A Review on Optimization Techniques for Minimizing Makespan and Idle Time in Small-Scale Manufacturing Systems

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Abstract — Production planning and scheduling are critical functions in manufacturing industries for improving productivity, reducing operational cost, and enhancing resource utilization. In small-scale manufacturing systems, improper scheduling often leads to increased makespan, higher machine idle time, production delays, and reduced operational efficiency. This review paper presents a comprehensive study of optimization techniques used for minimizing makespan and idle time in production scheduling systems. The study reviews traditional scheduling methods along with advanced heuristic, metaheuristic, and machine learning-based optimization approaches such as Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, Simulated Annealing, Artificial Neural Networks, and Reinforcement Learning. Comparative analysis of various techniques is carried out based on scheduling efficiency, computational complexity, and industrial applicability. The paper also discusses recent advancements in Industry 4.0, AI-driven scheduling, IoT-enabled manufacturing systems, and hybrid optimization frameworks. Research gaps related to real-time scheduling, SME-focused applications, and intelligent adaptive systems are identified. The review concludes that hybrid machine learning and heuristic optimization approaches offer significant potential for improving manufacturing productivity, reducing idle time, and enabling smart production scheduling systems for future industrial applications.

Keywords: Production Planning and Scheduling; Makespan Optimization; Machine Idle Time Reduction; Metaheuristic Optimization Techniques; Industry 4.0 Manufacturing; Intelligent Production Scheduling;

I. INTRODUCTION

A. Background of Production Planning and Scheduling

Production planning and scheduling play a significant role in improving the operational efficiency and productivity of manufacturing industries. In modern manufacturing environments, industries continuously aim to increase production output while reducing manufacturing time, operational cost, and resource wastage. Production planning involves the systematic allocation of resources, machines, labor, and materials to achieve efficient manufacturing operations, whereas scheduling determines the sequence and timing of jobs processed on available machines [1], [5]. Effective production planning helps industries maintain smooth workflow, proper inventory management, and timely delivery of products to customers.

Scheduling is considered one of the most critical functions in manufacturing systems because it directly affects machine utilization, production lead time, and delivery performance. In manufacturing industries, especially job shop and flow shop systems, proper scheduling ensures that jobs are processed in an optimized sequence to reduce delays and machine idle periods [6], [11]. Traditional scheduling approaches such as First In First Out (FIFO), Shortest Processing Time (SPT), and Earliest Due Date (EDD) have been widely used for production management; however, these methods often fail to provide optimal solutions in complex and dynamic manufacturing environments [2], [3].

In recent years, the rapid growth of industrial automation and intelligent manufacturing has increased the need for advanced optimization methods for production scheduling. Small-scale manufacturing industries particularly face challenges related to limited resources, fluctuating demand, and inefficient scheduling practices. Therefore, optimization of production planning and scheduling has become essential for improving production efficiency, reducing operational losses, and enhancing industrial competitiveness [7], [21]. Researchers have increasingly focused on heuristic, metaheuristic, and machine learning-based scheduling techniques to address these industrial challenges effectively [17], [19].

B. Importance of Makespan and Idle Time Reduction

Makespan is one of the most important performance indicators in production scheduling. It is defined as the total time required to complete all scheduled jobs from the beginning of the first operation to the completion of the final operation [5], [6]. Minimizing makespan is essential because it directly improves production throughput, reduces manufacturing delays, and increases machine utilization efficiency. In competitive manufacturing environments, shorter makespan enables industries to satisfy customer demands within specified deadlines and improve market responsiveness [12], [23].

Machine idle time refers to the duration during which manufacturing resources or machines remain unutilized due to improper scheduling, delays, or waiting conditions between operations. Excessive idle time negatively affects manufacturing efficiency and increases operational costs. Reduction of machine idle time helps industries achieve better equipment utilization, smoother workflow, and increased productivity [16], [22].

The industrial impact of minimizing makespan and idle time can be summarized as follows:

1) Industrial Benefits of Makespan and Idle Time Reduction

- Improved Productivity:

Efficient scheduling increases the number of completed jobs within a given time period, thereby improving overall production output [13].

- Reduced Operational Cost:

Proper machine utilization minimizes unnecessary energy consumption, labor waiting time, and maintenance-related expenses [24].

– Enhanced Delivery Performance:
Optimized schedules reduce production delays and improve on-time delivery performance, which increases customer satisfaction [15].
– Better Resource Utilization:
Reduction in idle time ensures effective utilization of machines, tools, and manpower resources [27].

Modern optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Reinforcement Learning have shown significant capability in reducing makespan and idle time in manufacturing systems [7], [21], [29].

C. Challenges in Small-Scale Manufacturing Systems

Small-scale manufacturing industries contribute significantly to industrial development and employment generation. However, these industries face numerous operational and technological challenges in implementing efficient production planning and scheduling systems. One of the primary challenges is the limitation of resources, including insufficient machinery, limited workforce, and financial constraints. Due to these limitations, small industries often experience production bottlenecks and scheduling inefficiencies [25].

Another major challenge is the occurrence of unplanned delays caused by machine breakdowns, material shortages, and sudden changes in customer demand. Such uncertainties disturb production flow and increase overall production completion time [24]. Small-scale industries frequently rely on manual scheduling practices, where production decisions are based on human experience rather than scientific optimization approaches. Manual scheduling methods often lead to poor job sequencing, higher waiting time, and increased machine idle periods [4].

Dynamic production environments also create complexity in scheduling operations. In modern manufacturing systems, job priorities, machine availability, and processing requirements continuously change, making it difficult to maintain optimal production schedules using traditional methods [18]. As product customization and market competition increase, small industries require flexible and adaptive scheduling systems capable of responding to real-time industrial conditions [20].

D. Need for Optimization Techniques

The increasing complexity of manufacturing systems has created a strong need for advanced optimization techniques in production planning and scheduling. Traditional scheduling methods are often unable to handle multi-objective industrial problems involving makespan minimization, idle time reduction, due date constraints, and machine allocation simultaneously [5]. Therefore, intelligent optimization techniques are increasingly adopted to improve production efficiency and decision-making capabilities.

Optimization techniques such as Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, and Simulated Annealing provide near-optimal solutions for complex scheduling problems within reasonable computational time [14], [16], [27]. These techniques are capable of handling nonlinear constraints, dynamic production conditions, and multi-objective optimization problems effectively.

Recently, the integration of Artificial Intelligence and Machine Learning in manufacturing systems has transformed traditional scheduling approaches into intelligent scheduling systems. Machine learning techniques can analyze historical production data, predict processing times, identify bottlenecks, and support adaptive scheduling decisions [19], [30]. Reinforcement learning and data-driven optimization models have demonstrated significant improvements in scheduling efficiency, resource utilization, and production flexibility [29].

The transition from traditional rule-based scheduling methods to AI-based optimization approaches represents a major advancement toward Industry 4.0 and smart manufacturing systems. Intelligent scheduling systems enable real-time monitoring, predictive analysis, and automated decision-making, which are essential for improving manufacturing competitiveness in modern industries [30].

E. Objectives of the Review Paper

The major objectives of this review paper are as follows:
– To review existing optimization methods used in production planning and scheduling systems.
– To analyze heuristic and metaheuristic optimization techniques for minimizing makespan and machine idle time.
– To compare machine learning-based scheduling methods with traditional optimization approaches.
– To study the industrial applications of optimization techniques in small-scale manufacturing industries.
– To identify existing research gaps and future research opportunities in intelligent production scheduling systems.

