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RESEARCH ARTICLE

An Investigative Approach Leveraging Digital Twin Technology for a CNC Machine

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ABSTRACT

Digital twin technology has emerged as an effective approach for improving the monitoring, validation, and optimization of Computer Numerical Control (CNC) machining operations. This study presents an investigative framework integrating Computer-Aided Design/Computer-Aided Manufacturing (CAD/CAM), Software-in-the-Loop (SIL), and Hardware-in-the-Loop (HIL) methodologies for diagnosing and rectifying machining defects in CNC systems using the digital twin - virtual model (component and asset twins). Four machining experiments were conducted using Aluminum 6061-T6, Polytetrafluoroethylene (PTFE), Brass, and Stainless Steel (AISI 304) on an EMCO CNC machine integrated with Siemens 840D controls. The first two experiments, involving turning and drilling operations, are presented in detail; the third and fourth experiments, conducted on Brass and Stainless Steel (AISI 304), are included as additional experimental validations under different machining conditions to evaluate the robustness and repeatability of the proposed methodology. Real-time machining parameters, including spindle speed, feed rate, axis offsets, and drilling depth, were synchronized between the virtual simulation environment and the physical CNC machine through digital twin-based validation. The proposed framework successfully identified dimensional deviations, tool offset errors, and drill alignment defects before and during machining operations. Experimental validation demonstrated a reduction in dimensional error from approximately $+0.50$ mm to within ± 0.05 mm tolerance limits after digital twin optimization. Furthermore, optimization of contour-turning strategy reduced the CAM simulation time from 5.0 min to 3.0 min, corresponding to approximately a 40% improvement in process efficiency. Repeatability tests conducted over three machining trials confirmed consistent machining accuracy and process stability. The results demonstrate that digital twin-assisted CNC machining can significantly improve dimensional precision, reduce machining errors, minimize setup time, and enhance production reliability in smart manufacturing environments.

Keywords: Machining using CNC, Digital Twin technology - virtual model (component and asset twins), CAD/CAM, Software-in-the-Loop (SIL) and Hardware-in-the-Loop (HIL)

1. Introduction

This paper investigates the importance of digital twin technology and its practical importance for analyzing errors during machining, and its remedial actions through various case studies. As technologies such as Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, and smart manufacturing are evolving rapidly, the application of the digital twin framework to the CNC-based production system is greatly promoted. The convergence between the physical and virtual manufacturing systems through these technologies has already contributed to precision management, process monitoring, and intelligent production control [1]. The concept of digital twin was originally introduced in the year 2003, which is related to product lifecycle management (PLM) and then further formalized by a white paper in 2014 [2]. It originally had three parts: a physical object in real space, a virtual object in digital space, and a data link for communication between these two objects. Later on, the

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concept of digital twin has been extensively evolved and extended into many different engineering disciplines and industrial applications, leading to the development of digital models, digital shadow, and cyber-physical systems (CPS). A digital model is generally a static or semi-static representation of a physical object in the virtual space where data can be transferred manually to a CNC machining environment using CAD and CAM software [3]. The transfer method from the CNC machining environment is usually via LAN, an external storage device, or through the integrated controller of the CNC machine. On the other hand, digital shadow allows one-way transfer of real-time data from the physical machine to the virtual space for process monitoring and analysis [4]. Cyber-physical systems can provide two-way interaction between physical and virtual systems, enabling a greater range of monitoring, synchronization, and intelligent control of manufacturing operations [5]. The common classification of digital twins in modern manufacturing systems includes component twin, asset twin, system twin, and process twin. A component twin represents specific components within the CNC machine, such as spindle systems, cutting tools, sensors, bearings, tool holders, etc., through which individual component performance can be monitored and analyzed. An asset twin represents an entire machine asset, such as a fully functional CNC machine, which incorporates multiple component twins in the virtual space, enabling monitoring and analysis of its operation and maintenance condition. A virtual model of the twin can be used for simulation, collision detection, process validation, and machining optimization before actual operation. Many studies have demonstrated that digital twins are being applied in machining and smart manufacturing. For example, the digital twin-driven smart manufacturing systems, which enhance operational efficiency and production optimization [5], have been introduced in cyber-physical production systems for applications in Industry 4.0 [17], and real-time synchronization and data management are the crucial factors of digital twin systems [23]. However, there are limited experimental investigations that quantitatively validate the synchronization between the virtual machining system and the physical CNC machine in practical machining operations. Among all the performance parameters for a machining process, product quality and cost-efficiency are the most crucial and directly influenced by CNC machine operation. Optimization of machining efficiency remains one of the top goals of the modern manufacturing industry. High precision and high productivity of CNC machines are well known; however, the machining performance should be further optimized to gain better production efficiency and higher operation reliability. Some published methods can help in optimizing the machining performance, including spindle speed, feed rate, and tool path optimization to shorten the cycle time and improve efficiency [6]. Product quality, which requires high dimensional accuracy of manufactured products and higher consistent machining precision, is another crucial goal of machining operations. Even a small difference in machining tolerance will cause deviation in product quality and result in manufacturing defects [7]. Predictive maintenance can effectively reduce operating costs through proper tool utilization and reduce unexpected machine shutdowns and wastage of materials [8]. Process optimization and lean manufacturing approaches also contribute significantly to reducing production waste and improving machining efficiency through data analysis [9]. The machining data from the CNC system can also provide useful information for machine maintenance planning, operation upgrades, and performance improvement with intelligent analysis and monitoring [10]. The purpose of this study is to apply digital twin technology using virtual models (component and asset twins) CNC machining approach to analyze machining defects and improve machining accuracy with practical case studies. Since it is difficult to determine the root cause of machining errors due to the complexity of the CNC machining system and interplay of multiple machining parameters, this research investigates machining discrepancies such as dimensional deviation, tool offset errors, and drilling misalignments. Through digital twin technologies, which involve CAD/CAM simulation, Software-in-the-Loop (SIL), and Hardware-in-the-Loop (HIL) verification approaches, this work has experimentally validated the synchronization between the virtual machining environments and the actual CNC machining. Machining parameters, tool path optimization, cutting conditions, and offset correction are analyzed in detail to determine the root cause of machining error. Corrective actions were then implemented and verified through the physical machining test and compared with simulation results. The proposed digital twin-assisted CNC machining framework provides an effective approach for improving dimensional accuracy, reducing machining error, optimizing simulation efficiency, and increasing CNC machining system reliability.

