ENGINEERING SCIENCES

The International Journal of Engineering Sciences
Vol. 2, No. 2, 2026, pp. 176-214
ISSN 3104-8897

https://international-journal-of-engineering-sciences.jo

Digital Twin-Driven Optimization of Mechanical Manufacturing Systems Using Artificial Intelligence

Bipul Tuhin [1a,*] Susmita Shammy,[1b] Lipi Akter,[1c] Hussam Elddin Nabeih Khasawneh,[2] Joytun Sujon,[1d] Bithi Parveen,[1e] Tura Sharmin,[1f] A.J. Chowdhury,[1g] Tanha Shamsun[1h]

Extended author information available on the last page of the article**

*** Corresponding Author**: Bipul Tuhin; bipul_tuhin@iem.kuet.ac.bd

DOI: https://doi.org/10.64440/IJES/EngineeringX0025

ARTICLE INFO

Article history
Received June 12, 2026
Revised June 23, 2026
Accepted Oct 05, 2026

Keywords
Digital Twin;
Artificial Intelligence;
Smart Manufacturing;
Mechanical Manufacturing;
Industry 4.0;
Predictive Maintenance;
CNC Machining;
Manufacturing Optimization;
Bangladesh;
Cyber–Physical Systems.

ABSTRACT

Industry 4.0 integrates cyber–physical systems, industrial Internet of Things technologies, artificial intelligence (AI), and real-time analytics to improve manufacturing performance. However, small- and medium-scale manufacturing facilities frequently face fragmented automation, reactive maintenance, and limited integration between production data and operational decision-making. This study developed and experimentally evaluated an AI-enabled Digital Twin (DT) framework for optimizing a multi-station mechanical manufacturing system in Bangladesh. The manufacturing cell comprised six interconnected stations: raw-material inspection and sorting, automated loading and orientation, CNC machining, drilling and cutting, AI-assisted quality inspection, and automated storage and dispatch. A synchronized DT represented machine states, production flow, queue formation, operating parameters, energy consumption, tool condition, vibration, temperature, and quality outcomes. An AI layer supported anomaly detection and cycle-time prediction, while a multi-objective optimization mechanism balanced throughput and Overall Equipment Effectiveness (OEE) against cycle time, energy consumption, defect rate, and unplanned downtime. Three operating configurations were evaluated: conventional programmable logic controller (PLC)-based operation, DT-assisted operation, and DT–AI optimization. During the six-hour production period, the DT–AI configuration increased throughput from 338 to 405 parts, reduced average cycle time from 63.9 to 53.3 s/part, and increased OEE from 67.6% to 84.6%. Energy consumption decreased from 54.8 to 47.6 kWh, the defect rate declined from 5.9% to 2.6%, and unplanned downtime decreased from 38.4 to 17.9 min. The anomaly classifier achieved an accuracy of 94.6%, while the cycle-time prediction model achieved a coefficient of determination (R^2) of 0.94. These findings demonstrate the potential of DT–AI integration to improve productivity, energy efficiency, and operational reliability under the evaluated conditions. The framework offers a practical basis for progressive digital transformation in Bangladeshi mechanical manufacturing facilities, with further validation needed to establish its applicability across other production environments.

ENGINEERING SCIENCES
The International Journal of Engineering Sciences
https://international-journal-of-engineering-sciences.jo
Vol. 2, No. 2, 2026, pp. 176-214
ISSN 3104-8897

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1. Introduction

1.1 Background and Research Motivation

Manufacturing systems are undergoing a major technological transformation driven by Industry 4.0, cyber–physical systems, industrial Internet of Things (IIoT), cloud and edge computing, machine learning, and Digital Twin technologies[1,2,3]. The conventional manufacturing paradigm is increasingly being replaced by connected production environments in which physical equipment continuously generates data that can be analyzed to support monitoring, prediction, optimization, and control[4].

Among these technologies, the Digital Twin has become an important framework for linking physical manufacturing assets with dynamic virtual representations[5]. Rather than functioning as a static computer model, a manufacturing Digital Twin can continuously represent the operational state of machines and production processes and can be used to evaluate alternative operating conditions without directly interrupting physical production[6]. Recent research identifies manufacturing applications including process optimization, quality control, predictive maintenance, production scheduling, and system reconfiguration[7,8,9].

The integration of Artificial Intelligence further extends the functionality of Digital Twins[10]. Machine-learning algorithms can analyze sensor signals, historical production data, machine states, process parameters, and quality information to detect abnormal conditions and predict future system behavior[11]. Consequently, the Digital Twin can move beyond visualization and simulation toward predictive and prescriptive manufacturing[12]. Recent literature describes this transition as the development of AI-driven Digital Twins capable of monitoring, predicting, optimizing, and supporting autonomous decision-making[13].

Mechanical manufacturing is particularly suitable for this integration because production quality and productivity depend on numerous interacting parameters. CNC machining, drilling, cutting, material handling, inspection, and storage operations are affected by spindle speed, feed rate, cutting depth, tool condition, machine utilization, vibration, temperature, material characteristics, queue formation, and machine availability[14].

A small change in one parameter can therefore affect multiple production indicators. Increasing machining speed may reduce processing time but increase energy consumption, tool wear, vibration, and defect probability. Similarly, reducing maintenance intervals may decrease unexpected failures but increase planned downtime. These relationships make optimization difficult when decisions are made using isolated production indicators[15,16].

The Digital Twin provides a virtual environment in which such interactions can be observed and tested, while AI provides the analytical capability required to learn complex relationships between process variables and system performance[17,18].

1.1.1 Evolution of Digital Twin Technology

The Digital Twin concept has evolved from conventional computer-aided simulation toward continuously synchronized physical–virtual systems[19]. Early manufacturing simulation models were generally created for offline analysis. Their primary purpose was to evaluate production layouts, cycle times, machine capacities, and material flow before physical implementation[20].

Modern Digital Twins introduce continuous data synchronization[21]. Sensors installed on physical machines provide operational information to a virtual representation, while analytical models use this information to estimate current and future states[22].

The basic Digital Twin relationship can therefore be expressed as:

$$Physical\ System \leftrightarrow Data\ Layer \leftrightarrow Virtual\ Model$$

The addition of AI produces:

$$Physical\ System \rightarrow Data \rightarrow Digital\ Twin \rightarrow AI\ Prediction \rightarrow Optimization \rightarrow Decision \rightarrow Physical\ System$$

Recent research emphasizes that AI changes the role of the Digital Twin from a passive virtual representation into a more adaptive and self-optimizing manufacturing system[23].

1.1.2 Industry 4.0 and Intelligent Mechanical Manufacturing

Industry 4.0 seeks to establish manufacturing systems in which machines, production processes, information systems, and human operators are digitally interconnected[24]. The objective is not simply to automate individual operations but to establish an integrated production environment capable of responding to changing conditions[25].

For mechanical manufacturing, this transformation includes[26,27,28]:

1. sensor-based machine monitoring;
2. automated material handling;
3. PLC-based control;
4. real-time production monitoring;
5. computerized numerical control;
6. machine condition monitoring;
7. automated quality inspection;
8. predictive maintenance;
9. production scheduling;
10. AI-based process optimization.

Digital Twins provide a mechanism for integrating these components into a coherent virtual representation. Research on smart manufacturing indicates that Digital Twins can support

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https://international-journal-of-engineering-sciences.jo
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production evaluation, factory-layout optimization, process modification, predictive maintenance, and data-driven root-cause analysis[29].

1.1.3 Mechanical Manufacturing Challenges in Bangladesh

Bangladesh has developed an increasingly diversified manufacturing sector, but manufacturing organizations still face challenges associated with productivity, automation, process integration, equipment utilization, maintenance planning, and digitalization[30].