F. Scope of the Review

This review paper mainly focuses on optimization techniques used in production planning and scheduling systems for small-scale manufacturing industries. The study covers traditional scheduling approaches, heuristic and metaheuristic algorithms, machine learning techniques, and hybrid optimization models applied for minimizing makespan and machine idle time.
The review includes research related to:
– Job shop scheduling
– Flow shop scheduling
– Flexible manufacturing systems
– Intelligent scheduling systems
– AI-driven optimization techniques
The scope of the review is limited to manufacturing industries where production efficiency, machine utilization, and scheduling optimization are major operational concerns. The paper also emphasizes recent developments in smart manufacturing and Industry 4.0-based scheduling systems [19], [30].

G. Organization of the Paper

The review paper is organized into six chapters for systematic presentation and analysis of the research topic.

- Chapter 1 presents the introduction, importance of production scheduling, challenges in small-scale manufacturing systems, objectives, and scope of the review paper.
- Chapter 2 discusses production planning systems, scheduling models, process parameters, and performance evaluation measures used in manufacturing industries.
- Chapter 3 explains various optimization techniques including heuristic, metaheuristic, and machine learning-based scheduling methods.
- Chapter 4 provides detailed literature review and critical comparative analysis of previous research studies related to scheduling optimization.
- Chapter 5 discusses research gaps, industrial challenges, future research directions, and emerging intelligent manufacturing approaches.
- Chapter 6 presents the overall conclusions and summarizes the major findings of the review study.

II. Overview of Production Planning and Scheduling Systems

A. Production Planning in Manufacturing

Production planning is one of the most important functions in manufacturing industries because it ensures the efficient utilization of resources, timely completion of products, and smooth coordination between different manufacturing activities. It involves planning of materials, machines, manpower, production sequences, and delivery schedules to achieve maximum productivity with minimum operational cost [5], [6]. Effective production planning enables industries to improve manufacturing performance, reduce production delays, and maintain product quality standards.

In manufacturing systems, production flow refers to the movement of materials and jobs through different processing stages. Proper production flow management is essential to maintain continuity in manufacturing operations and avoid unnecessary waiting or machine idle periods [1]. Production flow systems are generally classified into continuous flow systems, intermittent production systems, and batch manufacturing systems depending on the type of products and production volume. Continuous flow systems are commonly used for mass production industries, while intermittent systems are suitable for customized and small-batch production environments [4].

Job shop and flow shop manufacturing systems are widely used production environments in modern industries. In job shop manufacturing systems, different jobs follow different processing routes depending on customer requirements and product specifications. These systems are highly flexible but involve complex scheduling problems due to varying job sequences and machine requirements [11]. Job shop scheduling is considered one of the most difficult combinatorial optimization problems because of dynamic job arrivals, machine allocation constraints, and varying processing times [18].

Flow shop manufacturing systems, on the other hand, follow a fixed sequence of operations for all jobs. These systems are comparatively easier to schedule because all products pass through machines in the same order [2]. Flow shop systems are suitable for high-volume production where production flow is standardized. However, improper scheduling in flow shop environments may still result in increased makespan, bottlenecks, and machine idle time [12].

Modern manufacturing industries increasingly adopt intelligent production planning systems integrated with optimization algorithms, machine learning, and real-time monitoring technologies to improve operational efficiency and flexibility [19], [30].

B. Scheduling Types

Scheduling is the process of allocating jobs to available machines and determining the sequence of operations to achieve predefined production objectives such as minimizing makespan, reducing idle time, and improving resource utilization [5]. Depending on the complexity of manufacturing systems and machine arrangements, scheduling problems are categorized into different types.

1) Single Machine Scheduling

Single machine scheduling involves assigning multiple jobs to a single processing machine. The main objective is to determine the optimal sequence of jobs to minimize completion time, tardiness, or waiting time [6]. Single machine scheduling problems are comparatively simple and are commonly used as a basic foundation for more complex scheduling models.

2) Parallel Machine Scheduling

Parallel machine scheduling involves multiple machines performing similar operations simultaneously. Jobs are assigned to different machines based on machine availability, processing time, and scheduling objectives [3]. Efficient parallel machine scheduling improves production throughput and reduces machine idle time. However, balancing workloads among machines remains a major challenge in such systems [16].

3) Job Shop Scheduling

Job shop scheduling is one of the most widely studied scheduling problems in manufacturing systems. In job shop environments, each job follows a different processing route and requires different machine sequences [7]. The primary challenge in job shop scheduling is to optimize job sequencing while considering machine constraints, due dates, and varying processing times. Researchers have applied Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing, and Reinforcement Learning techniques to solve job shop scheduling problems effectively [21], [29].

4) Flexible Manufacturing Scheduling

Flexible manufacturing scheduling refers to scheduling systems where multiple machines are capable of performing similar operations. Such systems provide higher production flexibility and adaptability to changing manufacturing conditions [24]. Flexible scheduling systems are highly suitable for small-scale manufacturing industries dealing with customized products and variable production demand. Advanced optimization algorithms are commonly used in flexible manufacturing systems to minimize makespan and maximize machine utilization [27].

C. Traditional Scheduling Techniques

Traditional scheduling techniques are widely used in manufacturing industries because of their simplicity and ease of implementation. Although these methods are computationally efficient, they often fail to generate optimal schedules for complex production systems [13].

1) FIFO (First In First Out)

FIFO is one of the simplest scheduling methods where jobs are processed in the order of their arrival. The first job entering the system is processed first without considering processing time or due date [4]. FIFO is easy to implement but may lead to increased waiting time and poor machine utilization.

2) SPT (Shortest Processing Time)

The Shortest Processing Time rule prioritizes jobs with the minimum processing time [6]. SPT scheduling reduces average waiting time and improves throughput in many production systems. However, larger jobs may experience excessive delays under this method [12].

3) LPT (Longest Processing Time)

Longest Processing Time scheduling gives priority to jobs requiring maximum processing time. This method is often used in load balancing and parallel machine scheduling applications [5]. Although LPT can improve machine balancing, it may increase average completion time in some cases.

4) EDD (Earliest Due Date)

The Earliest Due Date method schedules jobs according to their due dates. Jobs with the earliest delivery deadlines are processed first to reduce tardiness and improve delivery performance [2]. EDD scheduling is widely used in industries where timely product delivery is critical.

Despite their industrial applications, traditional scheduling methods have limitations in handling dynamic and multi-objective manufacturing environments. Therefore, modern industries increasingly adopt heuristic and AI-based optimization approaches for improved scheduling performance [17], [19].

D. Key Process Parameters

Production scheduling performance depends significantly on various input and output process parameters. These parameters influence scheduling efficiency, machine utilization, and overall manufacturing productivity.

Key Process Parameters in Scheduling Systems

Input Parameters	Output Parameters
Processing time	Makespan
Due date	Idle time
Machine availability	Throughput
Job priority	Delay

Processing time represents the time required to complete a particular operation on a machine. Due dates determine the delivery deadlines assigned to manufacturing jobs [5]. Machine availability indicates the operational readiness of machines, while job priority determines the sequence importance based on customer requirements or production urgency [21].

The major output parameters include makespan, machine idle time, throughput, and production delay. Makespan represents the total production completion time, while throughput indicates the number of jobs completed within a specified duration [6]. Production delay occurs when jobs are completed beyond their due dates, affecting customer satisfaction and operational performance [24].

Optimization techniques mainly focus on improving these output parameters through intelligent scheduling decisions and efficient resource allocation [27].

E. Performance Evaluation Metrics

Performance evaluation metrics are used to measure the effectiveness of production scheduling systems and optimization algorithms. These metrics help researchers and industries compare different scheduling approaches and identify the most suitable optimization techniques [3].