In this study, the following research hypotheses are formulated for measuring the performance of the digital twin-assisted CNC machining framework.

H1: CNC set-up and machining can be enhanced by performing virtual machining validation using a digital twin, which in turn increases dimensional accuracy.

H2: CNC machining time and CAM simulation time can be minimized through toolpath optimization using digital twin simulation

H3: Digital twin implementation reduces machining defects such as tool offset error and drill misalignment.

2. Materials and methods

There are several steps involved in developing a replica of the specimen to be manufactured using the CNC machine. The process involves several steps to create a physical representation of the specimen. The materials used in this study are discussed in the respective case studies.

2.1. Modelling in computer-aided design (CAD)

The modeling procedure involves creating a detailed dimensional specification of the specimen to be manufactured using the CNC machine, including geometric tolerances and other drawing-related entities [11]. Several methods can be used for this purpose, including 3D scanning, CAD modeling using a laser scanner, and creating an accurate 3D model with an absolute coordinate system using software such as Mastercam, Delcam, or EMCO Concept [12]. The model can be further enhanced by incorporating functional components, such as a tool holder, while defining the geometric constraints of the part.

2.2. Simulation

Simulation is an essential step before commencing the machining process. The simulation represents the complete interaction between the workpiece and the tool. The interaction between the tool and the workpiece, along with the kinematic relationships of the X-, Y-, and Z-axes, can be simulated and verified [13]. Once the simulation is completed successfully without collisions between the workpiece and the cutting tool, the motion-control algorithm is generated by the software [14].

2.3. Predicting dynamic behavior

Since machining simulation requires point-to-point meshing and grid generation in software, such as Ansys Structural Analysis, the dynamic behavior of the machining process can be accurately represented [15]. Software simulation can be used to predict temperature, cutting forces, and other dynamic parameters while collecting useful data for future CNC machining operations. However, sensors installed within the CNC machine have measurement limitations because they cannot always capture data at the exact cutting location during machining [16].

Table 1. Real-time data acquisition parameters.

Parameter	Specification
CNC Controller	Siemens 840D
CNC Machine	EMCO Concept Turn 55
Sensor Type	Encoder-based position feedback
Monitored Parameters	Spindle speed, feed rate, axis position, tool offset
Sampling Interval	100 ms
Communication Interface	EMCO Concept Simulation Interface
Data Synchronization	Real-time bidirectional synchronization
Calibration Method	Standard CNC axis and spindle calibration

2.4. Integration and validation of data in real time

The relationship between the software and hardware output can also be examined. Machining performance with respect to controllable parameters such as feed rate and spindle speed can be verified in real time using sensors. Input-output sensors are installed within the CNC machine to monitor tool position, workpiece vibration, and the temperature generated during the cutting process [17]. Typically, software platforms such as Apache Spark are used for data processing. Mechanical measurement instruments, such as a surface roughness tester or Vernier caliper, are used for output validation [18].

The machining data were collected from the position feedback encoder in the EMCO Concept CNC controller along with the spindle sensors from the Siemens 840D control system. The measured machining parameters included spindle speed, feed rate, X- and Z-axis positions, and tool offsets. These data were acquired at a sampling interval of 100 ms to synchronize the CNC machine with the digital twin.

Table 1 provides various parameters and their specifications used in the Emco CNC machine and their machining purpose for getting the data.

2.4.1. Software in the loop (SIL) and hardware in the loop (HIL) validation

To virtually simulate and validate the CNC machining logic before physical machining, SIL testing was carried out. Each component of the CAD/CAM model, including toolpath generation, machining parameters, and motion control code, was evaluated on the EMCO Concept framework's simulator.

The validation allowed testing of tool path precision and accuracy, the detection of collisions, and monitoring of spindle speed, feed speed, and the

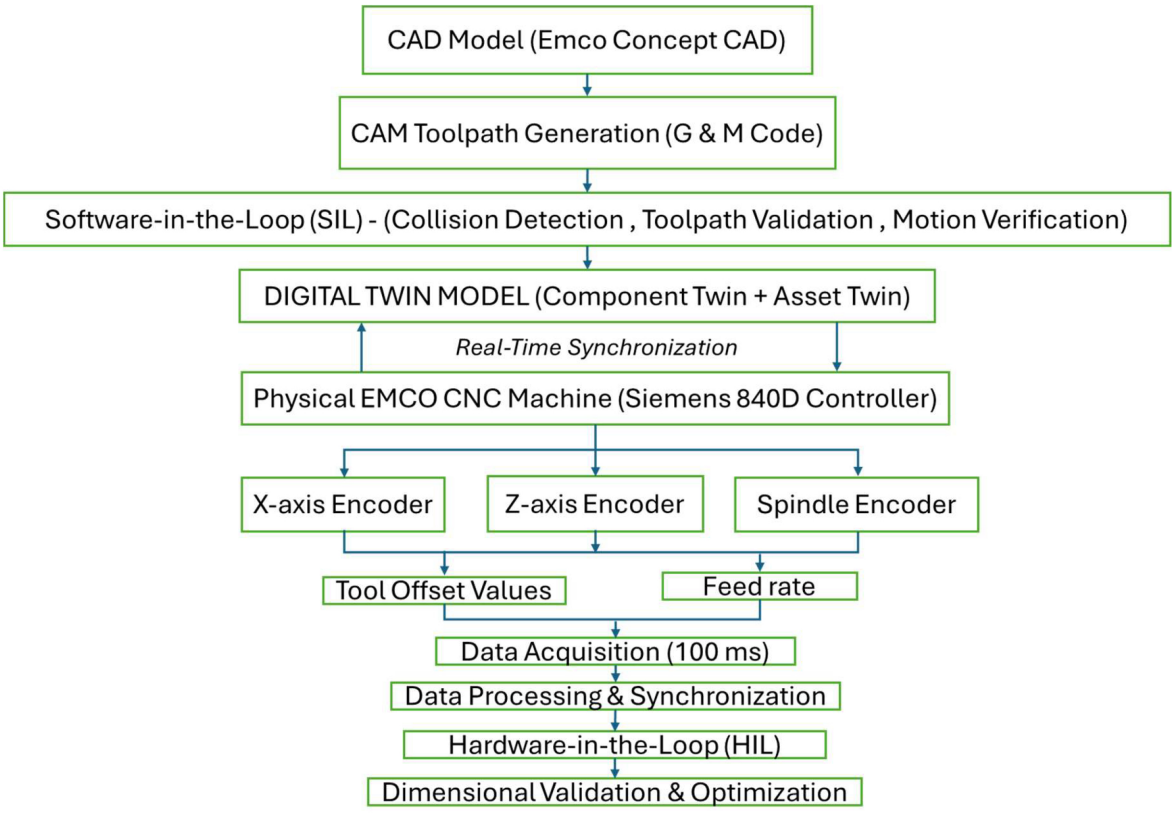


Fig. 1a. Complete sensing, synchronization, and digital twin validation workflow integrating CAD/CAM, Software-in-the-Loop (SIL), Hardware-in-the-Loop (HIL), real-timesensor acquisition, and machining validation.

overall sequence of machining, without the risk of damage to the actual machine. This approach reduced programming errors and increased the reliability of the G-code generated, prior to the code being loaded onto the CNC machine [19, 20].

