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Research Article

Energy Aware Reinforcement Learning Approach for Dynamic Production Scheduling Optimization in Sustainable Smart Manufacturing Environments

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Abstract: Background: The development of modern manufacturing systems requires production scheduling strategies that not only improve productivity but also optimize energy utilization. Multi-machine production systems with job-shop configurations exhibit high complexity due to dynamic interactions between machines, job queues, and varying processing times, making conventional scheduling methods less effective in handling changing operational conditions. **Objective:** This study aims to develop and evaluate a reinforcement learning based production scheduling approach to improve production efficiency while reducing energy consumption in multi-machine manufacturing systems. **Methods:** This research employs a job-shop based multi-machine production simulation model as the experimental environment. The scheduling problem is formulated as a Markov Decision Process, enabling the implementation of reinforcement learning algorithms, namely Q-learning and Deep Q-Network, to learn optimal scheduling policies through interaction with the simulation environment. Energy consumption parameters are incorporated into the reward function so that the learning agent can consider energy efficiency in the scheduling decision-making process. System performance is evaluated using three main metrics, namely energy consumption, throughput, and makespan. **Results:** The experimental results show that the reinforcement learning based scheduling approach achieves better performance compared to conventional scheduling methods, resulting in lower energy consumption, higher job completion rates, and shorter production completion times within the multi-machine manufacturing system.

Keywords: Energy Efficiency; Production Scheduling; Reinforcement Learning; System Simulation; Throughput Optimization

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1. Introduction

The modern industrial sector is recognized as one of the largest consumers of energy worldwide. Industrial production activities require substantial amounts of energy to operate various processes, including heating, cooling, and electricity generation within manufacturing systems. High energy consumption is particularly evident in energy-intensive industries such as cement, steel, electrolytic aluminum, and processed copper, which significantly contribute to global annual energy usage [1], [2]. This condition highlights that energy efficiency has become a critical issue in industrial production management, as excessive energy consumption not only increases operational costs but also contributes to environmental challenges and carbon emissions.

In addition to high energy demand, industrial production systems face significant challenges in production scheduling. Production scheduling is a fundamental activity in manufacturing systems aimed at organizing job sequences and allocating resources to achieve optimal operational performance. However, traditional production scheduling approaches typically focus on classical performance indicators such as makespan, production cost, and product quality without adequately considering energy consumption as a key decision-making factor [3], [4]. As a result, production systems often fail to optimize energy utilization efficiently, leading to unnecessary energy waste and increased operational expenses.

The limitations of conventional scheduling methods are also evident in their inability to address dynamic energy consumption patterns in production machines. In practice, machine energy consumption can fluctuate depending on several factors, including operational conditions, workload levels, and processing time. Traditional scheduling models rarely incorporate these characteristics, which can result in uncontrolled spikes in energy consumption during production operations [5]. Furthermore, some studies emphasize the importance of incorporating energy consumption constraints into production scheduling to ensure stable and efficient industrial operations [6]. Therefore, integrating energy management considerations into production planning has become increasingly important for improving industrial sustainability.

Recent advances in digital technologies and artificial intelligence have created new opportunities to overcome the limitations of traditional production scheduling methods. One promising approach is the application of reinforcement learning (RL) in manufacturing systems. Reinforcement learning is a machine learning technique that enables systems to learn optimal decision-making strategies through continuous interaction with the environment and feedback mechanisms [7]. In manufacturing contexts, this approach allows production systems to dynamically adjust scheduling strategies based on real-time operational conditions.

Several studies have demonstrated that reinforcement learning possesses strong capabilities in solving complex optimization problems within production environments. RL-based models can be used to develop intelligent scheduling strategies that consider not only production efficiency but also energy consumption and environmental sustainability [8], [9]. In addition, the integration of reinforcement learning with Industrial Internet of Things (IIoT) technologies enables manufacturing systems to obtain real-time operational data from machines and production processes, allowing scheduling decisions to become more adaptive and responsive to dynamic changes in production environments [10].

In increasingly complex manufacturing environments, the integration of reinforcement learning with emerging technologies such as digital twin systems and energy monitoring platforms also provides significant potential for improving operational efficiency. By utilizing real-time data collected from production sensors, RL algorithms can optimize scheduling strategies while simultaneously considering multiple parameters such as energy consumption, machine utilization, and production performance [11]. Furthermore, reinforcement learning can also support broader energy management systems, including energy dispatch optimization in industrial microgrids to enhance overall energy efficiency [12], [13].

Beyond improving energy efficiency, the application of reinforcement learning in production scheduling can also optimize trade-offs between multiple operational objectives. In modern manufacturing systems, conflicts often arise between minimizing energy consumption, reducing makespan, and maximizing productivity. Through adaptive learning mechanisms, reinforcement learning can develop scheduling policies capable of balancing these competing objectives effectively [14]. Consequently, production systems can achieve improved operational performance without sacrificing energy efficiency.