1) Makespan

Makespan is the total time required to complete all scheduled jobs. It is one of the most important optimization objectives in manufacturing scheduling because reduced makespan increases production throughput and machine efficiency [6], [12].

2) Machine Utilization

Machine utilization represents the percentage of productive machine operating time compared to total available time. Higher machine utilization indicates better resource management and reduced idle periods [16].

3) Waiting Time

Waiting time refers to the duration during which jobs remain unprocessed before machine allocation. Excessive waiting time reduces production efficiency and increases manufacturing lead time [11].

4) Production Efficiency

Production efficiency measures the ability of manufacturing systems to achieve maximum output with minimum resource consumption. Efficient scheduling systems improve productivity, reduce delays, and enhance overall operational performance [18].

Advanced optimization methods such as Genetic Algorithms, PSO, and Reinforcement Learning have demonstrated significant improvements in these performance metrics compared to traditional scheduling techniques [19], [29].

F. HD Figures & Diagrams Required

For effective presentation and better understanding of production planning and scheduling systems, high-definition figures and diagrams should be included in the review paper. These figures improve visualization of manufacturing processes, scheduling frameworks, and optimization methodologies.

Recommended HD Figures and Diagrams

- Production planning flowchart
- Manufacturing system architecture
- Job shop scheduling layout
- Flow shop process diagram
- Scheduling optimization framework
- Machine-job allocation diagrams
- Gantt charts for scheduling analysis
- Heuristic optimization workflow diagrams
- AI-based scheduling architecture

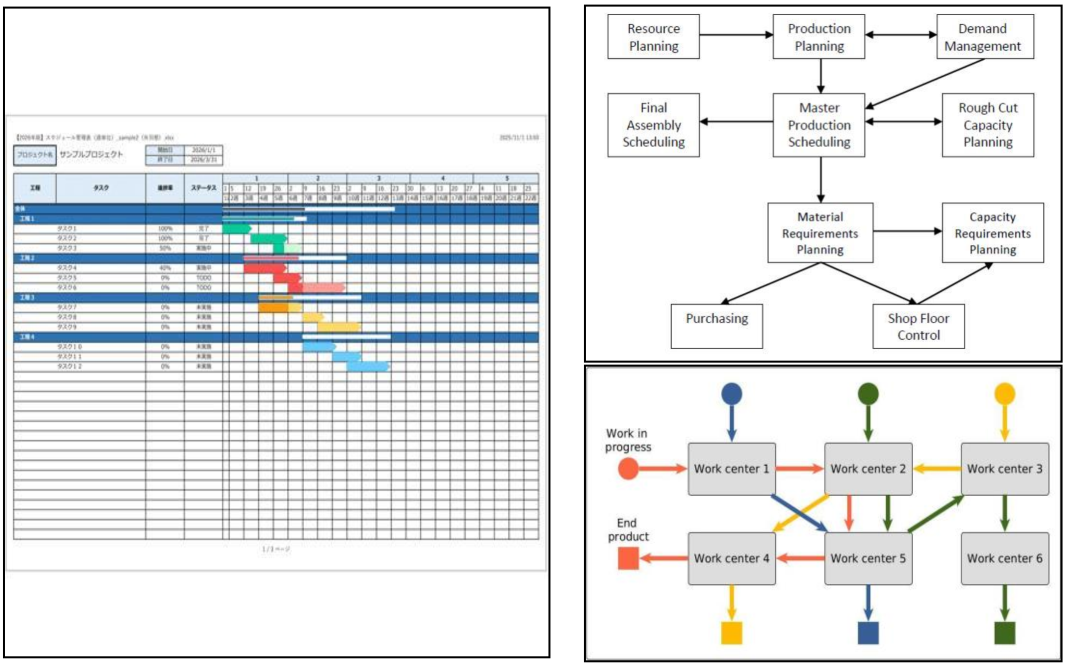


Fig. 1: (a) Production Scheduling Gantt Chart, (b) Production Planning and Control System Framework, and (c) Job Shop Manufacturing Workflow System

Figure 1 (a), (b), and (c) collectively illustrate important concepts related to production planning and scheduling systems in manufacturing industries. Figure 1 (a) presents a Gantt chart used for monitoring production schedules, task sequencing, activity duration, and workflow coordination to reduce delays and improve scheduling efficiency. Figure 1 (b) shows the Production Planning and Control (PPC) framework consisting of resource planning, demand management, master production scheduling, material requirements planning, capacity planning, purchasing, and shop floor control, which together support effective manufacturing management and resource utilization. Figure 1 (c) represents a job shop manufacturing workflow system where multiple work centers process jobs through different operational routes, highlighting the complexity of machine allocation and scheduling decisions in dynamic manufacturing environments. These figures collectively demonstrate the importance of systematic production planning, scheduling optimization, and workflow management for minimizing makespan, reducing machine idle time, and improving manufacturing productivity.

III. OPTIMIZATION TECHNIQUES FOR PRODUCTION SCHEDULING

A. Mathematical Modeling in Scheduling

Mathematical modeling plays an important role in production scheduling because it provides a systematic framework for analyzing manufacturing problems and developing optimized scheduling solutions. In production planning systems, mathematical models are used to represent machine allocation, job sequencing, processing constraints, and optimization objectives in the form of equations and inequalities [5], [6]. These models help industries minimize production time, reduce operational costs, and improve resource utilization.

In manufacturing scheduling problems, objective functions are formulated to optimize specific production goals such as minimizing makespan, reducing machine idle time, minimizing tardiness, and maximizing throughput. Among these objectives, makespan minimization is the most widely used criterion because it directly affects production completion time and manufacturing productivity [1], [12]. The commonly used objective function for makespan minimization is:

$$\text{Minimize } C_{max} = \max(C_i)$$

where:

- C_{max} represents the maximum completion time of all jobs.
- C_i represents the completion time of the i^{th} job.

The primary aim of this objective function is to minimize the total production completion time by determining the optimal sequence of jobs and machine allocation [11].

Constraint formulation is another important aspect of scheduling models. Constraints ensure that manufacturing operations follow practical industrial conditions and limitations. Common scheduling constraints include:

- Machine capacity constraints
- Job precedence constraints
- Processing sequence constraints
- Due date constraints
- Machine availability constraints

These constraints increase the complexity of scheduling problems, especially in job shop and flexible manufacturing systems [24]. Therefore, optimization algorithms are widely used to solve such combinatorial optimization problems efficiently.

Mathematical scheduling models are extensively applied in heuristic and machine learning-based optimization methods for industrial applications involving complex manufacturing environments [17], [21].

B. Heuristic Optimization Techniques

Heuristic and metaheuristic optimization techniques are widely used in production scheduling because traditional exact optimization methods become computationally difficult for large-scale and dynamic manufacturing systems [13]. These techniques provide near-optimal solutions within reasonable computational time and are highly suitable for minimizing makespan, machine idle time, and production delays [27].

1) Genetic Algorithm (GA)

Genetic Algorithm is one of the most widely used evolutionary optimization techniques inspired by the process of natural selection and genetics [14]. GA is highly effective in solving complex scheduling problems due to its global search capability and flexibility in handling nonlinear constraints.

The working procedure of Genetic Algorithm mainly consists of the following steps:

a) Selection

Selection is the process of choosing the best chromosomes or candidate solutions from the population based on their fitness value. Better-performing schedules have a higher probability of being selected for the next generation [7].

b) Crossover

Crossover combines two parent solutions to generate new offspring solutions. This operation helps in exploring new scheduling combinations and improving solution diversity [17].

c) Mutation

Mutation introduces random modifications in chromosomes to avoid premature convergence and maintain population diversity. Mutation improves the exploration capability of the algorithm [14].