In addition, Hardware-in-the-Loop (HIL) testing was implemented to connect the digital twin and physical CNC machine controller. The digital model exchanged real-time information with the physical hardware, including CNC drives and the machine controller.

The HIL framework allowed verification of actual machine responses, including axis positioning, spindle rotation, and tool offset correction during a machining operation. Based on comparison between simulated and real machine output, accuracy in the synchronization between digital and physical systems thereby improving machining precision and overall system reliability.

2.5. Implementation and instantaneous monitoring

The digital twin interface enables machine technicians to monitor machine performance; it will allow them to visualize the machine's performance and receive alerts for maintenance on different parts of the CNC machine. Another approach involves the use of machine-learning algorithms to help identify and address issues like tool wear and the high loads applied to the workpiece during milling [21]. By using the real-time data from the digital twin, continuous machine monitoring improves prediction accuracy [21]. A typical digital twin architecture, as shown in Fig. 1(a), is constructed as a multi-layer framework that provides a data link between physical entities and virtual entities.

The eight stations of the tool turret employ a combination of proximity sensors and Hall effect switches. They are located internally at the base of the turret disk where they detect internal magnets for checking tool number and tool positions.

In Fig. 1(b), the different components of the sensing architecture for the EMCO Concept Turn 155 CNC machine are illustrated. The spindle encoder measures the speed of rotation, while the linear encoders along the X-axis and Z-axis keep track of the position of the carriage. Tool offset is obtained when the CNC controller performs machine calibration and tool-setting operations. The X- and Z-axis measurements

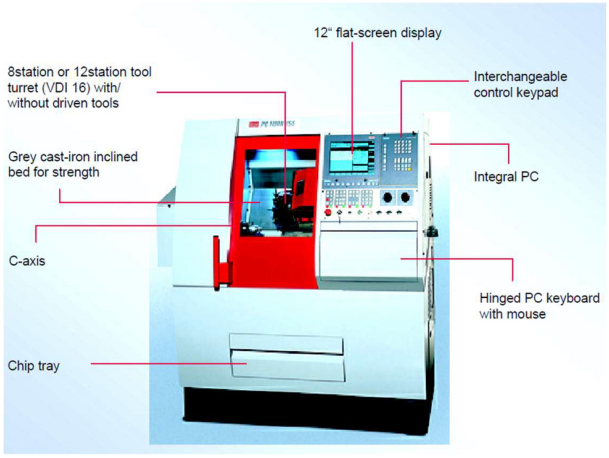


Fig. 1b. EmcoCNC machine.

are encoder-based position feedback, and the tool offset is controller/tool offset data. The machining parameters are collected by the Siemens SINUMERIK 840D controller every 100 milliseconds and synchronized with the EMCO Concept digital twin. By having a common set of data for the simulation and the machine, Software-in-the-Loop verification, Hardware-in-the-Loop validation, machining error detection, dimensional verification, and optimization of processes can be conducted in real time.

2.6. Case studies

It can be difficult to determine the true and underlying reason for the infrequent but frequent discrepancies between produced parts from a CNC machine. There are various factors that are related to the cause, such as dimensional error related to tolerances [22, 23], heat generated due to the machining process [24, 25], calibration of the machine [26, 27], and processing the specimen, such as quenching and annealing [28, 29].

Four machining experiments were conducted to evaluate the effectiveness of the proposed digital twin-assisted CNC machining framework. Experiments I and II are presented as detailed case studies because they demonstrate the complete workflow of error identification, digital twin validation, corrective actions, and machining optimization. Experiments III and IV were performed using Brass and Stainless Steel (AISI 304) under different spindle speeds and machining conditions to further validate the applicability and robustness of the proposed framework. Their quantitative results are summarized in the experimental validation tables and statistical analysis but are not discussed individually, as the machining methodology and digital twin implementation were identical to those presented in the first two case studies.

Table 2 provides the parameters for case study I, II, III, and IV with all the quantitative values used in CAD CAM software and thus machined with these parameters.

2.6.1. Case study I: Diagnosing machining defects

Case Study I focuses on the measurement errors observed between the CAD model and the machined product, as well as the corrective actions taken to eliminate these errors. EMCO Concept, a software package fully integrated with the EMCO Computer Numerical Control (CNC) machine and Siemens 840D controller, was used to create the CAD model and generate the machining control (G-code) for manufacturing. The dimensions of the part to be manufactured are shown in Fig. 2. The CAD model specifies diameters of 10 and 15 mm for the first step, respectively, with corresponding lengths of 10 and 20 mm. The CAM process generates the G-code and M-code required for CNC machining. The cutting tool used was a diamond-shaped SDJC left-hand tool with the following specifications: edge angle 55°, Edge Width 7.75, cutting angle 93°, and tool radius of 0.4 mm. These parameters cannot be modified because they are predefined in the machine tool configuration. The CAM output generated by the software is shown in Fig. 3 and represents one component of the digital twin technology. Fig. 4 shows the machined

Table 2. Machining parameters for each case study.