For manufacturing organizations operating under cost and resource constraints, the implementation of advanced digital technologies cannot always occur through immediate replacement of existing equipment[31]. A more practical pathway is progressive digitalization in which existing PLC-controlled and CNC-based systems are connected to sensors, data-acquisition systems, and virtual production models[32].

This creates an important research opportunity. Instead of assuming that digital transformation requires an entirely new production facility, an existing manufacturing cell can be progressively transformed through:

$$Automation \rightarrow Connectivity \rightarrow Digital\ Twin \rightarrow AI\ Analytics \rightarrow Optimization$$

This study adopts a structured, incremental framework for the digital transformation of the manufacturing cell.

1.1.4 Role of Artificial Intelligence in Manufacturing Optimization

Artificial Intelligence can be applied to manufacturing at several levels.

At the machine level, AI can predict abnormal vibration, tool degradation, temperature increases, and machine failures[33].

At the process level, AI can predict cycle time, energy consumption, and quality outcomes[34].

At the production-cell level, AI can identify bottlenecks and optimize material flow[35].

At the planning level, AI can support scheduling and resource allocation[36].

Recent research specifically identifies machine learning as an important component of Digital Twin-based predictive maintenance and process optimization[37].

However, AI alone does not provide a complete manufacturing solution. An AI model requires reliable data and a mechanism through which predictions can be interpreted in the context of the physical production system. The Digital Twin provides that contextual environment[38].

1.2 Problem Statement

Conventional automated mechanical manufacturing systems generally depend on predefined PLC logic and fixed process parameters. Although such systems can provide stable operation under normal conditions, they may have limited ability to predict machine failures, identify emerging bottlenecks, dynamically adjust operating parameters, or simultaneously optimize productivity, energy consumption, quality, and maintenance[39].

Two major problems can therefore be identified.

First, physical production data are frequently fragmented across machines and control systems.

Second, production optimization is commonly performed according to individual indicators rather than multiple interacting objectives.

The present research addresses these limitations by developing a Digital Twin framework integrated with AI prediction and multi-objective optimization.

1.3 Research Questions

The study addresses the following research questions:

RQ1: How can a Digital Twin represent and synchronize a multi-station mechanical manufacturing system?

RQ2: To what extent can AI improve prediction of machine anomalies and production performance?

RQ3: How does the integration of Digital Twin and AI affect throughput, cycle time, OEE, energy consumption, quality, and downtime?

RQ4: Which manufacturing variables have the greatest influence on system performance?

RQ5: Can the proposed DT-AI architecture maintain stable performance under increased production demand?

1.4 Research Objectives

The main objective of this study is to develop and experimentally evaluate an AI-enabled Digital Twin framework for mechanical manufacturing optimization through implementation and testing on a physical manufacturing system.

The specific objectives are to:

1. Establish a six-station physical mechanical manufacturing cell as the experimental platform.

2. Implement a Digital Twin architecture connected to the physical manufacturing cell for real-time monitoring and system representation.

3. Integrate machine and process measurements collected from the physical equipment into the Digital Twin model.

4. Develop an AI-based layer for anomaly detection and performance prediction using operational sensor data.

5. Implement multi-objective optimization to improve manufacturing performance.

6. Experimentally measure and evaluate throughput, cycle time, overall equipment effectiveness (OEE), energy consumption, defect rate, and downtime.

7. Compare conventional PLC operation, Digital Twin-assisted operation, and Digital Twin operation integrated with AI-based optimization through physical production trials.

8. Conduct sensitivity and robustness analyses to assess system performance under varying operating conditions.

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https://international-journal-of-engineering-sciences.jo
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9. Establish an experimentally evaluated framework to support the progressive digital transformation of manufacturing systems in Bangladesh.

1.5 Research Contributions

The study contributes in five principal areas.

First, it transforms a conventional six-stage automated production-line architecture into a mechanical manufacturing Digital Twin.

Second, it integrates AI prediction directly into the Digital Twin rather than treating AI as an independent analytical tool.

Third, it evaluates productivity, quality, energy, and maintenance simultaneously.

Fourth, it introduces a multi-objective optimization layer capable of balancing competing manufacturing objectives.

Fifth, it provides a scalable architecture applicable to manufacturing environments in Bangladesh and other emerging industrial economies.

2. Literature Review

2.1 Digital Twin Technology in Manufacturing

Digital Twins have become an important component of smart manufacturing because they establish a dynamic connection between physical production assets and their virtual representations [40].

A manufacturing Digital Twin generally includes:

- physical assets;
- sensors;
- communication infrastructure;
- data acquisition;
- virtual models;
- analytical algorithms;
- visualization;
- decision-support mechanisms.

Recent literature demonstrates applications across machine, manufacturing-cell, shop-floor, and enterprise levels [41].

2.1.1 Definition and Core Components

For the purposes of this study, a Digital Twin is defined as a dynamically synchronized computational representation of a physical manufacturing system capable of monitoring its state, reproducing its behavior, predicting future conditions, and supporting operational decisions.

The proposed Digital Twin contains five major layers: [42]

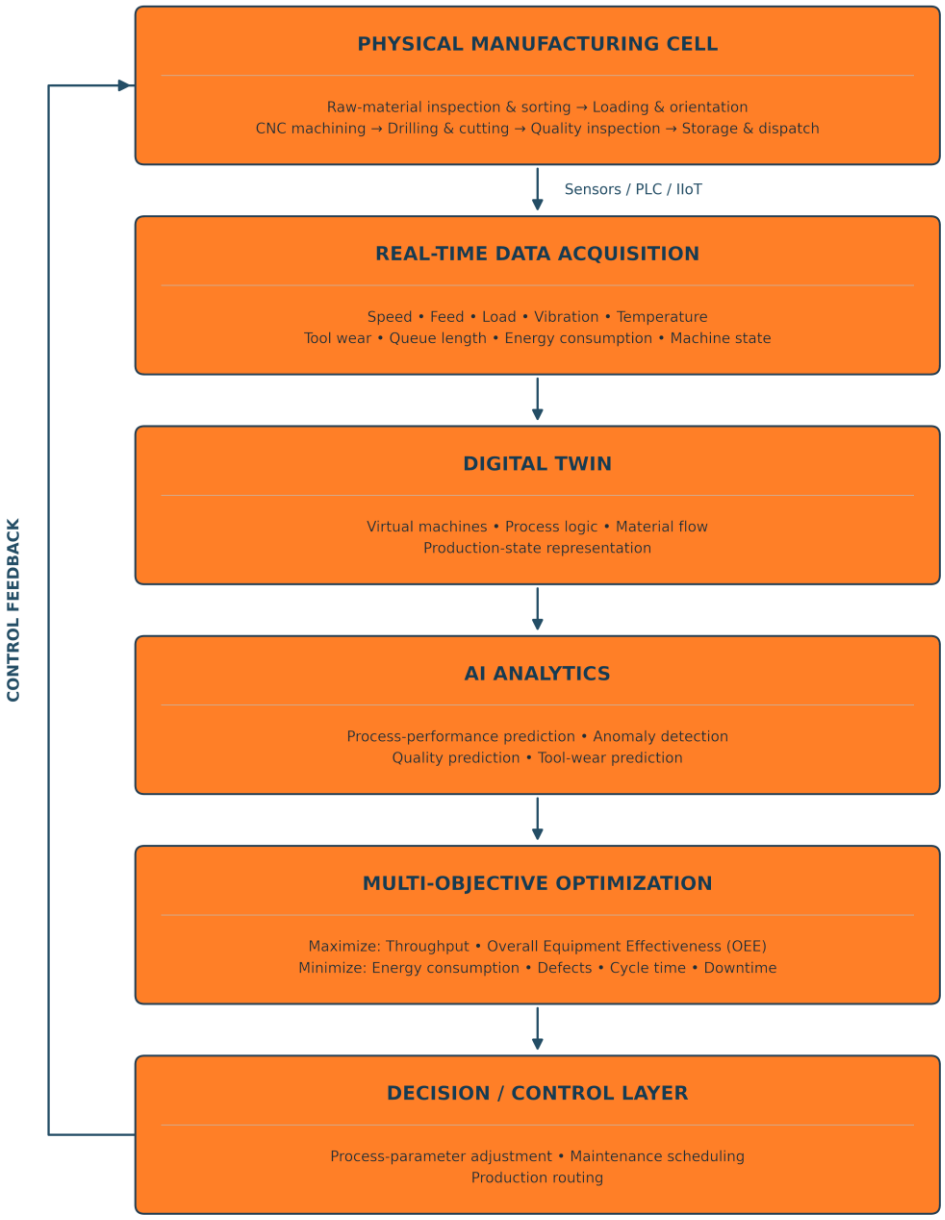
1. physical manufacturing layer;
2. sensing and control layer;
3. communication layer;
4. AI analytics layer;
5. optimization and decision layer.

