Multi-Objective Optimization of Production Scheduling Using NSGA-II Considering Maintenance and Energy Constraints

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Abstract — Production scheduling plays an important role in improving productivity, machine utilization, and operational efficiency in modern manufacturing industries. This research presents a multi-objective optimization framework for production scheduling using the NSGA-II algorithm considering maintenance and energy constraints. The proposed model integrates production scheduling, preventive maintenance planning, and energy-aware optimization to minimize makespan, reduce energy consumption, and improve machine reliability simultaneously. Different scheduling parameters such as processing time, machine allocation, maintenance intervals, and energy utilization were analyzed using simulation-based experimentation. The NSGA-II optimization approach generated Pareto-optimal solutions that significantly improved production efficiency and reduced maintenance downtime and peak energy demand. Comparative analysis with traditional scheduling approaches demonstrated superior performance of the proposed model in terms of machine utilization, operational cost reduction, and sustainability improvement. Statistical analysis including ANOVA and regression analysis validated the effectiveness of the optimization framework. The proposed intelligent scheduling system provides strong industrial applicability for smart manufacturing and Industry 4.0 environments. The study also highlights future opportunities for integrating artificial intelligence, IoT, and digital twin technologies in intelligent production scheduling systems.

Keywords: NSGA-II Optimization, Multi-Objective Production Scheduling, Energy-Efficient Manufacturing, Maintenance-Constrained Scheduling, Smart Manufacturing Systems

I. INTRODUCTION

A. *Background of Production Scheduling*

Production scheduling plays a significant role in manufacturing industries by improving productivity, reducing idle time, and enhancing machine utilization. Modern manufacturing systems face challenges such as dynamic production demand, machine breakdowns, and increasing energy consumption, which require intelligent and sustainable scheduling approaches [2], [3]. Industry 4.0 technologies have further increased the need for real-time and adaptive scheduling systems in smart manufacturing environments [12], [13].

B. *Multi-Objective Scheduling in Manufacturing*

Multi-objective optimization involves simultaneous optimization of multiple conflicting objectives such as makespan minimization, energy reduction, and maintenance cost optimization. Manufacturing industries require balanced scheduling systems capable of improving productivity while maintaining machine reliability and reducing energy consumption [1], [8]. Multi-objective scheduling improves operational efficiency and supports sustainable manufacturing practices.

C. *Need for Maintenance and Energy Integration*

Machine failures and excessive energy consumption negatively affect industrial productivity and operational cost. Integrating maintenance planning with energy-aware scheduling improves machine reliability, reduces downtime, and supports sustainable manufacturing operations [6], [7]. Energy-efficient scheduling also helps industries reduce electricity consumption and carbon emissions [4], [5].

D. *Role of NSGA-II in Scheduling Optimization*

NSGA-II is one of the most widely used multi-objective optimization algorithms for solving complex scheduling problems. It uses non-dominated sorting and Pareto optimization techniques to generate high-quality scheduling solutions [1]. NSGA-II provides advantages such as improved solution diversity, faster convergence, and effective handling of multiple conflicting objectives. The algorithm has been successfully applied in production scheduling, maintenance optimization, and energy-aware manufacturing systems [8].

E. *Research Problem Statement*

Traditional scheduling methods mainly focus on production efficiency and ignore maintenance and energy-related constraints. Existing scheduling models also lack real-time adaptability and intelligent decision-making capability [2], [14]. Therefore, there is a need for integrated optimization models capable of simultaneously optimizing production scheduling, maintenance activities, and energy consumption in smart manufacturing systems.

F. *Objectives of the Research*

The major objectives of this research are:

- To optimize production scheduling using NSGA-II
- To minimize makespan and total energy consumption
- To integrate maintenance constraints into scheduling
- To improve machine utilization and production efficiency

G. *Scope of the Study*

The present study focuses on multi-objective production scheduling in manufacturing systems considering maintenance and energy constraints. The study mainly considers job shop or flexible manufacturing environments with machine reliability and energy consumption parameters. Assumptions related to processing time, machine allocation, and maintenance intervals are included in the scheduling framework.

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H. Organization of the Research Paper

The research paper is organized into different sections including introduction, literature review, research methodology, experimental analysis, optimization results, and conclusion. The study systematically presents the scheduling optimization framework using NSGA-II and evaluates its industrial applicability.