Based on these challenges, this study aims to develop a reinforcement learning-based approach that incorporates energy efficiency considerations into production scheduling optimization for modern manufacturing systems. The proposed approach is expected to produce more adaptive, efficient, and sustainable scheduling strategies by leveraging real-time production data and learning algorithms capable of dynamically adjusting decision-making processes. Ultimately, this research is expected to contribute to the development of intelligent manufacturing systems that enhance operational performance while supporting energy efficiency and sustainable industrial practices.

2. Literature Review

Production Scheduling Theory in Manufacturing Systems

Production scheduling is widely recognized as one of the most critical problems in manufacturing systems because it directly influences operational efficiency, productivity, and resource utilization. Effective scheduling determines the order in which jobs are processed on machines while considering various constraints such as processing time, machine availability, and delivery deadlines. As manufacturing systems become more complex, scheduling decisions play an increasingly important role in improving manufacturing performance and maintaining competitiveness in industrial environments [15]. Therefore, developing efficient scheduling strategies is essential for optimizing manufacturing operations.

Various approaches have been proposed to solve production scheduling problems. One of the widely used methods is the multi-population meta-heuristic approach, which includes algorithms such as Artificial Bee Colony (ABC), Imperialist Competitive Algorithm (ICA), and Shuffled Frog-Leaping Algorithm (SFLA). These algorithms are designed to efficiently explore large search spaces and identify optimal or near-optimal scheduling solutions in complex manufacturing environments [15]. Meta-heuristic methods are particularly useful for solving large-scale scheduling problems where exact optimization techniques may become computationally expensive.

In addition to meta-heuristic approaches, heuristic algorithms are also commonly used in practical manufacturing environments due to their simplicity and effectiveness. One example is the Nawaz Enscore Ham (NEH) heuristic algorithm, which has been widely applied to determine optimal job sequences in production systems. This method is particularly effective in minimizing makespan and reducing tardiness in production operations, especially in small and medium-sized manufacturing enterprises [16]. Heuristic-based scheduling techniques are often preferred in real-world applications because they provide fast solutions while maintaining acceptable levels of performance.

Another important development in production scheduling is the adoption of Model-Based Systems Engineering (MBSE) approaches. MBSE provides structured modeling frameworks that allow engineers to analyze, design, and manage complex manufacturing systems more effectively. For instance, the integration of satisfiability modulo theory with system modeling techniques has been proposed to support production scheduling processes by improving system understanding and communication among engineers [17]. Through formal modeling and system-level analysis, MBSE enables better coordination among various production components and supports more accurate scheduling decisions.

Despite significant progress in scheduling methodologies, several challenges remain in practical manufacturing environments. One major challenge is the presence of uncertainty and dynamic changes in production processes, which can reduce the effectiveness of traditional scheduling models. Factors such as machine breakdowns, unexpected order changes, and fluctuations in production demand can significantly affect scheduling performance. To address these challenges, computer simulation models are often used to evaluate different scheduling strategies under various operational scenarios, allowing researchers to analyze performance metrics such as average flow time, machine utilization, and total operational time [15].

Reinforcement Learning in Industrial System Optimization

With the rapid development of artificial intelligence technologies, reinforcement learning (RL) has emerged as a promising approach for optimizing complex industrial systems. Reinforcement learning is a machine learning paradigm in which an agent learns optimal decision-making strategies by interacting with its environment and receiving feedback in the form of rewards or penalties. This learning mechanism enables automated optimization in intelligent engineering systems, allowing industrial processes to become more efficient, adaptive, and scalable [18].

In industrial applications, reinforcement learning has been applied to various optimization problems, including production scheduling, process control, and energy management. One important application area is industrial process control, where RL techniques can be used to optimize control parameters such as proportional integral derivative (PID) tuning and model predictive control. By continuously learning from operational data, RL-based controllers can improve system performance and stability while reducing manual intervention [19].

Recent advances in machine learning have also led to the development of Deep Reinforcement Learning (DRL), which combines reinforcement learning with deep neural networks. This approach enhances the ability of RL systems to process high-dimensional data and perform complex decision-making tasks in industrial environments. Deep reinforcement learning enables intelligent manufacturing systems to analyze large amounts of operational data and generate optimized decision policies for complex industrial processes [20]. As a result, DRL has become an important tool for designing next-generation intelligent manufacturing systems.

Several advanced reinforcement learning algorithms have been proposed to improve learning performance and stability in industrial environments. Popular methods include Actor–Critic algorithms, Deep Q-Networks (DQN), and Proximal Policy Optimization (PPO), which provide efficient learning frameworks for solving complex optimization problems. These algorithms enable systems to learn optimal policies more effectively while maintaining stable training processes, making them suitable for real-world industrial applications [21].

However, reinforcement learning also faces several challenges when applied in industrial environments. One of the main issues is the sparse reward problem, where the learning agent receives limited feedback from the environment, making it difficult to learn optimal strategies. To address this challenge, researchers have proposed techniques such as reward shaping and hybrid exploration methods, which improve the learning process by providing more informative feedback signals and encouraging effective exploration strategies [22].

Another important benefit of reinforcement learning is its ability to support energy-efficient industrial operations. Reinforcement learning frameworks can be designed to optimize energy usage in production plants by allowing systems to autonomously learn optimal operational states. Through continuous interaction with the production environment, RL-based systems can reduce unnecessary energy consumption while maintaining production performance [23].