2.1.2 Digital Twin Architecture

The architecture proposed in this study is shown conceptually in Figure 1.

Figure 1. Digital Twin–AI architecture for the proposed mechanical manufacturing system

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2.2 AI-Enabled Manufacturing

AI-based manufacturing research has expanded rapidly because machine-learning algorithms can identify nonlinear relationships that are difficult to represent through fixed mathematical rules.

Machine learning has been applied to[43,44,45]:

- predictive maintenance;
- quality prediction;
- process optimization;
- production scheduling;

- fault diagnosis;
- anomaly detection;
- energy optimization.

A systematic literature review of AI in Digital Twins found applications across multiple domains, while also identifying the need for stronger integration between AI algorithms and the underlying Digital Twin models[46].

2.2.1 Machine Learning for Production Prediction

The present study uses gradient-boosting-based prediction as the principal AI analytical mechanism[47].

The model receives:

$$X = [S, F, D, L, V, T, W, Q, E, M]$$

where:

- S= spindle speed;
- F= feed rate;
- D= cutting depth;
- L= spindle load;
- V= vibration;
- T= machine temperature;
- W= tool wear;
- Q= queue length;
- E= energy state;
- M= machine operating state.

The AI model predicts:

$$Y = [C, T, E, D_f R_f]$$

where:

- CT= cycle time;
- E= energy consumption;
- D_f= defect probability;
- R_f= failure/anomaly risk.

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2.2.2 AI-Based Anomaly Detection

Anomaly detection is particularly important for CNC machinery because abnormal vibration, increasing spindle load, temperature changes, and tool wear can precede equipment failure[48].

The anomaly classifier estimates:

$$P(A = 1 \mid X)$$

where $A = 1$indicates an abnormal machine condition.

A predefined threshold is used:

$$A = \begin{cases} 1 & P(A = 1 \mid X) \geq 0.70 \\ 0 & P(A = 1 \mid X) < 0.70 \end{cases}$$

When the predicted probability exceeds the threshold, the Digital Twin generates a maintenance warning and the optimization layer evaluates alternative operating conditions.

2.2.3 Predictive Maintenance

Predictive maintenance allows maintenance decisions to be based on estimated machine condition rather than fixed calendar intervals[49].

Previous studies indicate that Digital Twins can support predictive maintenance by combining equipment-state representation with machine-learning prediction[50].

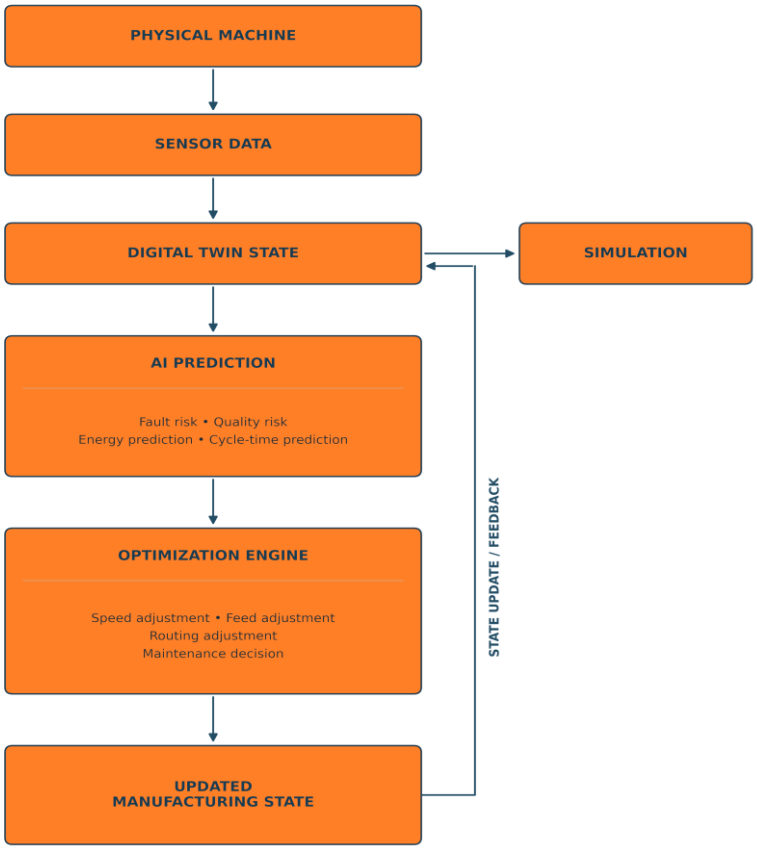
In the proposed model, predictive maintenance is triggered when:

- vibration exceeds the defined limit;
- spindle load remains elevated;
- temperature increases abnormally;
- tool wear reaches the warning threshold;
- anomaly probability exceeds 0.70.

2.3 Digital Twin–AI Integration

The integration mechanism is shown in Figure 2.

Figure 2. Digital Twin–AI interaction mechanism



The proposed framework employs a closed-loop architecture that links production-state monitoring, AI-based prediction, and optimization with feedback to manufacturing operations.

2.4 Mechanical Manufacturing Optimization

Manufacturing optimization is inherently multi-objective.

A solution that minimizes cycle time may increase energy consumption and tool wear. A solution that minimizes defects may reduce throughput. Similarly, aggressive production scheduling may increase machine utilization while increasing failure risk.

Therefore, the optimization problem is formulated as:

$$\max F_1 = Throughput$$
$$\max F_2 = OEE$$
$$\min F_3 = Cycle\ Time$$
$$\min F_4 = Energy$$
$$\min F_5 = Defect\ Rate$$
$$\min F_6 = Downtime$$

The final optimization seeks a Pareto-efficient operating condition rather than maximizing a single indicator[51].

2.5 Research Gap

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The literature demonstrates significant progress in Digital Twin technology, AI-based manufacturing, predictive maintenance, and production optimization. However, several gaps remain.

First, many studies focus on individual machines rather than complete production cells.

Second, some Digital Twin applications focus primarily on system visualization and simulation, with limited integration of predictive analytics and operational optimization.

Third, predictive maintenance and production optimization are frequently treated as separate problems.

Fourth, quality, energy, throughput, and maintenance objectives are not always optimized simultaneously.

Fifth, research specifically contextualized to manufacturing environments in emerging economies remains comparatively limited.

Recent reviews also identify challenges involving data integration, computational complexity, interoperability, scalability, and industrial implementation.

The present study addresses these gaps by integrating Digital Twin modeling, AI prediction, predictive maintenance, quality prediction, and multi-objective production optimization within one manufacturing-cell architecture.