Genetic Algorithms have shown significant improvement in minimizing makespan and balancing machine utilization in job shop and flexible manufacturing scheduling problems [23], [27].

2) Particle Swarm Optimization (PSO)

Particle Swarm Optimization is a population-based optimization algorithm inspired by the social behavior of bird flocking and fish schooling [21]. In PSO, each particle represents a potential scheduling solution, and particles continuously update their positions and velocities based on individual and global best solutions.

PSO is widely applied in manufacturing scheduling because of:

- Faster convergence speed
- Simplicity of implementation
- Reduced computational complexity

Researchers have successfully applied PSO for minimizing makespan, reducing idle time, and improving production throughput in flexible job shop scheduling systems [16], [22].

3) Ant Colony Optimization (ACO)

Ant Colony Optimization is a bio-inspired optimization technique based on the foraging behavior of ants. Artificial ants search for optimal scheduling paths using pheromone updating mechanisms [9].

ACO is highly effective for:

- Dynamic scheduling problems
- Multi-objective optimization
- Resource allocation problems

The algorithm continuously improves scheduling quality through pheromone reinforcement and probabilistic path selection [27]. ACO has been successfully applied in production planning systems for minimizing production delays and balancing machine workload [13].

4) Simulated Annealing (SA)

Simulated Annealing is a probabilistic optimization method inspired by the annealing process in metallurgy [11]. The algorithm searches for near-optimal solutions by allowing occasional acceptance of worse solutions during early iterations to avoid local optima.

The major advantages of Simulated Annealing include:

- Simplicity of implementation
- Effective local search capability
- Good performance in combinatorial optimization problems

SA has been widely used for job shop scheduling and flow shop optimization problems where exact optimization methods are computationally expensive [26].

C. Machine Learning Techniques

Machine Learning techniques are increasingly integrated into production scheduling systems to improve decision-making capabilities and enable intelligent manufacturing operations [19]. Unlike traditional optimization methods, machine learning models can learn scheduling patterns from historical production data and predict optimal scheduling decisions in dynamic manufacturing environments.

1) Regression Models

Regression models are used for predicting processing time, machine utilization, production delay, and throughput based on historical industrial data [30]. Linear regression and nonlinear regression techniques are commonly used for production performance forecasting and scheduling analysis.

2) Artificial Neural Networks (ANN)

Artificial Neural Networks simulate the functioning of the human brain and are capable of handling complex nonlinear scheduling relationships [19]. ANN models are used for:

- Predicting processing time
- Machine failure analysis
- Scheduling optimization
- Production forecasting

ANN-based scheduling systems improve production flexibility and adaptive decision-making capabilities [30].

3) Support Vector Machines (SVM)

Support Vector Machines are supervised machine learning models used for classification and regression analysis. SVM techniques are applied in manufacturing scheduling for pattern recognition, production prediction, and optimization of machine allocation [18].

SVM-based scheduling models provide:

- High prediction accuracy
- Robust performance
- Efficient handling of high-dimensional industrial datasets

4) Reinforcement Learning

Reinforcement Learning is an advanced AI-based optimization approach in which agents learn scheduling decisions through interaction with the manufacturing environment [29]. RL algorithms continuously improve scheduling performance by maximizing reward functions related to productivity, makespan reduction, and machine utilization.

Reinforcement Learning has emerged as a promising technique for:

- Real-time scheduling
- Dynamic production systems
- Smart manufacturing environments

D. Hybrid Optimization Techniques

Hybrid optimization techniques combine machine learning approaches with heuristic and metaheuristic algorithms to improve scheduling efficiency and optimization accuracy [30]. Hybrid models provide better exploration and exploitation capabilities compared to individual optimization techniques.

1) ML + GA

In ML-GA hybrid systems, machine learning models predict scheduling parameters such as processing time and machine behavior, while Genetic Algorithms optimize job sequences and machine allocation [19]. This integration improves scheduling adaptability and solution quality.

2) ML + PSO

Machine Learning combined with Particle Swarm Optimization enhances optimization performance by utilizing predictive analytics and intelligent search capabilities [16]. ML-PSO systems are highly suitable for dynamic production environments with changing industrial conditions.

3) Data-Driven Optimization

Data-driven optimization techniques use industrial production data, IoT sensors, and real-time monitoring systems to develop intelligent scheduling frameworks [30]. These systems enable:

- Predictive scheduling
- Adaptive resource allocation
- Real-time production optimization

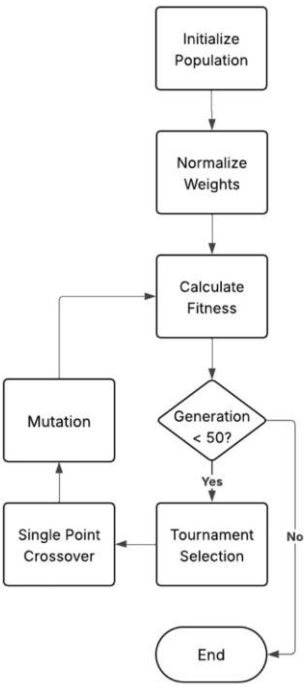
Hybrid optimization approaches are increasingly adopted in Industry 4.0-based manufacturing systems due to their ability to improve productivity, reduce idle time, and enhance scheduling flexibility [29].

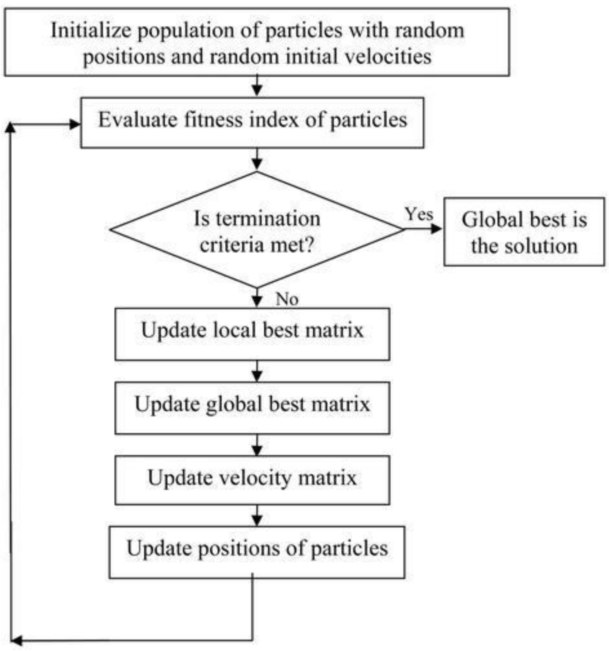
E. Comparative Analysis of Optimization Methods

Different optimization techniques possess unique advantages and limitations depending on manufacturing complexity, computational requirements, and industrial objectives.

Technique	Advantages	Limitations
Genetic Algorithm (GA)	Global optimization capability, flexible search	High computational time
Particle Swarm Optimization (PSO)	Fast convergence, simple implementation	May converge to local optimum
Ant Colony Optimization (ACO)	Effective for dynamic scheduling	Slow convergence in large systems
Simulated Annealing (SA)	Strong local search ability	Sensitive to parameter settings
Artificial Neural Networks (ANN)	Handles nonlinear relationships	Requires large training datasets
Reinforcement Learning (RL)	Adaptive real-time optimization	High computational complexity
Hybrid ML-Heuristic Models	Improved optimization accuracy	Complex implementation

Comparative studies indicate that hybrid optimization techniques generally outperform traditional scheduling methods in minimizing makespan and improving machine utilization [17], [30].