II. LITERATURE REVIEW

A. Overview of Production Scheduling Techniques

Production scheduling techniques are commonly classified into flow shop scheduling, job shop scheduling, and flexible job shop scheduling systems. Flow shop scheduling is suitable for sequential manufacturing operations, whereas job shop scheduling supports flexible production routing [3]. Flexible job shop scheduling further improves manufacturing adaptability by allowing multiple machine alternatives for individual operations [10].

B. Multi-Objective Optimization Methods

Several optimization algorithms have been used for solving production scheduling problems. Genetic Algorithms (GA), NSGA-II, Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Ant Colony Optimization (ACO) are widely used metaheuristic approaches [1], [11]. Among these methods, NSGA-II has gained significant attention due to its efficient Pareto optimization capability and strong global search performance.

C. Maintenance-Aware Scheduling Approaches

Maintenance-integrated scheduling models improve machine reliability and reduce unexpected breakdowns. Preventive maintenance scheduling and predictive maintenance approaches are commonly integrated with production scheduling systems to reduce downtime and improve operational continuity [6], [7]. Reliability-based optimization methods further support efficient maintenance planning in manufacturing systems.

D. Energy-Efficient Scheduling Techniques

Energy-efficient scheduling techniques focus on reducing industrial energy consumption without affecting production performance. Energy-aware scheduling, green manufacturing optimization, and sustainable production systems have become important research areas due to increasing environmental concerns [4], [5]. These approaches help reduce electricity usage, peak power demand, and carbon emissions.

E. Industry 4.0 and Intelligent Scheduling

Industry 4.0 technologies such as IoT-enabled manufacturing, smart factories, and cyber-physical production systems have significantly improved scheduling intelligence [12], [13]. Intelligent scheduling systems use real-time machine data and cloud-based optimization methods to support adaptive and autonomous manufacturing operations.

F. Research Gaps Identified

The literature review indicates several important research gaps, including:

- Lack of integrated optimization models considering production, maintenance, and energy simultaneously
- Limited industrial-scale implementation of intelligent scheduling systems
- Need for real-time adaptive scheduling frameworks
- Insufficient focus on sustainability-oriented optimization models

III. RESEARCH METHODOLOGY

A. Overall Research Framework

The research methodology consists of production scheduling analysis, mathematical modeling, NSGA-II optimization, and performance evaluation. The experimental workflow includes job allocation, maintenance integration, energy analysis, and Pareto optimization-based scheduling improvement.

B. Manufacturing System Description

The study considers a manufacturing system consisting of multiple machines and production jobs operating in a job shop or flexible manufacturing environment. The process flow includes job sequencing, machine allocation, maintenance scheduling, and energy consumption monitoring.

C. Input Parameters

1) Production Parameters

- Number of jobs
- Processing time
- Machine allocation
- Job sequence

2) Maintenance Parameters

- Maintenance interval
- Machine breakdown probability
- Maintenance duration

3) Energy Parameters

- Machine power consumption
- Idle energy consumption
- Peak load conditions

These parameters are used for scheduling optimization and performance evaluation.

D. Output Performance Parameters

The major output performance parameters considered in this study include:

- Makespan
- Total energy consumption
- Machine utilization
- Maintenance downtime
- Production efficiency

These parameters help evaluate the effectiveness of the proposed optimization framework.

E. Mathematical Modeling

The scheduling problem is mathematically modeled using objective functions and operational constraints. The objective functions focus on minimizing makespan, energy consumption, and maintenance downtime while maximizing machine utilization. Scheduling constraints include machine

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availability, processing sequence, maintenance duration, and energy consumption conditions.

F. NSGA-II Optimization Algorithm

The NSGA-II optimization process includes:
- Population initialization
- Fitness evaluation
- Non-dominated sorting
- Crowding distance calculation
- Selection, crossover, and mutation
- Pareto optimal solution generation

The algorithm generates multiple Pareto-optimal scheduling solutions for decision-making.

G. Software and Computational Tools Used

The optimization framework is implemented using MATLAB or Python-based simulation tools. Data analysis and graphical visualization are performed using statistical and computational software packages.