Parameter	Case study I	Case study II	Case study III	Case study IV
Material	Aluminum 6061-T6	PTFE	Brass	Stainless Steel (AISI 304)
Machining Process	Turning	Drilling	Turning	Turning
Spindle Speed (rpm)	717	100	500	450
Feed Rate (mm/rev)	0.20	0.10	0.15	0.12
Depth of Cut (mm)	0.50	1.00 (Peck)	0.40	0.25
Tool Type	SDJC Left-Hand Tool	HSS Twist Drill	SDJC Left-Hand Tool	Carbide Turning Tool
Tool Radius	0.40 mm	10 mm Drill	0.40 mm	0.40 mm
Cooling Condition	Dry	Dry	Dry	Dry
Purpose	Dimensional Accuracy Validation	Drill Alignment Validation	Material Validation	Material Validation

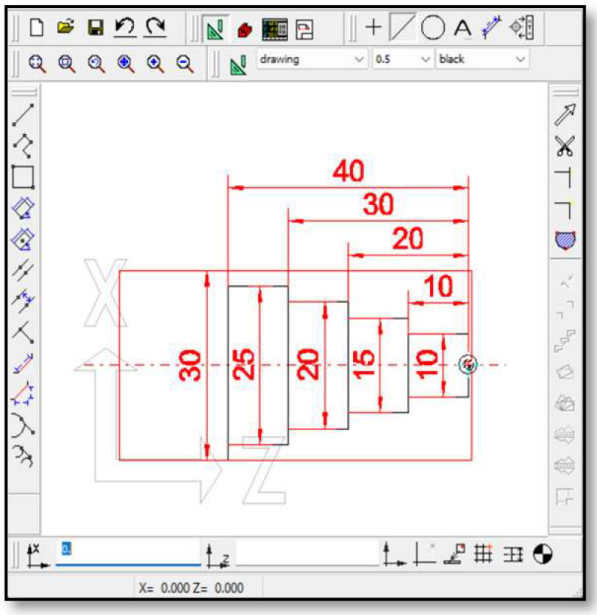


Fig. 2. CAD diagram.

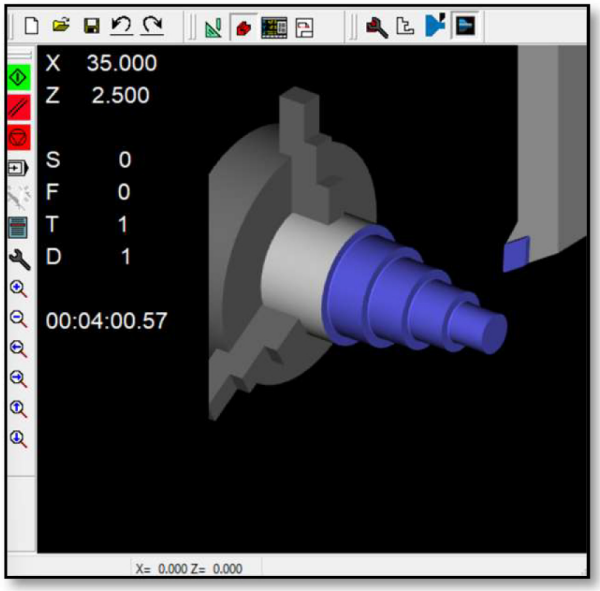


Fig. 3. CAM visualization.

workpiece and illustrates the dimensional error observed in the diameter of the machined component. A Vernier caliper was used to measure the diameter of the workpiece, and a dimensional error of approximately +0.50 mm was observed.

Various standardized methods are available for machine optimization, including defining the optimization objectives and constraints. These methods provide guidance for achieving objectives such as higher production rates [30]. The next step involves



Fig. 4. Diameter measurement.

data collection, followed by analysis to identify the most efficient operating conditions for the CNC machine. Real-time data facilitate the correlation between machining parameters and their corresponding outcomes [31]. Therefore, numerous optimization methods can be adopted. Among these methods, digital twin technology combined with software simulation was used for error detection and correction [32]. The machine setup, including the G56 machine offset parameter, was examined as shown in Fig. 5. An offset error was identified in one of the machine axes, and a complete calibration procedure was performed for all cutting tools. The SDJC L1212 left-hand tool was reanalyzed, and its offset value was adjusted to match the actual tool position. This adjustment provided insight into the machine setup and enabled accurate dimensional measurements.

The toolpath is also optimized to use a contour turning process, which is implemented. The post-machining inspection confirmed that the workpiece was free from errors, with all dimensions meeting the required dimensional accuracy, as shown in Fig. 6. The CAM simulation takes 3.00 minutes, and when compared to the simulation time in Fig. 3, the time is significantly reduced, which in turn reduces production time and Takt time overall.

The quantitative analysis for the dimensional accuracy validation (before and after machining) in different trials is given in Table 3 below.

Table 3. Case study I – dimensional accuracy validation.

Trial	Diameter Error Before Correction (mm)	Diameter Error After Correction (mm)
1	+0.52	+0.04
2	+0.48	+0.03
3	+0.51	+0.05
Average	+0.50	+0.04



Fig. 5. Offset setup for CNC machine.

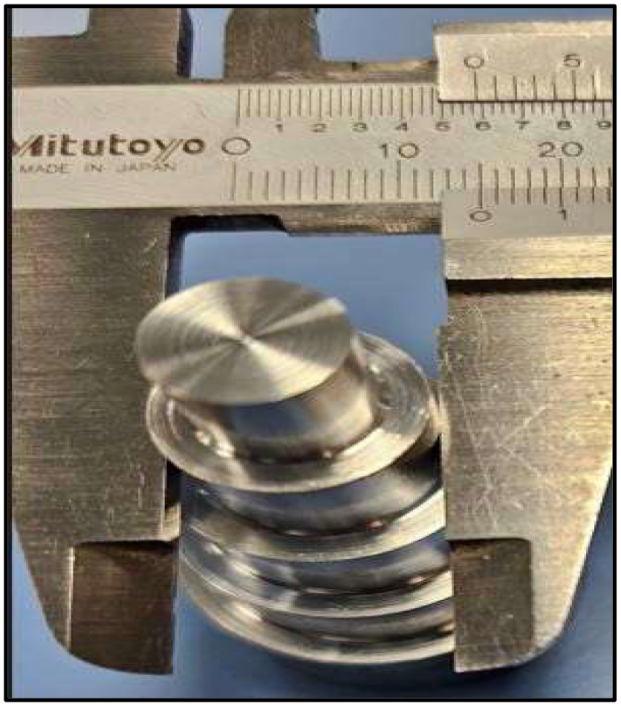


Fig. 6. Error-free workpiece.

Table 4. Simulation time comparison.

Machining Strategy	Simulation Time (min)
Conventional Turning	5.0
Optimized Contour Turning	3.0

Percentage reduction in simulation time:

$$\frac{5.0 - 3.0}{5.0} \times 100 = 40\%$$

Machining strategy vs time: The simulation time has been compared and shows a reduction in % with value 40 as given in Table 4 above.