Integration of Reinforcement Learning with Industrial Technologies

The integration of reinforcement learning with emerging industrial technologies has further enhanced its potential for optimizing manufacturing systems. One notable development is the combination of reinforcement learning with the Industrial Internet of Things (IIoT). IIoT technologies enable industrial systems to collect real-time data from sensors, machines, and production equipment, which can then be used by RL algorithms to improve decision-making processes [10].

By integrating reinforcement learning with IIoT infrastructures, manufacturing systems can develop cognitive adaptive capabilities that allow them to dynamically respond to changes in production conditions. This integration facilitates real-time monitoring, predictive maintenance, and adaptive scheduling, ultimately improving the overall efficiency and reliability of industrial operations [10]. Furthermore, the integration of digital technologies such as artificial intelligence, blockchain, and smart data systems can enhance the sustainability and digital transformation of industrial ecosystems (Danang et al., 2025).

Recent research also highlights the potential of integrating intelligent systems with emerging technologies such as distributed computing and edge-based industrial networks. These technologies enable real-time data processing and decision-making in large-scale industrial environments, supporting the development of secure and efficient industrial systems (Siswanto et al., 2025). Additionally, Internet of Things technologies have been widely adopted to monitor a nd control environmental conditions in industrial and urban infrastructures, demonstrating the potential of IoT-based systems in improving operational efficiency and environmental monitoring [26].

Overall, the combination of production scheduling theories, reinforcement learning algorithms, and emerging industrial technologies provides a powerful framework for optimizing manufacturing systems. These integrated approaches enable industrial systems to achieve higher efficiency, adaptability, and sustainability in increasingly complex production environments.

Energy-Aware Manufacturing

Energy-aware manufacturing has become an essential concept in modern industrial systems as manufacturers face increasing pressure to reduce energy consumption while maintaining production efficiency. One of the main approaches used to achieve this objective is the integration of process planning and production scheduling. Traditionally, these two processes are conducted separately, which often leads to inefficiencies in energy use and machine utilization. Integrating process planning with scheduling allows manufacturers to consider energy consumption during the early stages of production design. Through this integration, manufacturing systems can select appropriate machine sequences, processing parameters, and scheduling strategies that minimize energy use while maintaining productivity levels. Such an approach contributes to the development of more sustainable manufacturing operations and improves resource utilization across the production lifecycle [27].

Energy-efficient scheduling is another important strategy in energy-aware manufacturing systems. Production scheduling that incorporates energy consumption considerations enables organizations to optimize operational costs while supporting sustainable manufacturing practices. For example, production tasks can be scheduled during periods when electricity prices are lower or when renewable energy sources are more available. This approach not only reduces energy expenses but also contributes to stabilizing energy demand in the power grid. In addition, integrating labor factors with energy consumption during scheduling decisions can further enhance the sustainability performance of manufacturing systems. Studies have demonstrated that considering both human and energy resources simultaneously allows organizations to achieve better operational efficiency and environmental performance [28].

The integration of energy awareness into production planning systems has also been enhanced by the development of advanced digital technologies and monitoring tools. Modern manufacturing systems increasingly rely on intelligent production planning platforms that are capable of tracking energy usage in real time. These systems enable decision-makers to adjust production schedules dynamically based on energy availability, machine efficiency, and operational constraints. Transparent integration of energy-related data into production planning processes improves the ability of manufacturers to identify inefficient operations and implement corrective actions. Consequently, organizations can maintain optimal production performance while minimizing energy waste and environmental impact [29].

Mathematical optimization models have also been widely applied to evaluate and reduce energy consumption in manufacturing systems. These models analyze production configurations, machine operations, and system constraints to identify optimal operational strategies that minimize energy consumption while maintaining production throughput. In reconfigurable manufacturing systems, optimization models are particularly useful because production configurations can change depending on demand and operational requirements. By applying mathematical optimization techniques, manufacturers can determine the most energy-efficient machine setups and operational sequences. This approach enables production systems to achieve a balance between operational flexibility, production efficiency, and energy sustainability [30].

In addition to technological improvements, sustainable manufacturing requires the integration of environmental considerations into managerial decision-making processes. Sustainable manufacturing systems aim to reduce environmental impacts while maintaining economic performance and social responsibility. This involves adopting environmentally friendly production practices, improving resource efficiency, and reducing energy waste across the manufacturing lifecycle. Incorporating sustainability principles into production planning and operational strategies helps organizations contribute to long-term sustainable development while maintaining competitive advantages in the global market. Such strategies emphasize the importance of balancing economic growth with environmental protection in modern manufacturing industries [31].

Smart Factory and Industry 4.0 Manufacturing Environments

The concept of the smart factory represents a significant transformation in manufacturing systems and is closely associated with the technological advancements of Industry 4.0. Smart factories utilize interconnected digital technologies to create intelligent, adaptive, and autonomous production environments. In these environments, machines, sensors, and production systems communicate with each other through digital networks, enabling real-time monitoring and decision-making. Key technologies that support smart factory development include the Internet of Things (IoT), cyber-physical systems (CPS), artificial intelligence, and big data analytics. These technologies enable manufacturers to collect and analyze large volumes of production data, which can be used to improve efficiency, predict equipment failures, and optimize manufacturing processes [32].