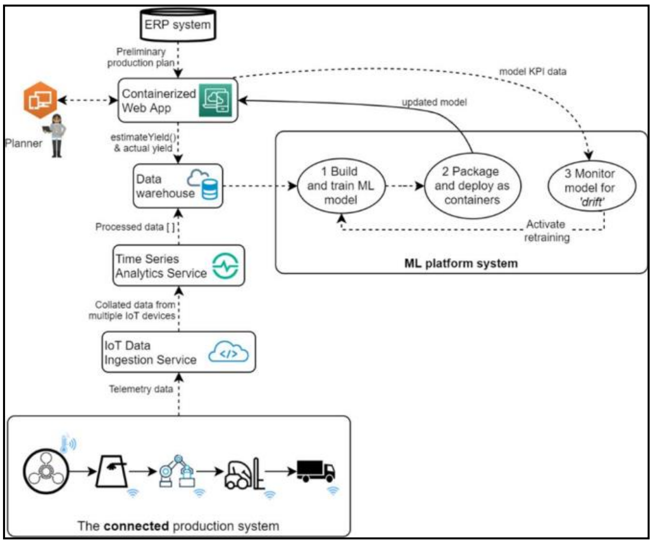


Fig. 2: (a) Genetic Algorithm Optimization Workflow, (b) Particle Swarm Optimization Process Flow, and (c) Machine Learning-Based Smart Production Scheduling Architecture

Figure 2 (a), (b), and (c) collectively represent advanced optimization and intelligent scheduling approaches used in modern manufacturing systems. Figure 2 (a) illustrates the workflow of the Genetic Algorithm (GA) optimization process, including population initialization, fitness evaluation, tournament selection, crossover, mutation, and iterative improvement for obtaining optimized scheduling solutions. Figure 2 (b) presents the Particle Swarm Optimization (PSO) process flow where particles update their local best and global best positions iteratively to achieve optimal scheduling performance and minimize production completion time. Figure 2 (c) demonstrates a Machine Learning-based smart production scheduling architecture integrated with ERP systems, IoT devices, data warehousing, analytics services, and ML platforms for real-time production monitoring and intelligent decision-making. These optimization frameworks collectively highlight the transition from conventional scheduling methods toward AI-driven and data-centric manufacturing systems aimed at reducing makespan, minimizing machine idle time, improving production efficiency, and enabling Industry 4.0-based smart manufacturing environments.

IV. LITERATURE REVIEW AND CRITICAL ANALYSIS

A. Review of Recent Research Papers

Production planning and scheduling optimization have received significant attention from researchers due to the increasing complexity of manufacturing systems and the growing demand for higher productivity with reduced operational cost. Several researchers have proposed heuristic, metaheuristic, and machine learning-based optimization methods to minimize makespan, reduce machine idle time, and improve manufacturing efficiency [5], [6].

Early research in production scheduling mainly focused on classical optimization methods and mathematical scheduling rules. Johnson introduced one of the earliest scheduling approaches for flow shop manufacturing systems to minimize production completion time [2]. Later, Garey et al. analyzed the computational complexity of job shop and flow shop scheduling problems and identified them as NP-hard optimization problems [1]. Due to the computational difficulty of exact optimization methods, heuristic and metaheuristic algorithms gained popularity for solving large-scale industrial scheduling problems [28].

Several studies have demonstrated the effectiveness of Genetic Algorithms in production scheduling optimization. Yamada and Nakano applied Genetic Algorithms to large-scale job shop scheduling problems and reported considerable reduction in makespan and improved scheduling flexibility [7]. Similarly, Della Croce et al. proposed a GA-based scheduling model that improved job sequencing and reduced production delays in manufacturing systems [14].

Particle Swarm Optimization techniques have also been extensively studied for scheduling optimization. Sha and Hsu developed a hybrid PSO algorithm for job shop scheduling and demonstrated significant improvement in machine utilization and production throughput [21]. Lin et al. further improved PSO-based scheduling approaches for industrial manufacturing systems and reported faster convergence and reduced computational complexity [22].

Recent studies increasingly focus on machine learning and AI-based scheduling systems. Reinforcement Learning-based scheduling environments proposed by Tassel et al. demonstrated adaptive scheduling capabilities for dynamic production systems [29]. Learning-based optimization approaches reviewed by Rihane et al. showed that AI-driven scheduling systems can significantly improve production flexibility and decision-making accuracy in smart manufacturing environments [30].

Industrial case studies indicate that optimization techniques are highly beneficial for small-scale manufacturing industries where machine utilization and resource allocation are critical factors. Flexible job shop scheduling methods proposed by Kacem et al. improved production efficiency and reduced machine idle time in industrial environments [9]. Wang et al. applied hybrid PSO algorithms to flexible manufacturing systems and achieved better scheduling performance compared to traditional methods [16].

Comparative findings from various studies suggest that hybrid optimization methods generally provide better performance than individual heuristic algorithms. Hybrid ML-GA and ML-PSO approaches combine predictive analytics with optimization capability, resulting in improved scheduling efficiency and reduced production delays [17], [19].

B. Comparative Literature Analysis

Comparative literature analysis helps in understanding the methodologies, objectives, and outcomes of previous research studies related to scheduling optimization.

Author	Technique Used	Objective	Key Findings
Johnson [2]	Flow Shop Scheduling Rule	Minimize completion time	Developed optimal sequencing rule for flow shop systems

Yamada and Nakano [7]	Genetic Algorithm	Job shop scheduling optimization	Reduced makespan and improved scheduling flexibility
Kacem et al. [9]	Multi-objective Evolutionary Optimization	Flexible job shop scheduling	Improved machine utilization and scheduling efficiency
Sha and Hsu [21]	Hybrid PSO	Job shop scheduling	Reduced idle time and improved convergence speed
Wang et al. [16]	Hybrid PSO	Flexible manufacturing scheduling	Improved production throughput
Della Croce et al. [14]	Genetic Algorithm	Production scheduling optimization	Enhanced job sequencing performance
Van Laarhoven et al. [11]	Simulated Annealing	Job shop optimization	Achieved near-optimal scheduling solutions
Zhang et al. [27]	Hybrid Genetic Algorithm	Flexible scheduling optimization	Improved scheduling adaptability
Tassel et al. [29]	Reinforcement Learning	Dynamic scheduling	Enabled real-time adaptive scheduling
Rihane et al. [30]	Learning-based Scheduling Review	AI-driven optimization	Identified future AI scheduling opportunities

The comparative analysis indicates that modern AI and hybrid optimization methods outperform conventional scheduling techniques in terms of makespan reduction, machine utilization, and adaptability to dynamic production environments [19], [30].

C. Statistical and Experimental Analysis in Literature

Statistical and experimental methods are extensively used in scheduling optimization research for validating algorithm performance and analyzing manufacturing efficiency improvements. Researchers apply various statistical tools to compare optimization techniques and evaluate scheduling outcomes under different industrial conditions [18].

1) ANOVA

Analysis of Variance (ANOVA) is widely used for determining the significance of process parameters and optimization variables in scheduling systems. ANOVA helps identify the effect of machine allocation, processing time, and sequencing rules on makespan and idle time reduction [24].

2) Regression Analysis

Regression analysis is commonly used to establish relationships between scheduling parameters and production performance indicators such as throughput, machine utilization, and delay [30]. Researchers use linear and nonlinear regression models to predict production outcomes and optimize scheduling strategies.