2.6.2. Case study II: Diagnosing machining defects

Drilling is a secondary machining process that is typically performed after the primary machining operation. It is used to produce precise holes. The drilling depth, feed rate, and spindle speed are selected according to the workpiece material. CNC drilling operations include several types, such as peck drilling, spot drilling, deep-hole drilling, and countersinking [33]. The EMCO software includes a built-in peck drilling cycle. All machining parameters are entered into the software, and the machining simulation is then performed [34]. The CAD model shown in Fig. 7 includes a machining process plan that ensures accurate alignment of the twist drill with the center point. In contrast, Fig. 8 illustrates a drill misalignment that results in tool collision during machining. The corresponding corrective procedure is discussed below.

Both the generated CNC program and the simulation function correctly during machining. However, the drill bit collided with the workpiece when the drilling operation was executed on the CNC machine, even though the facing and contour-turning operations were completed successfully. Although the drill-bit collision occurred during the actual machining process, the digital twin simulation enabled the problem to be identified and analyzed. The problem was corrected by adjusting the tool's Z-axis offset within the software or by modifying the offset value in the generated CNC program. Both case studies were carried out by analyzing the machine settings, toolpath optimization, and cutting

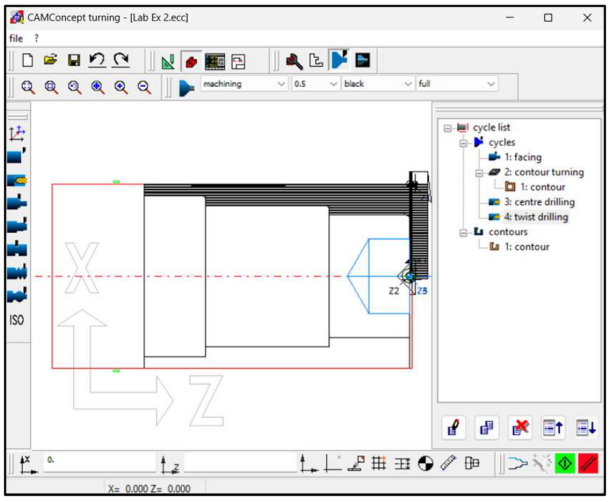


Fig. 7. CAM Process in drill operation.

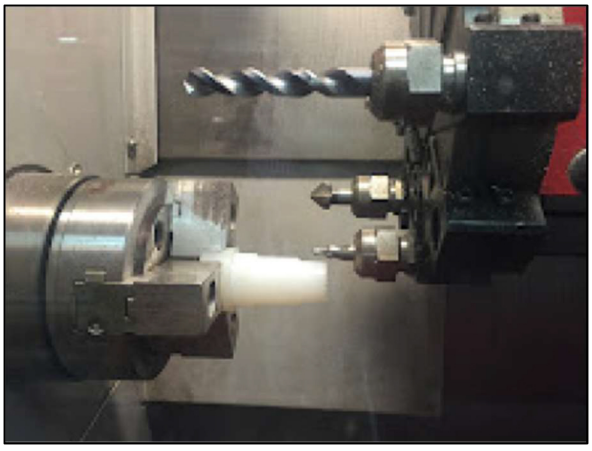


Fig. 8. Drill bit misalignment and tool collision.

conditions, after which appropriate corrective actions were implemented.

Table 5 compares the hole-position error, hole-depth error, and tool-collision status before and after correction in the CNC machine. Table 6 presents the experimental results for all four case studies, including Aluminum 6061-T6, PTFE, Brass, and Stainless Steel (AISI 304).

Table 6 presents the experimental results obtained for four different types of materials: aluminum, Brass, PTFE (Teflon), and stainless steel. The experiment is performed using different spindle speeds, feed rates, and depth of cut for each material.

Table 7 compares the dimensional errors before and after digital twin-based correction and presents the corresponding percentage improvement for each material.

Fig. 9 provides with an overall variation, having X axis as the spindle RPM, and material compared with

Table 5. Case study II – drilling accuracy analysis.

Parameter	Before Correction	After Correction
Hole Position Error	1.20 mm	0.08 mm
Hole Depth Error	0.90 mm	0.05 mm
Tool Collision	Present	Eliminated

that of Y axis with the dimensional error reduction using digital twin technologies.

2.7. Statistical and uncertainty analysis

To determine the reliability and repeatability of the proposed digital twin framework, a statistical evaluation was performed on the dimensional data collected on samples before and after the digital twin-based compensation process. There were three machining trials conducted for each material at varying spindle speeds. The measurements of the dimensional deviations were made using a Vernier caliper with an accuracy of ±0.02 mm.

2.7.1. Statistical analysis

The standard deviation, arithmetic mean, coefficient of variation, and standard error are calculated using the following formulas.

Mean

$$\tilde{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Standard Deviation

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

Standard Error

$$SEM = \frac{SD}{\sqrt{n}}$$

Coefficient of Variation

$$CV = \frac{SD}{\bar{x}} \times 100 \text{ [35]}$$

Table 8 provides an insight into the statistical analysis error and its reduction in percentage.

2.7.2. Repeatability analysis

The repeatability analysis is performed using three machining trials, which are performed under a machining operation. The repeatability was calculated as