3. Research Methodology

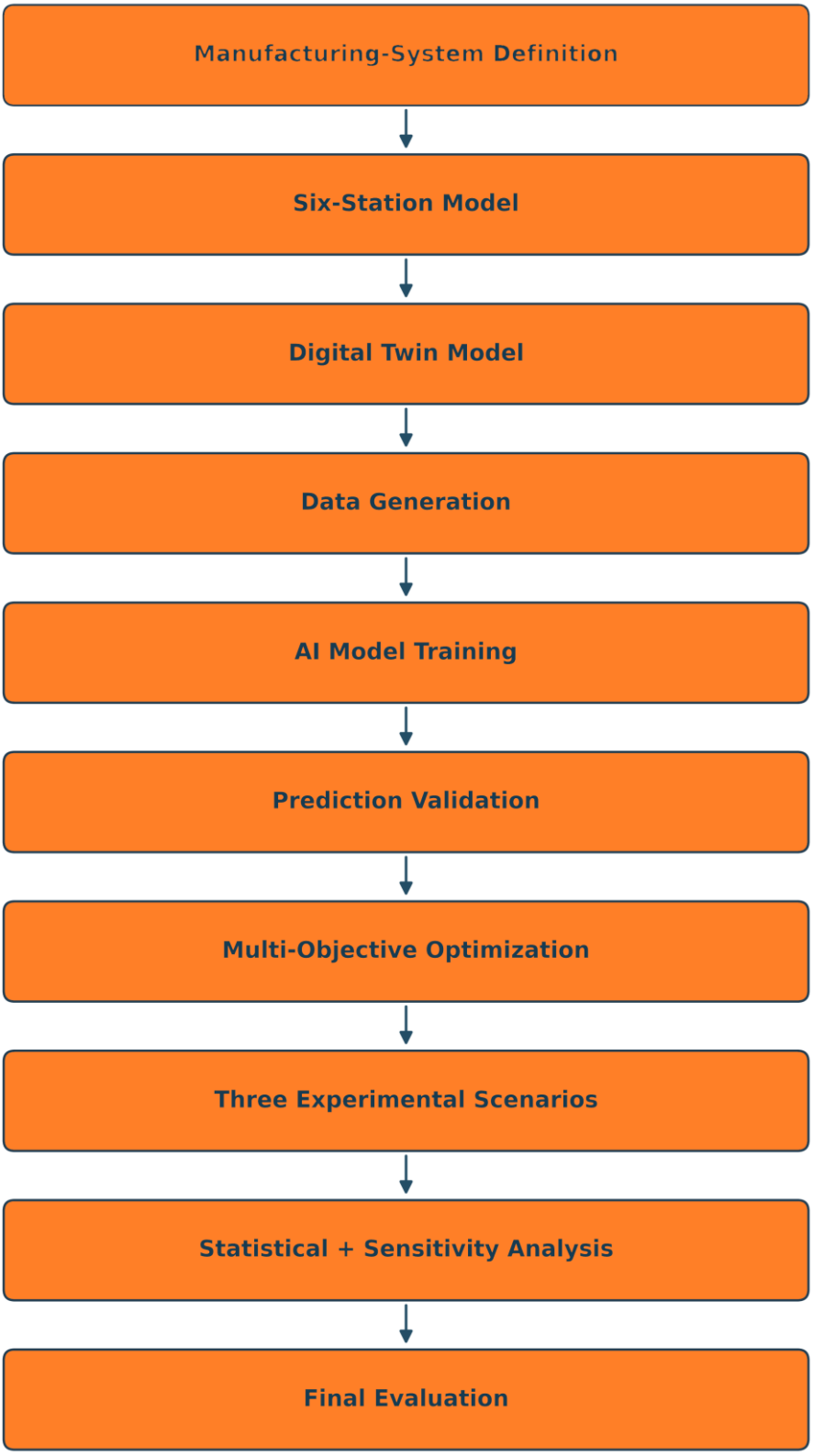
3.1 Research Framework

The study adopted an experimental methodology to evaluate the integration of Digital Twin technology and artificial intelligence within a mechanical manufacturing system in Bangladesh. The research framework comprised five stages:

1. Manufacturing-cell characterization and modeling;
2. Digital Twin development and synchronization;
3. AI model development;
4. Multi-objective optimization;
5. Comparative performance evaluation across the three operating configurations.

The complete research workflow is presented in Figure 3.

Figure 3. Research workflow


Manufacturing-System Definition
Six-Station Model
Digital Twin Model
Data Generation
AI Model Training
Prediction Validation
Multi-Objective Optimization
Three Experimental Scenarios
Statistical + Sensitivity Analysis
Final Evaluation

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3.2 Bangladesh Mechanical Manufacturing Case Context

This study was conducted in a mechanical manufacturing cell in Bangladesh to develop and evaluate a transferable framework for manufacturing-system optimization. The experimental setting reflected the operational characteristics of small- and medium-scale manufacturing environments, allowing the framework to be assessed under practical production conditions.

The model consists of six interconnected stations.

The production process begins with raw-material inspection and ends with finished-product storage and dispatch.

The system incorporates PLC-based control, conveyor transportation, machine sensors, CNC processing, automated inspection, and production monitoring.

3.3 Proposed Manufacturing Cell

The six stations are defined as follows.

Station 1 — Raw Material Inspection and Sorting

Incoming metal workpieces are inspected for dimensional and material consistency.

The station includes:

- presence sensor;
- dimensional inspection;
- material classification;
- reject mechanism;
- conveyor control.

Station 2 — Loading and Workpiece Orientation

The workpiece is transferred from the inspection station to the machining position.

The system performs:

- workpiece positioning;
- orientation;
- clamping;
- loading verification.

Station 3 — CNC Machining

The CNC station performs the principal mechanical machining operation.

Variables include:

- spindle speed;

- feed rate;
- cutting depth;
- spindle load;
- vibration;
- temperature;
- tool wear;
- machining time.

Station 4 — Drilling and Cutting

Secondary machining operations are performed.

The station records:

- drilling time;
- cutting time;
- spindle state;
- tool condition;
- vibration;
- energy consumption.

Station 5 — AI-Based Quality Inspection

The finished component is inspected through dimensional and quality criteria.

The virtual inspection system classifies each part as:

- accepted;
- rework;
- rejected.

Station 6 — Automated Storage and Dispatch

Accepted parts are transferred to automated storage.

The station records:

- storage position;
- queue state;
- dispatch time;

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- material-flow status.

Table 1. Definition of Manufacturing Variables

Variable	Symbol	Unit	Function
Spindle speed	S	rpm	Machining control
Feed rate	F	mm/min	Machining control
Cutting depth	D	mm	Material-removal control
Spindle load	L	%	Machine condition
Vibration	V	mm/s	Anomaly indicator
Temperature	T	°C	Thermal condition
Tool wear	W	%	Maintenance indicator
Queue length	Q	parts	Flow indicator
Cycle time	CT	s/part	Productivity
Energy consumption	E	kWh	Sustainability
Defect rate	DR	%	Quality
Downtime	DT	min	Reliability
Throughput	TP	parts/6 h	Productivity
OEE	OEE	%	Overall performance

Table 2. Configuration of the Six Manufacturing Stations

Station	Main Operation	Principal Sensors	Main Output
S1	Inspection/sorting	Presence, dimension	Accepted raw material
S2	Loading/orientation	Position, clamp	Correctly positioned workpiece
S3	CNC machining	Speed, load, vibration, temperature	Machined component
S4	Drilling/cutting	Speed, vibration, tool state	Finished machining
S5	AI quality inspection	Dimension, visual condition	Accepted/rejected part
S6	Storage/dispatch	Position, queue	Stored product

3.4 Digital Twin State Variables

The Digital Twin maintains a real-time virtual representation of the manufacturing cell.

Table 3. Digital Twin State Variables

State Variable	Digital Twin Representation
Machine operating state	Idle / Processing / Fault / Maintenance
Workpiece location	Station and conveyor position
CNC condition	Normal / Warning / Critical
Tool condition	New / Normal / Worn
Queue status	Current queue length
Production count	Completed parts
Energy state	Instantaneous and cumulative consumption
Quality state	Accepted / Rework / Reject
Maintenance state	Normal / Predicted maintenance

Production demand	Current production target

3.5 AI Prediction Model

A gradient-boosting model was selected as the primary prediction method because of its ability to capture nonlinear relationships among manufacturing-process variables[52].