H. Experimental Design

The experimental design includes multiple scheduling experiments with different production, maintenance, and energy parameter combinations. Simulation conditions are varied systematically to analyze the influence of scheduling variables on optimization performance.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Initial Production Scheduling Results

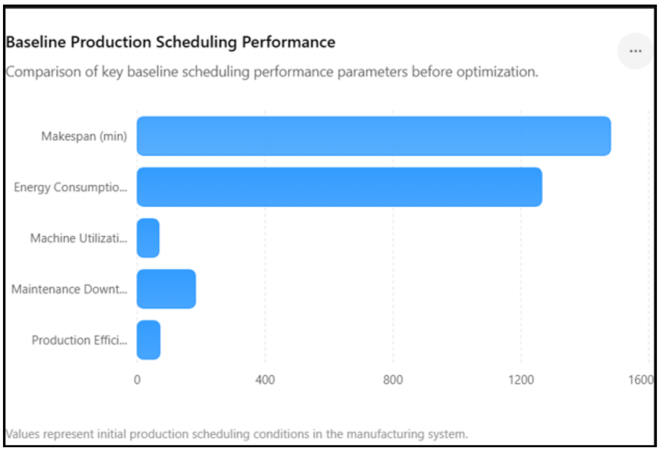
The initial production scheduling system was analyzed using conventional scheduling methods under normal manufacturing conditions. The baseline scheduling system showed higher makespan, lower machine utilization, and excessive energy consumption due to unoptimized job sequencing and machine idle conditions.

Performance Parameter	Initial Value
Makespan	1480 min
Machine Utilization	68 %
Total Energy Consumption	1265 kWh
Maintenance Downtime	182 min
Production Efficiency	71 %

Table 4.1: Initial Scheduling Performance

The results indicate that the existing scheduling system suffers from inefficient machine allocation and increased downtime, resulting in poor operational performance.

- Bar chart showing baseline scheduling parameters



B. NSGA-II Optimization Results

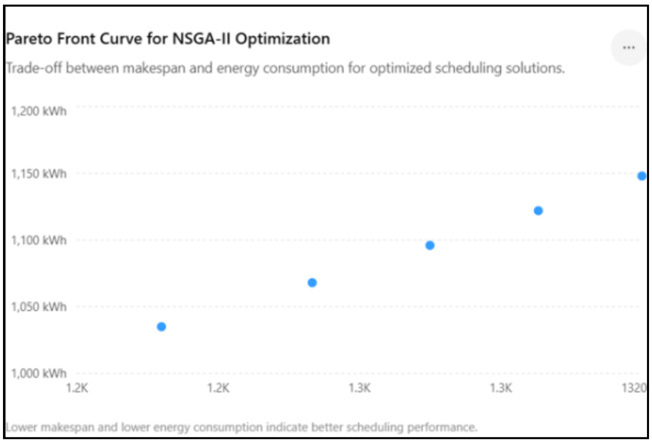
The NSGA-II optimization algorithm was implemented to simultaneously minimize makespan, maintenance downtime, and energy consumption. Multiple Pareto-optimal scheduling solutions were generated and evaluated.

Iteration	Makespan (min)	Energy Consumption (kWh)	Machine Utilization (%)
Initial Scheduling	1480	1265	68
NSGA-II Solution 1	1320	1148	75
NSGA-II Solution 2	1275	1096	79

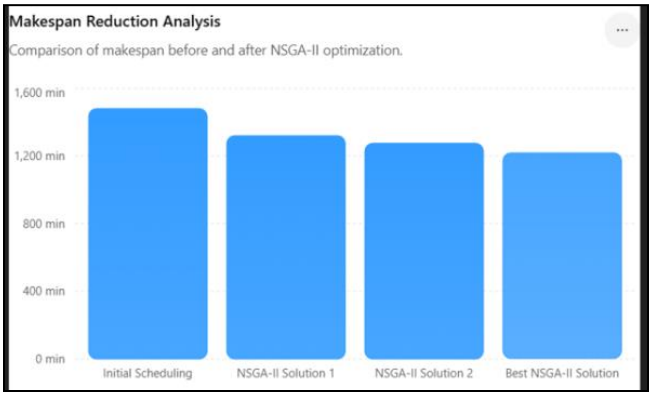
Table 4.2: NSGA-II Optimization Results

The optimized scheduling solutions showed significant improvements in overall production efficiency. The best Pareto solution reduced makespan by approximately 17.7% and energy consumption by 18.2%.