$$R = \pm 2SD \text{ [36]}$$

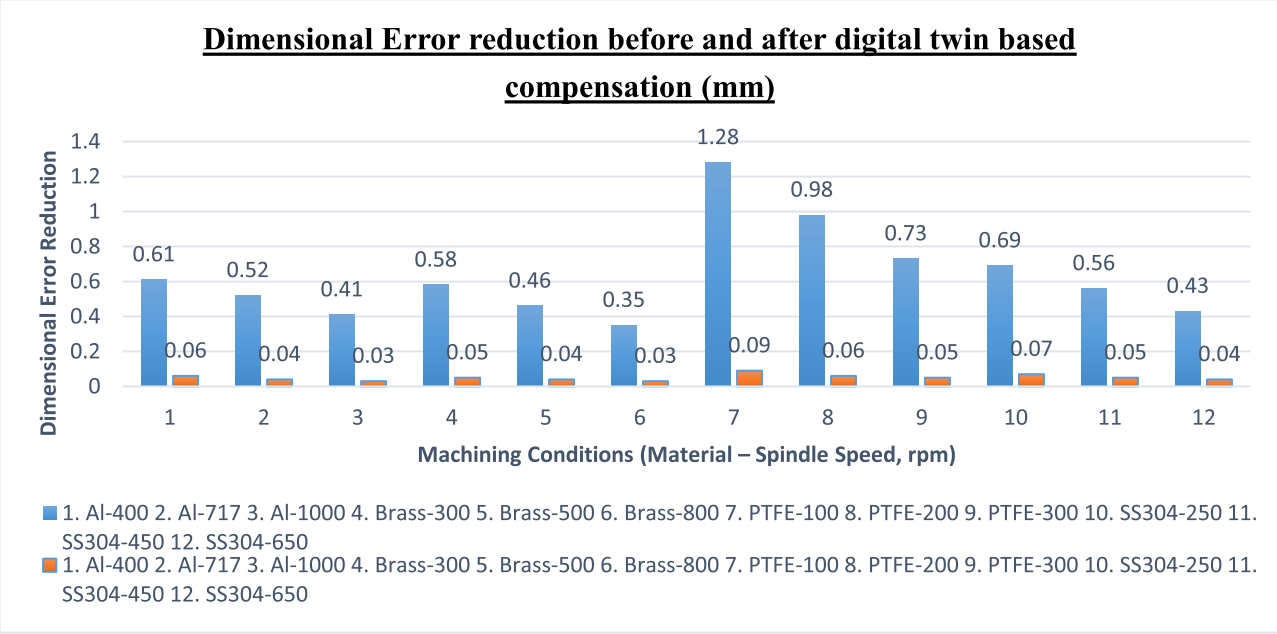


Fig. 9. Dimensional error before and after digital twin-based compensation.

Table 6. Experimental validation under different materials and variable spindle speeds.

Material	Spindle Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (mm)	Diameter Error Before (mm)	Diameter Error After (mm)	Surface Roughness Before Ra (μm)	Surface Roughness After Ra (μm)	Simulation Time Before (min)	Simulation Time After (min)
Aluminum 6061-T6	400	0.2	0.5	0.61	0.06	2.48	1.56	5.6	3.6
	717	0.2	0.5	0.52	0.04	2.22	1.36	5.1	3.1
	1000	0.18	0.4	0.41	0.03	1.94	1.18	4.6	2.8
Brass	300	0.18	0.5	0.58	0.05	2.36	1.48	5.4	3.5
	500	0.15	0.4	0.46	0.04	2.05	1.29	4.9	3
	800	0.12	0.3	0.35	0.03	1.72	1.1	4.4	2.7
PTFE (Teflon)	100	0.1	1	1.28	0.09	2.95	1.82	5.7	3.8
	200	0.1	0.8	0.98	0.06	2.46	1.55	5.2	3.3
	300	0.08	0.6	0.73	0.05	2.18	1.38	4.8	3
Stainless Steel (AISI 304)	250	0.15	0.3	0.69	0.07	2.88	1.72	5.9	3.9
	450	0.12	0.25	0.56	0.05	2.54	1.51	5.4	3.4
	650	0.1	0.2	0.43	0.04	2.16	1.31	4.9	3.1

Table 7. Comparison of dimensional error before and after digital twin-based correction under different machining conditions.

Material	Spindle Speed (rpm)	Error Before (mm)	Error After (mm)	Improvement (%)
Aluminum 6061-T6	400	0.61	0.06	90.16
Aluminum 6061-T6	717	0.52	0.04	92.31
Aluminum 6061-T6	1000	0.41	0.03	92.68
Brass	300	0.58	0.05	91.38
Brass	500	0.46	0.04	91.30
Brass	800	0.35	0.03	91.43
PTFE	100	1.28	0.09	92.97
PTFE	200	0.98	0.06	93.88
PTFE	300	0.73	0.05	93.15
Stainless Steel (AISI 304)	250	0.69	0.07	89.86
Stainless Steel (AISI 304)	450	0.56	0.05	91.07
Stainless Steel (AISI 304)	650	0.43	0.04	90.70

Table 8. Material and its statistical analysis values.

Material	Mean Before (mm)	Mean After (mm)	SD Before (mm)	SD After (mm)	SEM After (mm)	CV After (%)	Error Reduction (%)
Aluminum 6061-T6	0.513	0.043	0.100	0.015	0.009	34.9	91.6
Brass	0.463	0.040	0.115	0.010	0.006	25.0	91.4
PTFE	0.997	0.067	0.275	0.021	0.012	31.3	93.3
Stainless Steel (AISI 304)	0.560	0.053	0.130	0.015	0.009	28.3	90.5

Table 9. Repeatability analysis.

Material	Repeatability Before (mm)	Repeatability After (mm)
Aluminum	±0.200	±0.030
Brass	±0.230	±0.020
PTFE	±0.550	±0.042
Stainless Steel	±0.260	±0.030

It can be observed from Table 9 that a reduction in repeatability values after the digital twin-based correction provides a better machining value.

2.7.3. Measurement uncertainty analysis

The measurement was made with a vernier caliper with an accuracy of ±0.02 mm. In line with the Guide to the expression of uncertainty in measurement (GUM) guideline, the uncertainties were calculated as follows.

Type B Uncertainty (Instrument Resolution)

Assuming a rectangular probability distribution,

$$u_B = \frac{a}{\sqrt{3}} \text{ [37]}$$

Where, $a = 0.02\ mm$ Therefore,

$$u_B = \frac{0.02}{\sqrt{3}}$$

$$u_B = 0.0115\ mm$$

Type A Uncertainty (Repeatability)

The Type A uncertainty is obtained from repeated measurements.

For Aluminum,

$$u_A = \frac{SD}{\sqrt{n}} \text{ [37]}$$

$$= \frac{0.015}{\sqrt{3}}$$

$$= 0.0087\ mm$$

Combined Standard Uncertainty

The combined uncertainty is

$$u_c = \sqrt{u_A^2 + u_B^2} \text{ [37]}$$

Substituting the calculated values,

$$u_c = \sqrt{(0.0087)^2 + (0.0115)^2}$$

$$u_c = 0.0144\ mm$$

Expanded Uncertainty

Using a coverage factor

$$k = 2$$

the expanded uncertainty becomes

$$U = ku_c$$

$$U = 2\,(0.0144)$$

$$U = \pm 0.029\ mm$$

Thus, the dimensional measurements have an expanded uncertainty of

$$\boxed{\pm 0.029\ mm}$$

2.7.4. Error propagation analysis

The dimensional error is calculated as

$$E = D_m - D_n \text{ [37]}$$

Where, D_m = measured dimension D_n = nominal dimension.