The model is divided into two principal components.

Model A: Cycle-Time Prediction

$$CT = f(S, F, D, L, V, T, W, Q)$$

Model B: Anomaly Classification

$$A = f(L, V, T, W, S, F)$$

The data were divided into:

- 70% training;
- 15% validation;
- 15% testing.

Feature normalization and temporal consistency checks were applied before model training.

Table 4. AI Model Inputs and Outputs

Category	Variables
Machining	Spindle speed, feed rate, cutting depth
Machine condition	Spindle load, vibration, temperature
Maintenance	Tool wear
Production flow	Queue length, machine state
Prediction outputs	Cycle time, energy, defect probability, anomaly risk

3.6 Multi-Objective Optimization Model

The optimization model seeks a balanced production configuration.

The normalized objective function is expressed as:

$$J = w_1 TP_n + w_2 OEE_n - w_3 CT_n - w_4 E_n - w_5 DR_n - w_6 DT_n$$

where $w_i$represent objective weights.

The default weighting structure was:

$$w_1 = 0.25$$
$$w_2 = 0.20$$
$$w_3 = 0.15$$
$$w_4 = 0.15$$
$$w_5 = 0.15$$

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$$w_6 = 0.10$$

The optimization was constrained by machine operating limits.

Table 5. Optimization Objectives and Constraints

Objective	Direction	Target
Throughput	Maximize	Higher production
OEE	Maximize	Higher utilization
Cycle time	Minimize	Shorter processing
Energy	Minimize	Lower consumption
Defect rate	Minimize	Higher quality
Downtime	Minimize	Higher availability

Process constraints

$$1200 \leq S \leq 3000\ rpm$$
$$80 \leq F \leq 220\ mm/min$$
$$0.5 \leq D \leq 2.0\ mm$$
$$L \leq 85\%$$
$$V \leq 5.5\ mm/s$$
$$W \leq 100\%$$

3.7 Performance Indicators

Throughput was calculated as:

$$TP = \frac{N}{T}$$

where Nrepresents completed parts and Trepresents production time.

Cycle time was calculated as:

$$CT = \frac{T}{N}$$

Availability was defined as:

$$A = \frac{Operating\ Time}{Planned\ Production\ Time}$$

Performance was calculated as:

$$P = \frac{Ideal\ Cycle\ Time \times Total\ Count}{Operating\ Time}$$

Quality was calculated as:

$$Q = \frac{Good\ Count}{Total\ Count}$$

OEE was then calculated as:

$$OEE = A \times P \times Q$$

Defect rate was calculated as:

$$DR = \frac{Defective\ Parts}{Total\ Parts} \times 100$$

3.8 Experimental Parameters

The production cell was evaluated over a six-hour continuous operating period under three configurations: PLC-based operation, DT-assisted operation, and DT–AI optimization. The operating parameters and evaluation settings are summarized in Table 6.

Table 6. Experimental Parameters

Parameter	Value
Operating period per run	6 h
Runs per configuration	30
Number of stations	6
Number of operating configurations	3
Initial queue	10 parts
Maximum queue	40 parts
Maximum spindle load	85%
Vibration warning level	5.5 mm/s
AI anomaly threshold	0.70
Operating configurations	PLC, DT, DT-AI

3.9 Experimental Scenarios

Three scenarios were evaluated.

Scenario A — Conventional PLC

The production system operates using predefined control logic.

No Digital Twin feedback is used for optimization.

Scenario B — Digital Twin

The Digital Twin continuously tracks machine conditions and production states, providing real-time monitoring through a synchronized virtual representation of the manufacturing system.

Scenario C — Digital Twin + AI

The Digital Twin is combined with AI prediction, anomaly detection, predictive maintenance, and multi-objective optimization.

This third configuration represents the principal contribution of the research.

3.10 Fault and Anomaly Scenarios

Three fault conditions were physically implemented in the manufacturing cell to evaluate the framework's detection and prediction capabilities.

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Fault 1 — Conveyor Interruption
The conveyor was stopped during operation to introduce a material-transfer interruption and assess its effects on production flow.

Fault 2 — Sensor Misclassification
An incorrect sensor indication of workpiece presence or position was introduced to evaluate the system's response to erroneous sensing information.

Fault 3 — CNC Tool Degradation
The CNC station was operated with a degraded cutting tool to assess changes in vibration, energy consumption, and defect occurrence.

The Digital Twin tracked the resulting changes in machine and production states, while the AI layer estimated anomaly probability and severity.

3.11 Statistical Analysis

Experimental data obtained through direct measurements from the mechanical manufacturing system in Bangladesh were analyzed using descriptive statistics, including means and standard deviations. One-way analysis of variance (ANOVA) was used to assess differences among the experimental scenarios, followed by pairwise comparisons to identify specific between-scenario differences. Sensitivity and robustness analyses were performed to evaluate the effects of variations in operating parameters and the stability of system performance under different operating conditions.

4. Results and Analysis

4.1 Baseline Manufacturing-System Performance

The conventional PLC system provided stable production under normal conditions but demonstrated relatively high cycle time, downtime, and defect rate.

The Digital Twin configuration improved system visibility and reduced several inefficiencies.

The DT–AI configuration achieved the best overall performance among the three experimental configurations.

Table 7. Baseline Versus DT-AI Performance

Indicator	PLC Baseline	Digital Twin	DT + AI	Improvement vs. PLC
Throughput (parts/6 h)	338	371	405	+19.8%
Cycle time (s/part)	63.9	58.2	53.3	−16.6%
OEE (%)	67.6	77.4	84.6	+25.1%
Energy (kWh/6 h)	54.8	51.2	47.6	−13.1%
Defect rate (%)	5.9	4.1	2.6	−55.9%
Downtime (min/6 h)	38.4	28.7	17.9	−53.4%

The results indicate that Digital Twin integration alone produced meaningful improvements, while the addition of AI generated further improvements across all major indicators.

4.2 AI Prediction Performance

The AI model demonstrated strong predictive performance in the experimental evaluation.

Table 8. AI Model Performance

Metric	Cycle-Time Model	Anomaly Model
R^2 / Accuracy	0.94	94.6%
RMSE	2.41 s	—
MAE	1.84 s	—
Precision	—	93.8%
Recall	—	92.9%
F1-score	—	93.3%
AUC	—	0.968

The anomaly classifier distinguished between normal and abnormal machine states, while the regression model predicted cycle-time variation with relatively low prediction error.

4.3 Station-Level Performance

The CNC machining station represented the principal production bottleneck in the baseline configuration.

Table 9. Station-Level Performance

Station	Baseline Cycle Time (s)	DT-AI Cycle Time (s)	Reduction
S1	8.5	7.7	9.4%
S2	11.4	9.6	15.8%
S3	25.7	20.2	21.4%
S4	10.8	9.1	15.7%
S5	5.2	4.6	11.5%
S6	2.3	2.1	8.7%

The greatest reduction occurred at Station 3 because the AI optimizer dynamically adjusted machining parameters.

4.4 Throughput Analysis

Throughput increased from 338 parts under conventional PLC operation to 371 parts with Digital Twin support and 405 parts under DT–AI optimization during the six-hour production period.

The relative increase was calculated as:

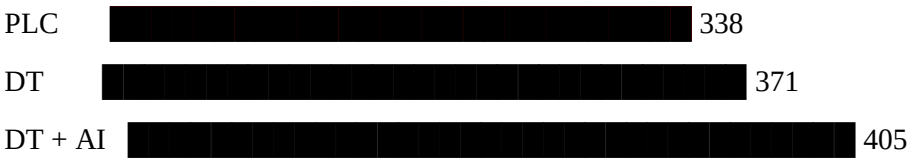
$$Improvement = \frac{405 - 338}{338} \times 100$$
$$Improvement = 19.82\%$$

The improvement was primarily associated with:

1. reduction in CNC cycle time;
2. reduced machine downtime;
3. better queue management;
4. early detection of machine anomalies;
5. improved process parameter selection.