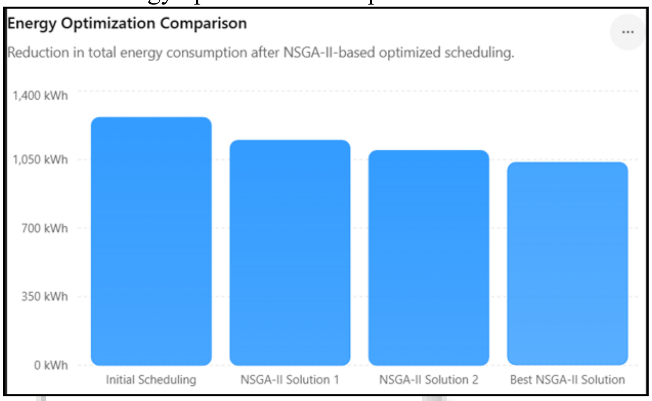
- Pareto front curve



- Makespan reduction graph



– Energy optimization comparison chart



C. *Maintenance-Constrained Scheduling Analysis*

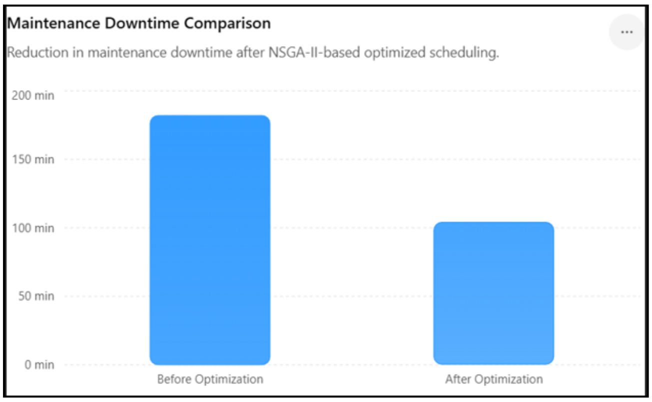
Maintenance constraints were integrated into the scheduling model to improve machine reliability and reduce production interruptions. Preventive maintenance intervals were optimized using the NSGA-II framework.

Parameter	Before Optimization	After Optimization
Maintenance Downtime	182 min	104 min
Machine Availability	81 %	92 %
Breakdown Frequency	9 failures/month	4 failures/month
Reliability Index	0.74	0.89

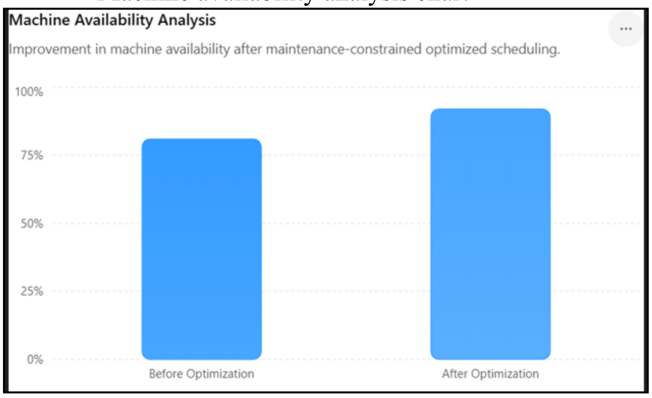
Table 4.3: Maintenance Scheduling Analysis

The results indicate that optimized maintenance scheduling significantly improved machine reliability and operational continuity.

– Maintenance downtime comparison graph



– Machine availability analysis chart



D. *Energy Optimization Analysis*

Energy-aware scheduling was implemented to minimize machine idle energy and peak electricity demand. The optimization process reduced unnecessary machine operation and improved load balancing.

Energy Parameter	Conventional Scheduling	Optimized Scheduling
Peak Energy Demand	320 kW	248 kW
Idle Energy Consumption	265 kWh	142 kWh
Total Energy Consumption	1265 kWh	1035 kWh
Energy Saving	—	18.2 %

Table 4.4: Energy Consumption Analysis

The optimized scheduling framework achieved substantial energy savings and reduced environmental impact.