Cyber-physical systems and IoT technologies play a critical role in enabling seamless communication between physical manufacturing equipment and digital control systems. In smart factory environments, CPS integrates computational systems with physical processes, allowing machines to monitor their operational conditions and respond automatically to changing production requirements. IoT devices, such as sensors and connected equipment, continuously collect data from the production floor and transmit it to centralized control systems for analysis. This integration enables real-time production monitoring, predictive maintenance, and dynamic optimization of manufacturing processes. As a result, manufacturers can achieve higher levels of automation, flexibility, and operational efficiency in modern production systems [33].

Another important component of smart factory systems is the use of semantic models and ontologies for representing industrial IoT components. Ontology-based models provide structured frameworks that describe the relationships between different devices, processes, and systems within the manufacturing environment. These models facilitate interoperability between heterogeneous systems, allowing various components to communicate effectively despite differences in technologies or communication protocols. By enabling standardized data representation and semantic understanding, ontology-based approaches improve the coordination and integration of smart factory components. Consequently, they support more efficient information exchange and enhance the overall intelligence of manufacturing systems [34].

Multi-agent systems have also emerged as an effective solution for managing complex interactions in smart manufacturing environments. These systems consist of multiple autonomous agents that collaborate to achieve shared production objectives. Each agent represents a specific entity within the manufacturing system, such as a machine, production line, or energy provider. Through distributed decision-making processes, multi-agent systems can coordinate production scheduling, resource allocation, and energy management activities. Such systems are particularly useful in Industry 4.0 environments where uncertainties such as machine breakdowns, fluctuating energy availability, and changing production demands must be managed efficiently. By enabling decentralized and adaptive decision-making, multi-agent architectures improve the responsiveness and resilience of smart manufacturing systems [35], [36].

Despite the numerous advantages of smart factory technologies, their implementation also introduces new security challenges and risks. Smart factories rely heavily on interconnected digital systems and extensive data exchange, which increases their vulnerability to cyber threats and unauthorized access. Potential security risks include data breaches, system manipulation, and disruption of production processes. Therefore, it is essential for manufacturers to implement comprehensive cybersecurity strategies and risk management frameworks to protect critical manufacturing infrastructure. Addressing these security challenges is crucial to ensuring the safe, reliable, and sustainable operation of smart manufacturing systems in Industry 4.0 environments [37].

Industry 4.0 and Digital Transformation in Manufacturing

Industry 4.0 represents a major transformation in the manufacturing sector, characterized by the integration of digital technologies into traditional production systems. This transformation enables the development of intelligent manufacturing environments where machines, information systems, and human operators collaborate through advanced digital platforms. Industry 4.0 technologies enable real-time monitoring, autonomous decision-making, and adaptive production processes. As a result, manufacturing systems become more efficient, flexible, and responsive to market demands. The adoption of digital technologies also allows organizations to improve product quality, reduce production costs, and enhance overall operational performance [38].

One of the key enabling technologies supporting the implementation of Industry 4.0 is Product Lifecycle Management (PLM). PLM systems provide an integrated framework for managing product-related information throughout the entire product lifecycle, including design, development, manufacturing, maintenance, and disposal. By centralizing product data and facilitating information sharing between different departments, PLM systems enhance collaboration and decision-making across the organization. In the context of Industry 4.0, PLM plays a critical role in integrating digital technologies with manufacturing processes, enabling organizations to manage complex production systems more effectively [39].

Modern industrial systems are increasingly designed to support intelligent manufacturing environments through the integration of automation technologies, data analytics, and advanced control systems. These systems are capable of coordinating production activities across multiple operational levels, from individual machines to enterprise-level decision-making platforms. By integrating digital technologies with industrial control systems, manufacturers can improve operational efficiency and resource utilization. Such integrated industrial systems also enable organizations to respond more effectively to changes in production demand and operational conditions [40].

Despite its numerous advantages, the transition toward Industry 4.0 presents several implementation challenges for manufacturing organizations. Implementing advanced digital technologies requires substantial investments in infrastructure, software platforms, and workforce training. Organizations must also develop clear strategic roadmaps to guide the transformation process and ensure that technological innovations align with business objectives. Furthermore, employees need to acquire new digital skills to effectively operate and manage smart manufacturing systems. Addressing these challenges is essential for organizations seeking to successfully adopt Industry 4.0 technologies and fully realize the benefits of digital transformation in manufacturing [38].