3) Simulation Models

Simulation techniques are highly useful for analyzing manufacturing systems under dynamic and uncertain conditions. Simulation models allow researchers to test scheduling algorithms without disturbing actual industrial operations [5]. Flexible manufacturing systems and job shop scheduling problems are often analyzed using discrete-event simulation models [16].

4) Design of Experiments (DOE)

DOE techniques are applied to systematically study the effect of scheduling parameters on production performance [13]. Experimental design approaches improve optimization accuracy and reduce computational complexity by identifying significant scheduling variables efficiently.

Experimental analysis in literature indicates that heuristic and AI-based optimization methods consistently outperform traditional scheduling approaches in minimizing makespan and improving machine utilization [17], [22].

D. Research Trends

Production scheduling research has evolved significantly with the advancement of Artificial Intelligence, Industry 4.0 technologies, and smart manufacturing systems. Modern research trends focus on intelligent, adaptive, and data-driven scheduling frameworks capable of handling real-time industrial complexities [19].

1) AI-Driven Scheduling

Artificial Intelligence-based scheduling systems use machine learning, neural networks, and reinforcement learning to optimize production operations dynamically [30]. AI-driven scheduling improves decision-making capabilities, predictive analysis, and production flexibility.

2) Industry 4.0 Integration

Industry 4.0 technologies such as IoT, cloud computing, cyber-physical systems, and digital twins are increasingly integrated into production scheduling systems [29]. These technologies enable real-time data acquisition, automated monitoring, and intelligent production planning.

3) Smart Manufacturing Systems

Smart manufacturing systems combine automation, AI, and optimization algorithms to create adaptive production environments [19]. These systems improve operational efficiency, minimize idle time, and enhance manufacturing responsiveness under changing industrial conditions.

Recent studies indicate a growing trend toward hybrid AI-optimization frameworks capable of solving complex scheduling problems with higher efficiency and reduced computational effort [30].

E. Identified Research Gaps

Despite significant advancements in production scheduling optimization, several research gaps still exist in the current literature.

1) Lack of Real-Time Optimization

Most existing scheduling methods are developed for static manufacturing environments and are unable to adapt efficiently to real-time production changes such as machine breakdowns, urgent job arrivals, and dynamic resource allocation [24].

2) Limited SME-Focused Studies

Many scheduling optimization studies focus on large-scale industrial systems, while small-scale manufacturing industries receive comparatively less attention [25]. SMEs face unique challenges such as limited resources, low automation, and insufficient computational infrastructure, requiring customized scheduling solutions.

3) Insufficient Hybrid Approaches

Although hybrid optimization methods show promising performance, limited research exists on integrating machine learning with heuristic optimization techniques for real industrial applications [19]. More research is required on adaptive and intelligent hybrid scheduling frameworks suitable for Industry 4.0 environments.

4) Limited Industrial Validation

Several optimization studies are simulation-based and lack practical industrial validation using real manufacturing datasets [18]. Experimental implementation in actual industrial environments remains a major research requirement.

V. Discussion and Future Research Directions

A. Critical Discussion of Existing Methods

Optimization techniques used in production scheduling differ significantly in terms of efficiency, computational complexity, and industrial applicability. Traditional scheduling methods such as FIFO, SPT, and EDD are computationally simple but fail to provide optimal solutions for complex manufacturing systems [2], [5].

Heuristic and metaheuristic algorithms such as GA, PSO, ACO, and SA provide better optimization capability and improved scheduling flexibility [14], [21]. Genetic Algorithms are highly effective in global optimization but require higher computational time for large-scale problems. PSO offers faster convergence; however, it may sometimes converge to local optima [16].

Machine learning and AI-based optimization methods have emerged as powerful scheduling approaches due to their adaptive learning capability and predictive performance [19]. Reinforcement Learning-based scheduling systems are particularly suitable for dynamic and real-time manufacturing environments [29].

From an industrial perspective, hybrid optimization techniques combining machine learning with heuristic algorithms demonstrate better scheduling accuracy, reduced makespan, and improved resource utilization compared to standalone optimization methods [30].

B. Challenges in Small-Scale Manufacturing

Small-scale manufacturing industries face several operational and technological challenges in implementing advanced scheduling systems.

1) Data Availability

Many SMEs lack sufficient historical production data required for machine learning and intelligent scheduling systems [25].

2) Resource Constraints

Limited financial resources, manpower, and automation infrastructure restrict the implementation of advanced optimization technologies in small industries [18].

3) Real-Time Scheduling Difficulties

Dynamic production conditions such as machine breakdowns, fluctuating demand, and urgent job arrivals make real-time scheduling highly challenging [24].

These challenges highlight the need for cost-effective, adaptive, and scalable scheduling solutions specifically designed for SME environments.

C. Future Scope

Future research in production scheduling is expected to focus on intelligent and real-time optimization systems integrated with Industry 4.0 technologies.

1) Digital Twin Integration

Digital Twin technology can create virtual manufacturing models for real-time monitoring and predictive scheduling optimization [29].

2) IoT-Enabled Scheduling

IoT sensors and smart devices enable continuous data collection and real-time production monitoring for adaptive scheduling systems [30].

3) Real-Time Optimization Systems

AI-driven real-time optimization frameworks can dynamically adjust production schedules based on changing manufacturing conditions [19].

4) Cloud Manufacturing

Cloud-based manufacturing systems provide scalable and collaborative scheduling platforms for distributed production systems and SME networks [25].

D. Proposed Conceptual Framework

A hybrid Machine Learning–Heuristic optimization framework is proposed for intelligent production scheduling in small-scale manufacturing industries.

The proposed framework includes:

- Industrial data acquisition
- Machine learning-based prediction models
- Heuristic optimization algorithms
- Real-time scheduling decision systems
- Performance evaluation modules

The framework aims to minimize makespan, reduce idle time, and improve machine utilization through adaptive scheduling strategies [30].

E. Suggested Experimental Framework

The experimental framework for future scheduling optimization research should include the following stages:

1) Industrial Data Collection

- Processing time
- Machine availability
- Due dates
- Production delays

2) Simulation Models

- Job shop simulation
- Flexible manufacturing system modeling
- Discrete-event simulation

3) Optimization Workflow

- Data preprocessing
- Model training
- Optimization algorithm implementation
- Statistical validation

– Performance comparison

This framework can help researchers validate optimization models under realistic manufacturing conditions [18], [24].

F. HD Conceptual Diagrams Required

The following HD conceptual diagrams should be included for effective visualization of future scheduling frameworks and intelligent manufacturing systems:

– AI-based scheduling architecture
– Hybrid ML-Heuristic optimization framework
– Digital Twin manufacturing model
– IoT-enabled smart factory architecture
– Cloud manufacturing scheduling framework
– Real-time scheduling workflow diagrams
– Data-driven optimization architecture

VI. CONCLUSION

A. Summary of Review Findings

Production planning and scheduling optimization have become essential components of modern manufacturing systems due to increasing industrial competition, customer demand, and the need for efficient resource utilization. The present review study analyzed various optimization techniques used for minimizing makespan and machine idle time in manufacturing industries, particularly in small-scale production environments. The review highlighted that efficient scheduling systems significantly improve manufacturing productivity, delivery performance, and operational efficiency [5], [6].

The study reviewed traditional scheduling techniques such as FIFO, SPT, LPT, and EDD along with advanced heuristic, metaheuristic, and machine learning-based optimization approaches. Traditional scheduling methods are easy to implement but are often unable to handle dynamic and complex manufacturing environments efficiently [2]. In contrast, heuristic optimization techniques such as Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, and Simulated Annealing have demonstrated superior capability in solving complex combinatorial scheduling problems [14], [21].