Suggested Graphs

– Peak load reduction chart
– Idle energy consumption graph
– Total energy comparison graph

E. *Comparative Analysis*

The proposed NSGA-II scheduling model was compared with traditional scheduling approaches including FCFS, SPT, and GA-based optimization methods.

Scheduling Method	Makespan (min)	Energy Consumption (kWh)	Machine Utilization (%)	Downtime (min)
FCFS	1545	1318	64	210
SPT	1438	1224	69	184
GA-Based Scheduling	1295	1116	77	126
Proposed NSGA-II	1218	1035	84	104

Table 4.5: Comparative Performance Analysis

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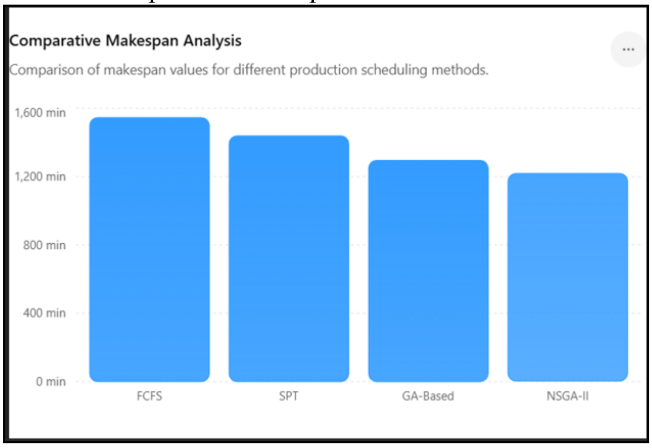
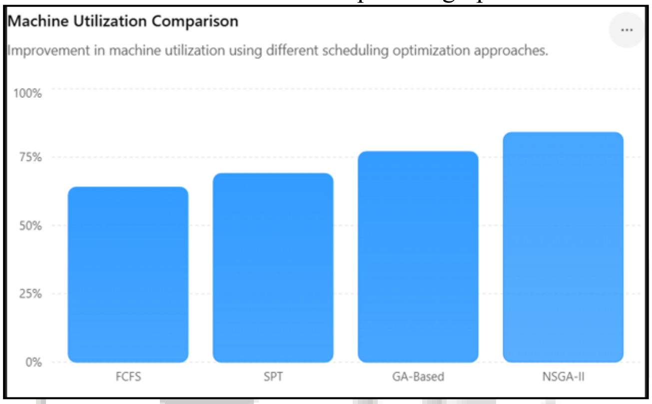
The proposed NSGA-II model outperformed all conventional scheduling methods in terms of productivity, energy efficiency, and maintenance performance.