The propagated uncertainty associated with the dimensional error is

$$u_E = \sqrt{u_{Dm}^2 + u_{Dn}^2}$$

Since the nominal CAD dimensions are considered exact, the uncertainty associated with the nominal value is negligible. Therefore,

$$u_E \approx u_{Dm}$$

Table 10. Measurement uncertainty summary.

Parameter	Value
Measuring Instrument	Vernier Caliper
Instrument Resolution	±0.02 mm
Type B Uncertainty	0.0115 mm
Type A Uncertainty	0.0087 mm
Combined Standard Uncertainty	0.0144 mm
Expanded Uncertainty (k = 2)	±0.029 mm

which gives

$$u_E = 0.0144\ mm$$

The expanded propagated uncertainty is therefore

$$U_E = \pm 0.029\ mm$$

Table 10 provides a parameter and its values using a vernier caliper with references to the uncertainty and combined standard uncertainty.

3. Results and discussion

The proposed digital twin-assisted CNC machining framework was experimentally validated through four machining experiments involving Aluminum 6061-T6, PTFE, Brass, and Stainless Steel (AISI 304). Experiments I and II are discussed as detailed case studies because they illustrate the complete methodology for digital twin implementation, defect diagnosis, and corrective actions. Experiments III and IV were conducted using the same digital twin workflow under different machining conditions to verify the robustness and repeatability of the proposed framework. Their quantitative results are summarized in Table 6–9 and are included in the statistical analysis. Quantitative analysis was performed to evaluate dimensional accuracy, simulation effectiveness, and process repeatability before and after implementing the digital twin framework.

In the digital twin scheme, the functions of the CAD/CAM simulation, the SIL verification, the HIL test, and the real-time machine parameter synchronization between the virtual and the physical machining processes were used. The machining parameters (spindle speed, tool offsets, feed rate, and drilling depth) were verified during machining processes.

3.1. CAD–CAM modeling and simulation outcomes

The EMCO Concept software provided accurate dimensional definition and geometric conformity to the specified design. The CAM-generated toolpath was verified through simulation to ensure error-free machining before actual manufacturing.

The simulation stage effectively identified potential tool–workpiece interactions and ensured collision-free machining along all axes: X, Y, and Z. Upon successful completion of the simulation, machining data were reliably transferred to the CNC system, forming a core component of the digital twin framework.

3.1.1. Physical–digital interface response analysis

The digital twin interface continuously compared the outputs of the virtual machining process with the real-time responses of the CNC machine in terms of machining parameters such as the speed of the spindle, feed rate, value of tool offset, positions of axes, and the depth of the hole being drilled. During Software-in-the-Loop (SIL) verification, the software environment accurately predicted potential collisions and verified dimensional accuracy. Input data were entered in the CAM module of EMCO Concept software, and the generated CNC program was transferred to the CNC machine for machining. The initial CAM inputs included a spindle speed of 717 rpm, a depth of cut of 0.5 mm, and a feed rate of 0.12 mm/rev for the facing and contour-turning operations.

For the drilling operation in Case study II, a 10 mm diameter drill bit was used. The total drilling depth was 10 mm, while the peck-drilling depth per pass was set to 1 mm. A dwell time of 5 ms was specified, and all machining parameters were entered into the software before generating the CNC program.

Offset compensation and toolpath modification enabled rapid correction by comparing the virtual model with the physical machining results. This closed-loop interaction between the physical and digital systems improved machining accuracy, reduced setup time, and minimized production errors.

3.2. Case study I: Dimensional accuracy improvement (Aluminum 6061-T6)

In Case Study I, dimensional error was found to occur in the stepped cylindrical component made using Aluminum 6061-T6. The average diameter error observed during the initial machining trials was approximately +0.50 mm, as the tool offset was miscalculated and there was misalignment along each axis.

Using digital twin-based simulation together with Hardware-in-the-Loop (HIL) validation, it was possible to determine the correct G56 offset and the SDJC tool parameters in addition to modifying the tool path based on the G56 offsets; the average diameter error was reduced to approximately 0.04 mm after performing three experiments under the same machining conditions to verify the repeatability. Calibration was performed using a microscope connected to the CNC

machine for more accurate results, and since it is proprietary technology on the EMCO machine, details are omitted. Additionally, contour turning-based optimization decreased the CAM simulation time from 5.0 to 3.0 minutes (approximately 40% reduction in simulation time) while retaining a comparable accuracy of the machining profile.

3.3. Case study II: Drilling process stability (PTFE)

In Case Study II, drilling offset error and tool collision during PTFE machining were studied through experiments. Although the CAM simulation showed correct tool alignment in the CAM simulation software, the actual machining process revealed offset error, which could be observed as the drill collided with the workpiece surface. After the physical CNC machine was linked with the digital model, the offset parameter errors of the physical machine were identified through synchronization with the virtual model. With the correction of the offset errors, the hole position error was decreased from 1.20 mm to 0.08 mm, hole depth error from 0.90 mm to 0.05 mm, and no tool collisions occurred during subsequent machining trials. In both case studies, it could be seen that through the application of the digital twin approach, the following advantages were achieved: Enhanced dimensional accuracy, identification and correction of defects during machining, reduction in production time, and improved reliability of CNC machining.

The results confirm that the use of digital twin simulation, as well as real-time validation, in CNC machining is a robust, cost-effective approach for the diagnosis of machining defects and the optimization of CNC machining processes for various materials.

The use of digital twin technology has proven to be extremely useful in offering a practical and economical means of attaining major industrial goals such as improving performance, optimizing operations, producing virtual representations, and ensuring product output alignment. Digital twins enable the simulation, monitoring, and assessment of numerous machining parameters, ensuring machinery efficiency and longevity while lowering costs and increasing accuracy. This approach uses real-time data to digitally recreate the physical system, allowing engineers and manufacturers to analyze, anticipate, and fine-tune machine operating performance prior to execution. Several evaluation areas must be addressed to provide better machine performance. These important focal areas are examined through case studies, demonstrating how digital twin technology enables more efficient machining operations.

