workshop operation systems using discrete event simulation. Although the energy consumption optimization method under static scheduling reduces the system energy consumption to a certain extent, due to its formulation of handling paths and distribution strategies based on fixed task plans, it lacks the response ability to dynamic changes in actual production and is difficult to meet the higher requirements for energy efficiency in complex scenarios such as mixed-flow assembly lines. Therefore, the energy consumption optimization problem in a dynamic environment has become a new research hotspot.

Zhang [29] proposed a dual-objective optimization method combining battery management and dynamic scheduling of AGVs. By maximizing long-term rewards through deep reinforcement learning, it significantly reduced delays and energy consumption in material handling. Ye [30] developed an algorithm based on Multi-agent Deep Deterministic Policy Gradient (MADDPG), which optimized the energy consumption minimization problem of multi-AGV systems in dynamic task allocation and path planning. Cheng [31] introduced a deep reinforcement learning framework for the multi-AGV scheduling problem in flexible workshops, constructed a reward function that jointly considered delay and energy consumption, and achieved energy-aware dynamic decision-making. Wei [32] designed a deep reinforcement learning algorithm based on the self-attention mechanism, which effectively improved the energy consumption control ability of the AGV dynamic scheduling system. Ren [33] integrated machine ranking algorithms and reinforcement learning methods to achieve real-time scheduling for energy consumption and efficiency balance in a dynamic flexible workshop environment. Song [34] proposed a dynamic job-shop scheduling method combining the Transformer structure and deep reinforcement learning. By modeling the dynamic scheduling problem as a Markov decision process and introducing a dual decision network and a priority experience replay mechanism, it achieved good results when dealing with changes in dynamic events. Grumbach [35] explored a robust and stable scheduling method based on deep reinforcement learning in the dynamic flow workshop environment. They proposed to improve the robustness and stability of the scheduling scheme by adjusting the job relaxation time. In the simulation experiment, they achieved a significant reduction in the computing time while ensuring the quality of the results. Liu [36] proposed a scheduling method based on deep reinforcement learning for the dynamic scheduling problem of flexible workshops. This study models the scheduling problem as a hierarchical and distributed decision-making architecture, trains the agent through the Double DQN algorithm, and realizes the autonomous mapping from the real-time status information of the workshop to the scheduling decision. Chang [37] proposed a deep reinforcement learning scheduling method for the dynamic flexible job-shop environment. Aiming at dynamic factors such as random workpiece arrivals and changes in processing time, by modeling the scheduling problem as a Markov decision process, the DQN algorithm is used to optimize the task allocation and path selection strategy of AGVs. Its method effectively improves the energy consumption control and scheduling efficiency under dynamic disturbance conditions by real-time learning of the optimal action selection under environmental changes. Zhang [38] proposed a dynamic scheduling method based on deep reinforcement learning, and adopted the Proximal Policy Optimization (PPO) algorithm to solve the dynamic scheduling problem in the job-shop manufacturing system. This method introduces the dynamic factors of machine tool failures in the modeling stage. It can continuously optimize the scheduling strategy and improve the sustainable operation ability and production efficiency of the system in the case of sudden failures in the production system. These studies show that energy consumption optimization under dynamic scheduling has become an important direction in AGV scheduling research, and deep reinforcement learning, due to its strong state representation ability and adaptive decision-making advantages, has gradually become the core technical route for solving dynamic energy consumption optimization problems.

4. Summary

After synthesizing a wide range of existing studies, it is evident that current research on AGV scheduling in workshop environments has gradually shifted from static scheduling based on fixed plans to dynamic scheduling that emphasizes real-time responsiveness and system adaptability. While many traditional approaches—such as scheduling rules, intelligent heuristics, and mathematical optimization—have achieved good performance in specific scenarios, they often struggle with scalability and adaptability in complex, multi-objective workshop environments. The recent introduction of energy-aware scheduling, especially in the context of green manufacturing, has added further complexity by requiring algorithms to jointly optimize for delivery timeliness, vehicle routing, and energy consumption. Although deep reinforcement learning (DRL) provides strong potential for capturing time-series dependencies and making autonomous decisions in high-dimensional state spaces, its performance is still affected by issues such as sparse reward signals, large action spaces, and training instability. Moreover, the current research on DRL-based scheduling often overlooks the interpretability and safety of decision-making under production disturbances. Therefore, future research needs to address how to effectively integrate energy consumption modeling, action feasibility masking, and semantic state encoding into DRL frameworks, so as to construct a robust scheduling model capable of simultaneously achieving timeliness, energy efficiency, and resilience under dynamic production scenarios.

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