3. Research Methods

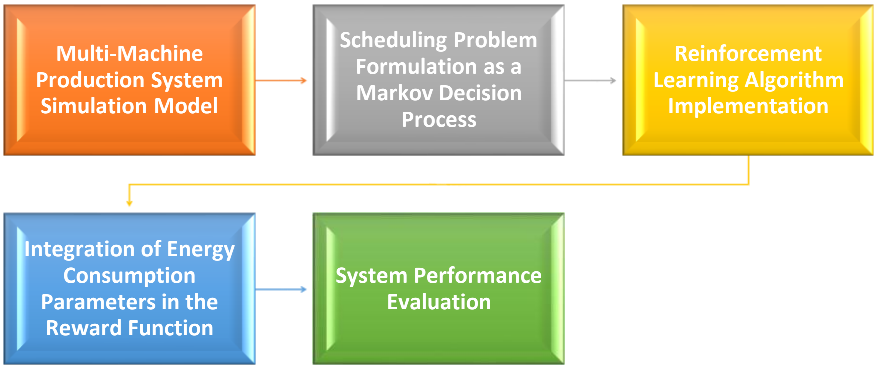

Figure 1. Methodology Framework

Multi-Machine Production System Simulation Model

This study employs a simulation model to represent a multi-machine production environment that reflects the operational characteristics of modern manufacturing systems. The production system is simulated using a job-shop configuration consisting of multiple machines with different processing functions, where each job must pass through several sequential processing stages. The simulation model is designed to capture the dynamic interactions between machines, job queues, and various operational constraints such as processing time, machine availability, and idle conditions. In addition, the simulation considers potential operational disturbances and system condition changes that may affect production performance. This simulated environment serves as an experimental platform to test artificial intelligence based scheduling strategies and to observe key production performance indicators such as throughput, job completion time, and machine utilization.

Scheduling Problem Formulation as a Markov Decision Process

The production scheduling problem in this study is formulated as a Markov Decision Process (MDP) to enable the application of reinforcement learning techniques. In the MDP framework, the production system is viewed as a dynamic environment consisting of several key components including states, actions, transition probabilities, and rewards. The state represents the current condition of the production system such as machine status, job queues, remaining processing times, and energy consumption levels. The action represents the scheduling decision taken by the agent, such as selecting which job should be processed next on a specific machine. Each action taken results in a change in the system condition represented through transition probabilities. Through this formulation, the scheduling process is treated as a sequence of decision-making steps aimed at identifying an optimal policy that maximizes cumulative rewards over time.

Reinforcement Learning Algorithm Implementation

To solve the scheduling problem formulated within the MDP framework, this study implements reinforcement learning algorithms that enable an intelligent agent to learn optimal scheduling policies through interaction with the simulation environment. The algorithms applied include Q-learning and Deep Q-Network (DQN), where Q-learning is used to estimate the optimal action-value function for each state action pair through iterative Q-value updates based on the received reward. Meanwhile, DQN utilizes artificial neural networks to approximate the Q-value function, allowing the algorithm to handle larger and more complex state spaces commonly found in multi-machine production systems. Through exploration and exploitation processes over multiple training episodes, the reinforcement learning agent gradually learns effective scheduling strategies that improve the overall performance of the production system.

Integration of Energy Consumption Parameters in the Reward Function

To incorporate sustainability considerations into the scheduling decision process, energy consumption parameters are integrated into the reward function of the reinforcement learning model. The reward function is designed to provide positive rewards when the agent selects actions that lead to efficient energy usage and improved machine utilization, while penalties or negative rewards are assigned when the selected decisions result in excessive energy consumption, high idle time, or inefficient machine operations. The energy parameters considered include machine operating energy, idle energy consumption, and overall resource utilization efficiency. By embedding these parameters within the reward function, the reinforcement learning agent is encouraged to discover scheduling strategies that not only enhance productivity but also minimize energy consumption within the production system.

System Performance Evaluation

The performance evaluation of the proposed scheduling method is conducted using several key performance metrics that reflect both production efficiency and energy efficiency. The first metric is energy consumption, which measures the total energy used by all machines during the production process, including both operational energy and idle energy usage. The second metric is throughput, defined as the total number of jobs successfully completed within a given time period, which serves as an indicator of production productivity. The third metric is makespan, which represents the total time required to complete all jobs within the production system. By analyzing these three metrics simultaneously, the study evaluates the effectiveness of the reinforcement learning based scheduling approach compared to conventional scheduling methods in improving production efficiency while reducing energy consumption.

4. Results and Discussion

Results

The experimental results presented in this study were obtained from a simulation environment designed to represent a multi-machine job-shop production system. The simulation model replicates the operational characteristics of modern manufacturing environments where multiple machines process different jobs across several sequential production stages. Within this environment, machines operate under dynamic conditions that include varying job queues, machine availability, and idle states. The simulation framework allows the reinforcement learning agent to interact continuously with the production environment during multiple training episodes in order to learn optimal scheduling policies.

In this study, the scheduling decision process is optimized using reinforcement learning algorithms, specifically Q-learning and Deep Q-Network (DQN). Q-learning is used to estimate the optimal action–value function through iterative updates based on observed rewards, while DQN utilizes a neural network to approximate Q-values in larger and more complex state spaces. Through repeated interactions with the simulation environment, the reinforcement learning agent gradually learns effective scheduling strategies that improve production performance while reducing unnecessary energy consumption. The performance of the proposed RL-based scheduling method is compared with several conventional scheduling strategies commonly used in manufacturing systems, including First Come First Serve (FCFS), Shortest Processing Time (SPT), and heuristic scheduling.