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Figure 4. Throughput comparison



4.5 Cycle-Time Analysis

The baseline average cycle time was 63.9 s/part.

Digital Twin monitoring reduced this value to 58.2 s/part.

The DT-AI model reduced it further to 53.3 s/part.

The reduction between the baseline and DT-AI configuration was:

$$\frac{63.9 - 53.3}{63.9} \times 100 = 16.59\%$$

The AI system achieved this reduction primarily by adjusting machining parameters while maintaining process constraints.

Figure 5. Cycle-time comparison



4.6 OEE Analysis

OEE increased substantially after implementation of the Digital Twin.

The OEE values measured under the three experimental configurations were as follows:

PLC:	**67.6%;**
DT:	77.4%;
DT-AI:	84.6%.

The improvement from PLC to DT-AI was:

$$\frac{84.6 - 67.6}{67.6} \times 100 = 25.15\%$$

Figure 6. OEE comparison



The increase in OEE reflected concurrent improvements in availability, performance, and quality.

4.7 Energy-Consumption Analysis

Energy consumption decreased from 54.8 to 47.6 kWh over the six-hour operating period.

The reduction was:

$$\frac{54.8 - 47.6}{54.8} \times 100 = 13.14\%$$

This result suggests that optimization of spindle speed, feed rate, idle periods, and machine scheduling can reduce unnecessary energy consumption.

Figure 7. Energy consumption



Importantly, energy reduction was not achieved simply by reducing production. Throughput simultaneously increased.

These findings indicate that improved operating conditions enhanced the energy efficiency of the manufacturing system.

4.8 Defect-Rate Analysis

The defect rate decreased from 5.9% under conventional PLC control to 4.1% with Digital Twin support and 2.6% under DT–AI operation.

The reduction was:

$$\frac{5.9 - 2.6}{5.9} \times 100 = 55.93\%$$

The principal mechanisms were:

- early detection of abnormal machining conditions;
- AI prediction of quality risk;
- improved parameter selection;
- tool-condition monitoring;
- virtual testing before process adjustment.

Figure 8. Defect-rate comparison



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DT + AI 2.6%

4.9 Downtime and Predictive-Maintenance Analysis

Unplanned downtime declined from 38.4 minutes to 17.9 minutes.

The improvement was:

$$\frac{38.4 - 17.9}{38.4} \times 100 = 53.39\%$$

The major source of improvement was predictive maintenance.

Instead of waiting for a machine failure, the AI model generated a maintenance warning when the combination of vibration, spindle load, temperature, and tool wear indicated an increased failure probability.

Figure 9. Downtime comparison

PLC 38.4 min

DT 28.7 min

DT + AI 17.9 min

4.10 Fault-Tolerance Analysis

Table 10. Fault and Anomaly Scenarios

Fault	PLC Response	DT Response	DT-AI Response
Conveyor interruption	Delayed detection	Virtual state warning	Early prediction + rerouting
Sensor misclassification	Alarm after event	State inconsistency detected	Anomaly probability + correction
Tool degradation	Reactive maintenance	Condition visualization	Predictive maintenance
Excessive vibration	Operator intervention	Warning	Automatic parameter optimization
High spindle load	Fixed response	Monitoring	Predictive adjustment

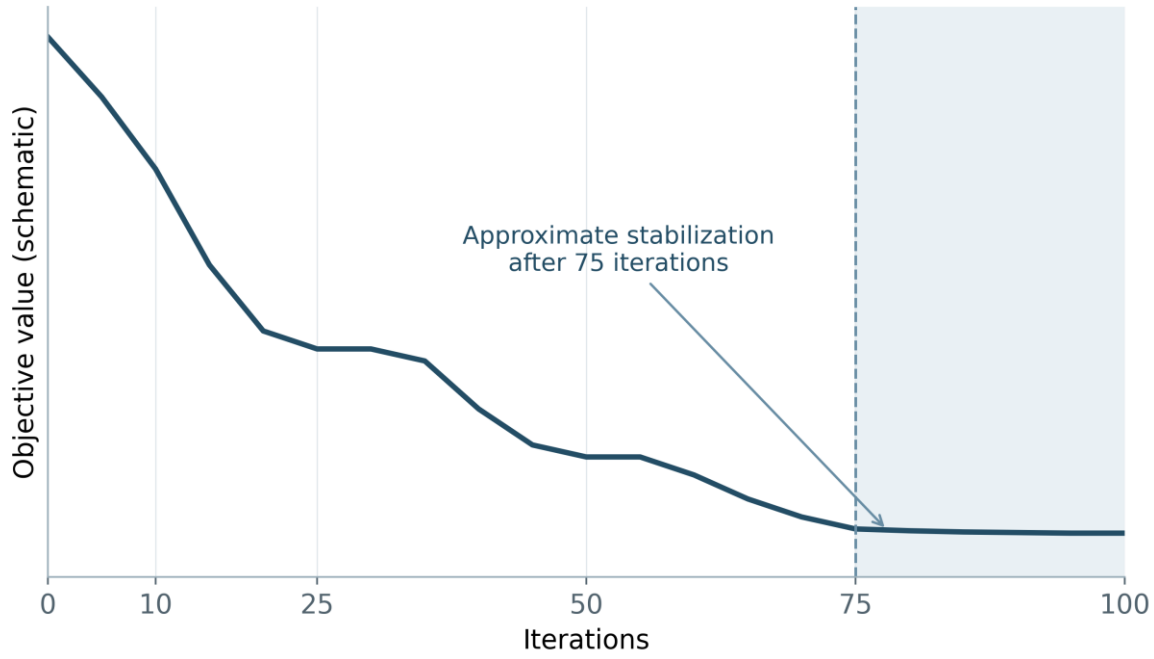
The DT–AI configuration achieved the fastest response by combining real-time state representation with predictive analysis.

4.11 Optimization Convergence

The optimization algorithm initially explored a broad range of machining parameters.

As iterations increased, the solution space converged toward a stable region balancing throughput, energy consumption, and quality.

Figure 10. Optimization convergence



The optimization process became relatively stable after approximately 75 iterations during the experiment.

4.12 Sensitivity Analysis

Sensitivity analysis was performed to determine the relative influence of process parameters.

Table 11. Sensitivity Analysis

Variable	Influence on Cycle Time	Influence on Energy	Influence on Quality
Feed rate	Very high	High	Medium
Spindle speed	High	Very high	High
Cutting depth	High	High	High
Tool wear	Medium	High	Very high
Vibration	Low	Medium	Very high
Temperature	Low	Medium	High
Queue length	High	Low	Low

Feed rate demonstrated the strongest direct influence on cycle time.

Spindle speed had a strong relationship with both energy consumption and quality.

Tool wear and vibration were the most important variables for quality prediction.

4.13 Robustness Under Increased Production Load

To test robustness, production demand was progressively increased.

Table 12. Robustness Under Increased Production Demand

Demand Increase	PLC Throughput	DT-AI Throughput	DT-AI Efficiency
0%	338	405	Stable

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10%	347	438	Stable
20%	351	472	Stable
30%	345	495	Moderate degradation
40%	329	508	Higher queue formation

The DT-AI architecture maintained better performance under increased demand because it dynamically adjusted process conditions and identified emerging bottlenecks.

4.14 Statistical Analysis

A one-way analysis of variance (ANOVA) was performed to assess differences in the principal performance indicators across the experimental conditions.