3.4. Accurate data creation in real time

Digital twin technology is a valuable tool to analyze data for improving machining precision. Parameters such as spindle speed, feed rate, and infeed relief angle are important factors affecting tool wear and optimizing the machining system. These data factors are integrated into the Computer-Aided Manufacturing (CAM) application to set up an accurate illustration of real machining conditions.

During machining, visual verification is performed to ensure that the programmed spindle speed and feed rate are observed exactly. This validation ensures that the system operates within the predefined parameters, ultimately enhancing machining accuracy and efficiency. In the machining process, applying an infeed relief angle of 0.1 resulted in several advantages, along with prolonged device life and reduced heat generation for the duration of machining operations. Reduction in heat generation helped reduce tool wear at the cutting device, thereby reducing maintenance and sudden downtimes. Real-time tracking and usage analysis make the framework promising for use in predictive maintenance. Early fault detection prevents highly-priced breakdowns, ensuring that maintenance interventions are scheduled proactively rather than reactively.

The real-time machining data was captured by means of position feedback sensors attached to the CNC controller, at 100 ms intervals. All values regarding the spindle speed, axis position, and tool offset were synchronized in real time between the physical and the virtual model through the EMCO Concept interface.

3.5. Enhancement of performance and system improvement

Digital twin technology enhanced machining performance and overall machine efficiency. By optimizing device paths and simulating CNC (Computer Numerical Control) operations under real conditions, the machinist can select the most efficient machining strategy.

In case 1, two different contour turning strategies were simulated, and the optimal approach was chosen based on the minimum machining time. This choice manner enabled a less production time at the same time as maintaining machining precision and accuracy. The capacity to simulate various machining techniques before actual implementation eliminates trial-and-error experimentation, saving manufacturing material resources and decreasing the chance of mistakes.

Similarly, in case 2, overall performance enhancements were carried out by implementing a peck drilling cycle and editing tool distances using an offset value. The peck drilling cycle optimizes material elimination through allowing intermittent retractions of the drill bit, preventing too much heat buildup and improving chip evacuation. Additionally, increasing tool safe distances with an offset value optimized machining time whilst retaining high precision degrees. These upgrades collectively advanced standard overall performance and confirmed the effectiveness of digital twin technology in refining machining operations.

3.6. Efficiency of resources and cost-effectiveness

One of the greatest advantages of digital twin technology is its potential to provide a comprehensive visual verification of machining techniques. This capability helps reduce prototyping requirements and decreases reliance on traditional trial-and-error techniques. By leveraging virtual simulations, manufacturers can accurately predict machining results, thereby decreasing material wastage.

For all case studies, complete simulations were performed, which extensively minimized the real machining trials. The trial-based machining conserves raw materials and additionally lowers operational costs related to machine wear and tear. Furthermore, through figuring out capability machining errors earlier than physical execution, digital twin technology improves process reliability, leading to better productivity and cost savings.

The primary evaluation criteria discussed real-time data acquisition, overall performance enhancement, and resource efficiency have collectively contributed to expanded manufacturing and widespread enhancements in production time. Despite these improvements, there is still scope for further refinement to machining techniques via the incorporation of additional parameters.

3.7. Future improvements and research directions - Algorithms or computational techniques

Machine learning models like Support Vector Machines (SVM) and Random Forests are used to detect anomalies in real-time data streams. These models use both historical and live data to detect deviations from optimal operational parameters. Furthermore, statistical process control (SPC) techniques are used to assure consistent quality by monitoring data trends and setting control limits to detect abnormalities in machining performance.

To enhance the integration of digital twin technology in production applications, future studies must focus on the inclusion of floor roughness parameters in the course of machining simulations. Surface roughness significantly affects product performance with regard to quality, and optimizing this parameter can further improve machining accuracy. Incorporating surface roughness evaluation in digital twin technology will provide a better approach to technique optimization, ensuring that the very last products meet standard product output.

Additionally, future studies can explore the application of virtual twin technology with a broader range of machining parameters to develop specific operational measurements. By constantly monitoring and reading operational uptime, manufacturers can achieve extra consistency in product quality and maximize return on investment. The utilization of synthetic intelligence (AI) and machine learning (ML) algorithms within digital twin technology provides an enhancement for reliability and performance.

In the future, large industrial data generation and high volume of data loading within the digital twin environment can be further explored. As CNC machine systems continuously generate real-time sensor data concerning vibration, spindle current, temperature, feed rate, and machining force, acquisition and processing methods with high speed are needed. With the application of cloud computing platforms, edge computing environments, and big-data analytics frameworks integrated with the digital twin systems for scalability, real-time processing capability, and computational power efficiency, smart manufacturing applications can be strengthened.

3.8. Limitations of the present study

While the framework that was developed showed advancements in machining accuracy and process optimization, there are several limitations of the developed work. The developed framework has only been demonstrated for two laboratory-based CNC machining case studies, and has not yet been validated using large-scale industrial manufacturing data. Furthermore, the real-time data acquisition framework only utilizes limited sensor integration with moderate sampling frequencies, and does not currently implement advanced industrial communication protocols or utilize cloud synchronization or high-frequency sensor networks.

4. Conclusion

This research was able to contribute by focusing on a digital twin-based CNC machining system by

embedding CAD/CAM simulation, SIL verification, HIL synchronization, and real-time machining validation. In turning and drilling experiments, considerable improvement in dimensional accuracy, stability, and dimensional deviation was achieved, reducing it from approximately 0.50 mm to within 0.05 mm tolerance limits, while simulation time was reduced by approximately 40% when optimized contour turning strategies were utilized for time reduction. This experiment results verify that the proposed digital twin-based machining verification system greatly improves machining reliability, setup accuracy, and machining efficiency in the application of smart manufacturing. Although issues in sensor integration and the laboratory environment are limitations of this work, a solid foundation for future work, including AI-aided machining optimization, predictive maintenance, and large-scale industrial digital twin application, is laid down.

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Conflicts of interest

The author declares that there are no conflicts of interest.

Author contribution

Anand Valiavalappil solely contributed to the conceptualization, methodology development, investigation, software simulation, case study execution, data analysis, visualization, manuscript writing, review, and final approval of the submitted manuscript.

Data availability

The author confirm that the data supporting the findings of this study are available from the corresponding author upon reasonable request.

The author declare that this manuscript is original, not under consideration elsewhere, and approved by author. There are no conflicts of interest and no external funding was received. Data supporting the findings of this study are available from the corresponding author upon reasonable request. Ethical approval was not required as the study involved no human or animal subjects.

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