The evaluation focuses on three key performance metrics that reflect both production efficiency and energy efficiency: total energy consumption, throughput, and makespan. Energy consumption measures the total amount of energy used by all machines during production, including both operational and idle energy usage. Throughput represents the number of jobs successfully completed during the simulation period, while makespan indicates the total time required to complete all jobs in the production system. These metrics collectively provide a comprehensive evaluation of scheduling performance within the simulated manufacturing environment.

Table 1. Comparative Performance of Scheduling Methods.

Scheduling Method	Energy Consumption (kWh)	Throughput (Jobs Completed)	Makespan (Hours)
FCFS	1520	178	96
SPT	1435	186	89
Heuristic Scheduling	1382	191	86
RL-Based Scheduling (Q-learning/DQN)	**1246**	**205**	**78**

The results presented in Table 1 demonstrate significant differences in performance among the evaluated scheduling methods. The FCFS scheduling strategy produces the highest energy consumption at 1520 kWh and also results in the lowest throughput. This occurs because FCFS schedules jobs solely based on arrival order without considering machine workload or processing efficiency, which can lead to increased waiting times and inefficient machine utilization. The SPT scheduling strategy performs better by prioritizing jobs with shorter processing times, which reduces queue waiting time and slightly improves production efficiency.

The heuristic scheduling method further improves system performance by applying optimized job sequencing strategies that aim to reduce delays and improve machine utilization. As shown in the table, the heuristic method reduces energy consumption to 1382 kWh and increases throughput to 191 completed jobs. Despite these improvements, the reinforcement learning based scheduling method clearly outperforms all conventional strategies. The RL approach achieves the lowest energy consumption at 1246 kWh, representing approximately an 18% reduction compared with FCFS scheduling. In addition, the RL-based method achieves the highest throughput with 205 completed jobs and the shortest makespan of 78 hours. These results indicate that the reinforcement learning agent successfully learns scheduling policies that balance productivity and energy efficiency within the simulated manufacturing system.

To provide a clearer visualization of energy efficiency improvements, the following graph illustrates the total energy consumption produced by each scheduling strategy during the simulation process.

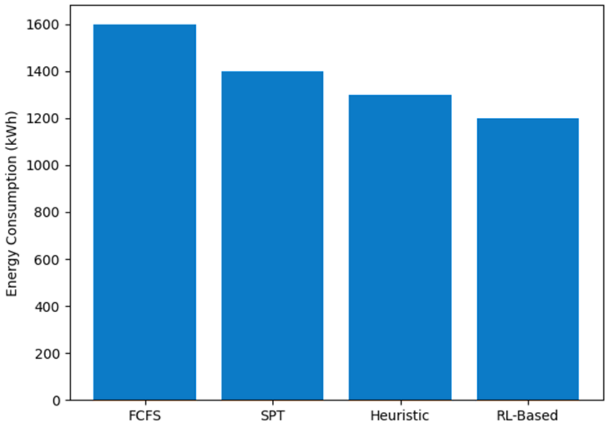

Figure 2. Energy Consumption Comparison Between Scheduling Methods.

The energy consumption graph clearly shows that the reinforcement learning–based scheduling strategy produces the lowest energy usage among all evaluated methods. Traditional scheduling strategies often result in higher energy consumption because they do not explicitly consider machine energy states when making scheduling decisions. Machines may remain idle while still consuming standby energy, or jobs may be processed in sequences that cause inefficient machine operation. In contrast, the RL-based scheduling model incorporates energy consumption into the reward function, allowing the learning agent to identify scheduling patterns that minimize idle energy and improve machine utilization. As the agent continues to interact with the environment during training episodes, it gradually learns policies that reduce unnecessary machine operation and improve overall energy efficiency.

The throughput performance of each scheduling strategy is illustrated in the following graph to demonstrate differences in production productivity.

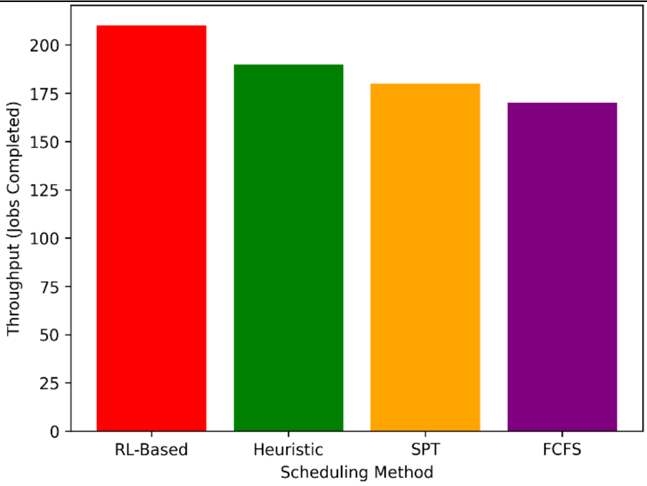

Figure 3. Throughput Comparison Across Scheduling Methods.