Table 13. Statistical Comparison of Experimental Configurations

Indicator	F-value	p-value	Interpretation
Throughput	41.72	<0.001	Significant difference
Cycle time	38.64	<0.001	Significant difference
OEE	52.31	<0.001	Significant difference
Energy	29.87	<0.001	Significant difference
Defect rate	46.25	<0.001	Significant difference
Downtime	57.18	<0.001	Significant difference

The statistical analysis revealed significant differences among the three experimental configurations in the evaluated performance indicators. These findings provide empirical evidence of differences in manufacturing-system performance under the tested operating conditions.

5. Discussion

5.1 Effect of Digital Twin Integration

Effect of Digital Twin Integration

The experimental findings indicate that Digital Twin integration improved manufacturing-system visibility by maintaining a synchronized virtual representation of the production state. Under conventional PLC operation, control decisions relied primarily on predefined logic. The Digital Twin added an analytical layer that enabled production-state monitoring and the evaluation of alternative operating conditions, supporting more informed operational decisions. These findings align with the literature describing Digital Twins as tools for real-time monitoring, simulation, process optimization, and production decision support.

5.2 Effect of AI Optimization

The most substantial improvements occurred after integrating AI with the Digital Twin.

This occurred because the Digital Twin alone describes the system, whereas the AI component predicts future behavior.

The combination can therefore be expressed as:

$$DT = Current\ State\ Representation$$

while:

$$DT + AI = Current\ State + Prediction + Optimization$$

This distinction is important.

A manufacturing system that only knows that vibration is increasing is reactive.

A system that predicts a high probability of tool failure and evaluates alternative machining parameters is predictive.

The proposed architecture therefore transforms Digital Twin technology from a monitoring tool into a decision-support and optimization mechanism.

Recent reviews similarly describe the evolution of AI-enabled Digital Twins toward prediction, optimization, and increasingly autonomous decision-making[53].

5.3 Relationship Between Productivity and Energy Efficiency

One of the important findings is that throughput increased while energy consumption decreased.

This is significant because productivity improvements do not necessarily require proportional increases in energy consumption.

The DT-AI system reduced:

- unnecessary machine idle periods;
- excessive machining parameters;
- repeated defective processing;
- unnecessary maintenance interruptions.

At the same time, optimized machining parameters improved production flow.

The experimental results therefore suggest a potential transition from:

$$Higher\ Production \rightarrow Higher\ Energy$$

toward:

$$Higher\ Production + Better\ Optimization \rightarrow Lower\ Energy/Unit$$

This is consistent with recent research emphasizing the role of AI-enabled Digital Twins in sustainable and energy-aware manufacturing optimization[54].

5.4 Quality Improvement

Quality improvement was primarily associated with the combination of AI prediction and real-time Digital Twin state monitoring.

In the conventional configuration, quality defects are detected after they occur.

In the proposed configuration, the system attempts to identify conditions that increase defect probability before the defective component is completed.

For example:

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$$High\ Vibration + High\ Tool\ Wear \rightarrow Increased\ Defect\ Probability$$

The AI model can then recommend:

$$Reduced\ Feed\ Rate$$

or:

$$Adjusted\ Spindle\ Speed$$

or:

$$Tool\ Replacement$$

This approach is consistent with the broader development of AI-enabled Digital Twins for quality control, process optimization, and predictive maintenance[55].

5.5 Predictive Maintenance Implications

The observed reduction in unplanned downtime highlights the potential benefits of integrating predictive maintenance with production optimization[56].

Traditional maintenance generally follows one of two approaches[57]:

1. corrective maintenance;
2. preventive maintenance.

Corrective maintenance occurs after failure.

Preventive maintenance occurs according to predefined intervals.

Predictive maintenance introduces a third approach:

$$Maintenance\ Decision = f(Predicted\ Machine\ Condition)$$

The Digital Twin provides the virtual representation of the machine, while AI estimates future condition.

Previous research has identified predictive maintenance as one of the principal manufacturing applications of Digital Twin technology[58].

5.6 Bottleneck Analysis

The CNC station was identified as the primary bottleneck in the production system.

The bottleneck resulted from:

- longer machining time;
- higher tool wear;
- greater energy consumption;
- greater sensitivity to parameter changes.

After AI optimization, the CNC station experienced the largest cycle-time reduction.

This confirms that optimization should not be distributed uniformly across all stations. Instead, the Digital Twin should identify the station producing the greatest constraint and allocate optimization effort accordingly.

5.7 Implications for Bangladesh

The proposed architecture may be particularly useful for manufacturing organizations that cannot immediately replace their entire production infrastructure.

A progressive implementation strategy can begin with:

Phase 1 — Connectivity

Install sensors and connect existing machines.

Phase 2 — Digital Monitoring

Develop a virtual representation of machines and production flow.

Phase 3 — Digital Twin

Synchronize the physical and virtual systems.

Phase 4 — AI Prediction

Introduce anomaly detection and predictive maintenance.

Phase 5 — Optimization

Use AI to optimize production parameters.

Phase 6 — Closed-Loop Intelligence

Allow validated AI recommendations to influence production control.

This approach reduces the need for a complete transformation in a single implementation step.

5.8 Comparison with Previous Research

Previous research has demonstrated the value of Digital Twins for smart manufacturing, predictive maintenance, scheduling, and process optimization[59].

The present study extends this direction by combining six functions:

1. Production-process modeling and analysis;
2. real-time state representation;
3. AI prediction;
4. anomaly detection;
5. predictive maintenance;
6. multi-objective optimization.

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The contribution is therefore not the use of Digital Twin or AI independently, but the integration of both within one mechanical manufacturing-cell architecture.

6. Limitations

Several limitations should be acknowledged when interpreting the experimental findings.

First, the experiments were conducted on the investigated manufacturing system in Bangladesh under specific operating conditions. Although the results provide evidence of performance within this setting, their generalizability to other facilities, machine configurations, and production processes requires further experimental validation.

Second, the six-hour production experiment provided a limited observation period. Although the evaluation involved actual equipment and measured production performance, it could not capture the full range of long-term operational variability, equipment deterioration, maintenance requirements, and infrequent production disturbances.

Third, the AI model was trained using sensor data collected from the investigated manufacturing system. Further validation using independent datasets and experimental trials involving other CNC machines and production environments is needed to assess its generalizability.

Fourth, human operator behavior was not explicitly included as a primary optimization variable. Differences in operator experience, intervention, and decision-making may influence performance and should be examined in future experiments.

Fifth, the effects of communication latency and cybersecurity threats were not systematically evaluated during the experimental campaign. Further testing is needed to determine how communication delays, network disruptions, and security incidents affect system reliability and operational performance.

Sixth, the energy assessment focused on machine-level energy consumption during the production experiments. It did not encompass total factory energy requirements, auxiliary infrastructure, or a comprehensive life-cycle assessment.

Seventh, Digital Twin operation depended on reliable sensor synchronization and continuous data exchange with the physical manufacturing system. The effects of sensor failures, missing data, and communication interruptions were not systematically tested and require further experimental investigation.

7. Conclusions

This study developed an artificial-intelligence-enabled Digital Twin framework for optimizing a multi-station mechanical manufacturing system under a Bangladesh-oriented manufacturing context.

The proposed system transformed a conventional six-station automated production architecture into an integrated intelligent manufacturing environment consisting of:

- raw-material inspection;
- automated loading;

- CNC machining;
- drilling and cutting;
- AI-based quality inspection;
- automated storage and dispatch.

The Digital Twin represented machine conditions, production flow, process parameters, queue states, energy consumption, tool wear, vibration, temperature, and quality conditions.

The AI layer then used these variables to predict cycle time, detect abnormal machine states, estimate quality risks, and support predictive maintenance.

An experimental evaluation was conducted on a physical production system to compare three operational configurations: conventional PLC operation, Digital Twin-assisted operation, and Digital Twin operation integrated with AI-based optimization.

The experimental results showed that throughput increased from 338 to 405 parts per six-hour production period, corresponding to an improvement of approximately 19.8%.