Machine learning and AI-driven scheduling systems have emerged as powerful approaches for intelligent manufacturing applications. Techniques such as Artificial Neural Networks, Support Vector Machines, and Reinforcement Learning provide adaptive and predictive scheduling capabilities that improve production flexibility and real-time decision-making [19], [29]. The review findings indicate that hybrid optimization frameworks integrating machine learning with heuristic algorithms offer better scheduling performance, reduced makespan, and improved machine utilization compared to standalone optimization methods [30].

B. Major Outcomes

The review study identified several important outcomes related to production scheduling optimization in manufacturing systems.

1) Makespan Reduction Potential

Most heuristic and hybrid optimization techniques demonstrated significant capability in reducing production completion time. Genetic Algorithms, PSO, and Reinforcement Learning approaches effectively minimized makespan in job shop and flexible manufacturing systems [7], [16]. Reduced makespan directly improves production throughput and enables industries to meet customer deadlines efficiently.

2) Idle Time Minimization Benefits

The reviewed studies revealed that intelligent scheduling techniques substantially reduce machine idle time through optimized job sequencing and efficient resource allocation [21], [24]. Reduction of idle time improves equipment utilization, decreases operational losses, and enhances manufacturing continuity.

3) Improved Productivity and Utilization

Advanced optimization methods improve production efficiency by increasing machine utilization and minimizing production delays. Hybrid optimization frameworks demonstrated better adaptability to dynamic manufacturing conditions and enhanced scheduling flexibility [17], [30]. Improved productivity enables industries to achieve higher output with minimum resource consumption.

The major industrial benefits observed from optimized scheduling systems include:

– Increased manufacturing efficiency
– Better resource utilization
– Reduced production delays
– Improved delivery performance
– Enhanced operational flexibility
– Lower manufacturing cost

These outcomes indicate that optimization-based scheduling systems play a crucial role in achieving sustainable and intelligent manufacturing operations [19].

C. Research Contributions

The present review paper provides several important contributions to the field of production planning and scheduling optimization.

1) Comprehensive Review Framework

The study presented a systematic and comprehensive review of scheduling optimization techniques including traditional methods, heuristic algorithms, machine learning approaches, and hybrid optimization frameworks. The review integrated research findings from various industrial and academic studies to provide a detailed understanding of modern scheduling systems [5], [30].

2) Identification of Industrial Gaps

The review identified several research and industrial gaps in existing scheduling optimization approaches. These gaps include:

– Lack of real-time scheduling systems
– Limited research focused on small-scale manufacturing industries
– Insufficient industrial implementation of AI-based scheduling models
– Limited integration of machine learning with heuristic optimization techniques [24], [25]

Identification of these gaps provides direction for future research and industrial development in intelligent manufacturing systems.

3) Comparative Optimization Analysis

The study performed comparative analysis of various optimization techniques based on scheduling efficiency, computational complexity, adaptability, and industrial applicability. Comparative findings indicated that hybrid machine learning–heuristic optimization methods provide better performance compared to conventional scheduling approaches [17], [29].

The review also emphasized the importance of Industry 4.0 technologies, IoT-enabled manufacturing systems, and data-driven optimization frameworks for future production scheduling applications [30].

D. Final Conclusion

The overall review concludes that optimization techniques have become indispensable for modern production planning and scheduling systems. Traditional scheduling methods are insufficient for handling complex, dynamic, and real-time manufacturing environments. Therefore, industries increasingly require intelligent scheduling systems capable of adaptive decision-making and efficient resource management [6], [19].

Artificial Intelligence and machine learning technologies are expected to play a major role in the future of production scheduling. AI-driven scheduling systems integrated with real-time data acquisition, predictive analytics, and intelligent optimization algorithms can significantly improve manufacturing productivity and operational flexibility [29], [30]. Reinforcement Learning and hybrid optimization frameworks are particularly promising for future smart manufacturing systems due to their ability to respond dynamically to changing industrial conditions.

For small-scale manufacturing industries, hybrid optimization approaches combining machine learning and heuristic algorithms provide an effective solution for minimizing makespan, reducing idle time, and improving machine utilization. These approaches offer better adaptability, computational efficiency, and scheduling accuracy under resource-constrained industrial environments [17], [21].

Future research should focus on:

- Real-time scheduling optimization
- IoT-enabled manufacturing systems
- Digital Twin integration
- Cloud-based scheduling platforms
- AI-driven adaptive manufacturing systems

In conclusion, intelligent and hybrid optimization techniques represent the future direction of production planning and scheduling systems for achieving sustainable, flexible, and efficient manufacturing operations in Industry 4.0 environments [30].

References

[1] M. R. Garey, D. S. Johnson, and R. Sethi, "The complexity of flowshop and jobshop scheduling," *Mathematics of Operations Research*, vol. 1, no. 2, pp. 117–129, May 1976.

[2] S. M. Johnson, "Optimal two- and three-stage production schedules with setup times included," *Naval Research Logistics Quarterly*, vol. 1, no. 1, pp. 61–68, Mar. 1954.

[3] E. Taillard, "Benchmarks for basic scheduling problems," *European Journal of Operational Research*, vol. 64, no. 2, pp. 278–285, Jan. 1993.

[4] J. Blazewicz, K. H. Ecker, G. Schmidt, and J. Weglarz, *Scheduling in Computer and Manufacturing Systems*, 2nd ed. Berlin, Germany: Springer, 1996.

[5] P. Brucker, *Scheduling Algorithms*, 5th ed. Berlin, Germany: Springer, 2007.

[6] M. Pinedo, *Scheduling: Theory, Algorithms, and Systems*, 5th ed. New York, NY, USA: Springer, 2016.

[7] T. Yamada and R. Nakano, "A genetic algorithm applicable to large-scale job-shop problems," in *Proc. Parallel Problem Solving from Nature (PPSN)*, Brussels, Belgium, 1992, pp. 281–290.

[8] S. Mirshekarian and D. N. Šormaz, "Correlation of job-shop scheduling problem features with scheduling efficiency," *Expert Systems with Applications*, vol. 54, pp. 126–139, Aug. 2016.

[9] I. Kacem, S. Hammadi, and P. Borne, "Approach by localization and multiobjective evolutionary optimization for flexible job-shop scheduling problems," *IEEE Transactions on Systems, Man, and Cybernetics Part C: Applications and Reviews*, vol. 32, no. 1, pp. 1–13, Feb. 2002.

[10] K. Rihane, A. Dabah, and A. AitZai, "Learning-based approaches for job shop scheduling problems: A review," *arXiv preprint arXiv:2505.04246*, 2025.

[11] P. J. M. Van Laarhoven, E. H. L. Aarts, and J. K. Lenstra, "Job shop scheduling by simulated annealing," *Operations Research*, vol. 40, no. 1, pp. 113–125, Jan.–Feb. 1992.

[12] R. Ruiz and T. Stützle, "A simple and effective iterated greedy algorithm for the permutation flowshop scheduling problem," *European Journal of Operational Research*, vol. 177, no. 3, pp. 2033–2049, Mar. 2007.

[13] B. Peng, Z. Lü, and T. C. E. Cheng, "A tabu search/path relinking algorithm to solve the job shop scheduling problem," *Computers & Operations Research*, vol. 53, pp. 154–164, Jan. 2015.

[14] F. Della Croce, R. Tadei, and G. Volta, "A genetic algorithm for the job shop problem," *Computers & Operations Research*, vol. 22, no. 1, pp. 15–24, Jan. 1995.