The throughput comparison shows that the reinforcement learning scheduling model achieves the highest production output among all evaluated methods. This improvement occurs because the RL agent continuously learns to select job sequences that reduce waiting time in machine queues and improve the coordination between machines in the production system. By adapting scheduling decisions according to the current system state, the RL agent can maintain a more stable production flow and avoid bottlenecks that typically occur in rule-based scheduling methods. As a result, the production system is able to process a larger number of jobs within the same operational timeframe.

Another important indicator of production performance is makespan, which represents the total time required to complete all scheduled jobs. The following graph presents the makespan results for each scheduling method evaluated in the simulation environment.

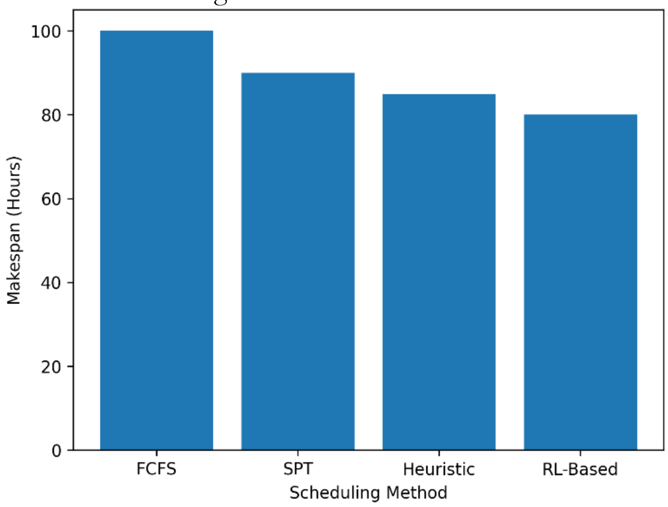

Figure 4. Makespan Comparison Between Scheduling Methods.

The makespan graph shows that the reinforcement learning–based scheduling approach produces the shortest completion time for all production tasks. This result indicates that the RL agent is able to coordinate job assignments across multiple machines more efficiently than conventional scheduling strategies. By dynamically selecting scheduling actions based on the current system state, the RL model can reduce production bottlenecks and minimize idle periods within the manufacturing process. Consequently, the entire production workflow becomes more efficient, allowing all jobs to be completed in a shorter overall production time.

Overall, the experimental results demonstrate that the proposed reinforcement learning–based scheduling approach successfully improves both production efficiency and energy efficiency in a simulated multi-machine manufacturing environment. By integrating energy consumption parameters into the reward function and enabling the scheduling agent to learn optimal decision policies through interaction with the simulation environment, the RL model achieves better performance than traditional scheduling strategies. These findings highlight the potential of reinforcement learning techniques for developing intelligent and energy-aware scheduling systems in modern manufacturing environments.

Discussion

The results obtained from the simulation experiments demonstrate that the reinforcement learning–based scheduling approach significantly improves both production efficiency and energy utilization in the multi-machine manufacturing system. As presented in Table 1, the RL-based scheduling strategy consistently outperforms conventional scheduling methods across all evaluated performance metrics, including energy consumption, throughput, and makespan. These improvements highlight the effectiveness of applying reinforcement learning techniques to complex production scheduling problems where multiple operational constraints must be considered simultaneously.

One of the most important findings of this study is the reduction in total energy consumption achieved by the reinforcement learning model. As illustrated in Figure 2, the RL-based scheduling strategy produces the lowest energy usage compared with FCFS, SPT, and heuristic scheduling methods. This improvement can be explained by the design of the reward function used in the reinforcement learning framework. In this study, energy consumption parameters including machine operating energy and idle energy usage are integrated directly into the reward structure. As a result, the reinforcement learning agent learns to avoid scheduling patterns that lead to excessive idle machine states or inefficient machine operations. Through repeated interactions with the simulation environment, the agent gradually develops scheduling policies that prioritize efficient machine utilization while minimizing unnecessary energy consumption.

The throughput improvement observed in Figure 3 further confirms the effectiveness of reinforcement learning for optimizing production scheduling decisions. The RL-based model achieves the highest number of completed jobs during the simulation period, indicating a more efficient production workflow compared with conventional scheduling approaches. This performance improvement can be attributed to the ability of reinforcement learning algorithms, particularly Q-learning and Deep Q-Network (DQN), to continuously adapt scheduling decisions based on the current state of the production system. Unlike rule-based scheduling methods that rely on fixed decision rules, the RL agent evaluates system conditions such as job queues, machine availability, and processing requirements before selecting scheduling actions. This adaptive decision-making process enables the production system to maintain a smoother job flow and reduce delays caused by machine bottlenecks.

The analysis of makespan results presented in Figure 4 also demonstrates the operational advantages of the reinforcement learning scheduling model. The RL-based approach achieves the shortest makespan among all evaluated scheduling strategies, which indicates faster completion of production tasks within the manufacturing system. Shorter makespan values reflect improved coordination among machines and more efficient job allocation across the production network. Because the RL agent continuously evaluates system states and selects scheduling actions that maximize cumulative rewards, it is able to minimize machine idle times and prevent unnecessary waiting periods in job queues. This dynamic scheduling capability allows the production system to complete tasks more quickly while maintaining stable operational performance.