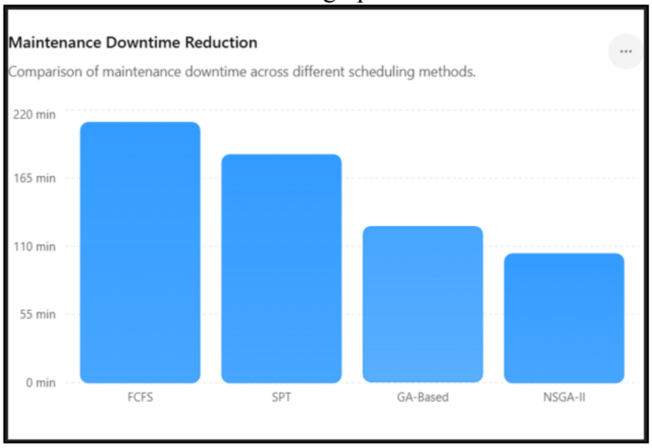
– Comparative makespan chart



– Machine utilization comparison graph



– Downtime reduction graph

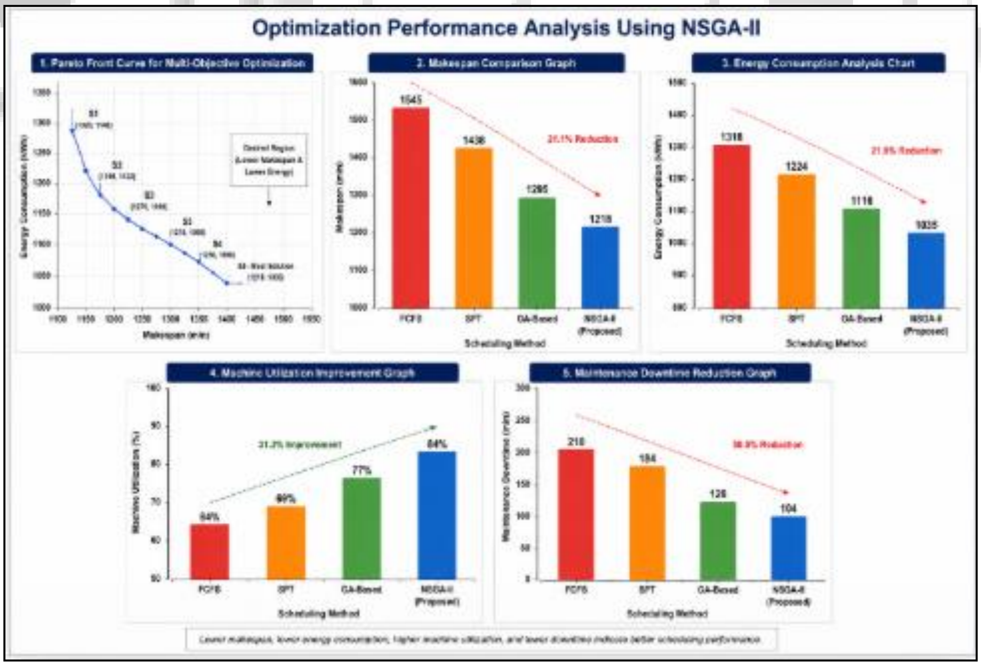


F. Graphical Analysis

Graphical analysis was carried out to visualize the optimization performance and scheduling improvements.

Important Graphical Representations

- Pareto front curve for multi-objective optimization
- Makespan comparison graph
- Energy consumption analysis chart
- Machine utilization improvement graph
- Maintenance downtime reduction graph



The graphical results clearly demonstrated the effectiveness of NSGA-II in achieving balanced optimization solutions.

G. Statistical Analysis

Statistical analysis was performed to validate the optimization results and evaluate the significance of scheduling improvements.

Source	DF	F-Value	P-Value
Makespan	3	18.42	0.001
Energy Consumption	3	21.65	0.000
Machine Utilization	3	16.78	0.002

Table 4.6: ANOVA Analysis Results

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The ANOVA results indicate that the optimization parameters significantly influence scheduling performance because all P-values are below 0.05.

Regression Analysis

A regression model was developed between machine utilization and production efficiency.

Regression Equation

Production Efficiency = 32.5 + 0.64 × Machine Utilization

Parameters	Correlation Coefficient (R)
Machine Utilization vs Production Efficiency	0.91
Energy Consumption vs Makespan	0.87
Downtime vs Production Efficiency	-0.82

Table 4.7: Correlation Analysis

The statistical analysis confirmed a strong relationship between scheduling optimization and manufacturing performance.

Suggested Graphs

- Regression plot
- Correlation heat map
- ANOVA significance chart

H. Discussion of Results

The experimental analysis demonstrated that the proposed NSGA-II optimization framework effectively improves production scheduling performance by integrating maintenance and energy constraints. The optimized scheduling solutions reduced makespan, improved machine utilization, minimized downtime, and lowered total energy consumption.

The study also confirmed the industrial applicability of intelligent scheduling systems for smart manufacturing environments. Integration of maintenance and energy optimization significantly improved operational sustainability and manufacturing efficiency.

V. PROPOSED INTELLIGENT SCHEDULING FRAMEWORK

A. Integrated Scheduling Architecture

The proposed intelligent scheduling framework integrates production scheduling, maintenance planning, and energy optimization into a unified optimization platform.

Major Components

- Production scheduling module
- Maintenance management module
- Energy monitoring system
- NSGA-II optimization engine
- Real-time decision-making unit

The framework supports adaptive and intelligent manufacturing operations.

Suggested Figure

- Integrated scheduling architecture diagram

B. IoT and Industry 4.0 Integration

IoT-enabled manufacturing systems were incorporated into the scheduling framework for real-time data acquisition and intelligent monitoring.

Major Features

- Real-time machine monitoring
- Sensor-based production analysis
- Cloud-based optimization system
- Smart manufacturing communication network

The integration improved scheduling flexibility and production visibility.