[15] U. Dorndorf and E. Pesch, "Evolution based learning in a job shop scheduling environment," *Computers & Operations Research*, vol. 22, no. 1, pp. 25–40, Jan. 1995.

[16] H. Wang, J. Fu, and H. Huang, "A hybrid particle swarm optimization algorithm for flexible job-shop scheduling problem," *International Journal of Advanced Manufacturing Technology*, vol. 67, no. 9–12, pp. 2487–2500, Aug. 2013.

[17] Q. Zhang, L. Gao, and X. Li, "A hybrid genetic algorithm for the job shop scheduling problem," *International Journal of Production Research*, vol. 51, no. 7, pp. 2028–2049, Apr. 2013.

[18] S. Mirshekarian and D. N. Šormaz, "Correlation of job-shop scheduling problem features with scheduling efficiency," *Expert Systems with Applications*, vol. 54, pp. 126–139, Aug. 2016.
[19] F. Zhang, Y. Mei, S. Nguyen, and M. Zhang, "Survey on genetic programming and machine learning techniques for heuristic design in job shop scheduling," *IEEE Transactions on Evolutionary Computation*, vol. 28, no. 1, pp. 147–167, Feb. 2024.
[20] P. Tassel, M. Gebser, and K. Schekotihin, "A reinforcement learning environment for job-shop scheduling," *arXiv preprint arXiv:2104.03760*, 2021.
[21] D. Sha and C.-Y. Hsu, "A hybrid particle swarm optimization for job shop scheduling problem," *Computers & Industrial Engineering*, vol. 51, no. 4, pp. 791–808, Dec. 2006.
[22] T.-L. Lin, S.-J. Horng, T.-W. Kao, Y.-H. Chen, R.-S. Run, R.-J. Chen, J.-L. Lai, and I.-H. Kuo, "An efficient job-shop scheduling algorithm based on particle swarm optimization," *Expert Systems with Applications*, vol. 37, no. 3, pp. 2629–2636, Mar. 2010.
[23] Y. Wang and L. Zheng, "A new hybrid genetic algorithm for job shop scheduling problem," *Computers & Operations Research*, vol. 39, no. 10, pp. 2291–2299, Oct. 2012.
[24] J. Xiong, L. N. Xing, and Y. W. Chen, "Robust scheduling for multi-objective flexible job-shop problems with random machine breakdowns," *International Journal of Production Economics*, vol. 141, no. 1, pp. 112–126, Jan. 2013.
[25] P. Sharma and D. Jain, "A review on job shop scheduling with setup times," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 230, no. 3, pp. 517–533, Mar. 2016.
[26] M. Faccio, J. Ries, and N. Saggiorno, "Simulated annealing approach to solve dual resource constrained job shop scheduling problems: Layout impact analysis on solution quality," *International Journal of Mathematics in Operational Research*, vol. 7, no. 5, pp. 609–629, 2015.
[27] G. Zhang, L. Gao, and Y. Shi, "An effective genetic algorithm for the flexible job-shop scheduling problem," *Expert Systems with Applications*, vol. 38, no. 4, pp. 3563–3573, Apr. 2011.
[28] M. R. Garey and D. S. Johnson, *Computers and Intractability: A Guide to the Theory of NP-Completeness*. San Francisco, CA, USA: Freeman, 1979.
[29] P. Tassel, M. Gebser, and K. Schekotihin, "A reinforcement learning environment for job-shop scheduling," *arXiv preprint arXiv:2104.03760*, 2021.
[30] K. Rihane, A. Dabah, and A. AitZai, "Learning-based approaches for job shop scheduling problems: A review," *arXiv preprint arXiv:2505.04246*, 2025.
[31] D. B. Magar and D. M. Khandare, "Study of Supply Chain Management and Buyer Supplier Relationship," *International Journal for Scientific Research & Development (IJSRD)*, vol. 4, no. 4, pp. 163–166, 2016.
[32] D. B. Magar, R. S. Pawar, M. S. Kadam, S. G. Chaudhari, N. V. Sawadekar, and D. M. Khandare, "Modern Supply Chain Management and Its Advantages for Efficient Working in Industries," *European Chemical Bulletin*, vol. 11, no. 11, pp. 1283–1292, 2022, doi: 10.53555/ecb/2022.11.11.115.
[33] D. B. Magar, R. S. Pawar, M. S. Kadam, and N. V. Sawadekar, "Historical Development and Evolution of Shot Peening: A Comprehensive Overview of the Origins of Shot Peening, Early Applications, and How the Technique Has Evolved Over Time," *International Journal of Mechanical Engineering*, vol. 6, no. 1, pp. 185–194, Jun. 2021.
[34] D. B. Magar and N. G. Phafat, "Review of Shot Peening and Shot Peening Parameters for Different Alloys to Improve Fatigue Life of the Components," *International Journal of Scientific Progress and Research (IJSPR)*, vol. 23, no. 1, pp. 1–4, 2016.
[35] D. B. Magar and N. G. Phafat, "Experimental Analysis of Shot Peening Parameters on EN9," *International Journal for Scientific Research & Development (IJSRD)*, vol. 4, no. 4, pp. 1495–1498, 2016.
[36] D. B. Magar, D. M. Khandare, R. S. Pawar, M. S. Kadam, and N. V. Sawadekar, "Study of Supply Chain Management and Buyer Supplier Relationship and Industry 4.0 Implementation in the Supply Chain," *International Journal of Management and Economics (IJM&E)*, vol. 1, no. 48, pp. 451–462, Nov. 2023.
[37] D. B. Magar, D. M. Khandare, R. S. Pawar, and M. S. Kadam, "Review of the Role of Technology in Modern Supply Chain Management and their Benefits for Efficient Working," *International Journal of Scientific Progress and Research (IJSPR)*, vol. 81, no. 10, pp. 1–5, Oct. 2023.
[38] D. B. Magar, R. S. Pawar, M. S. Kadam, S. G. Chaudhari, N. V. Sawadekar, and D. M. Khandare, "Cyber-Physical Systems for Resilient Supply Chain Management in the Face of Disruptions," *European Chemical Bulletin*, vol. 11, no. 8, pp. 327–345, 2022, doi: 10.53555/ecb/2022.11.8.39.
[39] D. B. Magar, R. S. Pawar, M. S. Kadam, and S. G. Chaudhari, "Optimization of Shot Peening Parameters for Surface Hardness Improvement in Steel Alloy Components," *Advanced Engineering Science*, vol. 55, no. 1, pp. 49–73, Jan. 2023.
[40] D. B. Magar, R. S. Pawar, D. M. Khandare, M. S. Kadam, and N. V. Sawadekar, "Assessing the Impact of Green Supply Chain Management on Reducing Carbon Emissions and Mitigating Climate Change," *European Chemical Bulletin*, vol. 12, no. 7, pp. 4129–4146, 2023.
[41] D. B. Magar, M. S. Desai, S. G. Chaudhari, S. R. Chinchkhedkar, N. V. Sawadekar, and K. R. Dachawar, "Integration of Smart Materials in Additive Manufacturing: Technological Challenges, Emerging Opportunities, and Future Prospects," *AIP Conference Proceedings*, vol. 3385, no. 1, p. 040006, 2026, doi: 10.1063/5.0316372.
[42] A. V. Wadagale, N. Hange, B. V. Ukarande, and D. B. Magar, "Prediction of Corona Lockdowns Using a Semi-Markov Poisson-Weibull-Wiener Framework (SILENT-COVID Model)," *Utilitas Mathematica*, vol. 122, no. 2, pp. 2583–2601, 2025.