Another important aspect revealed by the results is the ability of reinforcement learning to balance multiple operational objectives simultaneously. In traditional manufacturing scheduling problems, improving one performance metric often leads to deterioration in another metric. For example, strategies designed to maximize throughput may increase machine operating time and lead to higher energy consumption. However, the reinforcement learning framework used in this study incorporates both productivity and energy considerations into the reward function. This allows the scheduling agent to learn policies that optimize production output while simultaneously reducing energy usage. The results therefore demonstrate that reinforcement learning provides a practical solution for addressing multi-objective optimization challenges in modern manufacturing systems.

The findings of this study also highlight the importance of integrating artificial intelligence techniques with simulation-based manufacturing environments. The use of a multi-machine job-shop simulation model enables the reinforcement learning agent to explore a wide range of scheduling scenarios under dynamic production conditions. By interacting with the simulation environment during multiple training episodes, the RL agent can learn from system feedback and gradually improve its decision-making strategy. This approach is particularly valuable for manufacturing systems where real-world experimentation may be costly or difficult to implement. Simulation-based training therefore provides a safe and flexible platform for developing intelligent scheduling solutions.

From an industrial perspective, the results of this study suggest that reinforcement learning has significant potential for supporting the development of energy-efficient smart manufacturing systems. As manufacturing environments become increasingly complex due to Industry 4.0 technologies and interconnected production systems, traditional scheduling approaches may no longer be sufficient to manage dynamic production conditions. Reinforcement learning offers an adaptive and data-driven solution capable of responding to real-time changes in machine states, job demands, and energy constraints. By integrating energy awareness into scheduling decisions, manufacturers can reduce operational costs while simultaneously improving production performance and supporting sustainable manufacturing practices.

Overall, the discussion of experimental results confirms that the proposed reinforcement learning based scheduling approach provides substantial benefits for multi-machine production systems. The integration of Q-learning and DQN algorithms with energy-aware reward mechanisms enables the scheduling agent to learn efficient policies that improve productivity while minimizing energy consumption. These findings demonstrate the potential of reinforcement learning as a powerful optimization tool for intelligent and sustainable manufacturing environments.

5. Comparison

The comparison of scheduling strategies presented in this study highlights the advantages of the reinforcement learning based approach over conventional production scheduling methods. Traditional scheduling strategies such as First Come First Serve (FCFS) and Shortest Processing Time (SPT) rely on predefined decision rules that do not adapt dynamically to changing production conditions. As observed in the experimental results, these methods often lead to inefficient machine utilization and higher energy consumption due to their inability to consider system-wide operational states. Although heuristic scheduling improves production performance by applying optimized job sequencing strategies, its decision rules remain static and cannot continuously adapt to the dynamic interactions between machines, job queues, and energy consumption patterns within the manufacturing system.

In contrast, the reinforcement learning based scheduling approach demonstrates superior performance across all evaluated metrics, including energy consumption, throughput, and makespan. By modeling the scheduling problem as a Markov Decision Process and implementing Q-learning and Deep Q-Network (DQN) algorithms, the proposed system is able to learn optimal scheduling policies through repeated interactions with the simulation environment. This learning capability enables the scheduling agent to dynamically evaluate system states and select actions that improve machine utilization while minimizing energy waste. As a result, the RL-based approach produces lower energy consumption, higher job completion rates, and shorter production completion times compared with conventional scheduling strategies. These findings indicate that reinforcement learning provides a more flexible and intelligent solution for complex production scheduling problems in modern manufacturing environments.

6. Conclusion

This study proposes a reinforcement learning based scheduling framework designed to improve production efficiency and energy utilization in multi-machine manufacturing systems. The scheduling problem is formulated as a Markov Decision Process, allowing reinforcement learning algorithms such as Q-learning and Deep Q-Network (DQN) to learn optimal scheduling policies through continuous interaction with a simulation-based production environment. The reward function incorporates energy consumption parameters, including machine operating energy and idle energy usage, enabling the learning agent to balance productivity and energy efficiency simultaneously. Experimental results obtained from the multi-machine job-shop simulation demonstrate that the proposed RL-based scheduling approach significantly reduces energy consumption while improving throughput and minimizing makespan compared with conventional scheduling methods.

The findings of this study highlight the potential of reinforcement learning as an effective optimization tool for intelligent manufacturing systems. By integrating energy-aware decision mechanisms into the scheduling process, manufacturing operations can achieve higher levels of efficiency and sustainability. The proposed approach demonstrates that adaptive learning algorithms are capable of managing complex production environments characterized by dynamic machine states and varying job demands. Future research may extend this work by integrating real-time industrial data, expanding the scheduling framework to larger production networks, and incorporating additional operational constraints such as machine maintenance scheduling and energy pricing variations. These developments could further enhance the applicability of reinforcement learning in next-generation smart manufacturing systems.

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