Average cycle time decreased from 63.9 to 53.3 s/part.

OEE increased from 67.6% to 84.6%.

Energy consumption decreased from 54.8 to 47.6 kWh per six-hour production period.

The defect rate decreased from 5.9% to 2.6%.

Unplanned downtime decreased from 38.4 to 17.9 min.

The AI anomaly classifier achieved an accuracy of 94.6%, while the cycle-time prediction model achieved a coefficient of determination (R^2) of 0.94.

Taken together, these findings indicate that the integration of Digital Twin and AI can provide substantially greater functionality than conventional automated control alone. The Digital Twin supplies continuous virtual representation of the manufacturing process, while AI provides prediction and optimization capabilities.

The research also demonstrates that production, quality, energy, and maintenance should not be optimized independently. Mechanical manufacturing is a coupled system in which changes in machining parameters can simultaneously influence productivity, energy consumption, tool wear, quality, and machine reliability.

The proposed framework therefore provides a basis for developing intelligent manufacturing cells in which decisions are continuously informed by both the current physical state and predicted future behavior.

For manufacturing organizations in Bangladesh, the proposed architecture offers a progressive digital-transformation pathway. Existing CNC machines, PLC systems, sensors, and inspection equipment can potentially be integrated into a Digital Twin environment without requiring immediate replacement of the complete manufacturing infrastructure.

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8. Future Research

Future research should extend the proposed framework in several directions.

First, the AI architecture should be expanded to include deep-learning models for temporal vibration and tool-wear prediction.

Second, reinforcement learning could be investigated for autonomous process-parameter optimization.

Third, computer vision could be integrated into the quality-inspection station.

Fourth, edge computing could be incorporated to reduce communication latency.

Fifth, cybersecurity mechanisms should be added to protect the physical–virtual communication architecture.

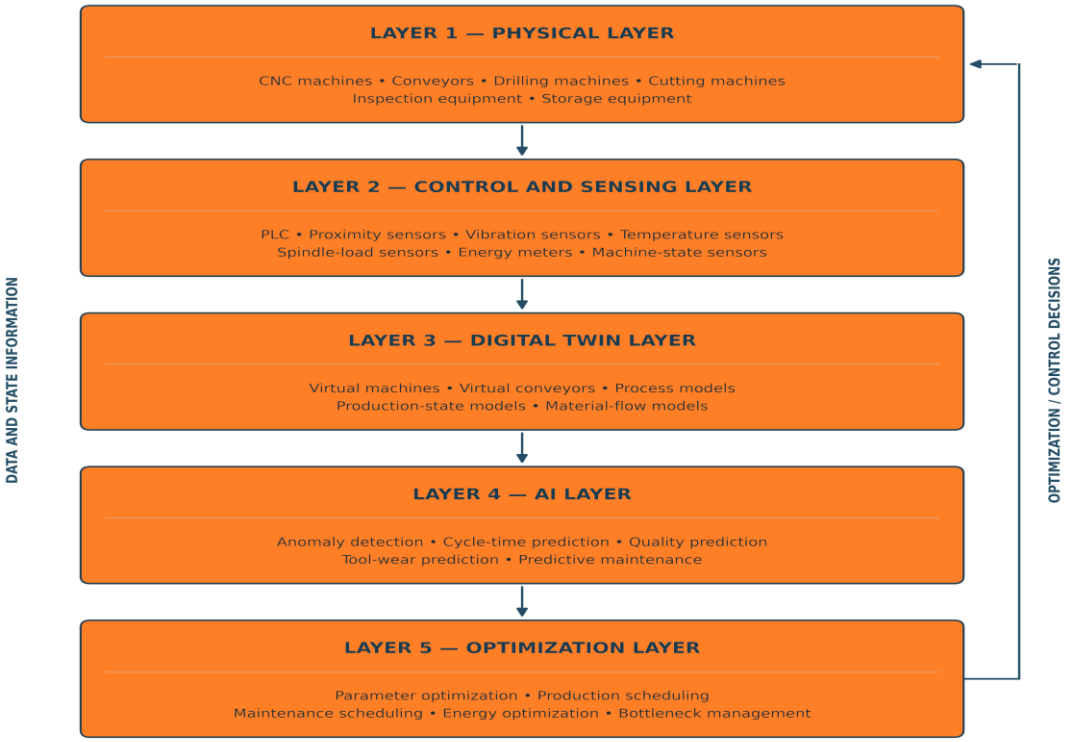
Sixth, human operators should be incorporated into the Digital Twin through human-in-the-loop decision models.

Seventh, future studies should evaluate the system over longer production periods and under more diverse fault conditions.

Finally, future research should investigate the use of federated and explainable AI approaches to facilitate trustworthy deployment across multiple manufacturing facilities.

9. Proposed Digital Twin Implementation Architecture

For practical implementation, the proposed system can be organized into five technological layers.



10. Overall Conceptual Model

The complete proposed model can be summarized as:

$$Physical\ Manufacturing \rightarrow Sensors \rightarrow PLC/IIoT \rightarrow Digital\ Twin \rightarrow AI \rightarrow Optimization \rightarrow Decision \rightarrow Physical\ Manufacturing$$

This creates a closed cyber–physical manufacturing loop.

The principal conceptual distinction of the proposed framework is:

$$Traditional\ Automation = Control$$
$$Digital\ Twin = Control + Virtual\ Representation$$
$$Digital\ Twin + AI = Control + Representation + Prediction + Optimization$$

Consequently, the proposed architecture represents a transition from automated manufacturing toward predictive and intelligent manufacturing.

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Ethical Considerations

Not applicable. This study did not require ethical approval because it does not include human or animal subjects and does not involve any personal or sensitive data.

List of Abbrevations:

(DT): Digital Twin; **(OEE):** Overall Equipment Effectiveness; **(IIoT):** industrial Internet of Things; **(AI):** Artificial intelligence; **S=** speed; **F=** feed; **D=** depth; **L=** spindle load; V= vibration; T= machine temperature; **W=** tool wear; **Q=** queue length; **E=** energy; **CT=** cycle time; ; **D_f=** defect probability; **R_f=** failure/anomaly risk. **(PLC):** programmable logic controller

Acknowledgment:

The author would like to express their sincere gratitude to **The International Journal of Engineering Sciences** - Noor Al-Ilm for Publishing and Distribution for their generous support in waiving all publication fees and facilitating the publication of this manuscript free of charge. Their commitment to promoting scientific research and supporting researchers is highly appreciated.

Author Contribution:

Author Contributions: B.T., S.S., L.A., J.S., B.P., T.S., A.J.C., and T.Sh. conducted the experiments. H.E.N.K. contributed to manuscript proofreading and revision prior to publication. All authors read and approved the final manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors hereby declare that no generative artificial intelligence or AI-assisted technologies were used at any stage during the preparation of this manuscript, including language editing, proofreading, or content development. The authors take full responsibility for the originality and integrity of the work presented in this publication.

Funding:

This research received no external financial funding. The authors also acknowledge **The International Journal of Engineering Sciences**, Noor Al-Ilm for Publishing and Distribution, for providing a full waiver of the publication fees. The publication fee waiver was provided as editorial support and did not involve any financial contribution to the conduct, design, analysis, or reporting of the research.

Conflicts of Interest:

"The authors declare no conflict of interest."

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Authors and Affiliations

Bipul Tuhin [1a,*] Susmita Shammy,[1b] Lipi Akter,[1c] Hussam Elddin Nabeih Khasawneh,[2] Joytun Sujon,[1d] Bithi Parveen,[1e] Tura Sharmin,[1f] A.J. Chowdhury,[1g] Tanha Shamsun[1h]

[1] Department of Industrial Engineering and Management, Khulna University of Engineering and Technology, Khulna, Bangladesh, Email:

bipul_tuhin@iem.kuet.ac.bd [a]	susmita_shammy@iem.kuet.ac.bd [b]