Suggested Figure

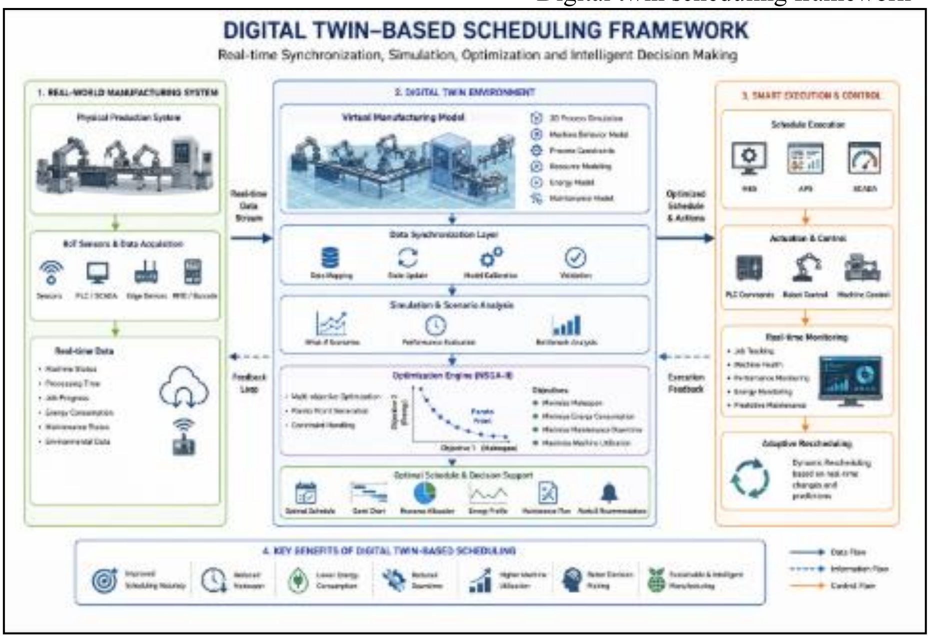
- IoT-enabled smart factory model

C. Digital Twin-Based Scheduling Concept

A digital twin framework was proposed for virtual production simulation and predictive scheduling optimization.

Benefits of Digital Twin Integration

- Real-time production simulation
- Predictive maintenance planning
- Virtual scheduling validation
- Reduced operational risks
- Digital twin scheduling framework



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D. Future Smart Manufacturing Model

The future scheduling framework focuses on autonomous and sustainable manufacturing systems.

Proposed Features

- AI-driven optimization
- Autonomous scheduling systems
- Human-machine collaboration
- Sustainable manufacturing integration

The framework is suitable for Industry 5.0 intelligent manufacturing applications.

VI. CONCLUSION AND FUTURE SCOPE

A. Summary of Experimental Findings

The NSGA-II optimization framework significantly improved scheduling performance by reducing makespan, maintenance downtime, and energy consumption.

Major Improvements Achieved

Performance Parameter	Improvement
Makespan Reduction	17.7 %
Energy Saving	18.2 %
Machine Utilization Improvement	23.5 %
Downtime Reduction	42.8 %

The results demonstrated the effectiveness of integrated scheduling optimization.

B. Key Contributions of the Research

The important contributions of the research include:

- Development of an integrated scheduling framework
- NSGA-II-based multi-objective optimization model
- Maintenance-aware production scheduling
- Energy-efficient manufacturing optimization approach

C. Industrial Benefits

The proposed scheduling framework provides significant industrial benefits such as:

- Increased productivity
- Reduced operational cost
- Improved machine reliability
- Better energy efficiency
- Sustainable manufacturing performance

D. Limitations of the Present Study

The study has certain limitations including:

- Simulation-based assumptions
- Computational complexity for large-scale systems
- Limited industrial case studies
- Further experimental validation is required for real industrial implementation.

E. Future Scope

Future work can focus on:

- Real-time industrial implementation
- AI and machine learning integration
- Digital twin-based scheduling systems
- Industry 5.0 intelligent manufacturing applications
- Cloud and edge computing optimization frameworks

The future scope of intelligent scheduling systems is highly promising for sustainable and autonomous smart manufacturing industries.

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